ANALYSIS OF RAINFALL TREND AND ITS IMPACT ON FUTURE HYDROPOWER GENERATION - CASE STUDY ON VICTORIA RESERVOIR

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Degree of Master of Science

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August 2021

DECLERATION

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ABSTRACT

Analysis of Rainfall Trend and Its Impact on Hydropower Generation

- Case Study on Victoria Reservoir

Mahaweli river basin is the major river basin for hydropower generation in Sri Lanka and it supplies about 1800 GWh annually to the national grid, but the expected generation is about 2400 GWh (2019). The annual hydropower generation in Sri Lanka is decreasing and the contribution of other nonrenewable sources are continuously increasing accordingly. There are eight reservoirs in the upper catchment of Mahaweli Basin which generate hydropower under the Mahaweli Complex. These reservoirs experience both drought periods and high flood periods as well throughout the year. As hydropower generation totally relies on the rainfall amount of the sub-catchment of the reservoirs, the planned hydropower generation cannot be achieved during the drought periods due to the failure in receiving expected rainfall to the sub-catchments of reservoirs. Hence, identifying the rainfall pattern, its peaks and troughs, and possible trend in future rainfall are crucial for managing and optimizing the reservoir operations such that hydropower generation can be maintained at the maximum possible capacity

This study is focused on the analysis of rainfall trends in the upper catchment of Mahaweli Basin and its impact on hydropower generation in Victoria reservoir according to the possible variations in future rainfall. The rainfall trend was analyzed for the Mahaweli Upper catchment considering rainfall data of seven rainfall stations with 30 years of monthly rainfall data. The base period for rainfall trend analysis was selected from the year 1981 to 2010 as per World Meteorological Organization (WMO) guideline. The missing rainfall data in selected rainfall stations were filled with the linear regression method. Rainfall trend was analyzed with the Mann Kendall test and the magnitude of the trend was estimated by Sen's Slope method which were performed using RStudio Software. According to the trend analysis, the rainfall trend is negative in dry periods and a positive trend is observed in rainy seasons and the negative trend is higher than the positive trend. It could be expected that dryer periods getting dryer with a high degree of variation and rainy periods getting even more rainfall to a lesser degree. This implies that overall annual rainfall has a negative trend in the study area. The future rainfall was estimated for further 30 years from 2020 to 2050 as monthly data with parameters obtained from Sens' slope method and Mann Kendall test. The average annual rainfall was about 2,390 mm in the study area for the selected base period and the estimated future mean annual rainfall for next 30 years will be around 1973 mm with a decrease of 18% compared to the last 30 years.

The catchment runoff was calibrated for Victoria reservoir with HEC HMS model for the five years from 2001 to 2005 and the model was validated for the period 2006-2010. The future inflows were predicted for the period 2021 - 2025 with generated monthly future rainfall data. The future annual inflow of Victoria reservoir in next 5 years will be reduced by 10% compared to recent 5 years of inflows of Victoria reservoir. The HEC ResSim model was developed and applied for Victoria reservoir to obtain the potential power generation and the analysis of reservoir operations of Victoria reservoir. HEC ResSim model was calibrated with reservoir operational data in the year 2015 and validated with reservoir operational data in the year 2016. Future power generation was obtained for the time period of 2021 - 2025. It was found that the future annual power generation of the Victoria power plant will be reduced by 23% compared to the last five years due to the predicted decrease in rainfall. This future scenario was analyzed based on monthly data, hence the peak events were not taken into account. Since the hydropower generation in the Victoria reservoir is decreased yearly, optimization of reservoir operations is necessary considering the variation of future rainfall trends.

Keywords: Catchment runoff, HEC ResSim, Mann Kendall, Reservoir simulation

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LIST OF ABBREVIATIONS

BBS	:	Block Bootstrap
CN	:	Curve Number
DEM	:	Digital Elevation Model
Est	:	Estimated
GIS	:	Geographic Information System
GWhr	:	Giga Watt hours
HEC HMS	:	Hydrologic Engineers Center - Hydrologic Modeling System
IPCC	:	Intergovernmental Panel on Climate Change
LR	:	Linear Regression
MAR	:	Missing at Random
MCAR	:	Missing completely at Random
MCM	:	Millions of Cubic Meter
MK	:	Mann Kendall
MLR	:	Multiple Linear Regression
MSL	:	Mean Sea Level
MW	:	Mega Watt
NCAR	:	Not Missing at Random
NSE	:	Nash – Sutcliffe Efficiency
Obs/ Ob	:	Observed
RF	:	Rainfall
RMSE	:	Root Mean Square Error
SCS	:	Soil Conservation Service
T_c	:	Time of Concentration
WMO	:	World Meteorological Organization

LIST OF APPENDICES

1 INTRODUCTION

Mahaweli river basin is the major river basin in Sri Lanka which contributes to the Sri Lankan economy in several disciplines. The basin area is about 10,924 km^2 and Mahaweli river is the longest river in Sri Lanka with a length of 335 km. Mahaweli Master plan was implemented as a multipurpose irrigation and hydropower project in 1970s. There are eight reservoirs constructed for power generation and irrigation purposes under the Mahaweli Complex with an installed capacity of 815.2 MW (Annual Report, CEB, 2016). The upstream of Mahaweli basin consists of five (5) major reservoirs, namely Kothmale, Polgolla, Victoria, Randenigala and Rantambe. The present study is based on the rainfall trend and power generation of Victoria Reservoir. The study area considered is from the upstream area of Mahaweli basin up to the Victoria reservoir for rainfall trend analysis and the impact on power generation was analysed for Victoria reservoir. There is a considerable variation in rainfall trend globally due to rapid climate change in the world. Accordingly, this study is based on the impact analysis of rainfall trend on hydropower generation of Victoria power plant.

1.1 Background

Climate change impacts are known to trigger changes in precipitation, temperature, wind condition, groundwater table, snow melting, ocean level and atmospheric conditions. Recently, rapid climate changes are observed spatially and temporally in many parts of the globe (IPCC, 2014). These rapid climate changes mainly occur due to human activities with rapid developments and those impact on all living beings. The changes in precipitation and atmospheric temperature are the most sensitive parameters which are highly detrimental to the world. Abrupt changes in precipitation temporally and spatially cause water scarcity and flood conditions. That results in dry periods and dry zones getting dryer quantitatively, spatially and temporally, while the wet seasons and wet zones getting more rainfall in return. Hence, the climate change issues are getting worse day by day all over the world.

In Sri Lanka too, it is experienced that the dry periods are getting more dryer while wet periods are getting wetter. This affects the water related industries in the country such as hydropower generation and agricultural activities which highly rely on irrigation water or seasonal rainfall. The quantitative changes in precipitation pattern both spatially and temporally highly affect the hydropower generation in Sri Lanka. In other countries, the contribution of hydropower generation to the national grid is about 75% of the total generation. But in Sri Lanka, it is merely about 24.5% of total generation (in the year 2016) due to water scarcity (Annual Report, CEB, 2016).

There are three main sources used to generate electricity in Sri Lanka, which are hydropower, fuel and coal. Apart from those, there is a moderate trend to use solar power and wind power systems to generate electricity in Sri Lanka. Among the above three major sources, hydropower is the only renewable source, which sustainable and eco-friendly. Further, the operational cost is lower than that of the other two major sources. However, due to water scarcity and unreliability of rainfall pattern, hydropower generation is recently decreased and the power generation by the other two major sources is increased. In 2016, the hydropower generation is 24.5% with coal - 35.6% and fuel - 31%, while in 2015, the hydropower generation is 38% and power generation from other two major sources were 34% and 17% of total generation, respectively (Figure 1-1) (Annual Report, CEB, 2016). Even though water scarcity is an issue, it is advisable to take actions to increase hydropower generation as it is a renewable source with low operation cost, eco-friendly and sustainable. Accordingly, it is required to analyse the rainfall trend in future and foresee how it affects the future hydropower generation and how far it could fulfil the future power requirement by optimizing the hydropower generation.

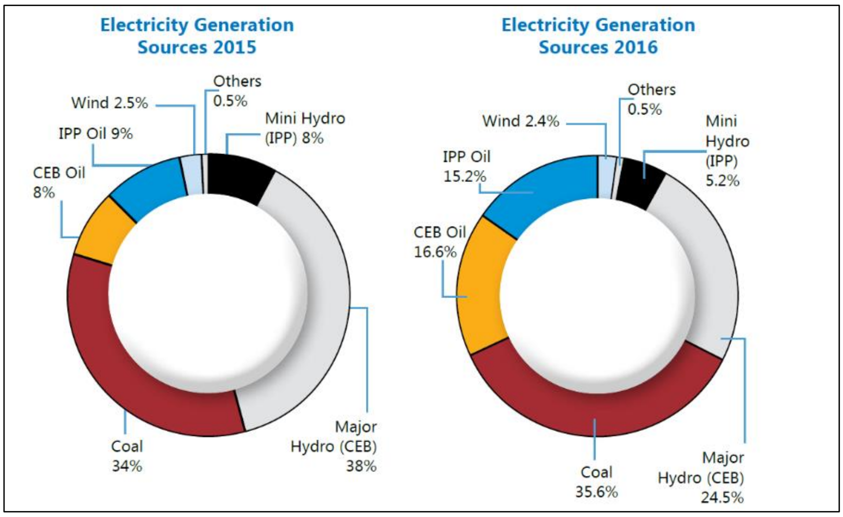


Figure 1-1 Comparison of Contribution of Electricity Sources in Year 2015 and 2016 (Annual Report, CEB, 2016)

Victoria reservoir belongs to the Mahaweli river basin and Victoria powerstation is the largest power plant in Mahaweli Complex which is located at Theldeniya, Kandy. It has 210 MW installed capacity by three numbers of 70 MW turbines. The annual power generation of the Victoria power plant is about 589 GWh (Annual Report, CEB, 2016). Victoria reservoir has a full capacity of 720 MCM and a surface area of about 27 km^2 at its Full Supply Level (FSL) of 438 m MSL. Victoria Dam is a concrete double-curved arched dam with eight spillways.

1.2 Problem Identification

Climate change has induced to reduce the renewable surface water and groundwater resources in most dry subtropical regions and increase the competition for water (IPCC, 2014). Generally in Sri Lanka, the annual rainfall and seasonal rainfall trend are highly varied spatially, temporally and quantitively. This variation is highly affected the hydropower generation in Sri Lanka. Therefore, many hydropower stations can not achieve their target supplies to the national grid due to scarcity of water during the drought period.

This study addresses the impact on future hydropower generation due to future rainfall trend. The study is carried out as a case study based on Victoria reservoir, power plant and the upper catchment of Mahaweli basin focusing on the drought period, during which the reservoir capacity is at a very low level and it is unable to supply the required discharge to generate hydropower. Based on this, the future rainfall trend and magnitude are analyzed to find out its impact on hydropower generation.

1.3 Objectives

1.3.1 Overall Objective

The overall objective of the research is to study the rainfall trend in the upper catchment of Mahaweli basin and its impact on future hydropower generation of Victoria reservoir by performing catchment modelling and reservoir simulation for Victoria reservoir.

1.3.2 Specific Objectives

a. Reliability analysis of available data by data checking and filling of missing daily rainfall data using Regression method or any other suitable approach

b. Analysis of rainfall trend in the upper catchment of Mahaweli basin using modified Mann Kendall Test – package Block Bootstrap (BBS)

c. Estimating the magnitude of rainfall trend using Sen’s Slope method – package Zyp Sen

d. Catchment modelling, observing catchment characteristics and estimating HEC HMS parameters for upstream of Mahaweli basin – Arc GIS, Arc tool and HEC Geo HMS tool

e. Estimating of catchment runoff volume of sub-catchments in Victoria Reservoir

f. Analysis of future inflows to the Victoria reservoir with estimated future rainfall data – HEC HMS

g. Performing reservoir simulations, modelling reservoir operations of Victoria reservoir and modelling the hydropower generation of Victoria power plant – HEC ResSim

h. Analysis of impact on future hydropower generation due to rainfall trend and deriving recommendations

1.4 Study Area

This study is carried out for the Mahaweli upper catchment which is in Kandy and Nuwara Eliya districts in upcountry of Sri Lanka (Figure 1-2). Mahaweli basin is the largest river basin (10,924 km^2) and Mahaweli river is the longest river (335 km) in Sri Lanka. The study area is bounded to the Mahaweli upper catchment area (catchment area is 1,897 km^2) which consists of four major reservoirs, namely Kothmale, Upper Kothmale, Polgolla and Victoria, which contribute to hydropower generation and irrigation works in intermediate and dry zone area. The selected upper catchment area is divided into eight (8) sub-catchments for catchment modelling.

Mahaweli basin is spread over three climate zones such that the upstream part in the wet zone, and downstream in both intermediate and dry zones. Accordingly, the rainfall pattern over the basin is highly varied. The study area is upstream of Mahaweli basin which is in the wet zone and the Victoria reservoir is located in the interchange area of the wet zone to the intermediate zone.

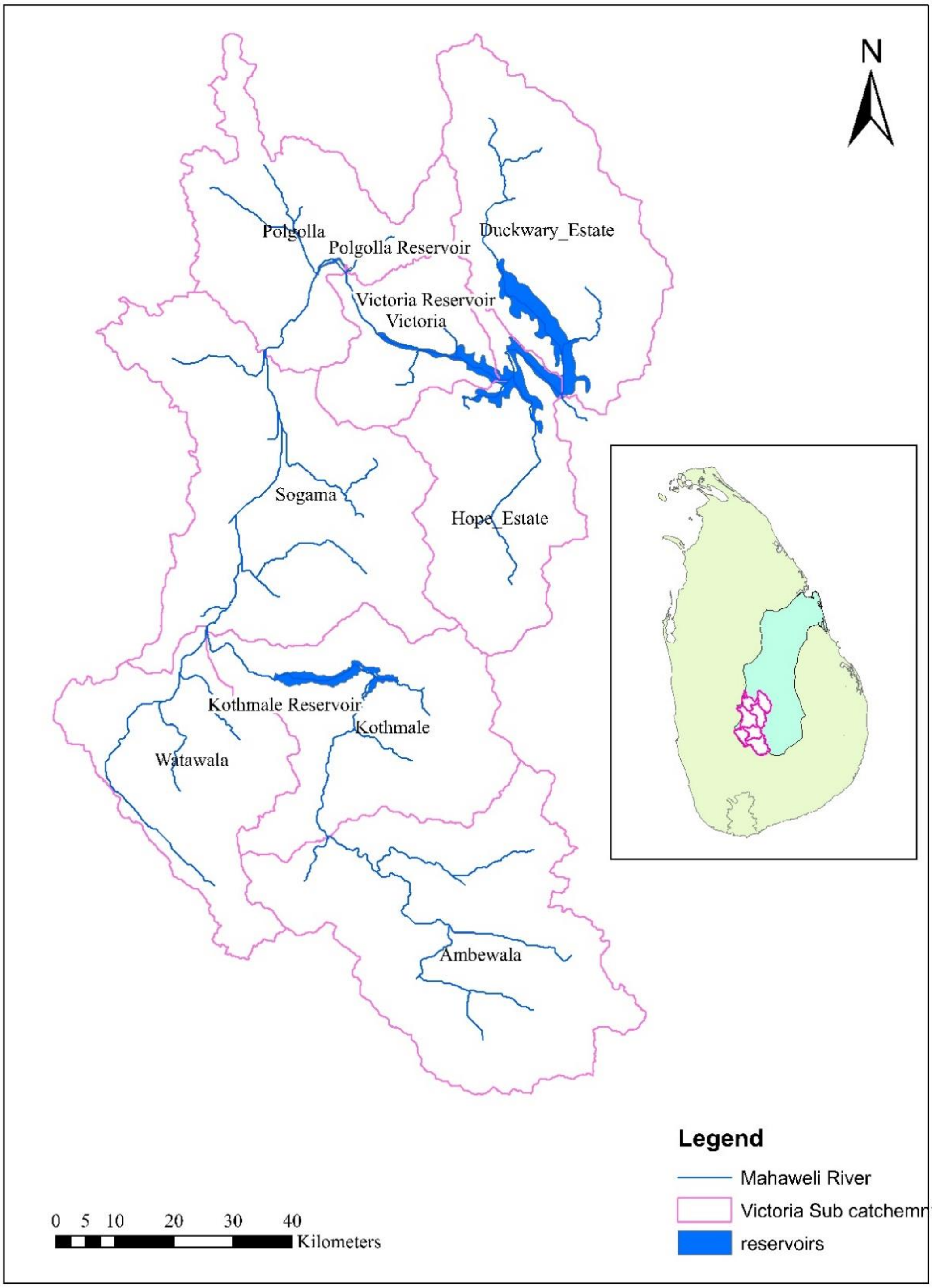


Figure 1-2 Location Map of Mahaweli upper catchment

1.5 Research Outline

Rainfall trend analysis was carried out for the study area by performing the Modified Mann Kendall Test and the magnitude of the trend was obtained by Sen's slope method by means of R software. The rainfall trend was analyzed for 30 years of monthly rainfall data from 1981 to 2010 and the future rainfall was estimated for further 30 years from 2020 - 2050.

Catchment modelling was carried out with Arc Hydro Tool (ESRI, USA) and HEC Geo HMS (US-ACE, USA) tools in ArcGIS (ESRI, USA) and runoff volume to the Victoria reservoir was obtained from HEC HMS model (US-ACE, USA). The hydrological modelling was performed to obtain the inflow of Victoria reservoir, calibrating with 5 years of monthly rainfall data (from 2001 - 2005) and validating with monthly data from 2006 - 2010. Then the future inflow of the Victoria reservoir was estimated for the years 2021-2025.

The reservoir operations and power generations were analyzed with HEC ResSim software (US-ACE, USA). The model calibration was performed for the year 2015 and validated for the year 2016 with reservoir operations and power generation data of Victoria reservoir. Future power generation was obtained from HEC ResSim software for the years 2021-2025 with estimated future inflows. Accordingly, the impact of future rainfall trend on future hydropower generation was analyzed.

1.6 Data Requirement and Data Collection

This research is mainly based on rainfall data, catchment characteristics, reservoir operations and hydropower generation of Victoria reservoir. Accordingly, data requirement was found out mainly from literature surveying data. Daily rainfall data were collected for 30 years from 1981 to 2010 for rainfall trend analysis (WMO, 2008). Catchment characteristic data, reservoir operational data and hydropower generation data were also collected (from 2001 - 2018) from relevant agencies for catchment modelling and reservoir simulation.

1.7 Scope of the Study

The study was focused on rainfall trend analysis using 30 years of historical data (WMO, 2008) and future hydropower generation. Accordingly, the study area was selected as the Mahaweli Upper catchment area for trend analysis and future hydropower generation was modelled only for Victoria reservoir considering the feasibility of the study with available data and methodology.

The trend analysis was performed considering the base period as for 30 years data from the year 1981 to 2010. The most recent base period is 1991-2020 as the base period was updated every 10 years. But that adjusted time period would be used from the year 2021 (WMO, 2008). Accordingly, rainfall data were collected from the year 1981 to 2010 for rainfall trend analysis.

The trend analysis was carried out using Mann Kendall test and the magnitude of the trend was calculated from Sen's slope method. The trend analysis and magnitude were calculated with monthly data since Mann Kendall test could be applied assuming the trend is monotonic; hence, if we need to perform the test for daily data, the test has to be repeated for 365 times as the test has to be performed separately for each day. Since it is not practical, the test was performed monthly for each month. Accordingly, the future rainfall was estimated on monthly basis.

It is better to use daily rainfall data for runoff modelling in HEC HMS since peak rainfall events are omitted when using monthly values. Consequently, it results in missing peak runoff (inflows) events of the catchment (Hua & Chi, 2014). Since the estimated rainfall was obtained as monthly data, the peak runoff, peak inflows were omitted and therefore peak power generation events were also omitted. Therefore, it could not be analyzed for the extreme events in this study.

The trend analysis was performed for the whole upper catchment of Mahaweli upstream area considering seven sub-catchments. The future rainfall trend was also estimated for these seven sub-catchments. However, the runoff modelling and reservoir operation modelling were carried out only for Victoria reservoir, because this study was only focused on hydropower generation of Victoria reservoir. The catchment model was carried out to obtain the inflows to the Victoria reservoir. The inflows to the Victoria reservoir from downstream of Polgolla reservoir and from the direct sub-catchments of Victoria, Hopes Estate and Duckwary Estate. Since the downstream release of Polgolla Barrage is known, it is unnecessary to consider the other upper catchment reservoirs of Kothmale, Upper Kothmale and Polgolla reservoirs.

2 LITERATURE REVIEW

This study is mainly focused on rainfall trend analysis, Data checking, catchment modelling, reservoir simulation, analysis of the impact on hydropower generation due to rainfall variation and Mahaweli upper catchment and its reservoirs. The literature reviews were carried out based on these topics.

2.1 Data Checking and Filling Missing Data

The observed data should be subjected to a checking process to make sure its consistency, reliability, homogeneity and accuracy. There may be data errors or missing data in a raw data set due to some reasons such as human errors, data unavailability, instrumental errors, etc. However, it is important to take a complete continuous data set for any data analysis otherwise the results will give errors or inaccurate outcomes or biased results. Therefore, data checking must be carried out for all observed data before analyzing to check whether there are any missing data or data errors in the data set.

There are two types of tests to check the consistency and homogeneity of the observed data set which are parametric tests and non-parametric tests. If the data set is normally distributed, parametric tests can be used while non-parametric tests could be used for non-normally distributed data sets. Following tests can be used for data checking for hydrological time series data (Wijesekera & Perera, 2016).

a. Visual examination of data

b. Outlier testing

c. Homogeneity testing (test for serial correlation, pre-whitening, normality, double mass analysis etc.)

There can be missing data in an observed data set due to various reasons such as human errors, data recording difficulties, etc., but for data analysis, it is required a continuous data set. Therefore, it is very important to fill missing data in a data set even it is extremely difficult. The problem is how to recover missing data since it is deemed to be impossible to recover the actual missing values. The other issue is the selection of correction and suitable recovery approach and identification of the missingness mechanism. When filling in missing data, two basic assumptions are taken into consideration regarding the data set (Hasana & Croke, 2013). Those are;

a. The rainfall data of the missing period have similar statistical properties to the data from available periods.

b. Spatial correlations exist among rainfall occurrence and amounts of neighbouring stations.

There are three data missingness mechanisms (Presti, Barca, & Passarella, 2010).

a. Missing completely at Random (MCAR)

   The missingness mechanism does not depend on the variable under investigation or any other variable, which is observed in the data set. This rigorous assumption is considered for the application of a case deletion procedure, but it must be underlined that missing data is very rarely MCAR in practical application.

b. Missing at Random (MAR)

   Data is missing, but conditioned by some other variable observed in the data set, i.e. other than the variable under investigation.

c. Not Missing at Random (NCAR)

   Missingness mechanism depends on the actual value of missing data. This is the most difficult condition to model.

It is considered that the missingness mechanism for daily rainfall data is Missing at Random (MAR). The regression method could be used for filling missing data for which the missingness mechanism was MAR (Presti, Barca, & Passarella, 2010).

Regressive techniques applied in filling missing daily rainfall data series include simple substitution, parametric regression, ranked regression and Theil method (Hasana & Croke, 2013). Linear regression method is an approach for modelling the relationship between scaler dependent variable y and one or few independent parameters denoted x_1, x_2, … and x_n. There are two approaches in the regression method, first one is Linear Regression (LR) method which has one independent variable while the other one is

Multiple Linear Regression (MLR) method which has two or more independent variables. The MLR identifies the best weighted combination of independent variables to predict the dependent or criterion variable V_o (Eq 2.1) (Sattari, Joudi, & Kusiak, 2016) as per:

$$\mathbf{V_o} = \mathbf{a_0} + \sum_{\mathbf{k=1}}^{\mathbf{n}} \mathbf{a_k}\,\mathbf{V_k} \qquad \textit{-Eq 2.1}$$

where a_1, a_2,… a_k ,….a_n are regression coefficients, a_0 is a constant and V_k are the independent variables.

This equation is simplified the form of $y = mx + c$,

where, $\mathrm{mx} = \sum_{\mathrm{k=1}}^{\mathrm{n}} \mathrm{a_k}\,\mathrm{V_k}$ and $\mathrm{c} = \mathrm{a_0}$

2.2 Rainfall Trend Analysis

Rainfall vary with time and variation is dependent on temperature, seasonal trends, anthropogenic activities, natural causes, etc. The variation of rainfall may be having a pattern over time yearly, monthly or seasonally. This pattern or trend can be detectable by parametric or non-parametric procedures. The trend analysis consists of estimating the magnitude of the trend and its statistical significance. Statistical significance of trend can be examined by Mann Kendall test while the magnitude of trend is estimated by non-parametric test called Sen’s Slope method (Fiaz, Ghulam, & Waseem, 2015).

2.2.1 Mann Kendall test

The purpose of the Mann Kendall (MK) test is to statistically assess if there is a monotonic upward or downward trend of the variable of interest over time. A monotonic upward (or downward) trend means that the variable consistently increases (decrease) through time, but the trend may or may not be linear. The MK test can be applied for parametric regression analysis, which can be used to test if the slope of the estimated linear regression line is different from zero. The regression analysis requires that the residuals from the fitted regression line to be normally distributed; an assumption not required by the MK test, that is the MK test is a non-Parametric (distribution free) test (Visual Sample Plan (VSP), n.d.).

The Mann Kendall test is mostly used to check the null hypothesis of no trend versus the alternative hypothesis of the existence of monotonic increasing or decreasing trend of hydroclimatic time series data (Fiaz, Ghulam, & Waseem, 2015).

If $(y_j - y_i) > 0$,

$$S = \sum_{i=1}^{n-1} \sum_{j=i+1}^{n} sgn(y_j - y_i) \qquad \text{- Eq 2.2}$$

The MK test statistic (Eq 2.2) computes the number of positive differences minus the number of negative differences. If the statistic *S* is a positive number, the observations obtained later in time tend to be larger than observations made earlier. If *S* is negative, the observations obtained later in time tend to be smaller than observations made earlier (Visual Sample Plan (VSP), n.d.). Accordingly, if *S* is positive, it indicates an upward trend in time series data and if *S* is negative, it indicates a downward trend in time series data (Khaliq, Ouarda, Gachon, Sushama, & St-Hilaire, 2009).

For *N* >= 8, the statistic *S* is approximately normally distributed with the mean (Eq 2.3) and variance (Eq 2.4) (Khaliq, Ouarda, Gachon, Sushama, & St-Hilaire, 2009) as,

$$E[S] = 0 \qquad \text{- Eq 2.3}$$

$$Var\ (S) = {[N(N\text{-}1)\ (2N+5)\ \text{-}\ \sum_{i=1}^{n} t_i\, i(i-1)(2i+5)]}/{18} \qquad \text{- Eq 2.4}$$

where t_i is the number of ties of extent *i* (that is the number of data in the tied group) and *n* is the number of tied groups. The standardized test statistic *Z* is computed by equation (Eq 2.5),

$$Z = \begin{cases} {(S-1)}/{\sqrt{Var(S)}}, & S > 0 \\ 0, & S = 0 \\ {(S+1)}/{\sqrt{Var(S)}}, & S < 0 \end{cases} \qquad \text{- Eq 2.5}$$

At α_L (where L stands for Local) significance level, the null hypothesis of no trend is rejected if the absolute value of $|Z|$ is greater than the theoretical value of $Z_{1-\alpha L/2}$ (Drápela & Drápelová).

The most of studies that investigated trends in time series of hydrological variables assumed that the recorded observations to be serially independent. The existence of positive serial correlation within a time series increases the possibility of the null hypothesis of no trend being rejected while the null hypothesis is actually true. Similar to the effect of serial correlation on the outcome of the tests, the presence of positive cross-correlation within a stream gauging network or within a hydrological homogeneous region will increase the possibility of the null hypothesis of no field significance of identified trends being rejected. The field significance analysis of identified trends helps to ascertain whether the stations identified with significant trends at local scales are real or just coincidental because of cross-correlation among the set of stations studied. In spite of these important issues, trend identification tests are still commonly used but without due consideration of the effects of serial and cross-correlations for evaluating the local and field significance respectively (Khaliq, Ouarda, Gachon, Sushama, & St-Hilaire, 2009).

When performing Mann Kendall test, it gives following outputs:

a. Kendall tau statistic - *Tau*

b. Two-sided *P* Value - *P* value (This is the significant level of the time series and it should be < 5%, that is the time series should achieve more than 95% of significance level)

c. Kendall Score - *S* (shows whether trend is upward ((+) value) or downward ((-) value))

d. Standard test statistic - *Z* (at α level of significance, H_0 is rejected if $|Z| > Z_{1-\alpha/2}$ where the $Z_{1-\alpha/2}$ is obtained from the standard normal cumulative distribution table)

2.2.2 Sen’s Slope method

Sen’s slope method is a non-parametric method which is used to estimate the magnitude of trend in the time series data. Sen’s slope method is used for linear models for trend analysis to estimate the slope (T_i) of all data pairs (Eq 2.6) (Fiaz, Ghulam, & Waseem, 2015) as:

$$T_i = \frac{x_j - x_k}{j-k} \qquad for\ i = 1, 2, 3, \ldots \ldots \ldots n \qquad \text{- Eq 2.6}$$

where x_j and x_k are data values at time j and k ($j > k$), respectively. The Sen's slope of estimation (Q_i) (true slope) is considered as the median value of T_i (Eq 2.7). Sen's slope value depends on the value of n which is either odd or even. This Sen's slope value is calculated with *100 (1-α) %* confidence level using non-parametric test depending upon normal distribution. The positive value of Q_i indicates an upward trend while the negative value of Q_i indicates a downward trend (Fiaz, Ghulam, & Waseem, 2015).

$$Q_i = \begin{cases} T_{\frac{n+1}{2}}, & \text{for n is odd} \\ \frac{1}{2}\left(T_{\frac{n}{2}} + T_{\frac{n+2}{2}}\right), & \text{for n is even} \end{cases} \qquad \text{-Eq2.7}$$

2.2.3 Modified Mann Kendall test

If the time series is serially correlated, the Mann Kendall test cannot be used without any modification. It has to be done in conjunction with the Block Bootstrapping method in order to account for the serial correlation present in the precipitation data. The presence of serial correlation among monthly rainfall level can be investigated by checking with autocorrelation (*acf*) and partially correlation (*pacf*) function in R. If the calculated correlation of monthly data is within the autocorrelation boundaries given by R functions, then the time series do not appear to be significant, and Mann Kendall test can be carried out without any modifications (Mann-Kendall Trend Test in R , n.d.)

If the autocorrelation of the time series of monthly rainfall levels has revealed the presence of significant temporal dependency in the data across years, a modified Mann Kendall test can be used with the conjunction of the Block Bootstrap method. Further, if the *P* valuewhich is given from the Mann Kendall test is higher than 5%, then this Block Bootstrap method can be used by giving the significant level of 95% in the program.

To incorporate the effect of serial correlation, a block resampling approach specified as Block Bootstrap (BBS) can be used. In this approach, the original data is resampled in predetermined blocks for a large number of times to estimate the significance of the observed test statistic, i.e. the MK test S and Sen's Slope (SS) trend magnitude b_{sen}. The block size depends upon the number of contiguous significant serial correlations. The important fact in this method is that this method does not involve modification of the original data (Khaliq, Ouarda, Gachon, Sushama, & St-Hilaire, 2009).

The steps in the BBS method are estimating the test statistic of the selected trend identification test from original time series, estimating the number of significant contiguous serial correlation k, resampling the original time series in blocks of $k+\eta$ for a large number of times while estimating the trend identification test statistic for each simulated sample in order to develop a simulated distribution of the test statistics and estimating the significance of the observed test statistic estimated in 1st step from the simulated distribution developed in the third step. If the original test statistic lies in the tails of the simulated distribution, then the test statistic is likely to be significant. That is a temporal trend more likely to be present in data. The whole time series is resampled as one block and that is an unrealistic value for resampling. A trial-and-error approach is needed to estimate a near optimum value for η it could be considered as $\eta = 1$.

The Trend analysis was carried out on R Studio platform in which the R Studio is an integrated development of "R" which is a programming language for statistical computations. The trend analysis is carried out with "Kendall", "Modifiedmk" and "Zyp" packages in R Studio for following statistical computations (R Studio, Help, n.d.).

a. Package "Kendall" – Compute Kendall's rank correlation and various trend tests

b. Package "Block Bootstrap (BBS)" – Analysis trend incorporate with Mann Kendall trend test when the significant serial correlation present in time series.

c. Package "Zyp" – Computes the Thiel-Sen estimate of slope for vector data, which gives the intercept and slope of the graph of time series data.

2.3 Catchment Modelling on ARC GIS

Catchment modelling and hydrological modelling is carried out by HEC HMS with Arc GIS software. Extension of Arc Hdro Tool in Arc Map is used to processing of Digital Elevation Model (DEM), defining stream network, topography and watershed characteristics (Abdessamed, Abderrazak, & Kamila, 2018). HEC-GEO HMS is a tool to process hydrological parameters of the catchment from the processed model from Arc Hydro tool. HEC_GEO HMS is used to derive river network, creating drainage network by analyzing the digital terrain data and transforming the drainage paths and watershed boundaries into a hydrological data structure to represent the drainage network (Salwa Ramly, authorWardah Tahir, 2016).

2.4 Hydrological Model with HEC HMS

HEC HMS is used to simulate the hydrological process of the watershed system. This is a mathematical model which simulates precipitation runoff and routing process in a natural or controlled watershed. The spatial data from HEC HMS is imported to HEC HMS platform, and the model computes the outflows of the basins. There are three main basin models in HEC HMS which are basin model, meteorological model and control specification. The basin model which produces the stream flow by means of atmospheric conditions. The basin model consists of the basin and sub-basins, the connectivity and runoff parameter. The main purpose of the meteorological model is to prepare meteorological boundary conditions of the created basin model. The meteorological model consists of rainfall and evaporation data. The start/end timing and calculation interval for the run are specified in the control specification (Salwa Ramly, authorWardah Tahir, 2016).

2.4.1 Basin model

Basin model describes the physical properties of the watershed and the topology of the stream network. In addition to that, it contains components of engineered structures such as diversions, reservoirs and etc. The basin model contains modelling components in the watershed such as local flow, flow ratio, canopy interception, surface storage, infiltration, surface runoff, base flow and channel routing.

a. Local flow

Local flow means the sum of all sub-basin and source outflows to the junction.

b. Flow Ratio

Flow ration is used to decreased or increased the computed flow by a fixed ratio.

c. Canopy method

Canopy method describes the presence of plants in the landscape which computes the evapo-transpiration of the sub-basin. There are three methods for canopy methods which are Dynamic method, Gridded simple method and Simple canopy.

d. Surface method

This component represents the ground surface condition where water may accumulate in surface depression storage. The depression storage is zero for impervious surface and it will be high for agricultural field and forest areas where conservation tillage is practised. Surface method can be applied in two methods such as Gridded simple surface and simple surface method.

e. Loss Method

Loss method provides to calculate the actual infiltration contained within the sub-basin. There are twelve different methods given in HEC HMS to calculate the infiltration. Some of the methods are designed for simulating events and continuous simulations. Among them SCS (Soil Conservation Service) curve Number Loss is used as the Loss method since it requires the initial abstraction, curve Number and impermeability of the soil. The SCS curve number represents the combination of a different soil group and land use in the sub-basin. The curve Number is defined except impervious areas and impervious areas are defined as a percentage of impervious area. No losses calculate in impervious areas and all precipitation on impervious areas are converted to excess precipitation and subject to direct runoff.

2.4.2 Time of concentration

There are few definitions for the time of concentration (T_C), and the most commonly used definition is the physical based definition of T_C which is the time required for runoff, as a result of effective rainfall, with a uniform spatial and temporal distribution over a catchment, to contribute to the peak discharge at the catchment outlet. There are several methods to calculate the time of concentration developed by several researchers such as Kerby method, SCS method, NRCS velocity method, and USBR method (Gericke & Smithers, 2014). But none of these methods is highly accurate or consistent in providing the true value of time of concentration. Especially when applied to the out of their base region's characteristics (Gericke & Smithers, 2014).

The value of T_C can be estimated using hydrometric data, but measured streamflow or precipitation data for a particular point in a catchment for analysis is rarely available. Therefore, for ungauged catchments, in order to estimate T_C, the physical characteristics relating to T_C of the catchment has been used (John, Bahram, & Ramesh, 2018). Many researchers have developed empirical equations to predict the T_C for ungauged catchments of varying size and physiography, which are, Williams (1922), Kirpich (1940), Chow (1962), Kenedy and Watt (1967), Watt and Chaw (1985), Kaktainar and Sezen (1990) etc. these equations were developed basically with the function of the longest flow path (Lc) and slope of the basin (Sc) (John, Bahram, & Ramesh, 2018).

Kirpich Equation is used to calculate the time of concentration Tc and lag time (Eq 2.5 and Eq 2.6) (John, Bahram, & Ramesh, 2018).

$$\mathrm{T_C} = 0.066 * \left(\frac{\mathrm{L_C}}{\sqrt{\mathrm{S_C}}}\right)^{0.77} \qquad \text{- Eq 2.5}$$

$$\textit{Lag time} = 0.6 \times T_C \qquad \text{- Eq 2.6}$$

Where Tc is the time of concentration in hours, Lc is the main channel length in kilometers and Sc is the slope which is dimensionless.

2.5 Reservoir Simulation with HEC Res Sim

HEC ResSim software was developed by Hydrologic Engineering Center, United State Army Corps (US-ACE, USA) which facilitates to develop the reservoir simulations, and power generation. It gives to simulate various operations such as power generations, flood controlling, water supply environmental quality and etc. HEC ResSim has three stages in developing reservoir simulation which are Watershed modelling, Reservoir network and Simulation (Meshkat & Klipsch, 2018).

The catchment properties such as reaches, junctions, reservoirs were added in watershed modelling. Reservoir physical properties, reservoir operations, time series data, observed data, operational rules and alternatives were given under reservoir network. The simulation time periods, selection of alternatives were given in the simulation process. Time series data were fed through HEC DSS files and suitable parameters and units and unit types should be given correctly.

2.6 Objective Functions for Performance Analysis of Models

The model performance is evaluated for the calibrated model to verify the accuracy of variables of the model before applying to the model for the predictions. The outputs of calibrated model should be closely matched with particular observed data. The evaluation of the accuracy of model data is analysed with graphically or statistical measurements. Objective functions were selected to examine the model performance or goodness of fit criteria (Efficiency measures). The efficiency criteria are derived from the residual (error) between the simulated and observed data (Muleta, 2012). Following objective functions (Eq 2.8 and Eq 2.9) were used to analyse the performance of the simulated mode to verify the accuracy (Muleta, 2012).

a. Nash – Sutcliffe Efficiency (NSE)

$$NSE = 1 - \frac{\sum_{i=1}^{N}(S_i - O_i)^2}{\sum_{i=1}^{N}(O_i - O_{mean})^2} \qquad Eq\ 2.8$$

Here,

S_i = Simulated output $\qquad$ O_i = Observed variable corresponds to S_i

O_{mean} = mean value of observed values of O_i $\qquad$ N = Total number of observations

The NSE ranges from negative infinity to 1 and if NSE =1, that indicates a perfect model. If the NSE value is zero, the model mean value is good as the observed mean value. If the NSE is negative, then the model is a worse predictor (Muleta, 2012).

b. Root Mean Square Error (RMSE)

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(S_i - O_i)^2} \qquad \text{Eq 2.9}$$

Here, S_i and O_i are the simulated value of the model and correspond to the observed value, respectively. The value N is the number of observations. The RMSE ranges from zero (ideal model) to positive infinity (worst model) (Muleta, 2012).

3 METHODOLOGY

This study is focused on rainfall trend and its magnitude, catchment modelling and reservoir simulation for Mahaweli upper catchment. Past research papers related to the topic were studied and suitable analyzing methods and modelling methods were identified. When selecting suitable methods, data availability, reliability and simplicity of methods or tools to be used were taken into consideration. Accordingly, the study was carried out as per the following methodology flow chart (Figure 3-1).

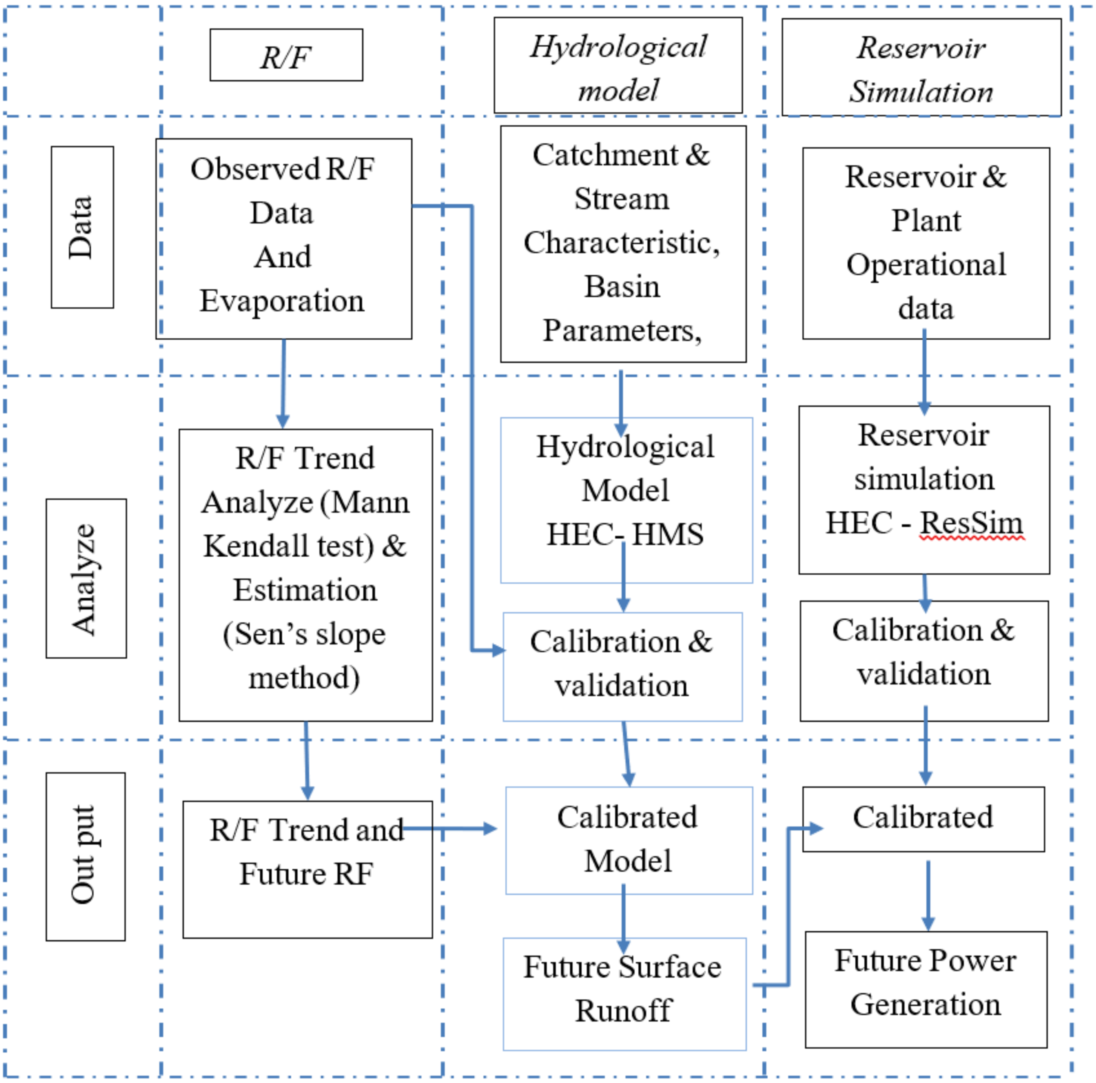


Figure 3-1 Methodology Flow Chart

3.1 Data Collection

The required meteorological data, reservoir operational data and catchment characteristic data were identified considering data availability and software and methods to be used.

3.1.1 Rainfall data

Rainfall stations were selected considering the data availability, basin area and time period required for trend analysis were determined as per the World Meteorological Organization (WMO) guideline.

The number of required stations were selected considering the recommended minimum densities of rainfall stations as stated in the WMO report (Figure 3-2) (WMO, 2008).

Table I.2.6. Recommended minimum densities of stations (area in km^2 per station)

Physiographic unit	*Precipitation*		*Evaporation*	*Streamflow*	*Sediments*	*Water quality*
	Non-recording	*Recording*				
Coastal	900	9 000	50 000	2 750	18 300	55 000
Mountains	250	2 500	50 000	1 000	6 700	20 000
Interior plains	575	5 750	5 000	1 875	12 500	37 500
Hilly/undulating	575	5 750	50 000	1 875	12 500	47 500
Small islands	25	250	50 000	300	2 000	6 000
Urban areas	–	10–20	–	–	–	–
Polar/arid	10 000	100 000	100 000	20 000	200 000	200 000

Figure 3-2 Minimum Area Densities for Rainfall Stations

According to the WMO guideline, seven rainfall stations were selected (Table 3-1) for the study. The time base period for the trend analysis was also selected as per the WMO guideline (WMO, WMO Guidelines on Generating a Defined Set of National Climate Monitoring Products, 2017). A base period is a fixed period against which changes in the climate can be assessed. This base period is also known as a climate normal. For operational climate monitoring, this base period is defined as rolling of 30 years period and updated every 10 years. Accordingly, the most recent based period could be taken as 1981-2010 (WMO, WMO Guidelines on Generating a Defined Set of National Climate Monitoring Products, 2017). Rainfall stations were selected considering both data availability for 30 years and area density for stations (Table 3-1).

Table 3-1 Selected Rainfall Stations

Station ID	Station Name	Data Availability	Latitude	Longitude
01KY317N	Kothmale reservoir	1989-2018	7.00 ° N	80.60 ° E
01NE0010	Ambewela	1976-2015	6.90 ° N	80.80 ° E
01KY0099	Duckwari estate	1976-2015	7.40 ° N	80.80 ° E
01KY317O	Polgolla	1976-2018	7.30 ° N	80.60 ° E
01NE534B	Watawala, mount jean	1976-2015	7.00 ° N	80.50 ° E
01NE0167	Hope estate	1981-2015	7.10 ° N	80.80 ° E
01KY0471	Sogama estate	1976-2015	7.10 ° N	80.60 ° E
43444	Katugasthota	1981-1993	7.30 ° N	80.63 ° E
01KY0370	Nawalapitiya	1981-1989	7.07 ° N	80.50 ° E

Daily rainfall data for the above stations were collected from the Meteorological Department and Mahaweli Authority of Sri Lanka. Since some stations do not have continuous daily rainfall data for 30 years, seven rainfall stations were selected from the above stations for the study considering data availability and satisfying area density for rainfall stations given in WMO guideline (Table 3-2). The missing data within that time period were filled considering rainfall data in nearby stations with the linear regression method. The area covered by a rainfall station was generated by creating Thyssen polygon area in Arc GIS (Figure 3-3). Evaporation data were obtained from Evaporation stations of Kothmale, Polgolla and Victoria reservoirs from the year 2000 to the year 2018.

Table 3-2 Area of Covered from each Rainfall Stations

Station ID	**Name**	**Area (km^2)**	**Latitude**	**Longitude**
01KY317N	Kothmale reservoir	226	7.0 N	80.6 E
01NE0010	Ambewela	293	6.9 N	80.8 E
01KY0099	Duckwari estate	322	7.4 N	80.8 E
01KY317O	Polgolla	390	7.3 N	80.6 E
01NE534B	Watawala, mount jean	194	7.0 N	80.5 E
01NE0167	Hope estate	245	7.1 N	80.8 E
01KY0471	Sogama estate	236	7.1 N	80.6 E
Total Area		1,904		

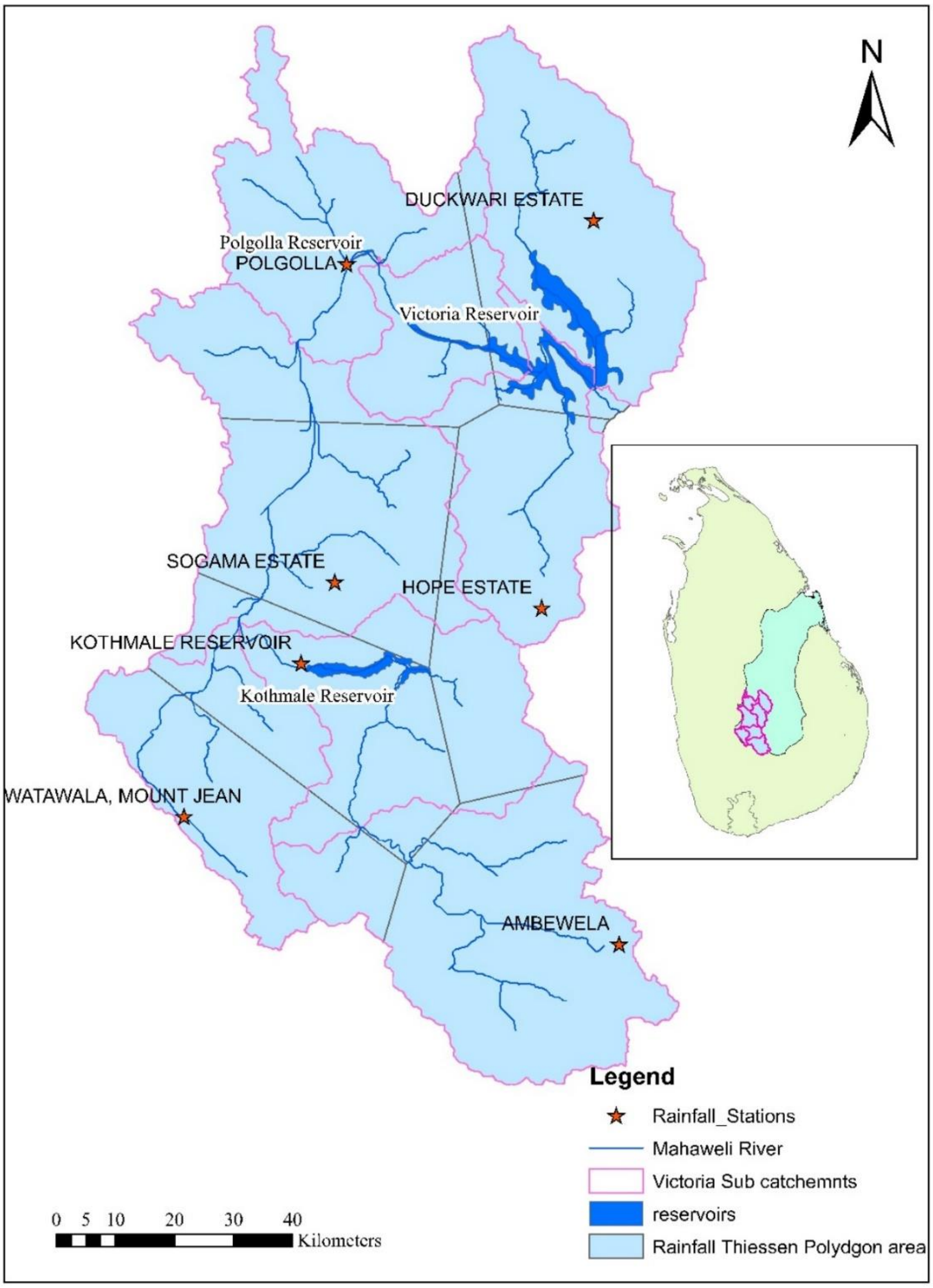


Figure 3-3 Created Thiessen Polygon Areas for selected Rainfall stations

3.1.2 Catchment characteristic data and GIS maps

Basically, the Digital Elevation Model (DEM) of the selected catchment area is required to model the catchment characteristics in Arc GIS. In addition to that, required GIS shapefiles were collected (Table 3-3).

Table 3-3 Required Data for GIS mapping

Shape File/ Raster file	Data type	Resolution	Requirement
DEM File	Raster	30m	For catchment modelling
Stream	Vector-Polyline		To generate drainage network and stream networks
Rainfall station	Vector - Point		To create Thiessen polygon
Soil type	Vector - polygon	1:50000	To generate Curve Number Grid
Land Use			

3.1.3 Reservoir operational data

Mahaweli upper catchment area has three reservoirs which are Kothmale reservoir, Polgolla Barrage and Victoria reservoir. The reservoir simulation was carried out only for the Victoria reservoir. It was considered that the inflows to the Victoria reservoir are the downstream release from Polgolla barrage and direct runoff from other sub-catchments (Victoria, Hope Estate and Duckwary Estate). Accordingly, the daily operational data (Table 3-4) were collected from the Mahaweli Authority of Sri Lanka.

Table 3-4 Detail of Reservoir Operational Data

Reservoir	Data	Data Availability
Kothmale Reservoir	Inflow and Downstream release	1989-2018
Polgolla Barrage	Inflow and Downstream release	2000-2018
Victoria Reservoir	Inflow, Water level, Storage, Spilling, Power release	1992-2018

3.1.4 Data Checking and Filling Missing Data in Rainfall Data Set

The collected rainfall data and reservoir operational data were evaluated for accuracy, consistency and homogeneity by visual checking, graphical checking and consistency checking. The outliers in the data set were identified by visual checking and consistency was checked by single mass curve and double mass curves. It was observed that some of the inflow data of three reservoirs were minus values and those data were corrected by regression method. All selected stations do not have continuous data set for 30 years (Table 3-5). Accordingly, missing data and outliers were filled using the linear regression method. The regression method was carried out with the regression tool in analysis extension in Excel.

Table 3-5 Percentage of Rainfall Data missingness

Total Number of Rainfall events – 10,957		
Rainfall Station	**Missing data events**	**% of Missingness**
Ambewala	671	6%
Duckwary	243	2%
Sogama	810	7%
Watawala	1,023	9%
Kotmale	350	3%
Polgolla	1,198	11%
Hope Estate	1,647	15%

Multiple linear regression method was carried out to fill the missing data of each rainfall stations. The independent variables (x_1, x_2, .. x_n) are the time series data of nearby rainfall stations which has continuous rainfall data, and the dependent variable (y_0) is the time series data of a particular station which has missing rainfall data. The linear relationship of these two time series data could be plotted in form of $y=mx+c$ graph. The graph of the intercept (c) and slope (m_1,m_2,...m_n) of the above equation is obtained from regression analysis in EXCEL. The intercept (c) is given as “0” such that obtaining days of zero rainfall.

After filling the missing data by regression method, data checking was performed by plotting single mass curves and double mass curves for rainfall data of each station. The single mass curve was plotted for cumulative rainfall values of a particular station against the time period. the double mass curve was plotted for the cumulative rainfall values of a particular station against the average of cumulative rainfall values of other stations for the same time period.

Further, rainfall data and reservoir operational data were further checked by plotting those annual time series data such that rainfall and inflow data of each reservoir and inflow and pool elevation of each reservoir against the time to identify the outliers of the data set.

3.2 Rainfall Trend Analysis

3.2.1 Mann Kendall test

Mann Kendall test was carried out on R software to determine the trend of the rainfall over 30 years. The rainfall trend was analyzed using the package “Mann Kendall” and “Modified Mann Kendall” and the trend was estimated using the package “Sen ZYP” with R commands (Appendix D). The rainfall trend is analyzed with monthly rainfall data for 30 years and the trend is analyzed for monthly basis of all stations.

First the “Mann kendall” package shall be loaded to the R platform (R – 3.1)

library(Kendall) *R - 3.1*

The monthly rainfall data were fed to R software by assigning each month as a dependent variable such that (x_1=> *Jan*, x_2=> *feb*, x_3=>*Mar,……..*x_{12}=>*Dec*) (R – 3.2)

for *x1=> Jan ,*

x1<-MK1$Jan *R - 3.2*

Before applying the Mann Kendall test, it is required to check whether the data series is serially correlated or not. If the data series is serially correlated, the correlation coefficient (R_N) satisfies the following requirement.

The significance of the *lag -1* serial correlation at the significance level of α = 0.05, of the two-tailed tests shall satisfy the following condition (Eq 3.3) (R.L.Anderson, 1942). (George, Bob, Paul, & Sheng, 2002) as:

$$\frac{-1-1.645\sqrt{(N-2)}}{N-1} < R_N(0.05) < \frac{-1+1.645\sqrt{(N-2)}}{N-1} \qquad Eq\ \ 3.3$$

where N is the number of observations. Here N=30 since the analysis was carried out for each month separately for 30 years of observed data

The correlation of the data series was calculated from the correlation function in EXCEL and it was checked if the calculated correlation satisfied the above conditions given in Eq 7. The autocorrelation for time series could be found from R software (R – 3.4).

```
acf(x1,lag.max = 1)
    acf(x1,lag.max = 1)$acf                                    R -  3.4
```

3.2.2 Modified Mann Kendall Test (BBS)

Time series data of most of the subbasins are serially correlated, and the modified Mann Kendall test is performed by performing the Mann Kendall test in conjunction with Block Bootstrap Method.

To perform Block Bootstrap method (BBS), it is required to load the "*modifiedmk*" to the R platform (R – 3.5),

```
library(modifiedmk)                                            R -  3.5
```

And then BBS method was used to find Kendall statistic for 12 months from x_1 to x_{12} variables (R – 3.6)

For *January x1,*

```
    bbsmk(x1,ci = 0.95,nsim = 2000,eta = 1,bl.len = NULL)      R -  3.6
```

here "*ci*" means confidence level and it is 95%, "*nism*" means number of simulations which is normally taken as 2000 (Svensson, Kundzewicz, & Thomas , 2009), and "*eta*", *(η)* = 1 (Khaliq, Ouarda, Gachon, Sushama, & St-Hilaire, 2009) the modified Mann Kendall test was carried out for all 12 months with 30 years monthly data and following values were obtained.

a. Standard statistic value Z
b. Sens slope value
c. Kendall test statistic S

If the S value is positive then there is an upward trend and if the S value is negative, it indicates a downward trend. Further, the Sens slope value is the increment (*m*) of the trend. Therefore, if the Sens slope is positive the trend is upward and if the Sens slope is a negative value, then the trend is downward. Therefore from this test, it could be identified whether the behaviour of the trend is upward or downward.

3.2.3 Estimating Rainfall Trend

The Mann Kendal test is basically assessed by assuming that the particular time series data set has a monotonic trend in upward or downward (Visual Sample Plan (VSP), n.d.) (Fiaz, Ghulam, & Waseem, 2015). The trend can be assumed as a linear trend which follows the $y=mx+c$ graph. The Sens slope obtained from the BBS method is the increment (*m*) of the trend and the intercept (*c*) can be found from zyp.sen package in R software.

Here it is required to define the dependent variable (*y*) and independent variable (*x*) of the trend. It was assumed that dependent variables are the monthly rainfall data of each month and the independent variable is the year. Since the trend is plotted by plotting monthly rainfall data against each year (30 years). Hence the monthly rainfall data is considered as a function of years. Then two variables x and y are assigned in the R software (R – 3.7).

Independent variable (*x*) – years (1981, 1982, 1983, ….., 2010),

x<-ZYP1$Years *R - 3.7*

Dependent variable (*y*) – Monthly rainfall data of each month for 30 years (R – 3.8)

For month of January,

y1<-ZYP1$Jan *R - 3.8*

After assigning variables, the zyp.sen command was used to find the intercept of the trend line (R – 3.9).

For January, as the January data were assigned as y1

df=data.frame(x=c(x),y=c(y1))

zyp.sen(y~x,df) *R - 3.9*

Monthly rainfall was estimated using the linear regression method since the trend was taken the form of $y=mx+c$. Since the Mann Kendall test and Sens Slope methods were applied to estimate rainfall trend and magnitude assuming that rainfall trend has a monotonic trend. The intercept "*c*" and slope "*m*" of this equation were obtained from *zyp sen* command and BBS methods respectively. Accordingly, monthly rainfall was estimated assigning years as the independent variable (x) and monthly rainfall as dependent variable (y) (Saplıoğlu, 2015 and Thenmozhi & Kottiswaran, 2016).

The monthly rainfall data for 30 years were estimated using the Sens Slope method and the estimated rainfall data were compared with historical data.

3.3 Hydrological Model

Hydrological model was developed on Arc GIS and HEC HMS software. Basically, the hydrological model was developed in two stages. The Catchment Modelling was performed in Arc GIS with Arc Hydro tool and preparation of HEC HMS parameters and hydrological network by means of HEC Geo HMS. The hydrological model was performed in HEC HMS with rainfall data and other hydrological data and catchment runoffs were obtained for each catchment.

3.3.1 Catchment Modelling with Hydro Arc Extension

Catchment modelling was done basically by means of DEM (30 m) file and Streamline shapefile for Upper catchment area. Then catchment modelling proceeded with tools in Arc Hydro extension in Arc GIS.

3.3.2 Catchment Characteristic in HEC Geo HMS

Catchment characteristics required to develop the HEC HMS model was processed with HEC GeoHMS extension in Arc GIS with previously created files from Hydro Arc Extension.

After the creation of the HMS project file in HEC Geo HMS, it was opened in HEC HMS software and the hydrological model was analyzed in HEC HMS

3.3.3 Hydrological Model in HEC HMS

The generated HEC HMS file in HEC Geo HMS was open in HEC HMS and Sub Basin and the river shapefile were fed to the Basin model. The hydrological data for Sub basins, reaches were given under the basin model, rainfall data in the Time series data model and Control specifications were given for each basin as below.

a. Basin Model

In Basin Model, there are three types of elements which are sub-basins, reaches and junctions. The basin area and curve numbers for each sub-basin were computed in HEC GeoHMS hence it was not necessary to feed those data manually. But following details were given for sub-basins.

i. Loss Method – SCS Curve number

Initial abstraction was assumed as zero, Curve number was generated from HEC Geo HMS and Impervious areas were defined considering soil type and land use areas

ii. Transform method – Clerk unit hydrograph

Initially, the lag times of sub-basins were taken from the HEC GEO HMS model and the lag times were adjusted such that the model inflow data corresponded to the observed inflow data under model calibration.

iii. Baseflow method – Recession

Parameters under Base flow were given based on assume values and adjusted at the calibration.

Assumed values: Initial Discharge = 0. 1 m^3/s

Recession Constant = 0.1

Threshold type – Ratio to peak, Ratio = 0.1

For reaches, the routing method was selected as the Lag method and lag time was calculated by Kirpich equation. Initial type of reaches was considered as a specified discharge of 2 m^3/s.

Here the lag times were calculated from Eq 2.5 and Eq 2.6 in section 2.4 (John, Bahram, & Ramesh, 2018)**.** The accurate and exact *Tc* values cannot be computed from any equation developed by many researchers, the lag time was given as trial-and-error basis based on calculated lag times from the above equations and adjusted at the calibration.

b. Meteorological Model

Under the HEC GeoHMS model, precipitation gauges and evaporation gauges for each sub-basin were assigned. Precipitation data and evaporation data were fed into meteorological data.

Evaporation data were given as Specified Evapotranspiration for each sub-catchment. Daily evaporation data were collected from Victoria, Polgolla and Kothmale reservoirs.

Specified hyetograph method was used for assigning precipitation data in the meteorological model and daily rainfall data were fed into the time series data model.

Monthly rainfall data were used for the analysis of future scenario as monthly data estimated from Sen's slope method were obtained as monthly data. Accordingly, calibration and validation were performed with observed monthly rainfall data. Then the future scenario was analyzed with estimated monthly rainfall data. Monthly rainfall data were fed as time series data through a HEC DSS file (Appendix E).

c. Time series Data

Daily rainfall data were given for each station for 5 years data from 2001– 2005. The Theisen polygons were created and rainfall weights for each catchment were calculated considering the Thiessen polygon area and catchment area. (Eq 3.2 and Eq 3.3, Table 3-6 and Figure 3-3) (Hua & Chi, 2014). The daily rainfall values for each sub-catchment were calculated from the total daily rainfall data of particular rainfall stations multiplied by the particular weighting factors. Rainfall data units were given as “increment millimeter”; the time interval is as 1 for daily rainfall data. The Model Calibration was performed from the years 2001 - 2005 and validation was performed for the time period of the years 2005-2010.

$$P_{av} = \sum_{i=1}^{n} w_i P_i \qquad Eq\ 3.1$$

$$\sum_{i=1}^{n} w_i = 1 \qquad Eq\ 3.2$$

Table 3-6 Area weighting factor for Each Catchment with respect to Thiessen Polygon

Rainfall Stations / Catchment Area	Duckwary_ Estate	Hope Estate	Polgolla	Sogama	Watawala	Kothmale	Ambewala
Polgolla	0.03		0.51				
Duckwary_ Estate	0.79						
Victoria	0.06		0.22				
Sogama		0.06	0.24	0.92		0.12	
Hope_Estate	0.1	0.6	0.03	0.01			
Watawala					0.69	0.26	
Kothmale		0.31		0.07	0.07	0.55	0.02
Ambewala		0.02			0.24	0.07	0.98

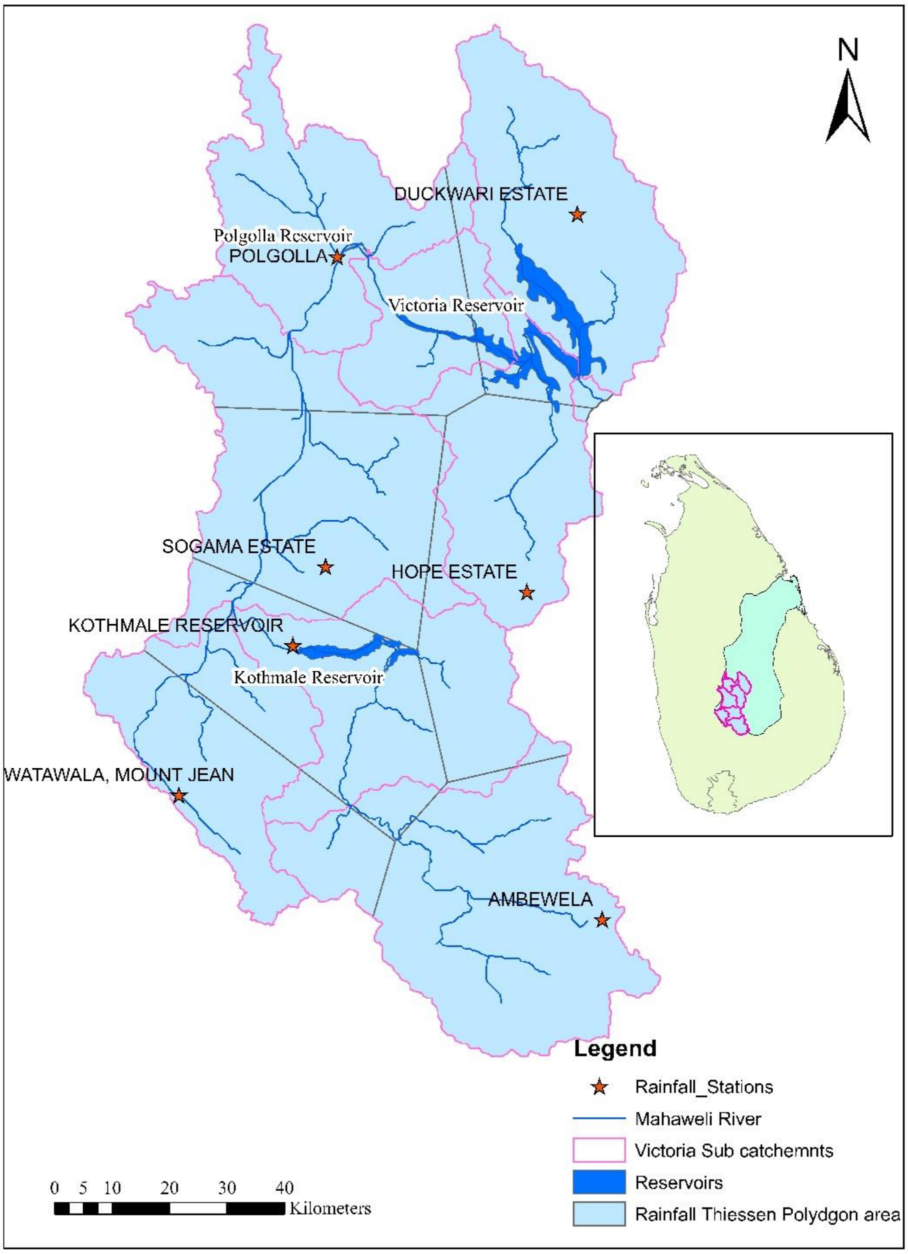


Figure 3-3 Map of Thiessen Polygon area for rainfall stations

d. Control Specifications

The control specification was assigned to run the model by giving the start date (01.Jan.2001) and time (00:00) and end date (31.Dec.2005) and time (00:00) with a 1-day time interval for simulation.

Then the model run was performed to get the catchment runoff volumes from each sub-catchment to each reservoir (Kothmale, Polgolla and Victoria). Then considering the downstream releases of each reservoir, the inflow volumes of each reservoir was calculated. The modelled inflow of the reservoir was fed into HEC ResSim model for reservoir simulations.

3.3.4 Model Calibration and Validation

The HEC HMS modelling for rainfall runoff simulation for upper catchment was performed to obtain the inflows to the reservoirs from each sub-catchment. The model was calibrated with 5 years of daily rainfall, monthly evaporation data and operational data (from 2000-2005). The variables of the model were fixed with calibration of the model by comparing with observed data. Then validation was carried out for another 5 years with daily data from 2005 to 2010.

Following variables were considered in the model calibration

a. Loss Method in Basin model
b. Initial abstraction, imperviousness and Curve Number
c. Baseflow in Basin model
d. Initial discharge was taken as 0.1 m^3/s, Recession constant was taken as 0.5 while the threshold type was considered as ratio to peak with 0.1 ratio.
e. Lag time in reaches and sub-catchments of the basin model

The lag time was calculated from “Kirpich” equation and adjusted by multiplying all lag times with a constant factor.

After the variables were fixed, the model was run for another 5 years from 2005 to 2010 and compared the results with actual inflow data under validation. The future inflow to Victoria reservoir was simulated for the year 2020 to 2025 with calibrated parameters.

3.4 Reservoir Simulation in HEC ResSim Model

Reservoir operations were performed on HEC ResSim platform, which is also introduced by Hydrologic Engineering Centre US Army Corps of Engineers. HEC ResSim consists of three model setups which are watershed setup, reservoir network and Reservoir simulation.

Physical properties of the watershed such as adding maps, reaches, reservoirs, and control points are created under watershed setup. The physical properties of reservoirs, operational data, observed data, scheduling, power plant detail, alternatives and time series data were set up under the reservoir Network model. Simulation time interval, start and end time and date and model compiling are performed under simulation.

The power generation and reservoir operations were modelled in HEC ResSim software with the year 2015 and 2016 operational data. Then future scenario was modelled for 5 years from the year 2021 to 2025.

The HEC ResSim model was calibrated for reservoir operations and power generation of Victoria reservoir for the year 2015 adjusting the efficiency of the power plant and the model was validated for the year 2016. Then future power generation and reservoir operations were simulated on HEC ResSim for the year 2020 and period of the year 2020 to 2025.

3.5 Objective Functions for Performance Analysis of Models

The model performances were evaluated statistically with NSE (Eq 2.8) and RMSE (Eq 2.9) methods for simulation models and graphically by plotting output values and observed values over time (Time series curves and flow duration curves). In this study, there are 3 models simulated, which are rainfall trend analysis, HEC HMS model for inflow of reservoir and HEC ResSim model for power generation. The simulated monthly rainfall for 30 years, inflows to Kothmale, Polgolla and Victoria reservoirs and power generation of Victoria reservoir were evaluated by comparison of simulated data with corresponding observed data. The model calibration was performed with a trial-and-error basis such that the model outputs were given high performance statistically and graphically.

4 RESULT AND ANALYSIS

4.1 Data Checking and Data Filling

4.1.1 Rainfall data

The collected rainfall data and reservoir operational data were subjected to checking for accuracy and reliability of the results of the study. The rainfall data of the selected seven stations were checked for consistency, homogeneity and correlations of each station by performing Single mass curve analysis (Figure 4-1) and Double mass curve analysis (Figure 4-2).

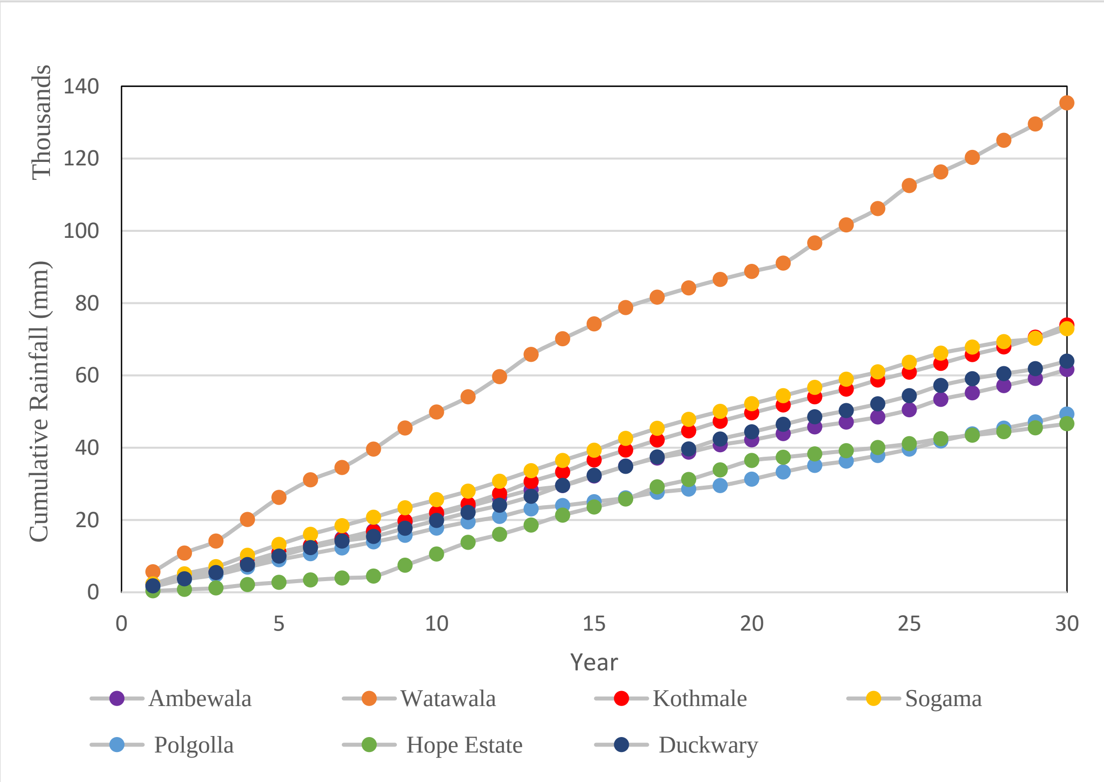


Figure 4-1 Single Mass curve for Rainfall Station

Single mass curve was plotted (Figure 4-1) and identified the consistency and correlation of each station. The highest rainfall values can be observed in Watawala station while the lowest rainfall values are shown in Hope Estate. The best correlation is shown by Kothmale, Sogama rainfall stations and Ambewala and Duckwary rainfall stations throughout 30 years. The graph of Hope Estate has deviated from a single line at 8th and 20th years since most of the rainfall data were missing in this station in those two years. Those missing data were filled with considering other stations' data. Further, the graph of the Watawla rainfall station deviated from the straight line at 16th and 21st years due to missing rainfall data.

The double mass curve was plotted (Figure 4-2) for each rainfall stations to identify the correlation between each station, relative consistency of time series, and homogeneity of the data series (Wijesekera & Perera, 2016). The relative consistency and homogeneity are high in Sogama, Kothmale Duckwary and Ambewala rainfall stations. Watawala, Hope Estate and Polgolla rainfall stations show less relative consistency and homogeneity since the graphs of double mass curves of those stations do not show a continuous straight line and the lines are broken at several points.

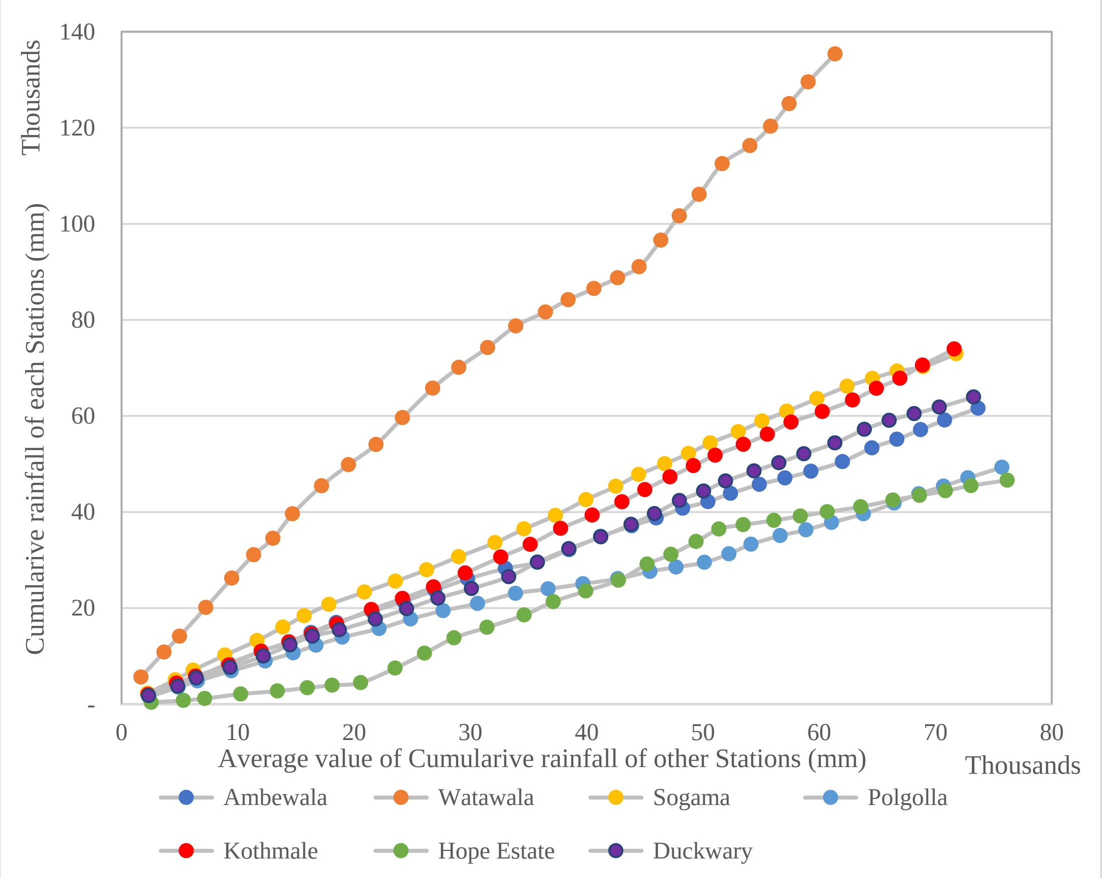


Figure 4-2 Double Mass curve for Rainfall Stations

The missing rainfall data of those stations were filled considering the relative consistency, homogeneity and correlation of each station.

Further, the rainfall data of selected rainfall stations were checked with inflows of Kothmale, Polgolla and Victoria reservoir to identify the outliers of recorded inflow data and rainfall data. The rainfall stations were selected for each reservoir considering the contribution to the inflow of each reservoir by the direct catchment runoff. The monthly total inflows of each reservoir and monthly total rainfall of each sub-catchment were plotted over time (from Figure 4-3 to Figure 4-11) from the year 2000 to the year 2010. The time period was selected considering the data availability of each reservoir and the time period considered for HEC HMS model.

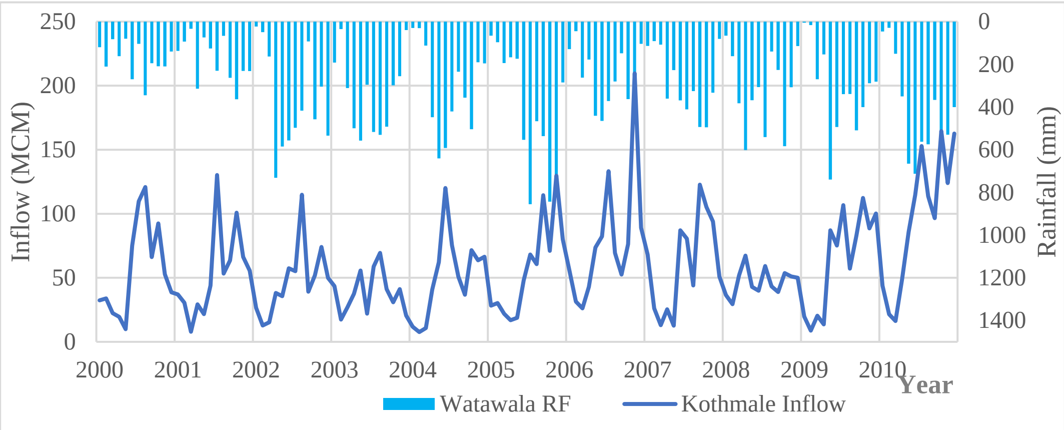


Figure 4-3 Kothmale Reservoir Inflow and Rainfall of Watawala catchment

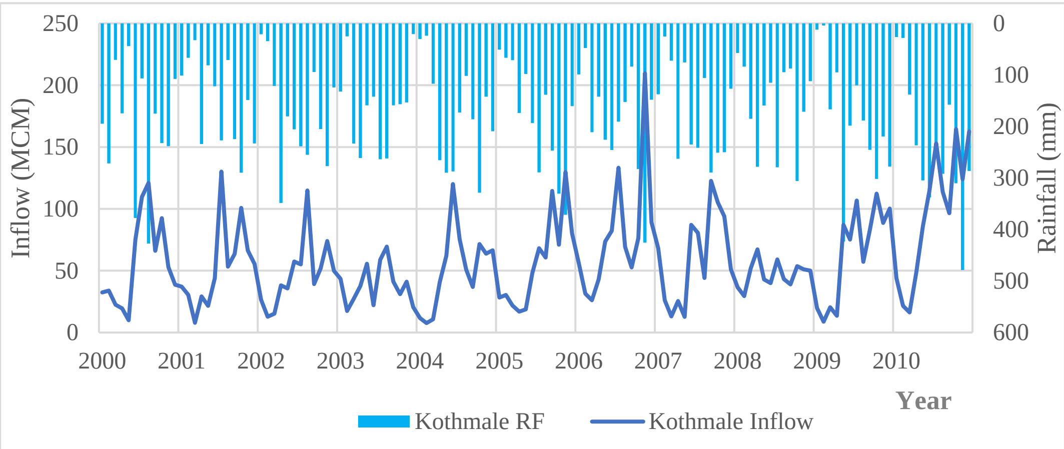


Figure 4-4 Kothmale Reservoir Inflow and Rainfall of Kothmale Catchment

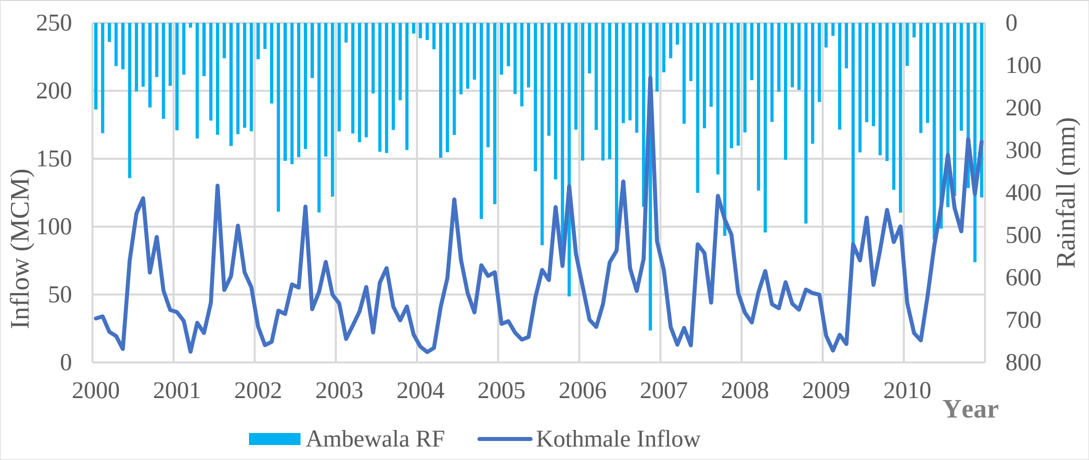


Figure 4-5 Kothmale Reservoir Inflow and Rainfall of Ambewala catchment

According to Theisen weighted average area for rainfall stations (Figure 3-3), the effective rainfall stations for Kothmale reservoirs are Ambewala, Kothmale and Watawala stations. According to Theisen weighted values (Table 3-6, Table 3-2), the highly affected rainfall station for inflow to Kothmale reservoir is Ambewala rainfall station. It is observed that rainfall variation of the above three stations and inflow to Kothmale reservoir followed up the same pattern (Figure 4-3, Figure 4-4 and Figure 4-5). Accordingly, there were no outliers in rainfall data of the above three stations or inflows of the Kothmale reservoir for the time period of the year 2000 to 2010.

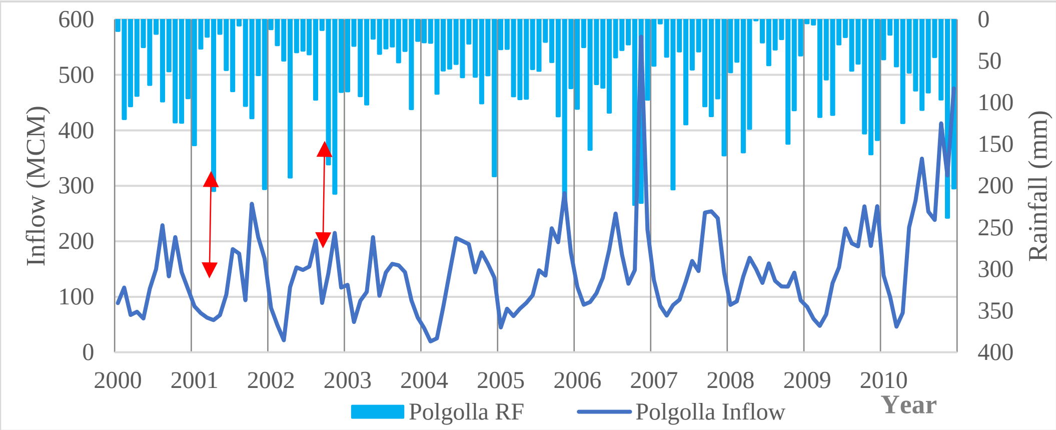


Figure 4-6 Monthly inflow of Polgolla Barrage and Rainfall of Polgolla catchment

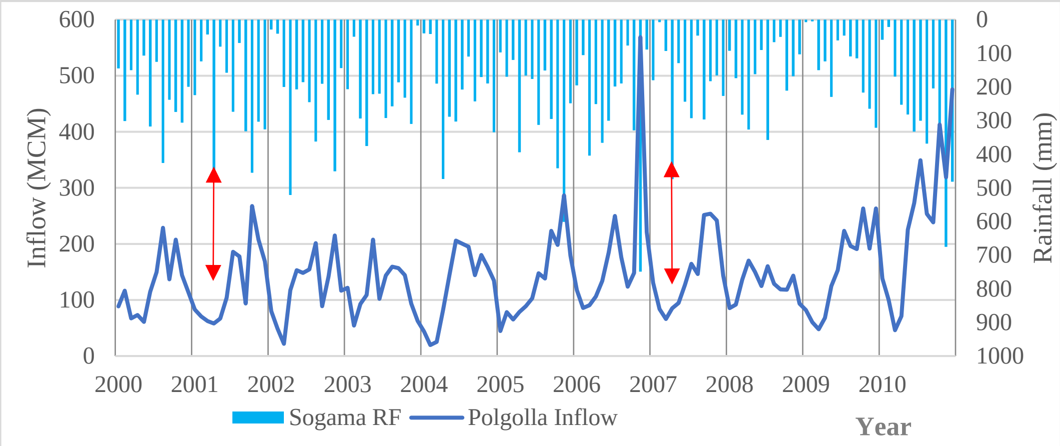


Figure 4-7 Monthly inflow of Polgolla Barrage and Rainfall of Sogama catchment

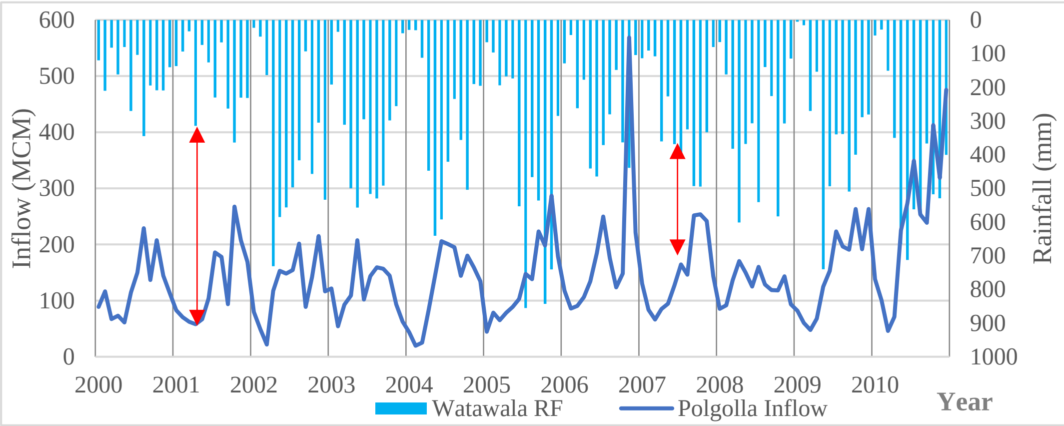


Figure 4-8 Monthly Inflow of Polgolla Barrage and Rainfall of Watawala catchment

Inflow to Polgolla barrage is affected by the downstream release of Kothmale and Upper Kothmale power stations, Watawala, Sogama and Polgolla catchment runoffs (Figure 3-3). Accordingly, Watawala, Sogama and Polgolla rainfall stations data were checked with inflow to Polgolla Barrage (Figure 4-6Figure 4-7 and Figure 4-8). It was observed that there were outlier values in monthly rainfall data of these three stations in the months of April 2001 and April 2007 since the rainfall value is higher while the inflow values are low. These rainfall values could be considered as outliers according to Polgolla barrage inflow values and monthly variation of rainfall values of adjacent months. But these outliers were neglected since downstream releases of reservoirs of the upper catchment (from power plants) were also taken into consideration. Therefore, these rainfall station values were taken in to account as they were without any changes.

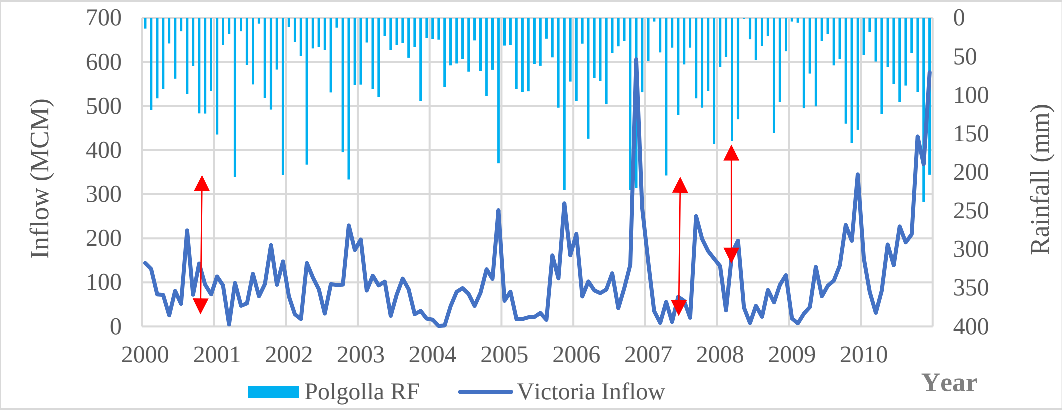


Figure 4-9 Monthly Inflow of Victoria Reservoir and Rainfall of Polgolla Catchment

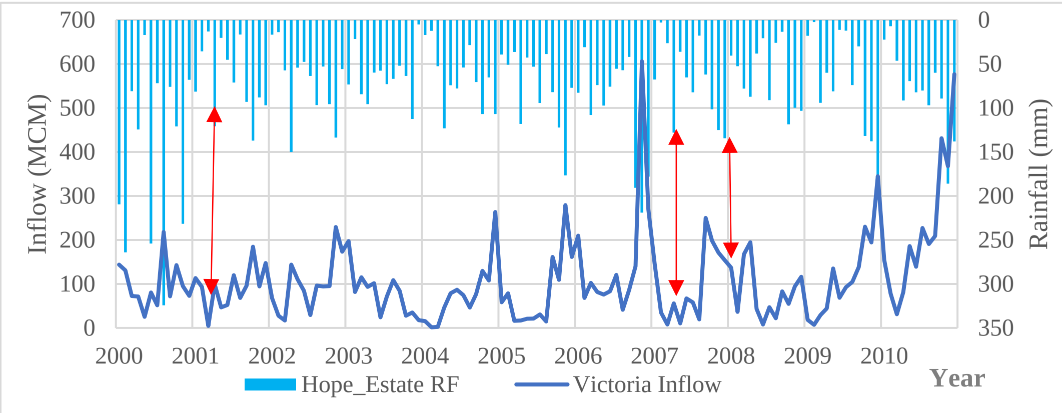


Figure 4-10 Inflow of Victoria Reservoir and Rainfall of Hope Estate Catchment

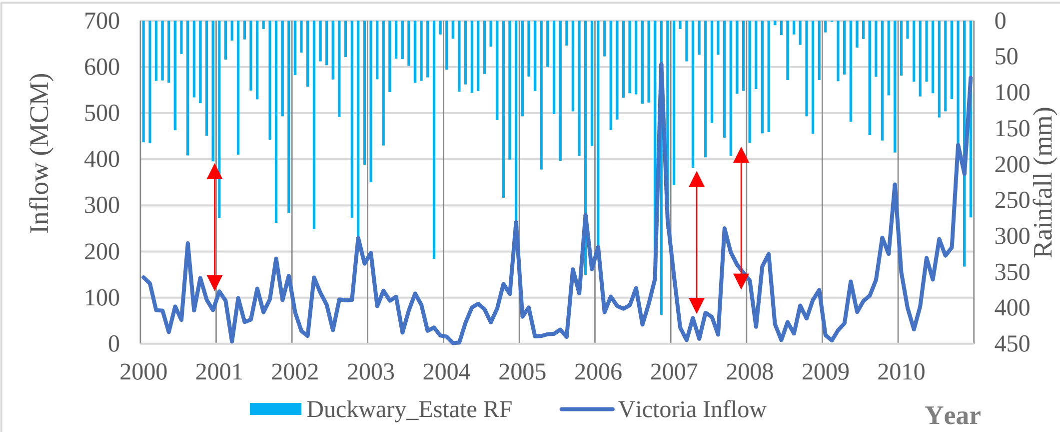


Figure 4-11 Inflow of Victoria Reservoir and Rainfall Duckwary Estate catchment

The rainfall data of Duckwary Estate, Hope Estate and Polgolla catchments were checked with inflow data of Victoria reservoir since those catchment run-offs directly affect the inflow of Victoria reservoir (Figure 4-9, Figure 4-10 and Figure 4-11). Further, the downstream release of Polgolla reservoir also affects the Victoria reservoir. It was observed three outliers in rainfall data of each catchment. That is the rainfall data in the months of April 2001, April 2007 and January 2008 are considerably higher than those in adjacent months while the inflow to the reservoir is low. But those high rainfall values were also observed in upstream rainfall stations and the inflow to Victoria reservoir was also affected by the downstream release of Polgolla barrage, Upper Kothmale and Kothmale power stations. Therefore, those rainfall data or inflow data of Victoria reservoir were taken as they without any changes.

4.1.2 Reservoir Operational data

It was required to have reservoir operational data of Polgolla barrage and Victoria reservoir for HEC HMS modelling and HEC Res Sim modelling, which are the downstream releases of Polgolla barrage and inflow, reservoir water level, power generation spill discharge, power releases and reservoir storage of Victoria reservoir. Therefore, those data were visually checked by plotting those operational data over time.

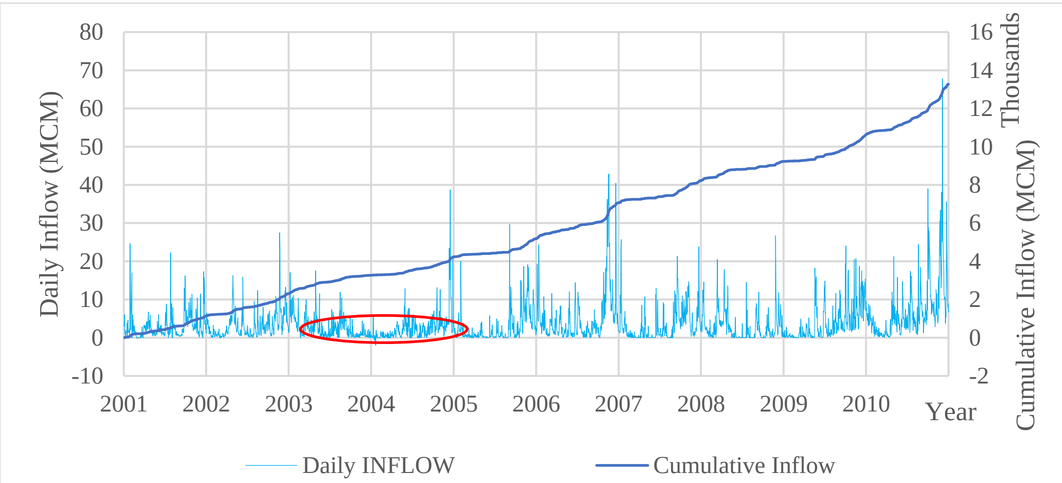


Figure 4-12 Daily Inflow variation of Victoria Reservoir

It was observed that daily inflows of Victoria reservoir were recorded as negative values on some days of the year 2000, 2001, 2003 and 2004 (Figure 4-12). This may have happened; since the inflow to the reservoir was obtained by doing a water balance on the reservoir for the particular date considering reservoir storage, downstream releases and power discharges. The reservoir storage was calculated according to the reservoir water level and capacity elevation curve. But these calculation data may be wrong since the capacity elevation curves are not updated recently and power discharge data may not be correct since it was not a measured discharge value. Due to these calculation errors in water balance, it gives the inflow values as minus values on some days. Therefore, those minus value inflow data were corrected assigning 0.01 MCM as inflow for those days.

The reservoir water level was plotted from the year 2011 to 2018 with Minimum Operational Level (MOL) and Fully Supply Level (FSL) (Figure 4-13). This time period was taken into account for HEC ResSim model. The water level was considerably low on 02.11.2017 due to typing error and it was corrected considering the water level and inflows of other adjacent days. The power generation data and power discharge data were plotted from the year 2011 to 2018 and the outliers were checked (Figure 4-14). Few outliers due to data recording errors were identified and corrected considering power discharge data of particular date and power generation data of adjacent days.

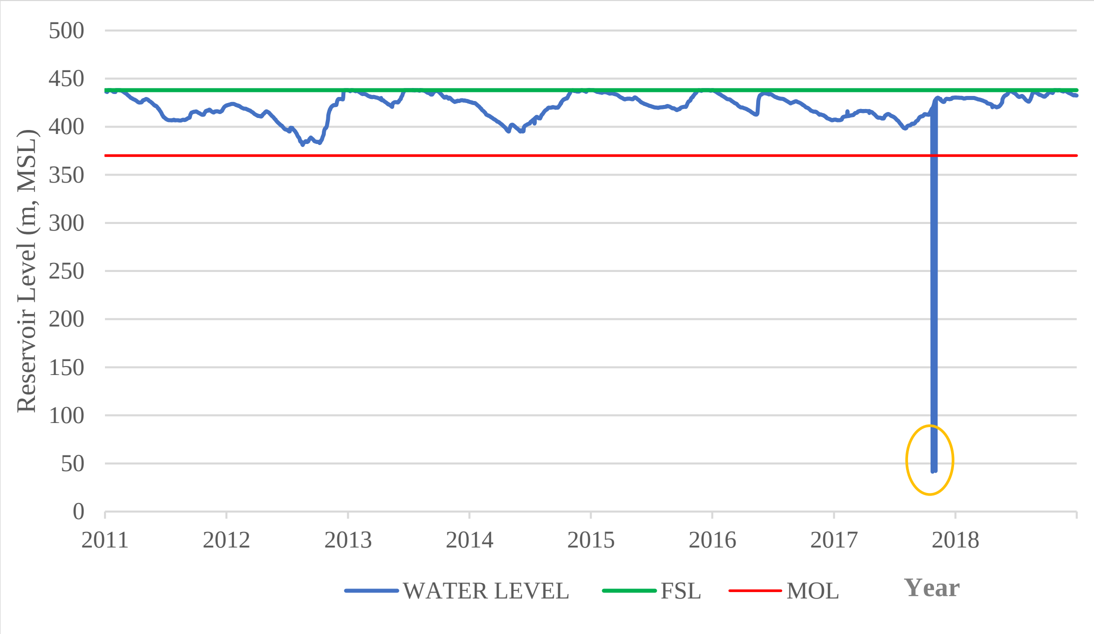


Figure 4-13 Reservoir water level Variation - Victoria Reservoir

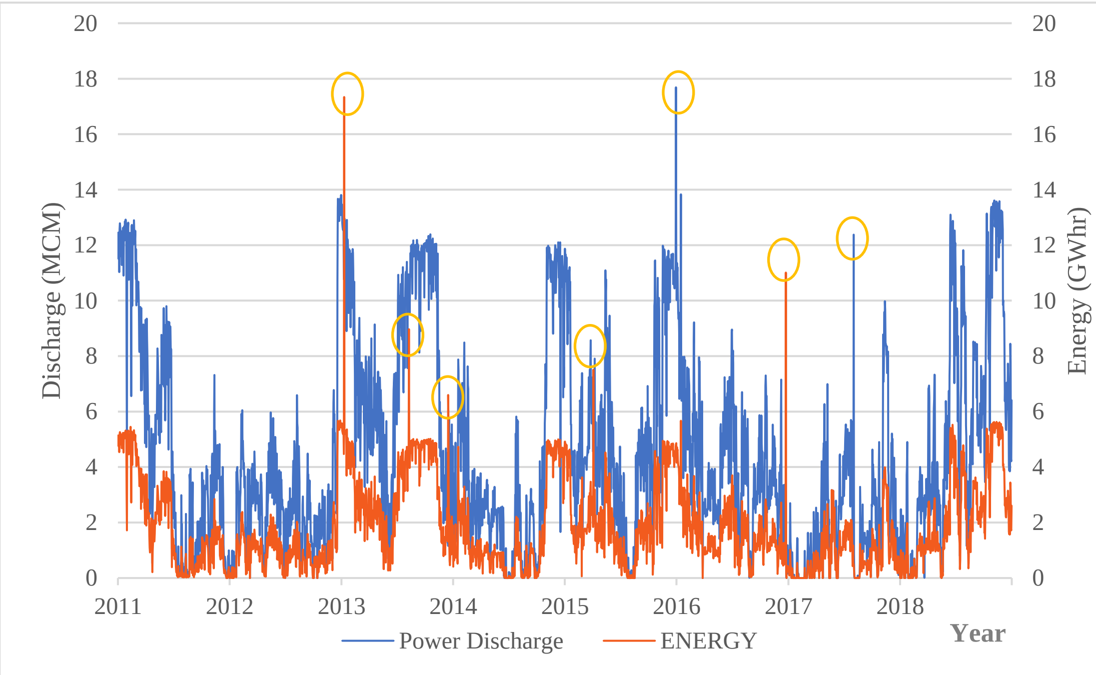


Figure 4-14 Power generation - Victoria Reservoir

4.2 Rainfall Trend Analysis

Rainfall trend was analyzed using by modified Mann Kendall test and trend magnitude was estimated with Sen's slop method for monthly rainfall data from the year 1981 to

2010. It was assumed that the monthly rainfall trend was a monotonic trend (Visual Sample Plan (VSP), n.d.). Hence the graph of monthly variation of rainfall trend over time gives a straight line and monthly rainfall was estimated with linear regression method. Mann Kendall test was performed to identify the trend of the rainfall pattern (whether it was a negative trend or a positive trend). Sen's Slope method was used to estimate the trend magnitude by obtaining the slope and intercept of the graph of rainfall variation over time (Table 4-1).

The rainfall trend variation over the year was analyzed by estimating the slope (m) of the trend. If the slope is negative there is a downward trend and positive slopes indicate the upward trends (Table 4-1). The trend is negative from May to September in all rainfall stations except Hope estate. That means, in these months the rainfall is decreasing and in other months the rainfall is increasing yearly. It is observed that the magnitude of the negative trend is higher than the magnitude of the positive trend. That means the dry months are getting more dryer rapidly rather than rainy periods getting more rainfall.

The estimated annual rainfall trend of each catchment was plotted over the time with respect to observed rainfall data (Figure 4-15-1 and Figure 4-16). The slope of annual rainfall was positive only for Hope Estate and Kothmale rainfall station while Watawala, Ambewala, Duckwary Estate and Sogama rainfall stations show a negative slope for annual rainfall trend. This indicates that it will increase annual rainfall in Kothmale and Hope estate rainfall stations while the annual rainfall is decreased yearly in the other four stations.

According to these results, the overall rainfall trend is negative since dryer periods get more dryer than rainy periods getting more rainfall. Hence this will make a depletion of inflows to the reservoirs and it will lead to reduce the water availability for hydropower generation.

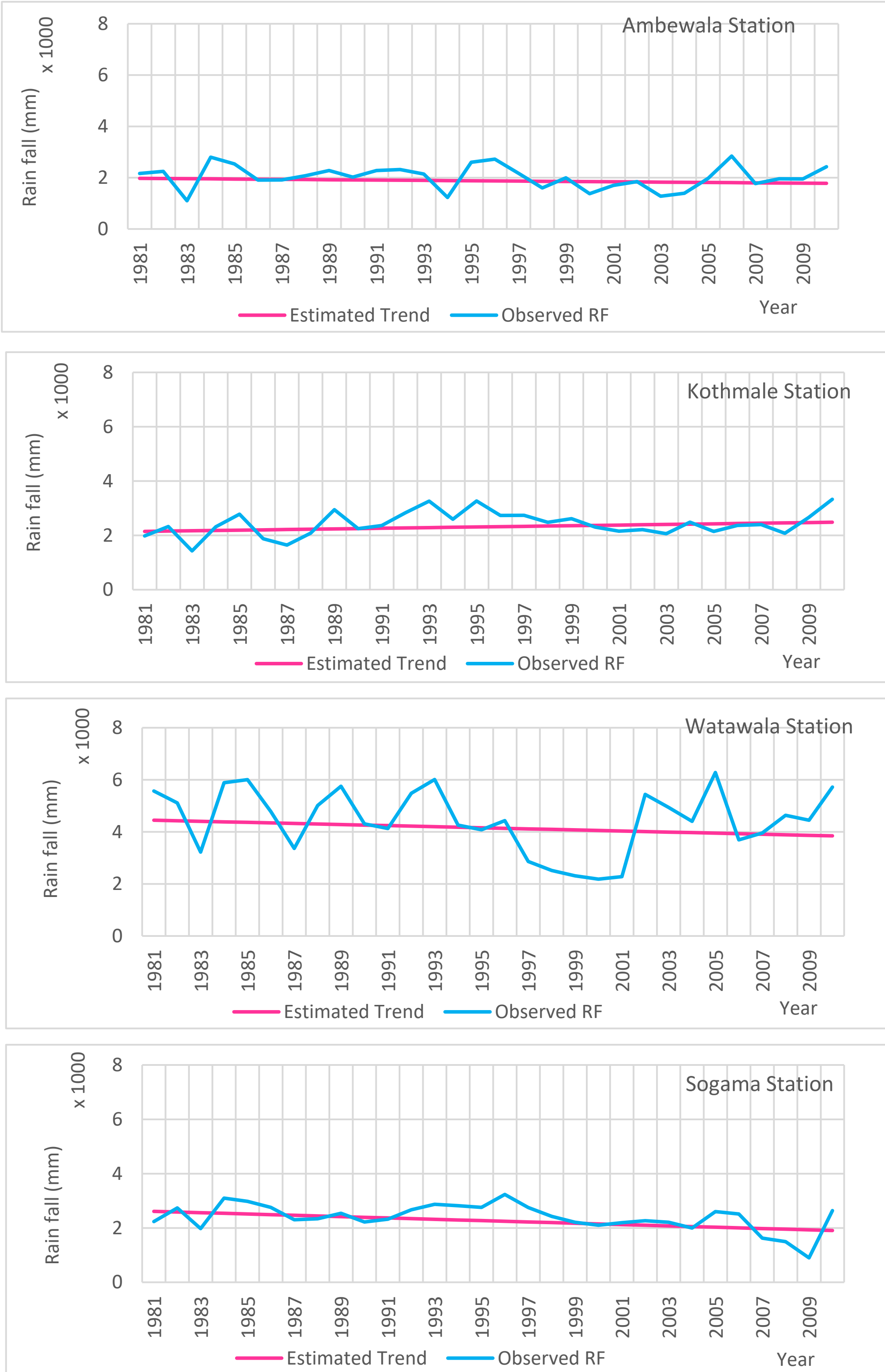


Figure 4-15-1 Estimated Rainfall Trend and Observed RF of Ambewala, Kothmale, Watawala and Sogama Stations

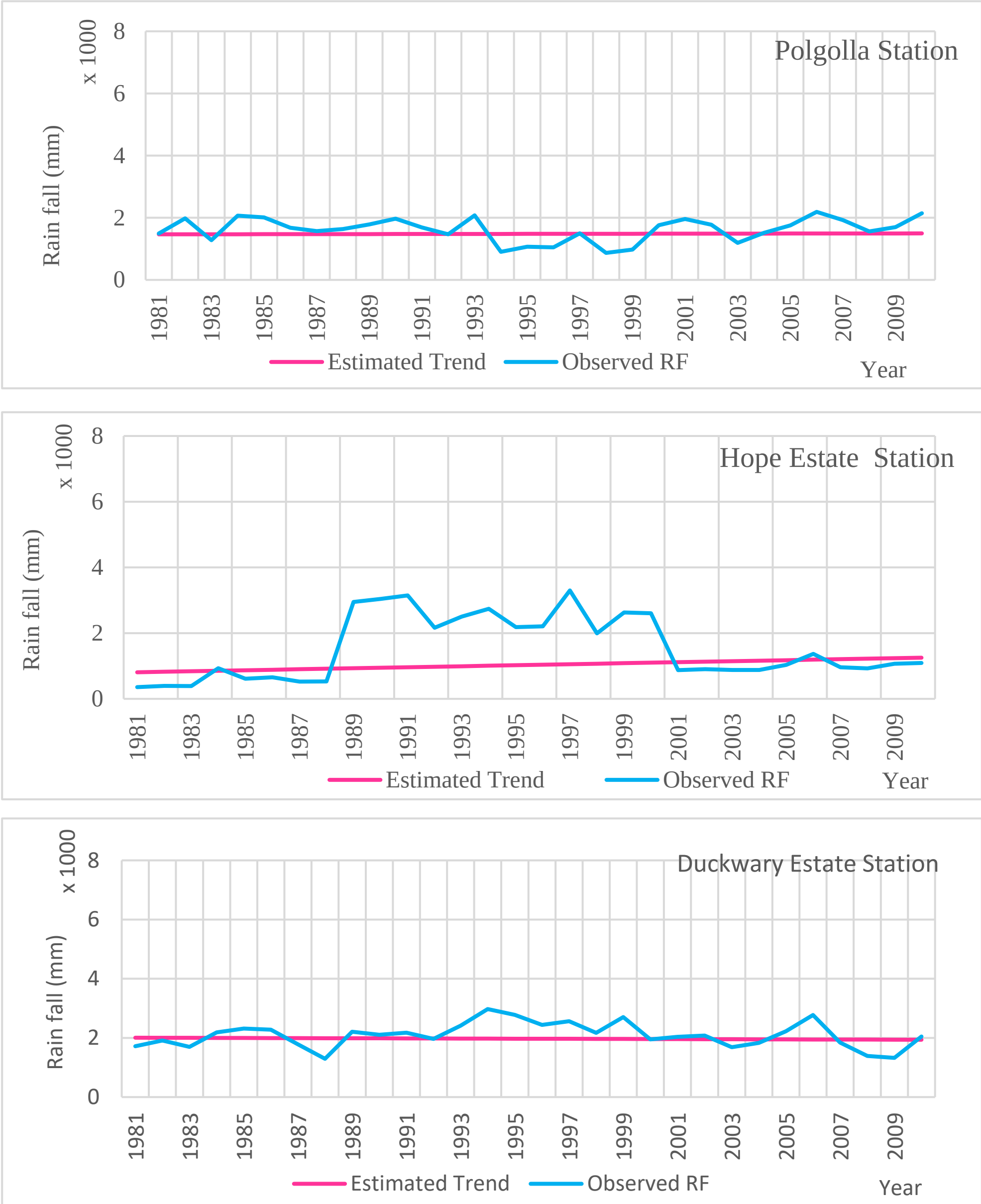


Figure 4-16 Estimated Rainfall Trend and Observed RF of Polgolla, Hope Estate and Duckwary Estate Stations

Table 4-1 Mann Kendall and Sens slope test results

	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
Hope Estate												
Slope (m)	-0.02	0.00	0.06	0.11	0.04	0.02	0.06	0.05	0.02	0.05	0.09	0.03
Intercept (c)	33.15	0.24	-117.31	-211.84	-67.89	-40.96	-113.24	-105.20	-39.24	-89.49	-182.67	-47.72
Duckwary Estate												
Slope (m)	0.07	0.02	0.03	0.06	-0.06	-0.05	-0.08	0.00	-0.07	-0.03	0.03	0.00
Intercept (c)	-142.40	-35.42	-57.75	-110.94	117.53	105.37	159.14	-4.10	155.21	78.21	-59.71	17.25
Polgolla												
Slope (m)	0.01	0.02	0.10	0.08	-0.06	-0.05	-0.09	-0.02	-0.06	0.04	-0.02	0.09
Intercept (c)	-15.69	-29.65	-198.13	-156.63	121.06	105.66	176.25	49.77	129.14	-66.85	43.63	-178.01
Sogama												
Slope (m)	0.00	0.00	0.06	0.14	-0.10	-0.23	-0.10	-0.10	-0.10	-0.24	-0.15	0.01
Intercept (c)	-6.63	1.48	-108.53	-265.27	211.57	475.97	201.13	200.25	212.38	483.70	309.05	-20.84
Kothmale												
Slope (m)	0.01	0.01	0.08	0.17	0.00	-0.14	-0.01	-0.03	0.00	0.12	0.10	0.08
Intercept (c)	-22.59	-27.90	-148.98	-325.88	-0.21	287.88	38.27	71.03	4.60	-220.29	-190.51	-164.82
Watawala												
Slope (m)	-0.03	0.01	0.06	0.22	0.08	-0.56	-0.28	-0.19	-0.10	0.09	-0.07	0.10
Intercept (c)	68.37	-15.42	-106.65	-421.78	-143.62	1132.24	587.08	399.05	223.52	-164.03	150.33	-193.66
Ambewala												
Slope (m)	0.03	0.00	0.02	0.03	-0.12	-0.13	-0.07	-0.08	-0.11	0.11	0.07	0.03
Intercept (c)	-49.29	2.12	-37.65	-59.68	248.80	275.76	147.05	167.53	221.01	-214.11	-142.11	-52.86

The efficiency of the model was evaluated statistically with objective functions of RMSE and NSE methods (Table 4-2 and Table 4-3) for 30 years. Further, the estimated rainfall model was evaluated graphically by plotting monthly average rainfall data over time (from Figure 4-17 and Figure 4-18 and Appendix A) for 30 years.

The range of RMSE is varied from zero to positive infinity with an ideal model to the worst model, respectively. RMSE values for each rainfall stations were calculated for monthly rainfall data of 30 years (Table 4-2).

The estimated rainfall for Watawala station gives a high RMSE value (7.19) while Polgolla station gives the lowest RMSE value (2.72). The NSE values range from negative infinity to 1 and the ideal model indicates NSE value of 1 while the worst model indicate negative NSE values. It was calculated the NSE values for 30 years of monthly rainfall data of each rainfall stations (

Table 4-3). According to the results, all NSE values were between 0 and 1 and that implies the model is reasonably fitted with observed rainfall data.

Table 4-2 RMSE and NSE values for Estimated Monthly Rainfall data

Sub-catchment	**RMSE Value (mm)**	**NSE value**
Ambewala	3.24	0.18
Watawala	7.19	0.46
Kothmale	3.57	0.42
Sogama	3.63	0.36
Polgolla	2.72	0.32
Hope Estate	4.33	0.02
Duckwary	3.39	0.30

Table 4-3 Variation of Predicted future Mean Annual Rainfall and Season Rainfall

<table>
<tr><th></th><th>Year</th><th>2025</th><th>2030</th><th>2050</th></tr>
<tr><td rowspan="6">Predicted Rainfall Data for Mahaweli upper catchment Base Period (1981-2010)</td><td>Mean Annual Rainfall</td><td>2068</td><td>2047</td><td>1973</td></tr>
<tr><td>Mean Annual Rainfall variation with base period</td><td>-14%</td><td>-15%</td><td>-18%</td></tr>
<tr><td>First Inter Monsson March-April</td><td>19%</td><td>25%</td><td>51%</td></tr>
<tr><td>South West Monsoon May - September</td><td>-26%</td><td>-31%</td><td>-48%</td></tr>
<tr><td>Second Inter Monsoon Octomber - November</td><td>-10%</td><td>-10%</td><td>-9%</td></tr>
<tr><td>Noth East Monsoon Decmber - February</td><td>-9%</td><td>-7%</td><td>3%</td></tr>
<tr><td rowspan="3">Precipitation Projection (Source :Ahmed and Supachalasai (2014)) (Base Period 1961-1990)</td><td>Scenario A2</td><td></td><td>7.4%</td><td>15.8%</td></tr>
<tr><td>Scenario A1B</td><td></td><td>11%</td><td>25%</td></tr>
<tr><td>Scenario B1</td><td></td><td>3.6%</td><td>16.5%</td></tr>
</table>

The predicted rainfall for 30 years (from 2021-2050) are compared with the precipitaton projections caried out based on Regional Climatic Models (RCM) of IPCC applicable for Sri lanka (Table 4-3 – Scenario A2, A1B and B1). According to the Mann Kendall Test results, the Mean Aannual Rainfall (MAR) for year 2030 will be decreased by 15% while in year 2050 it will be decrased by 18% . The based period for Mann Kendall test was used from year 1981 to year 2010. And predicted data for year 2025, 2030 and 2050 also taken as mean annual rainfall of 30 years data with time periods of year 2010-2039, year 2020-2049 and year 2035 -2064 respectively. The predicted mean annual precipitation is slightly deviated from projected precipitation . this may causes due to use of different base periods and the use of monthly rainfall data for prediction of precipitation. The average mothly rainfall of Mahaweli upper catchment area is about 175 mm and monthly rainfall is varied from 50mm to 300mm. It was identified the dry periods and wet periods in the study area by plotting annual rainfall over the year. It was defined wet periods as monthly rainfall is above 200 mm and dry periods as monthly rainfall is below 150 mm (Figure 4-16).

The predicted 30 years rainfall data were compared with historical data of base period. The First inter monsson shows positive trend with significant increment while less negative trend is shown in second inter monsoon nad North east monsoon periods (Table 4-3). The high rainfall are occurred in first inter monsson and second inter monsoon (Figure 4-16). Accordingly the high rainfall events increased in these periods. Significantly high negative trend shows in South West monsoon season (Table 4-3) and the low rainfall events are occurred during this period (Figure 4-16). Hence it is explained that dry periods are getting dryer with high intensity while wet periods are get more rainfall with time. The overall trend of Mahaweli uppercatchment is negative and it was decreased 14% by year 2025 and 18% by year 2050. This values are very significant and highly affected to the total inflow of the reservoirs in Mahaweli uppercatchemnt. It was defined below 150mm monthly rainfall as low intensity rainfalls events and above 200mm monthly rainfall as high intensity rainfall events

Further past studies revealed that the precipitation in mAhaweli upper catchment has been reduced by 39.12% past 100 years and the future rainfall trend is decreased by 16.6% in year 2025 (W.W.A.Shantha & J.M.S.B. Jayasundara, 2005). Under this study, it was get the estimated Mean annual rainfall of Maahweli upper catchment in year 2025 is about 14% and this value is camparable with the above atudy (W.W.A.Shantha & J.M.S.B. Jayasundara, 2005). And also the the estimated increment value of mean annual rainfall in year 2030 and 2050 compared to historiacal rainfall data (year 1981-2010) are compaed with the precipitation projection based on regional climatic model carried out by Ahmed and Supachalasai (2014)) (Base Period 1961-1990). (Ministry of Mahaweli Development and Environment, 2016). The estimated future rainfall in year

2030 is approximately camaprable with Scenario A1B and precipitation data for uear 2050 shall be approximately comparable with sceanario A2 and scenario B1 (table 4-3).

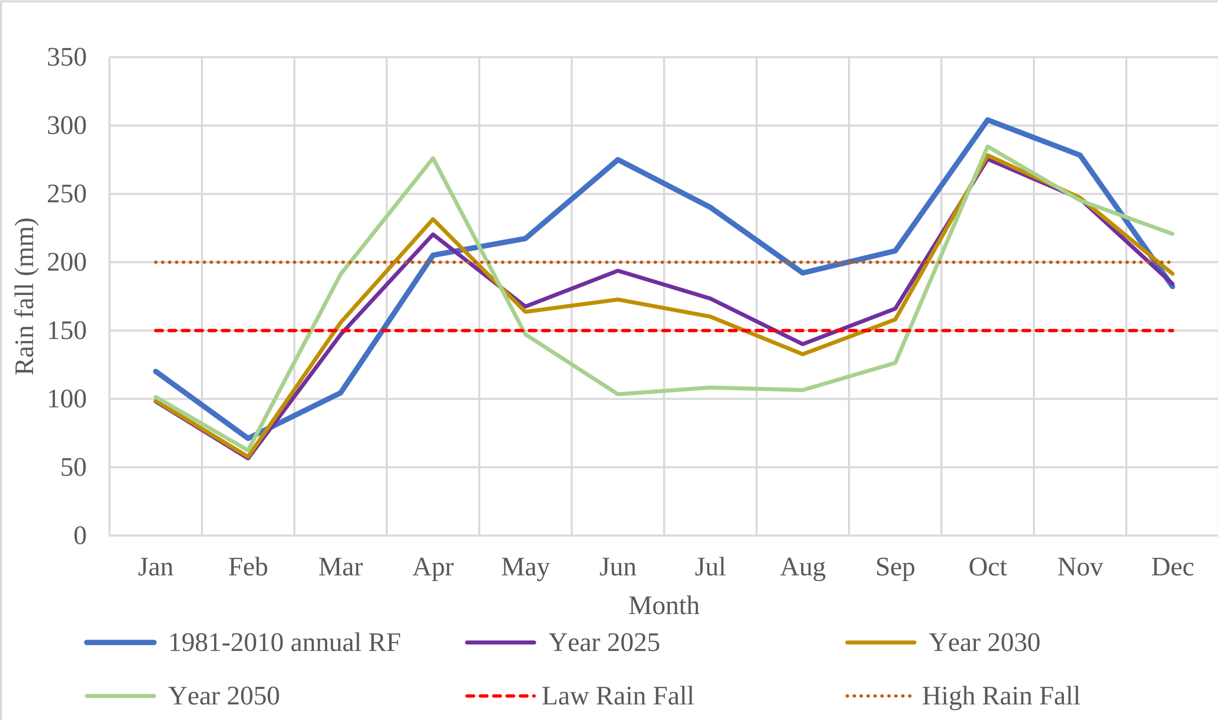


Figure 4-16 Variation of Predicted Future Rainfall throughout the year

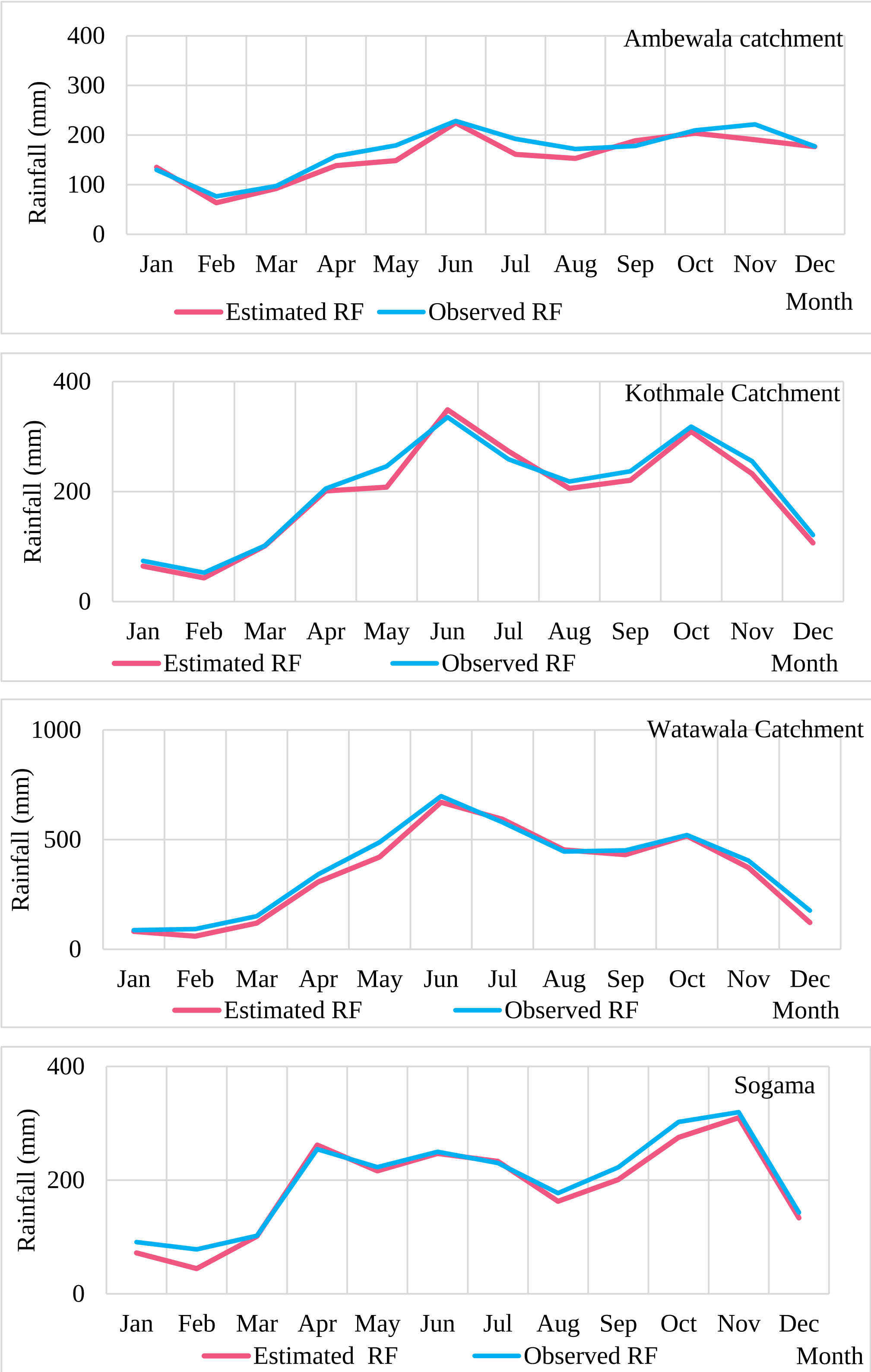


Figure 4-17 Estimated and historical Monthly rainfall variation (Ambewala, Soagama, Watawa, Kothmale)

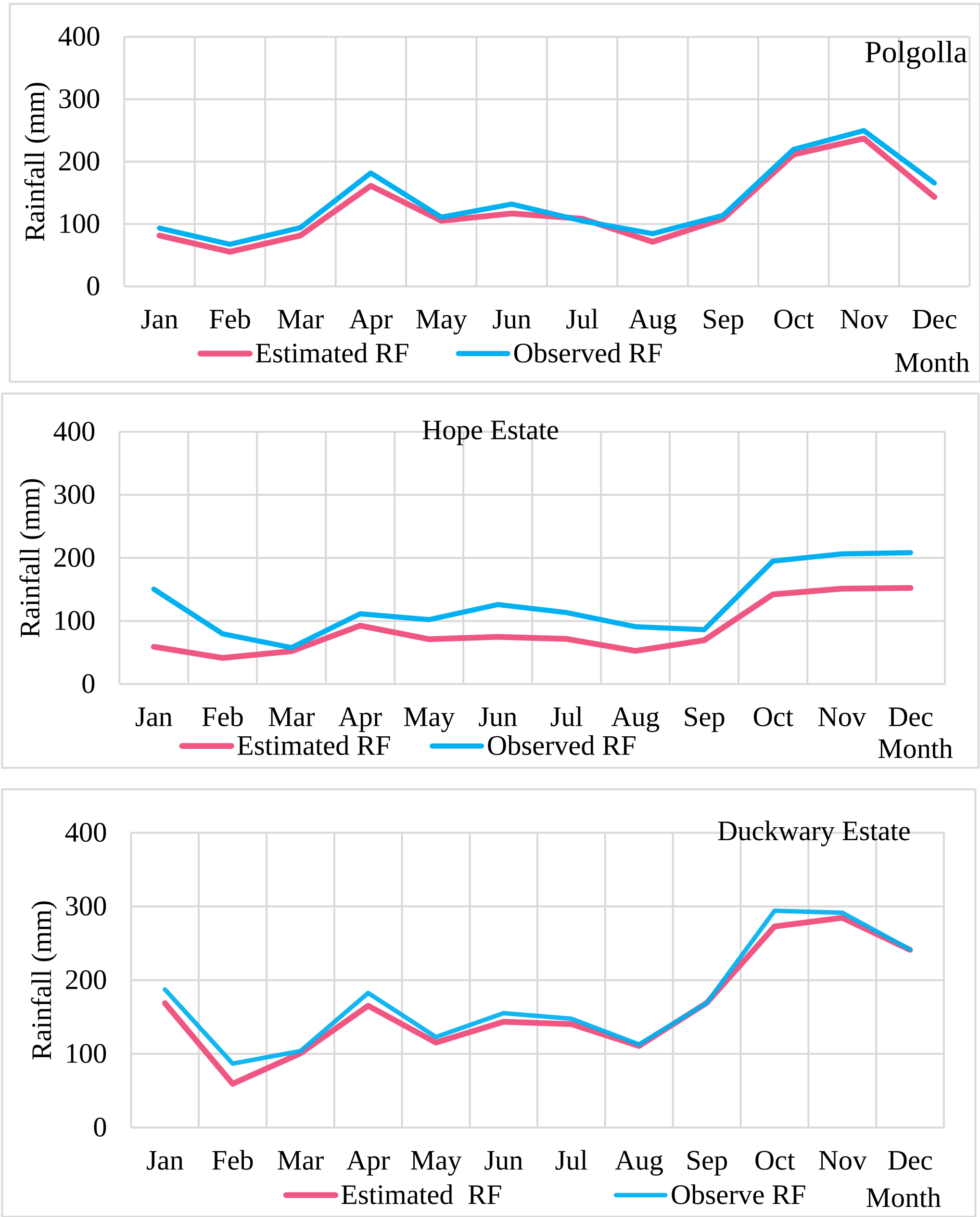


Figure 4-18 Estimated and historical Monthly rainfall variation (Polgolla, Duckwary Estate and Hope Estate)

According to the rainfall variation graphs for each catchment, it is observed that the rainfall was low from February to March and May to August in Polgolla, Hope Estate, Duckwary Estate and Sogama sub-catchments while rainfall is high from September to January and March to May. Further, the rainfall is increased from February to June and then decreased from August to January in Ambewala, Kothmale and Watawala sub-catchments.

The rainfall trend is negative in months of low rainfalls were experienced and the trend is positive in months of high rainfalls were experienced (Table 4-1). This reveals that dry periods are getting dryer and wet periods are getting wet in future. This phenomenon is not good for water management aspects as it is difficult to balance the water supply and demand curve. This highly affects the hydropower generation as the water availability for hydropower generation in dry periods is very low and it will lead to low hydropower generation. But in rainy periods the trend is positive and there may be an excess of water rather than the water demand of hydropower generation and full capacity of the reservoir.

Analyzing rainfall trend and predicting future rainfall and inflows to the reservoirs is very important to analyse the impact on hydropower generation due to rainfall trend in future. The future rainfall was estimated for a further 30 years (2020 -2050) from the Sen's slope method and estimated future rainfall and historical rainfall were compared to identify the rainfall variation in future with respect to historical rainfall data (Table 4-4 and Appendix B and Appendix C). And those estimated rainfall data are used to predict the future catchment runoff volumes with HEC HMS modelling and to analyse the water availability for hydropower generation in future by performing reservoir simulation on HEC Res Sim software.

Table 4-4 Comparison of Estimated future Annual Rainfall (in mm) and Observed Present Annual Rainfall (in mm)

Catchment	Present Rainfall	Future Rainfall	Variation
Ambewala	2052.00	1774	-14%
Kothmale	2465.00	2833	15%
Watawala	4511.00	2849	-37%
Sogaama	2431.00	1261	-48%
Polgolla	1643.00	1,546	-6%
Hope Estate	1553.00	1718	11%
Duckwary Estate	2131.00	1782	-16%

4.3 Catchment Model in HEC Geo HMS and Arc Hydro Tool in Arc GIS

Hydrological model for the upper catchment of the Mahaweli basin was created on HEC HMS platform to obtain the rainfall runoff for each sub-basin. Before creating the hydrological model on HEC HMS, a catchment model was created on Arc Map using HEC Geo HMS and Arc tool to delineating sub-catchments and their physical properties. The Sub-catchments, Physical properties, hydrological properties and other required parameters were generated on Arc Map

a. Drainage path, centroids and flow paths – to compute the time of concentration of each basin

b. SCS curve numbers for each sub-catchment

c. Catchment areas and reaches and flow path length

d. Assigning rainfall gauges, selection of runoff calculation methods and losses methods

The basic parameters and hydrological characteristics of the basin model were assigned based on HEC GeoHMS platform. The HEC HMS project was created on HEC GeoHMS and required files and maps were generated accordingly. The HEC HMS catchment model project (Figure 4-19) was created on Arc GIS and the project was exported to HEC HMS (Figure 4-20).

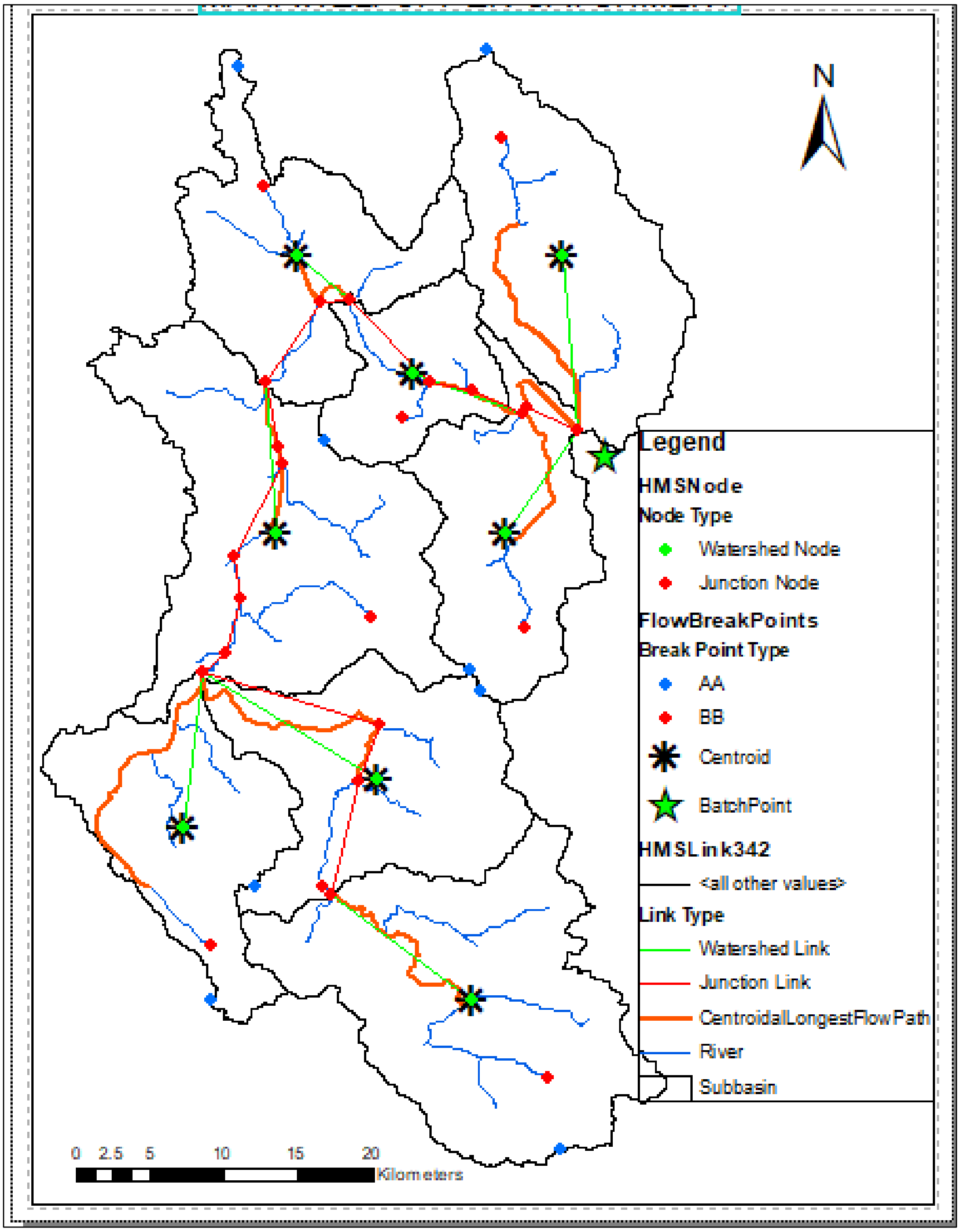


Figure 4-19 HEC HMS Schematic Diagram

4.3.1 Hydrological Model in HEC HMS for Upper Catchment of Mahaweli Basin

The generated HEC HMS project in Arc GIS was exported to HEC HMS Software in HEC HMS, rainfall runoff was generated for each sub-catchment and the inflows to each reservoir were obtained. The model was calibrated with daily rainfall data for 5 years from the year 2001 – year 2005 and validation was performed with daily rainfall data for 5 years from the year 2006 – year 2010. The generated inflow volumes were compared with the observed inflows of each reservoir (Kothmale, Polgolla and Victoria) to calibrate the model. The diversion of polgolla reservoir was taken as 56 m^3/s. The inflows were generated as a flow rate and observed inflow data were recorded as an amount in MCM units. Hence the flow rate was converted to total daily inflow volume to each sub-catchment.

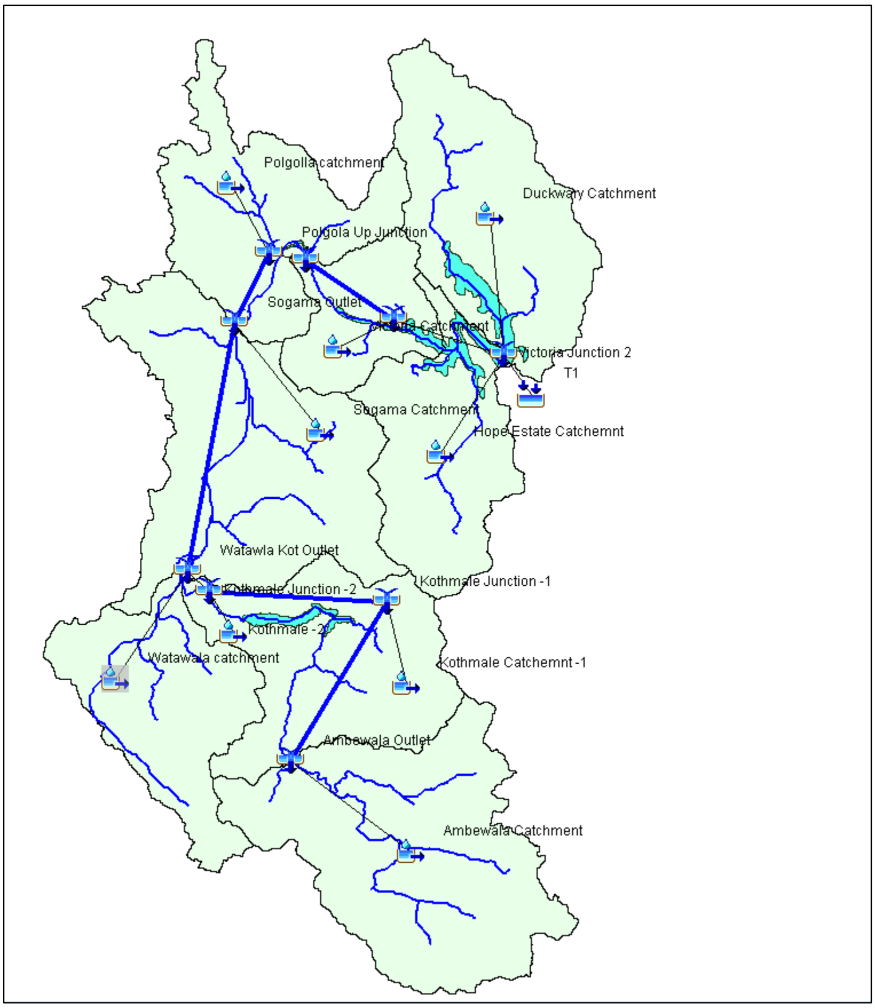


Figure 4-20 The schematic diagram of HEC HMS Model

Model calibration was performed adjusting hydrological parameters of the model and model performance was evaluated by applying objective functions of Root mean square error (RMSE) and Nash – Sutcliffe Efficiency (NSE) methods (Table 4-5). The model calibration was carried out on a trial-and-error basis until a minimum RMSE value and NSE value in between 0-1 were obtained (Table 4-5).

Table 4-5 RMSE and NSE values for Estimated Inflow data for three reservoirs

Reservoir	**NSE**	**RMSE (MCM)**
Kothmale	0.055	1.44
Polgolla	-0.34	2.91
Victoria	0.36	2.34

The model performances varied ideal to worst with 1 to negative infinity for NSE values and 0 to positive infinity for RMSE values (Muleta, 2012). Accordingly, the simulated HEC HMS models for the above three reservoirs could be considered as reasonably fitted with the observed data.

The inflow hydrographs were plotted for simulated and observed inflow (Figure 4-21) of these three reservoirs to analyse the catchment parameters and model calibration was performed until obtaining well-fitted graphs and minimum error of the model.

Further flow duration curves were plotted for modelled inflow data and compared the simulated and observed inflow data of Kothmale, Polgolla and Victoria reservoirs. It was defined as 20% of exceedance as margin for low flows and 80% exceedance as margin for high flows. The low flows and high flows of the simulated inflows were shown considerable deviation with respect to observed inflows of Kothmale and Polgolla reservoirs (Figure 4-22 and Figure 4-23). High flows of the simulated model of Victoria reservoir slightly deviated from the observed inflow. But the flow duration curve for simulated inflow of Victoria reservoir was almost followed the flow duration curve of observed inflow.

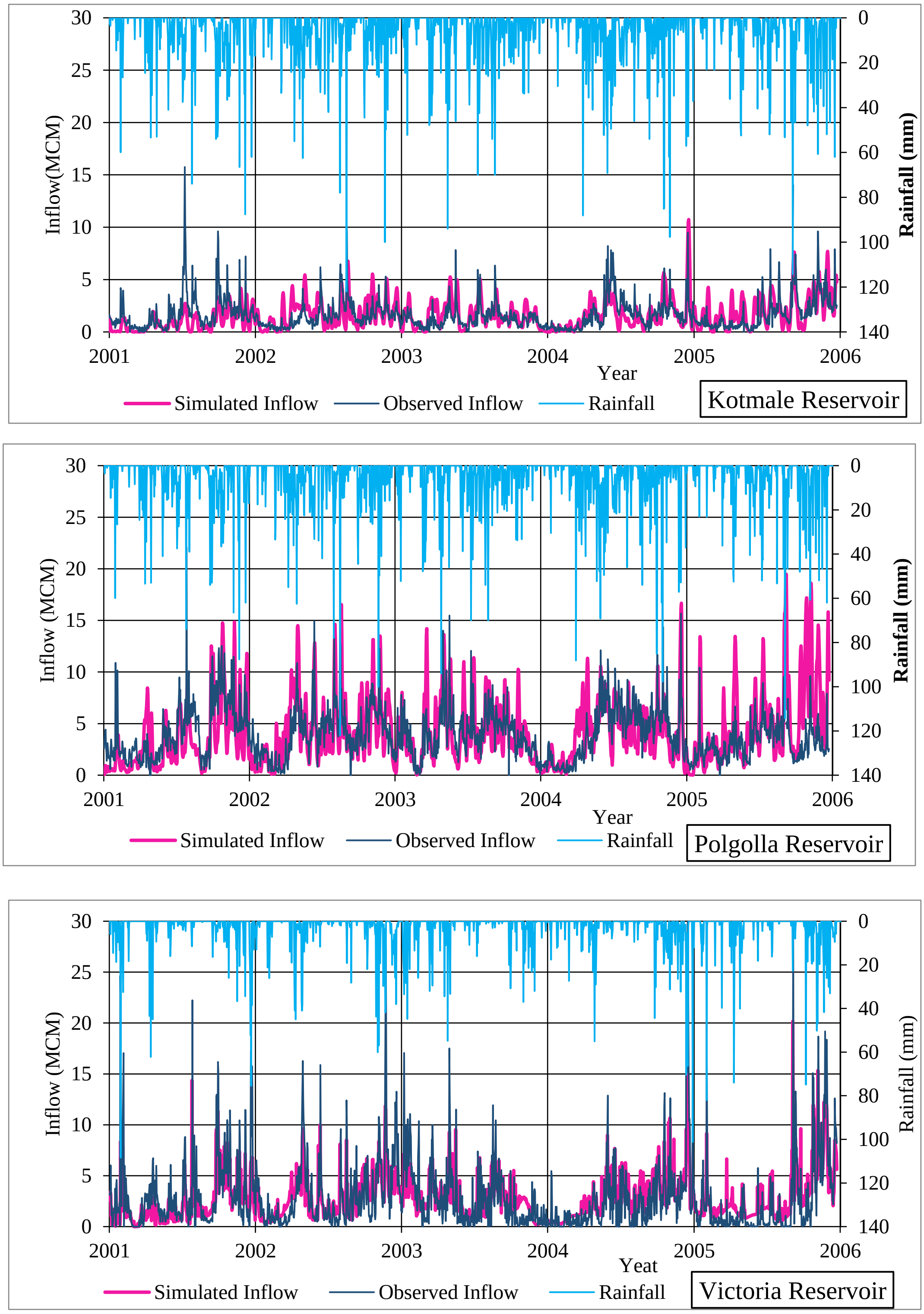


Figure 4-21 Inflow Hydrograph for reservoirs in Mahaweli upper catchment

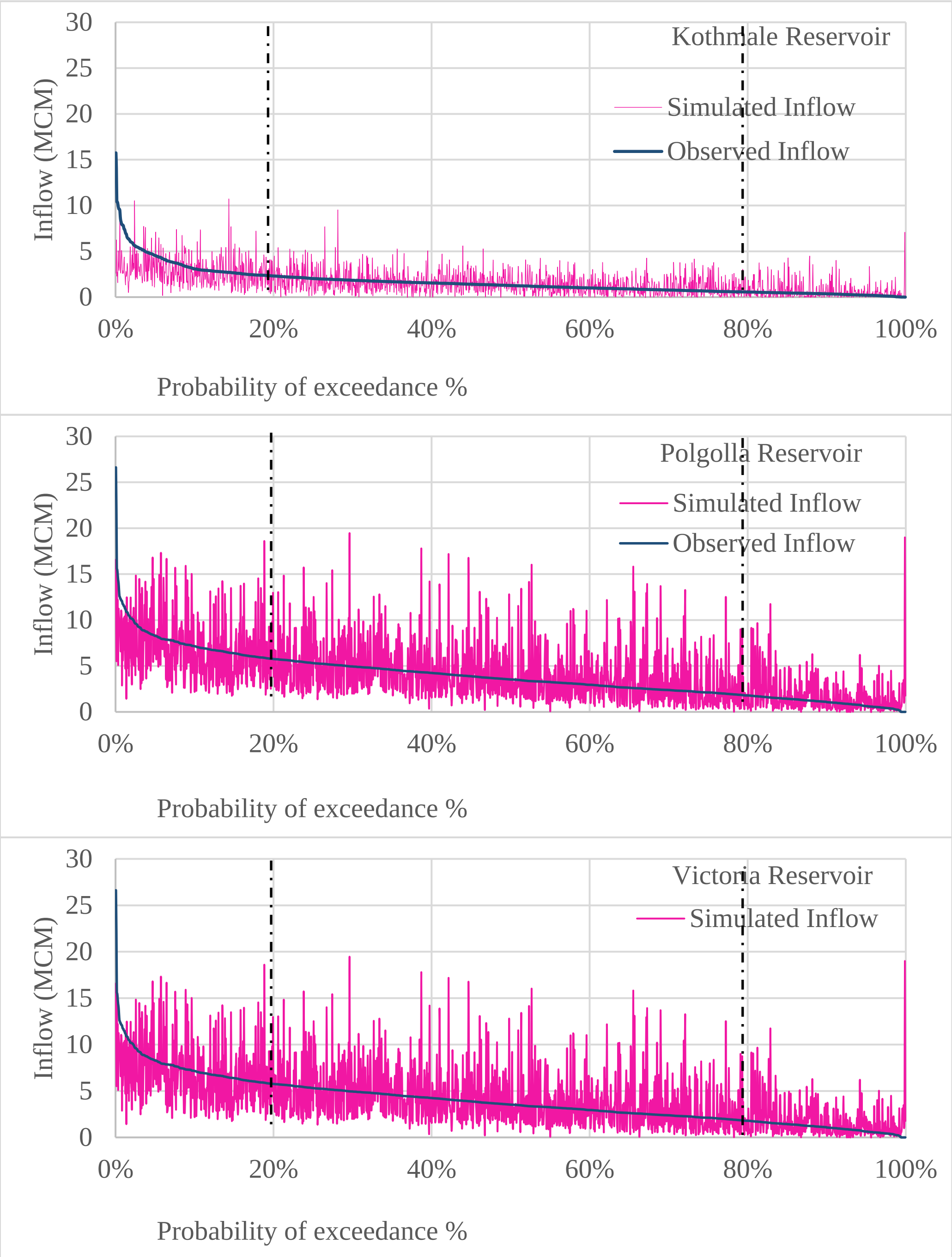


Figure 4-22 Flow Duration Curve for reservoirs in Mahaweli upper catchment

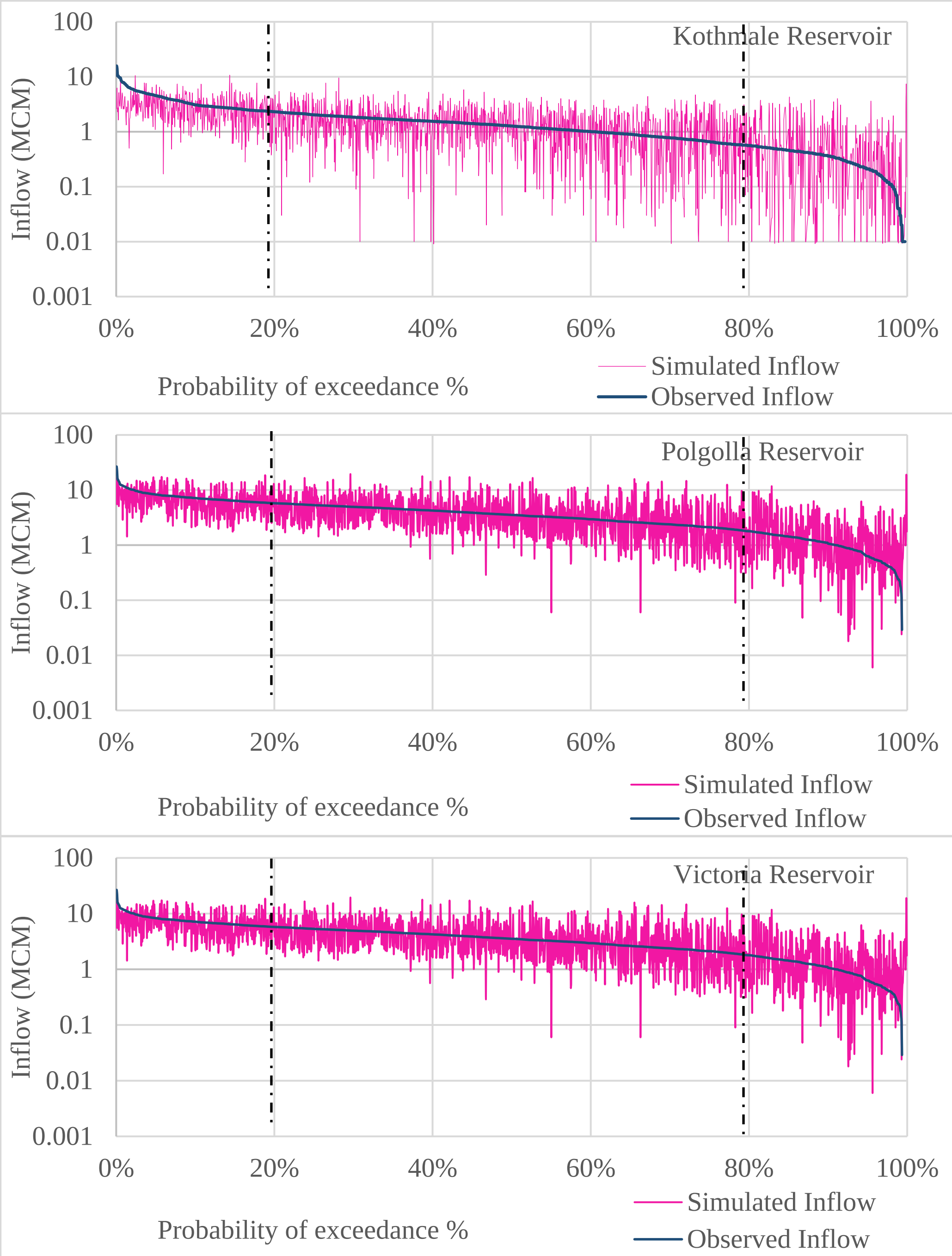


Figure 4-23 Flow Duration Curve for reservoirs in Mahaweli upper catchment (log scale)

The lag time of basins, Curve Number and impervious percentages were highly sensitive to the rainfall runoff of sub-catchments. The hydrological model was performed considering the downstream releases from upstream reservoirs of a particular reservoir and a hydrological model was created considering three reservoirs separately. But the whole reservoir operations were not taken into consideration, since the hydrological model was performed to obtain the catchment runoff only. When comparing the inflows to the reservoir, the actual downstream releases of each reservoir were considered for calibration of the model. This study was basically focused on reservoir operations and hydropower generation of the Victoria reservoir. But catchment modelling was performed for three reservoirs initially to calibrate the model.

4.3.2 Hydrological Model for Victoria Sub-catchment

The inflow to the Victoria reservoir could be generated in two methods. The hydrological model shall be performed for the whole Mahaweli upper catchment up to the Victoria reservoir with reservoir operations of the Kothmale and Polgolla reservoirs and get the inflows to the Victoria reservoir. But this method is complicated in modelling on HEC HMS and model performance may be low. Further, the recorded storages were not accurate as the reservoir capacity curves are not updated recently in Kothmale, Polgolla and Victoria reservoirs. Hence, in order to minimize the errors in hydrological models in inflow calculations, the hydrological model was developed considering direct inflows to Vicotria reservoir which are sub-catchments of Victoria reservoir and downstream release of Polgolla reservoir (Figure 4-24). Since the simplicity of this method and required less hydrological data, the hydrological model was performed by this method in order to predict the future inflow to Victoria reservoir.

The predicted future rainfall data were obtained as monthly data from Mann Kendall test. Hence, the HEC HMS model for future scenario has to be done for monthly data. Therefore, the model was calibrated for monthly rainfall data for the year 2001 – 2005 and validated for the year 2006 – 2010. This model was performed only for inflows to Victoria reservoir by considering Polgolla downstream release, and runoff from sub-catchments of Victoria reservoir (Duckwary Estate, Victoria and Hope Estate) (Figure 4-24 and Figure 4-25). The rainfall data were given as the cumulative value of particular month starting from the 1st day of the month and time lag was given such that distributing the generated runoff throughout the whole month due to rainfall on 1st day of the month. Accordingly, the time lag was given in the range of 600 – 800 hours in Clark unit hydrograph method. The time lag, SCS curve number and base flows were adjusted such that model inflows corresponded to observed inflows of the Victoria reservoir.

The HEC HMS model is used only for obtaining the sub-catchment inflows to the Victoria reservoir. Hence it is considered the total inflows up to Polgolla barrage by the downstream release of Polgolla barrage instead of considering total upstream catchments inflows and reservoir operations of Kothmale and Polgolla barrage. The Victoria sub-catchment, Hope Estate and Duckwary estate sub-catchments inflows were taken as direct runoff to the Victoria reservoir. Accordingly, the downstream release from Polgolla reservoir was given as a source tool and the release amount was given through a discharge gauge of the source tool (Figure 4-25). The rainfall data were fed as monthly data for three sub-catchments through a DSS file and downstream release of Polgola barrage was given as daily data. The model was calibrated for 5 years from the year 2001 to the year 2005 and validated for 5 years from the year 2006 – 2010. The model was calibrated such that the modelled total inflows to the Victoria reservoir correspond to the observed total inflows of Victoria reservoir (Figure 4-26 and Figure 4-27). The Calibrated model was validated with a further 5 years (Year 2006 - 2010) and observed and validated inflow data were plotted monthly and Daily basis (Figure 4-32Figure 4-33). The model performances were evaluated by calculating the RMSE value and NSE values for modelled inflow data. HEC HMS model was calibrated until getting the values of RMSE and NSE values within the acceptable range (Table 4.6). Further, the flow duration curves were plotted for calibrated and validated inflows of Victoria reservoir (Figure 4-28, Figure 4-29, Figure 4-30, Figure 4-31, Figure 4-34, Figure 4-35, and Figure 4-36). The simulated high flows were deviated compared to the observed inflows in both calibrated and validated model

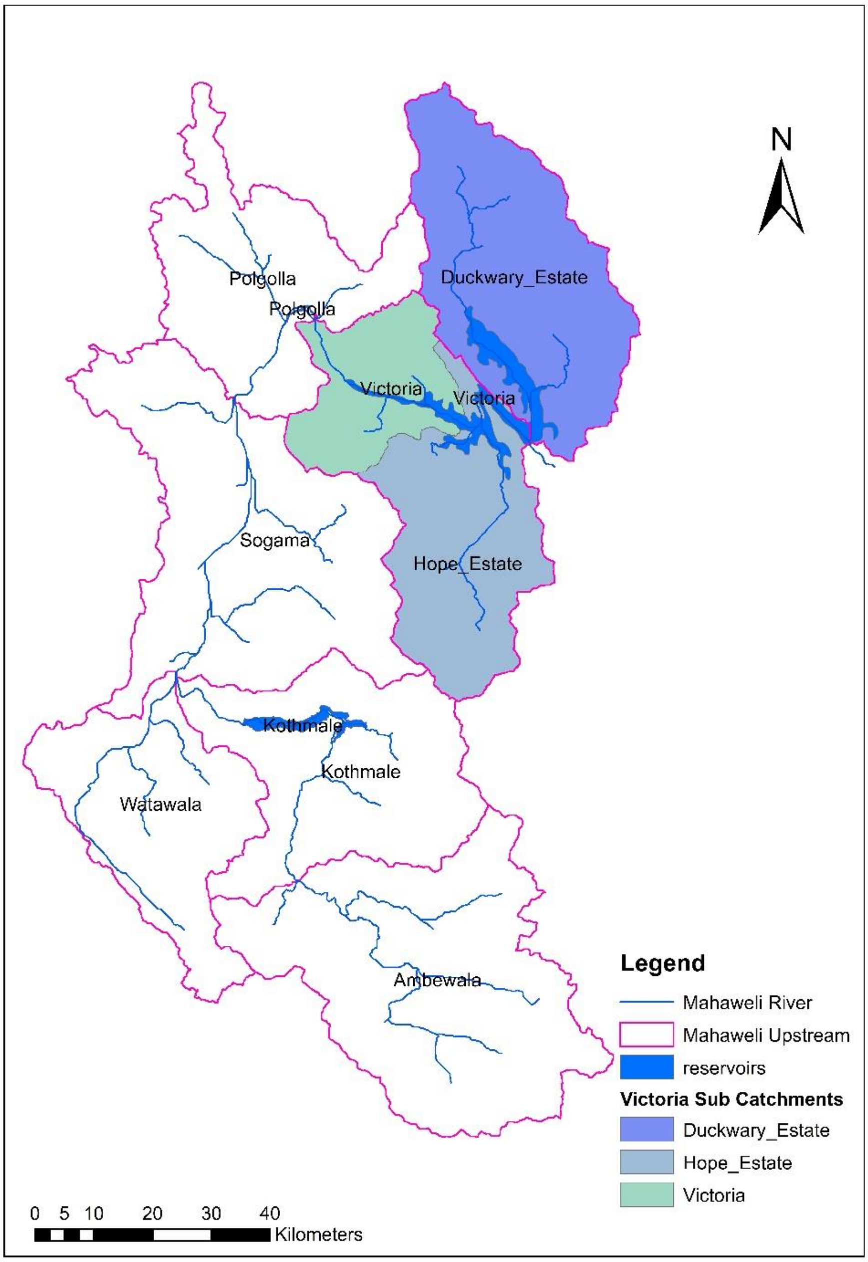


Figure 4-24 Delimitation of sub-catchments for Victoria reservoir

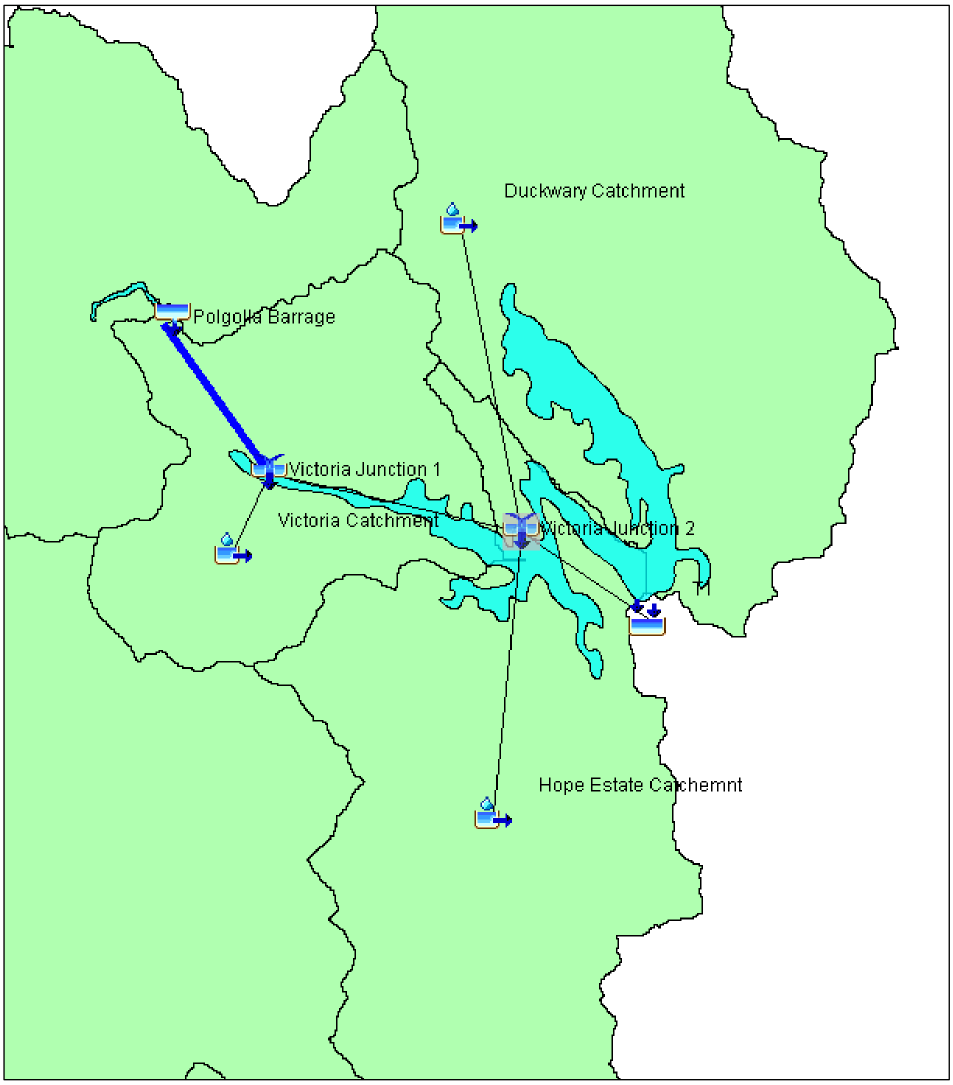


Figure 4-25 Schematic diagram for Victoria reservoir in HEC HMS Model

The catchment runoff model was simulated for a period of 5 years from 2021 – 2025 with future monthly rainfall data which were derived from Mann Kendal and Sen's Slope tests. The inflows to Victoria reservoir were obtained from catchment runoff simulated from HEC HMS model and downstream release of Polgolla Barrage.

4.3.2.1 Analysis of Model performance for calibrated Model (Year 2001-2005)

HEC HMS model was calibrated for a period of 5 years (from the year 2001 to the year 2005) until the simulated inflow data were follow up by the observed inflow data. The inflow Hydrographs were plotted for simulated and observed inflow data over time on a yearly and daily basis (Figure 4-26 and Figure 4-27). The flow duration curves for simulated and observed inflow data were plotted for each year in normal scale and semi-log scale (Figure 4-28, Figure 4-29, Figure 4-30 and Figure 4-31). The model performance was analyzed numerically by developing objective functions of NSE, RMSE and annual mass balance (Table 4-6)

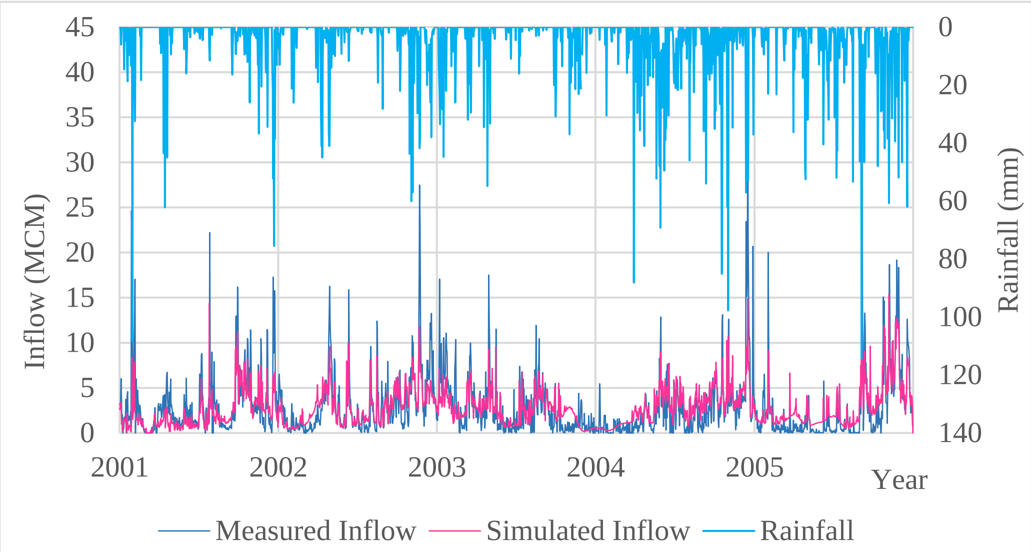


Figure 4-26 Daily Inflow hydrograph of Victoria reservoir - Calibrated Model (Year 2001 - year 2005)

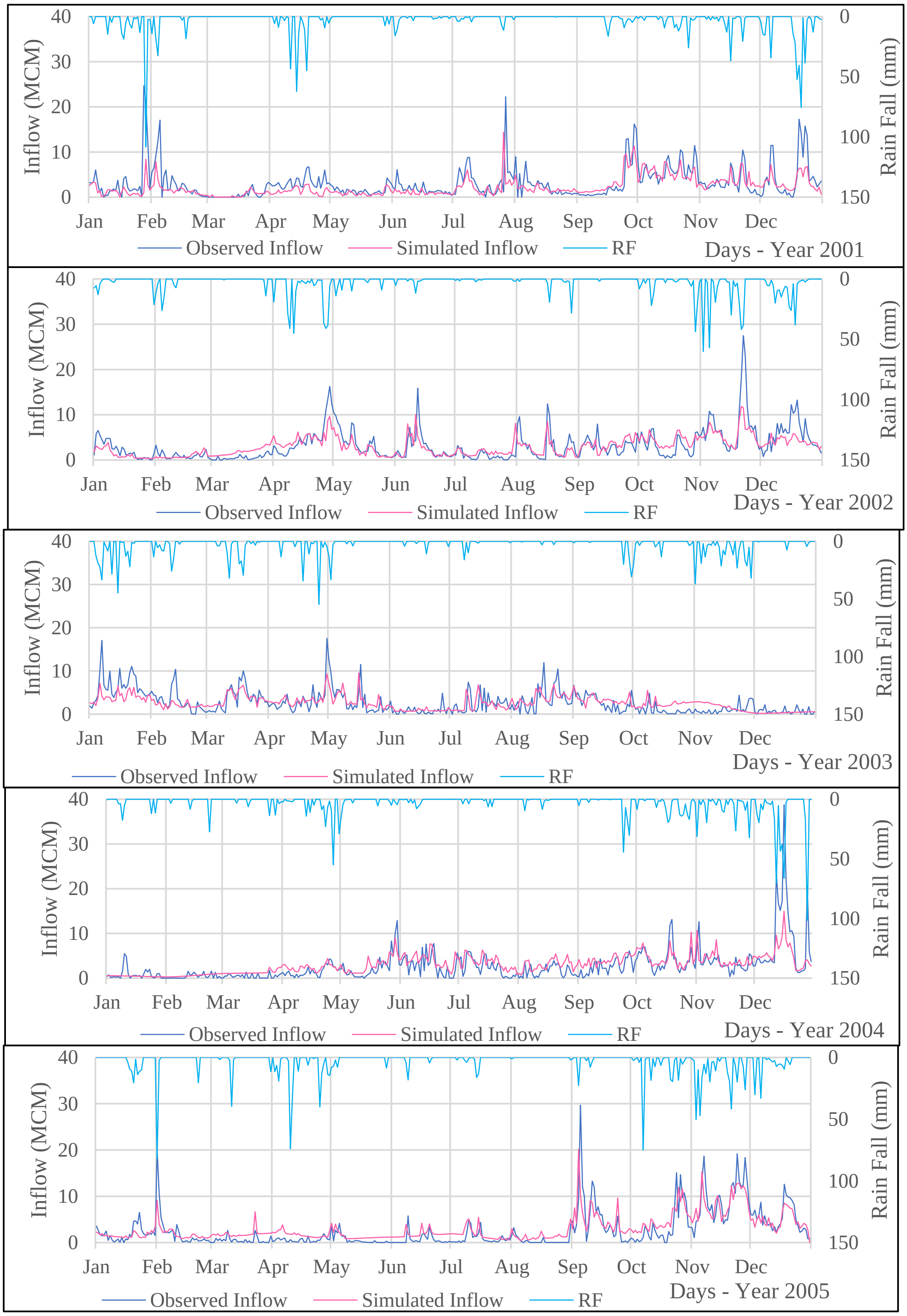


Figure 4-27 Daily Inflow hydrograph of Victoria reservoir in each year- calibrated Model (year 2001-year 2005)

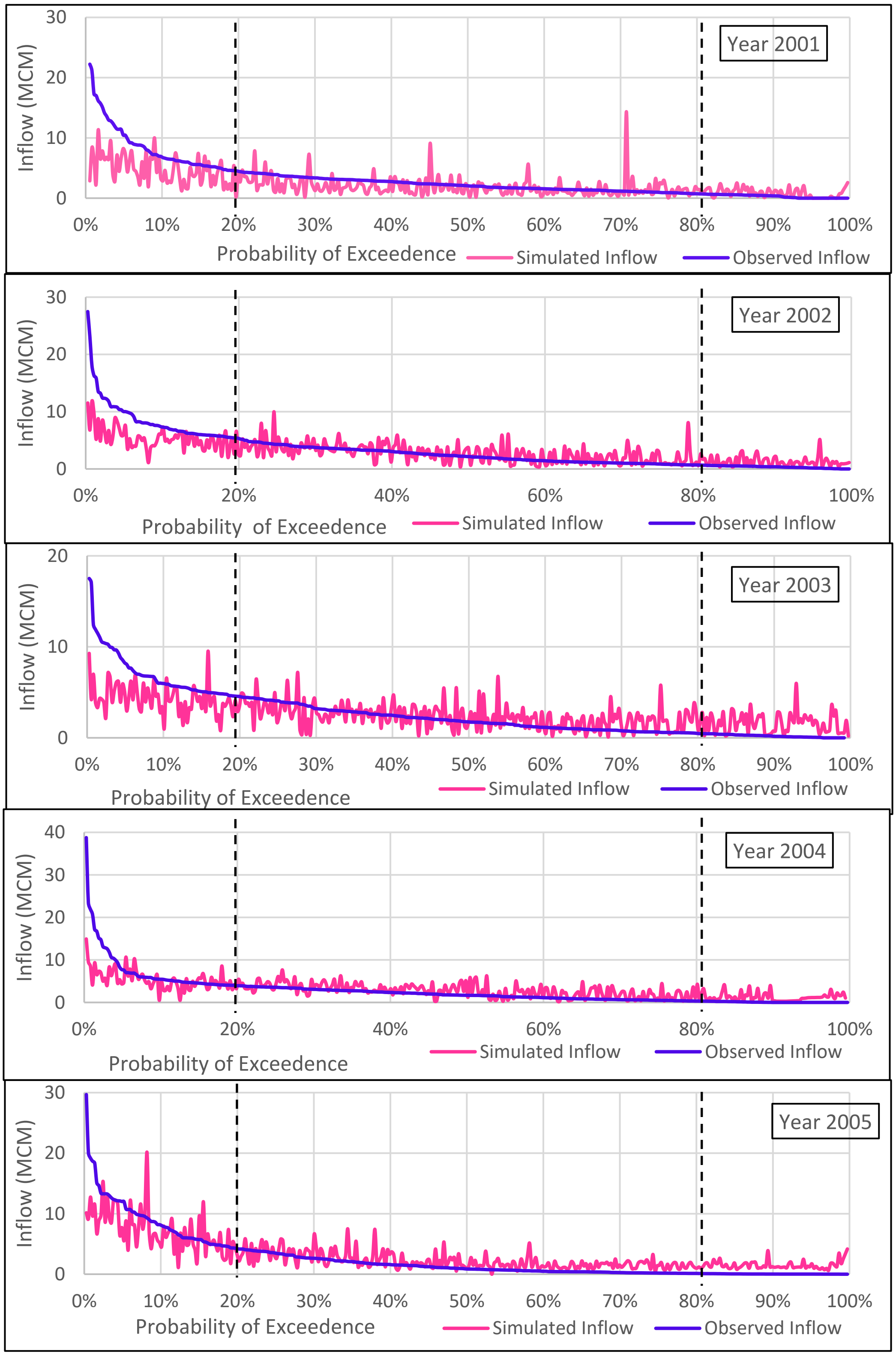


Figure 4-28 Flow Duration curve for of Victoria reservoir for each year – Calibration Model (Year 2001 – Year 2005)

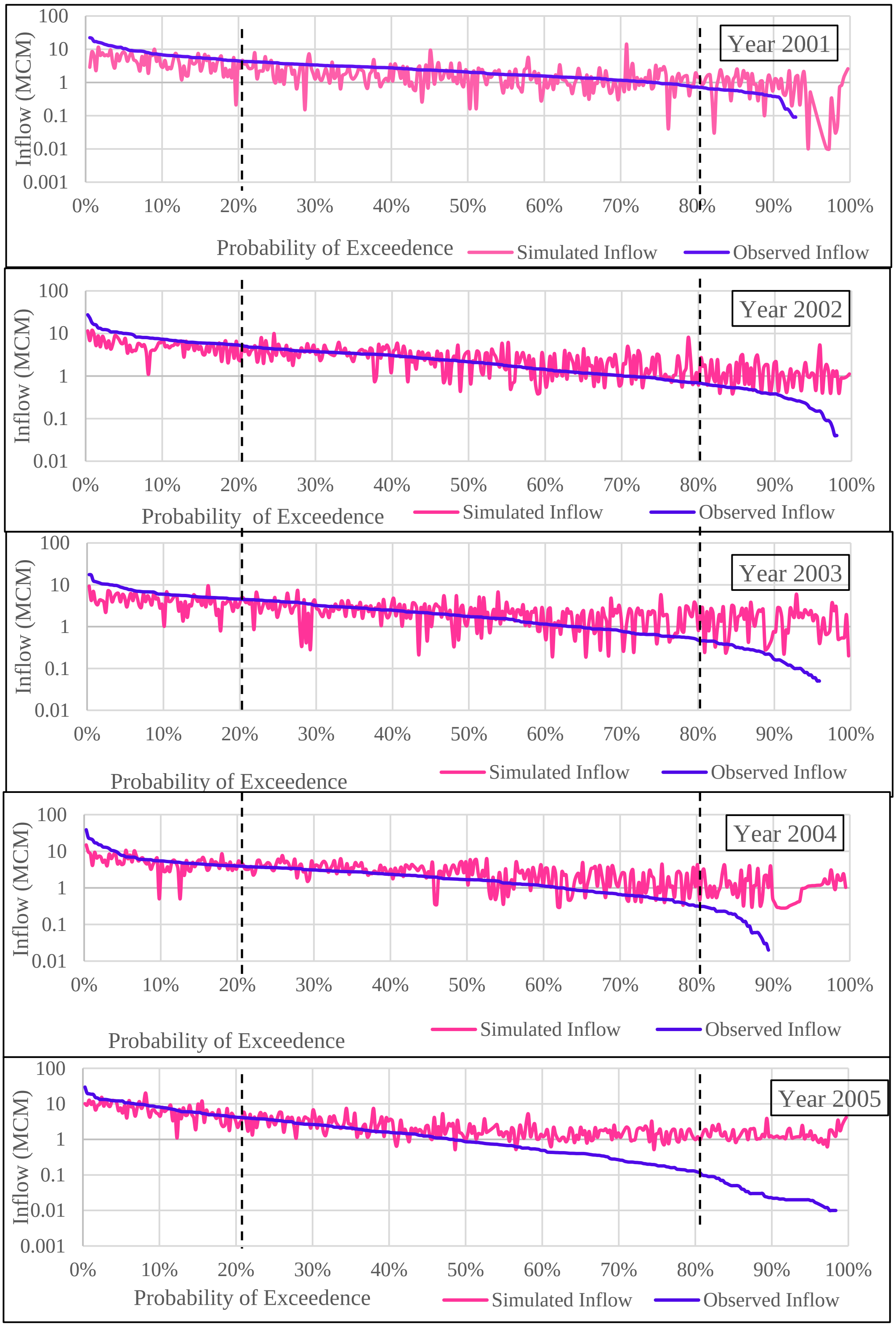


Figure 4-29 Flow duration curves of Victoria Reservoir for each year in log scale–calibrated Model (year 2001-year 2005)

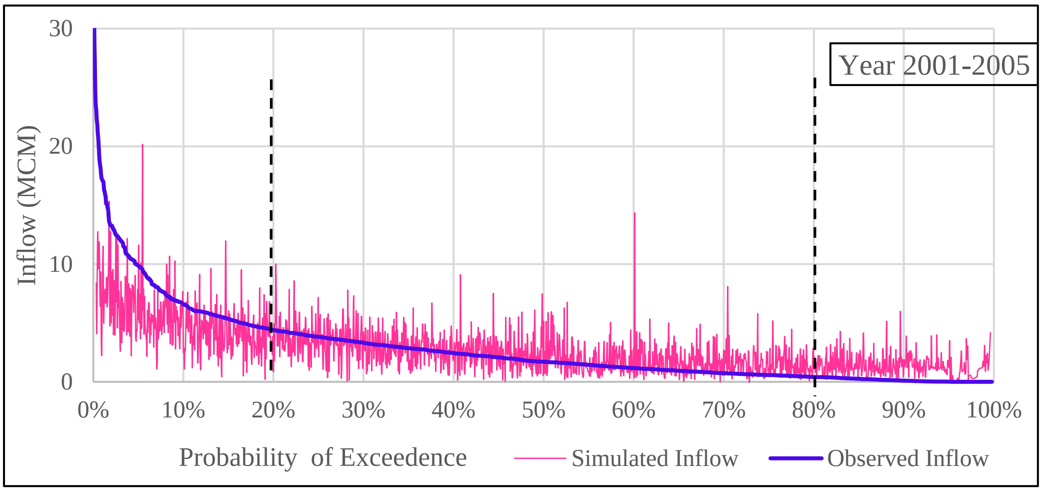


Figure 4-31 Flow duration curves of Victoria Reservoir – calibrated Model (year 2001-year 2005)

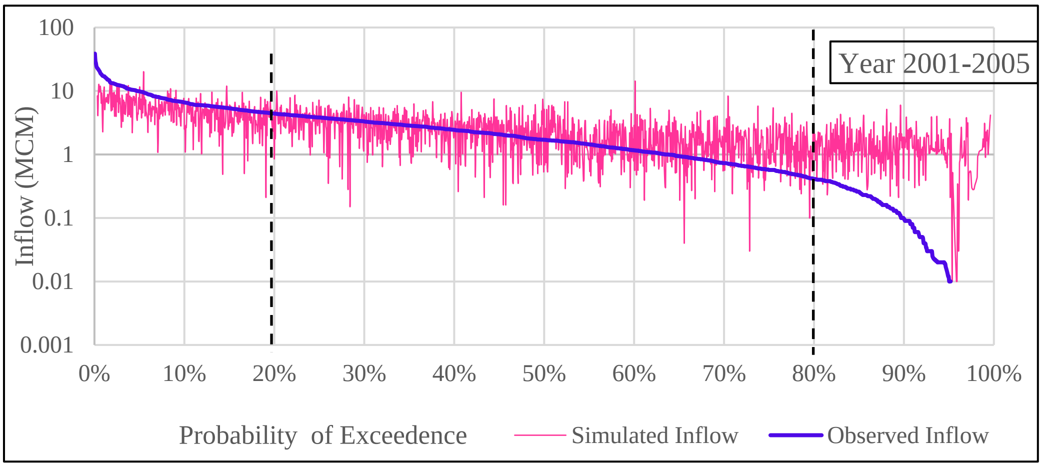


Figure 4-30 Flow duration curves of Victoria Reservoir in log scale – calibrated Model (year 2001-year 2005)

The hydrographs show that there is a significant gap at the peaks and falls of the graphs of simulated inflow and observed inflow. The hydrograph for simulated inflow is almost follow up the observed inflow hydrograph in pattern and values (Figure 4-26 and Figure 4-27). The rainfall data were fed into the HEC HMS model as monthly data since the expected future rainfall data were generated from Man Kendal and Sen's slope method were given as monthly data. Hence the rainfall data were fed into the HEC HMS model as monthly data and the lag time was adjusted such that distribution of the effect of monthly rainfall over the entire month. the model was calibrated by changing parameters in the basin model such that the simulated inflow data were almost follow up the observed inflow data.

The simulated inflow hydrographs were almost following up observed inflow hydrographs and the particular rainfall hydrograph except for few events (Figure 4-26). The flow duration curves show the simulated and observed inflows with respect percentage of time of a particular inflow event. It was considered 20% of exceedances as the limit of low flows, 80% of exceedances as the limit of high flows and between these two limits consider average flows (Figure 4-28, Figure 4-29, Figure 4-44 and Figure 4-31). The high flows and low flows of simulated inflows significantly deviated from observed inflows. This may have caused since it was modelled in the HEC HMS model on a monthly basis instead of a daily basis. But the average flows were almost following up the observed inflow graph.

Table 4-6 Results of objective functions for calibrated model

Time Period	**NSE**	**RMSE**	**Annual Mass Balance error**
2001-2005	0.48	2.53	3%
2001	0.31	2.94	28%
2002	0.52	2.39	7%
2003	0.39	2.15	2%
2004	0.47	2.71	-14%
2005	0.64	2.37	-17%

For an ideal model, the NSE value shall be close to 1 and the RMSE value shall be close to zero. The high positive or negative values mean the developed model deviates from the actual conditions. The NSE values for 5 years are in between 1 and zero, and it shows that the developed model is almost in the acceptable range. Further, RMSE values also in an acceptable range. The annual mass balance error is high in the year 2001 and low in the year 2002 and 2003. The average annual mass balance error for 5 years is 3% and it is also in the acceptable range (Table 4-6). Hence, the calibrated model is almost following up the actual conditions in average flows except for high and low flows. According to the inflow duration curve, it shows considerably high deviations in high and low flows in calibrated model. Further the simulated inflows are lower than observed inflows in high flow event s and low flow events. Hence, the overall inflow in the calibrated model is giving low inflows than the actual condition.

4.3.2.2 Analysis of Model performance for validation Model (Year 2006-2010)

The validation model is also subjected to the performance analysis with the same objective function analyzed for the calibrated model.

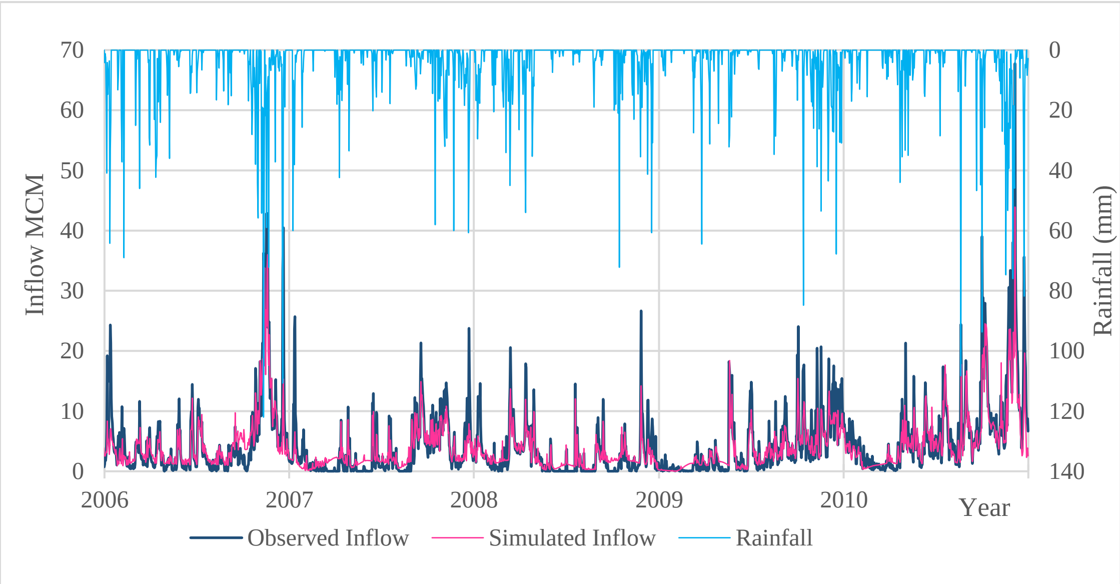


Figure 4-32 Daily inflow hydrograph of Victoria reservoir - Validation model (Year 2006-Year 2010)

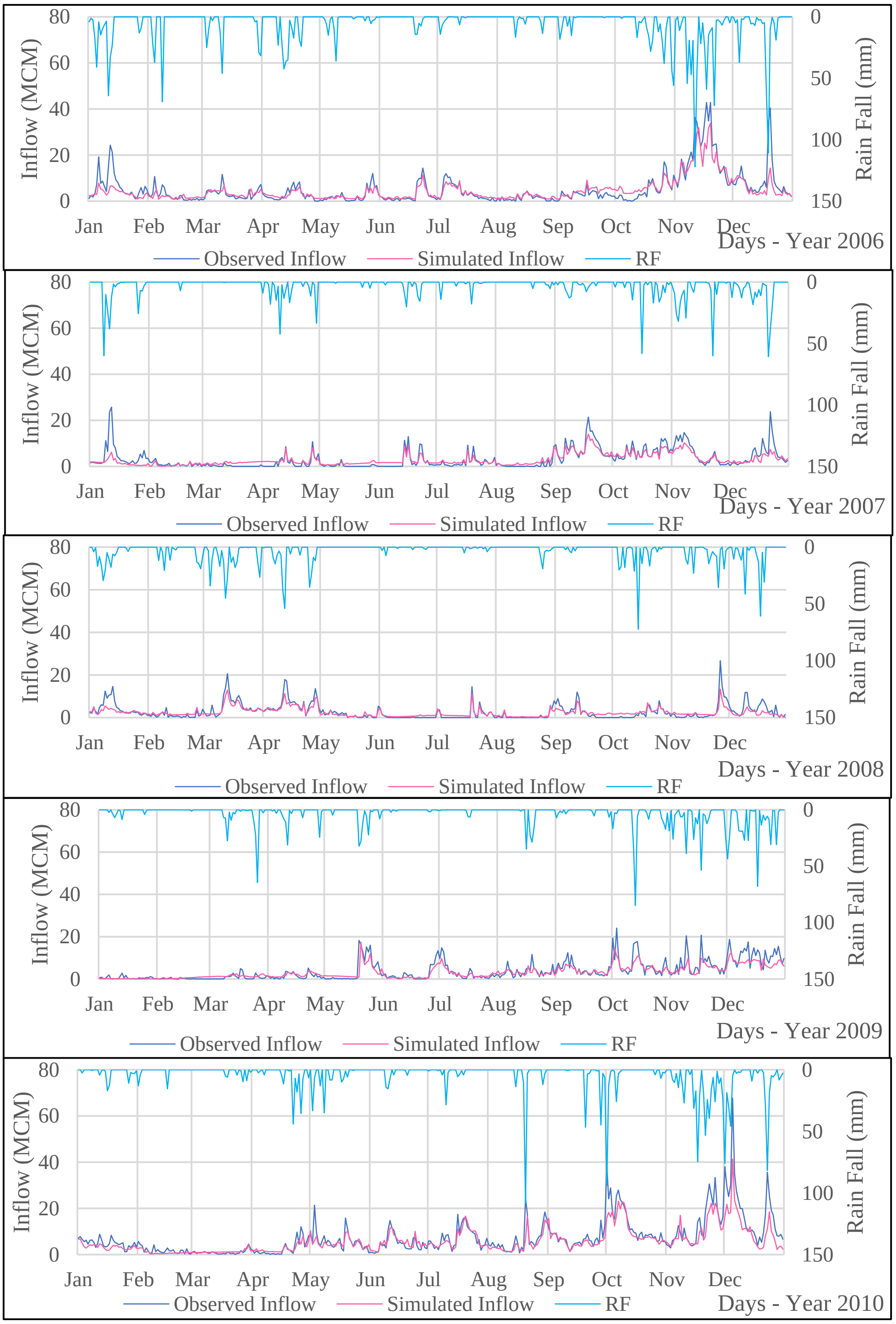


Figure 4-33 Daily Inflow hydrograph of Victoria reservoir - validated Model (year 2006-year 2010)

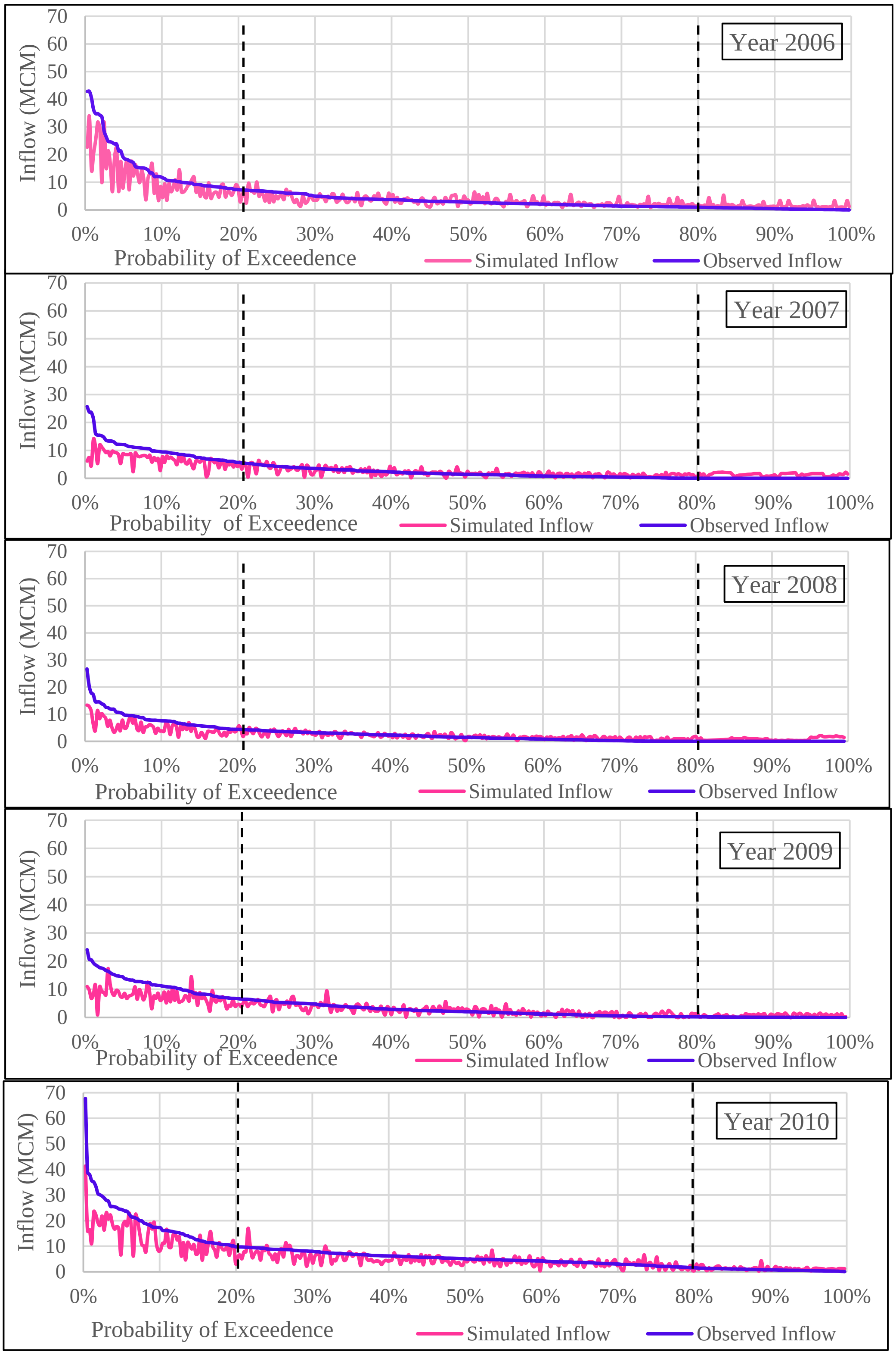


Figure 4-34 Flow Duration curves for validated model - (Normal scale)

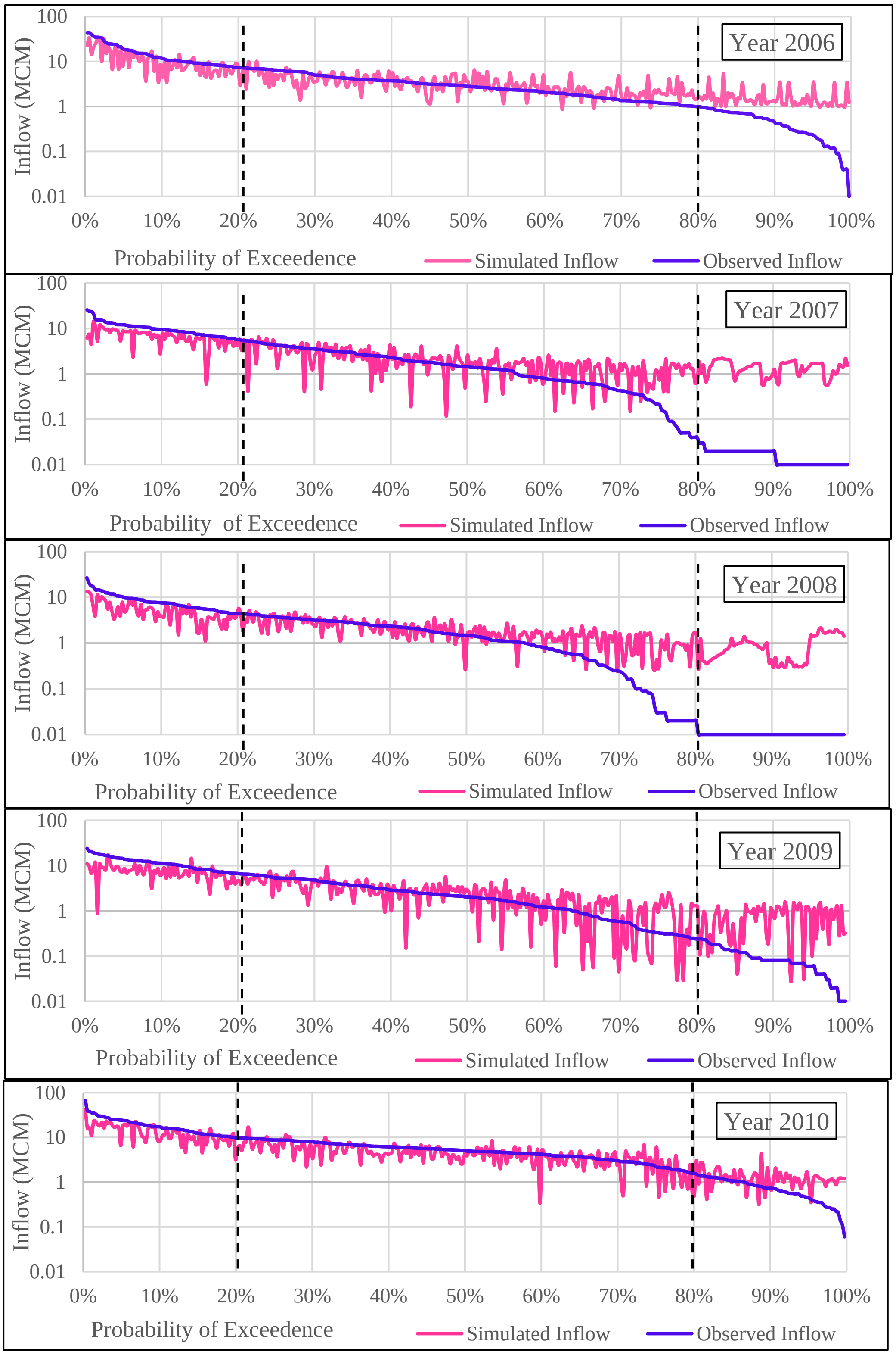


Figure 4-35 Flow Duration curves for validated model - (In log scale)

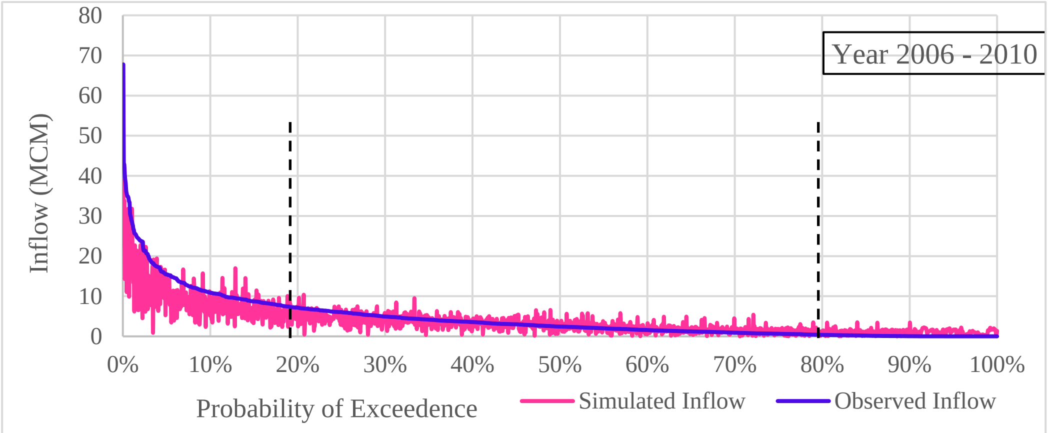


Figure 4-36 Flow duration curves of Victoria Reservoir in log scale – Validated Model (year 2001-year 2005)

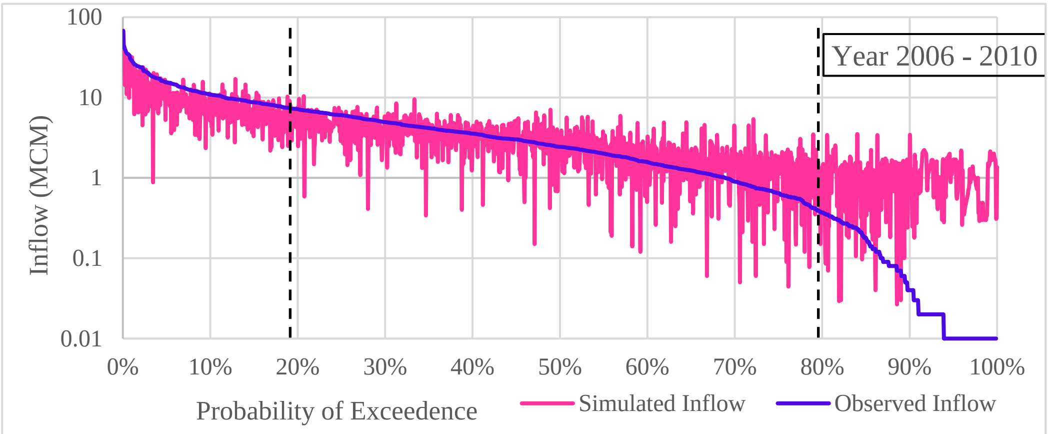


Figure 4-37 Flow duration curves of Victoria Reservoir in log scale for validated Model in log scale (year 2001-year 2005)

The simulated inflow hydrographs of the validated model also follow the observed inflow hydrograph (Figure 4-32 and Figure 4-33) for average flows except for high and low flows. The calibrated model deviated in high and low flows (limit of 20% for low flows and limit of 80% for high flows) slightly rather than the actual conditions. This may cause due to the use of monthly data instead of daily rainfall data.

4.3.2.3 Prediction of Future inflows of Victoria reservoir (from year 2021 - 2025)

The future inflow of the Victoria reservoir was predicted with the estimated rainfall data of Victoria sub-catchments and downstream release of Polgolla reservoir. The estimated rainfall was obtained from Mann Kendall test and Sen's slope methods as monthly data. Further, the predicted inflows (Year 2021 - 2025) were compared with the historical data (Year 2014 - 2018)

The predicted future rainfall data were obtained as monthly data from Mann Kendall test. Hence the HEC HMS model for future scenario has to be done for monthly data. Therefore, the model was calibrated for monthly rainfall data for the year 2001 – 2005 and validated for the year 2006 – 2010. This model was performed only for inflows to Victoria reservoir by considering Polgolla downstream release, and sub-catchments to Victoria reservoir (Duckwary Estate, Victoria and Hope Estate) (Figure 4-24 and Figure 4-25). The rainfall data were given as the cumulative value of a particular month starting from the 1st day of the month and time lag was given such that distributing the generated runoff throughout the whole month due to rainfall on the 1st day of the month. Accordingly, the time lag was given in the range of 600 – 800 hours in Clark unit hydrograph method. The time lag, SCS curve number and base flows were adjusted such that model inflows corresponded to observed inflows of the Victoria reservoir.

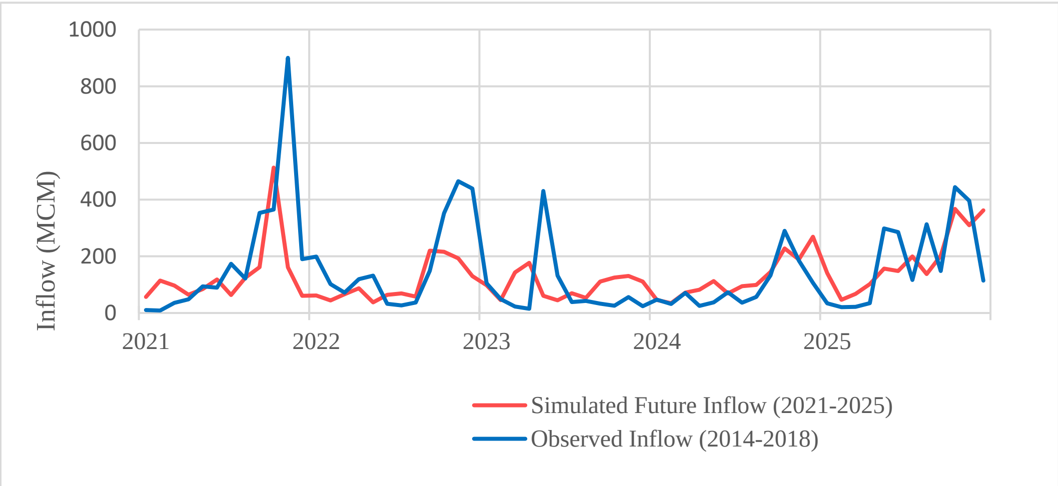


Figure 4-38 Estimated Monthly average Future Inflow variation of Victoria reservoir (Year 2021-2025) and Historical Inflow (Year 2014-2018)

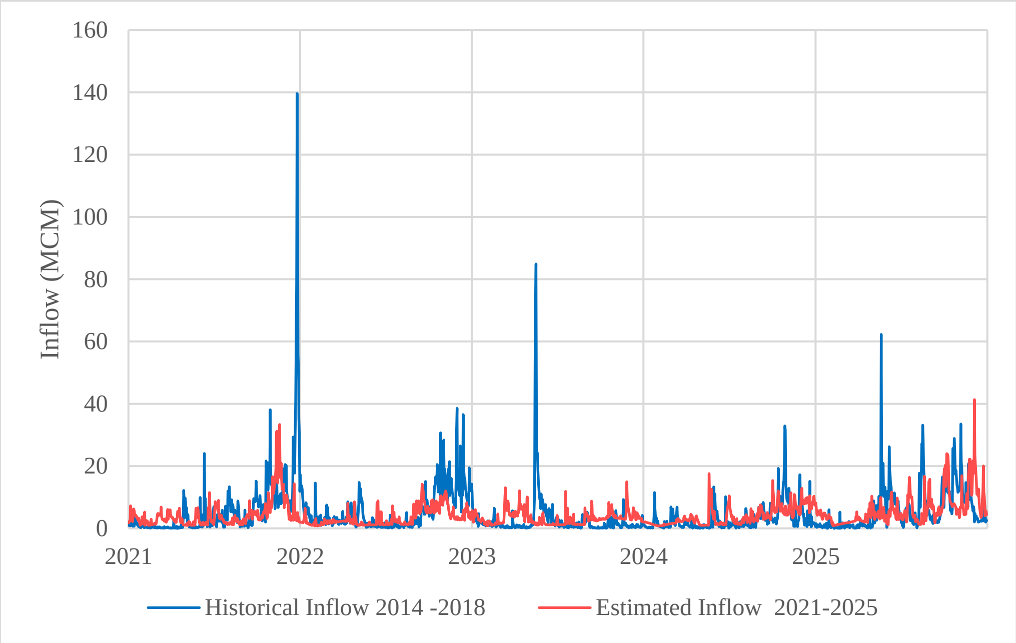


Figure 4-39 Estimated Daily future Inflow to Victoria reservoir (Year 2021-2025) and Historical Daily Inflow (Year 2014-2018

Table 4-7 Estimated Future Inflow

Estimated Data		**Historical Data**	
Year	**Estimated Inflow (MCM)**	**Year**	**Historical inflow (MCM)**
2021	1646	2014	2223
2022	1236	2015	2098
2023	1159	2016	956
2024	1429	2017	1083
2025	2211	2018	2209
Annual Average	1536	Annual Average	1714
Deficit	10%		

The average annual inflow to the Victoria reservoir in the year 2014 to 2018 is 1714.00 MCM and future inflow to the Victoria reservoir in year 2021 – 2025 will be 1,536 MCM. Accordingly, the next 5-year inflows to the Victoria reservoir are reduced from 10% than the present situation (Table 4-7). This will affect the Victoria reservoir storage and power generation.

4.4 Reservoir simulation in HEC ResSim

HEC ResSim model was developed for generating the hydropower potential of the Victoria reservoir based on observed and predicted inflows to the reservoir.

The following parameters were given as physical properties of the power plant.

Installed Capacity = 210 MW (3 turbines with capacity of 70 MW per each)

Overload factor = 110%

Efficiency = 85%

Station Used = 0 (Since No releases for Irrigation or other than Hydropower)

The model was calibrated for the year 2015 (Figure 4-40, Figure 4-41 and Figure 4-42) and validated for the year 2016 (Figure 4-43**,** Figure 4-44 and Figure 4-45) with available daily inflow data and operational data. The efficiency of the power plant was adjusted such that the model Power generation corresponded to observed power generation data. Accordingly, the efficiency was taken as 85%.

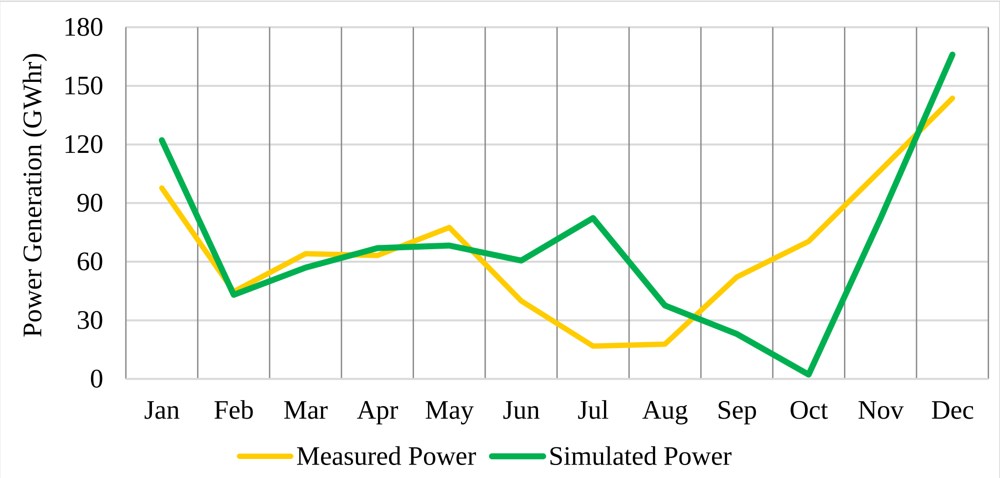


Figure 4-40 Simulated Power Generation of Victoria Reservoir Year 2015 - Calibration Model

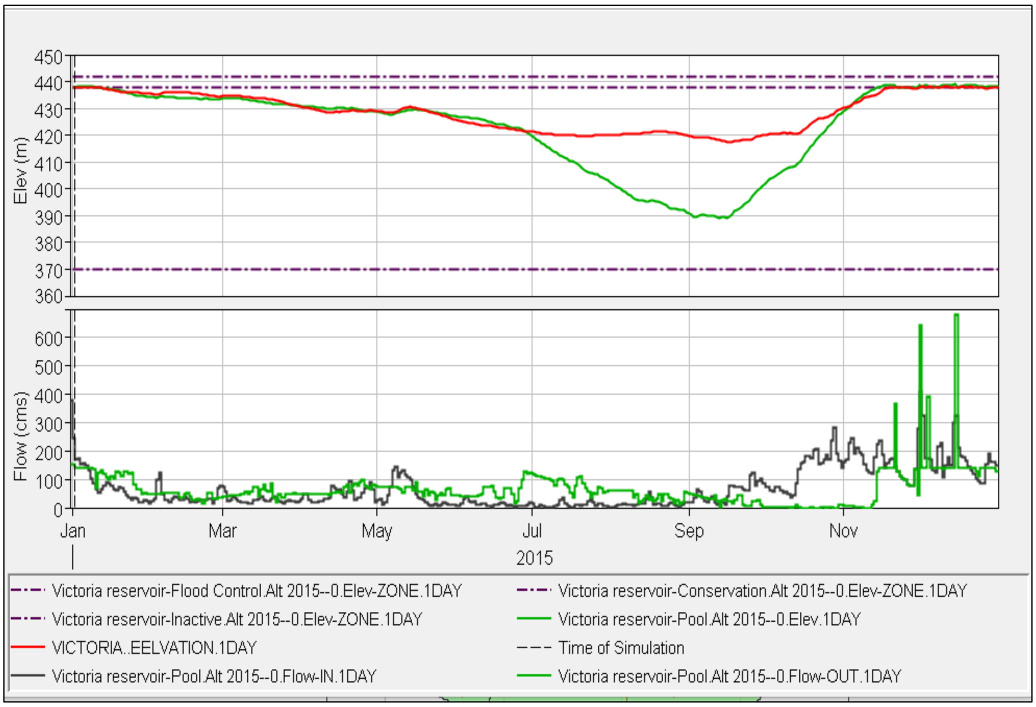


Figure 4-41 Power Generation of Victoria Reservoir Year 2015 - Calibration Model in HEC ResSim

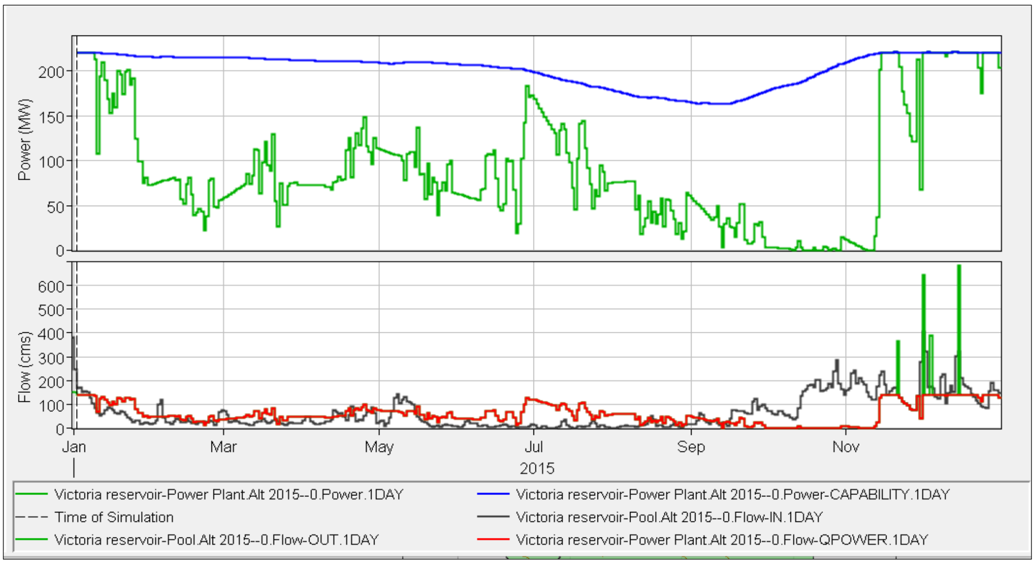


Figure 4-42 Reservoir Elevation and Inflow variation in Calibration model - HEC Res Sim (year 2015)

According to the simulation results, the model followed up the observed Power generation from January to May and from that, it was deviated up to November (Figure 4-41 and Figure 4-43). Further, the simulated pool elevation was followed the observed pool elevation up to the month of July and then simulated pool elevation was considerably lower than the observed elevation and again the model has followed the observed pool elevation in the months of November and December (Figure 4-42 and Figure 4-45). The power discharge amount was recorded in units of MCM as a volume in the site. But power release data has to be given as a discharge rate with units of m^3/s in the HEC ResSim model. Further, the amount of power generation was recorded as Energy in units of GWhr, but the amount of power has to be feed into the model as power in units of MW. Therefore, it has to be found out the time duration for power releases of each day for these conversions. But there is no such information available. however, the total hours of monthly power generation were available. Therefore, the daily average time period of power generation was taken for the conversion. But the power generated hours could be changed daily due to power requirement and reservoir capacity.

The reservoir elevation was decreased rather than the observed elevation from July to September since the power release amount is higher than the actual values. This could be proved, that the simulated power generation is high in July and August rather than actual values.

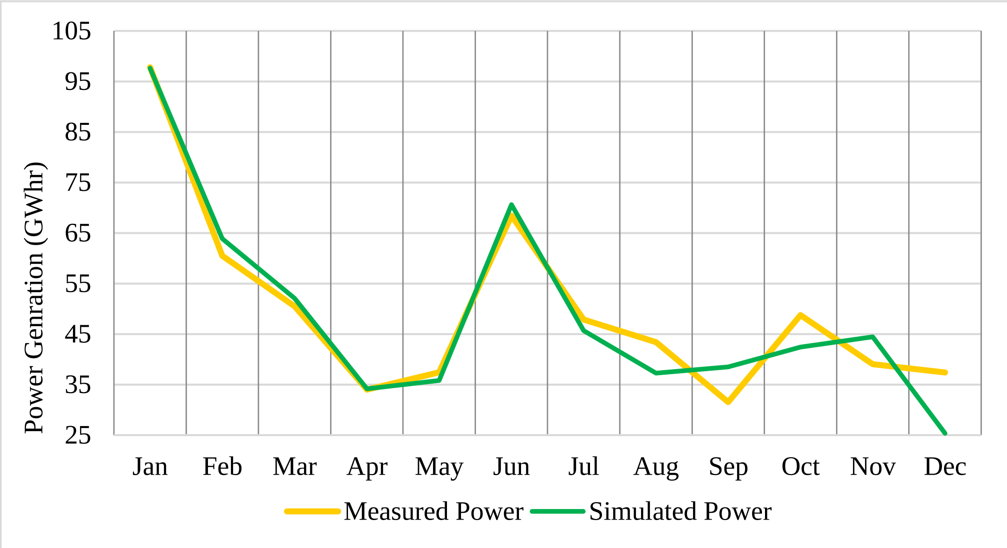


Figure 4-43 Simulated Monthly total Power Generation of Validated model - year 2016

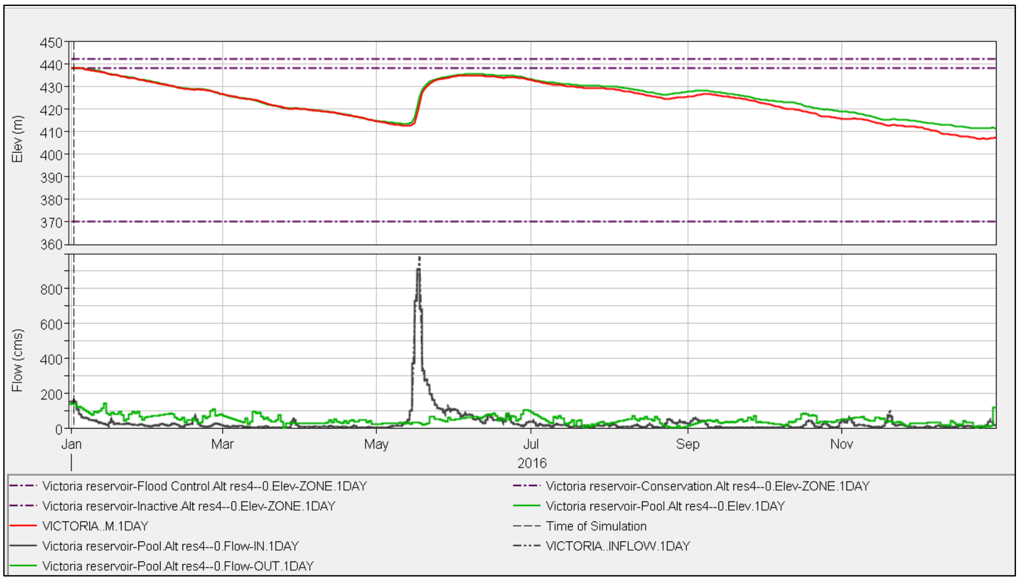


Figure 4-44 Simulated Power Generation and pool elevation variation of Validated model - year 2016

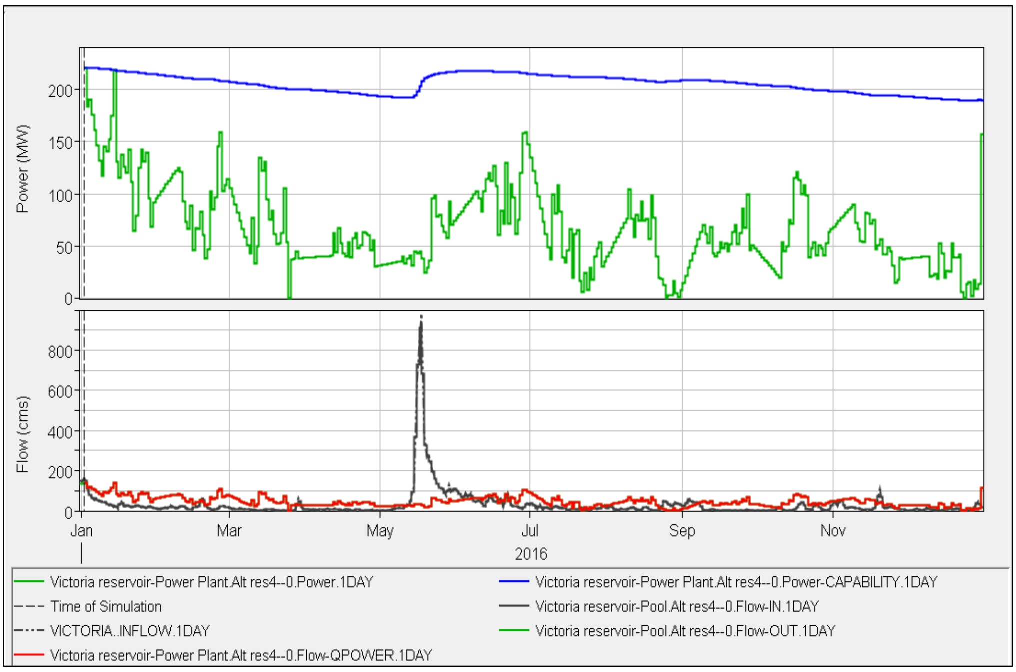


Figure 4-45 Reservoir Pool Elevation and Inflow of Victoria Reservoir – Validation Model - HEC Res Sim – Year 2016

The Validation model is almost followed up the observed data of Power generation, Reservoir elevation and inflow (Figure 4-43, Figure 4-44 and Figure 4-45). Therefore, it could be considered that the simulated model reasonably represents the actual conditions of the reservoir operations and power generation.

The future power generation was simulated with this model by feeding predicted future inflows to the Victoria reservoir for 5 years from 2021 to 2025 which were previously obtained from Mann Kendal test and Sen's slope test. The amounts of power releases were given as a function of pool elevation in the HEC Res Sim Model. The generated future Power generation and reservoir operational data are given below.

The calibrated and validated power generation models were evaluated for model performance by calculating RMSE and NSE values for simulated power generation (Table 4-8). The NSE values and RMSE values for both calibrated and validated models were within the acceptable range.

Table 4-8 NSE and RMSE values for power generation in HEC Res Sim Model

Year	NSE	RMSE
2015	-0.005	1.43
2016	0.331	0.83

4.4.1 Prediction of Future Power Generation

The model was simulated to predict the power generation for the next 5 years (year 2021 - 2025) with predicted inflow data. The predicted power generation data were compared with recently available power generation data for the year 2014 – year 2018 of Victoria reservoir (Table 4-9). The power discharge was given as specified discharge which is varied with pool elevation. Accordingly, it was scheduled to release maximum discharge through the tunnel for power generation. Since the inflow was decreased due to low rainfalls in sub-catchments, the reservoir capacity (pool elevation) was decreased and the available discharge for power generation was decreased. The power generation will be reduced with the decrease in inflow to the reservoir. The annual average future inflow will be about 1,536.00 MCM for the next five years (from the year 2021 to 2025) and that of the recent five years was 1,714.00 MCM. The Annual average Power generation was about 622.00 GWh for the recent 5 years (from the year 2014 to 2018) and the predicted average annual power generation 480.00 GWh for the next 5 years (from the year 2021-2025) (Figure 4-46, Figure 4-47 and Figure 4-48). Hence the average annual power generation will be reduced by 23% as a result of the reduction of annual average inflow by 10% compared to power generation in the past 5 years (Table 4-9)

The inflow pattern and power generation pattern over the next five years (year 2021-year 2025) is following the almost same pattern as the last five years (year 2014 - year 2018) throughout the year. But the amount of Inflow and power generation is decreased in the next five years (Figure 4-46, Figure 4-47 and Figure 4-48). The power generation was decreased in months from March to August where the rainfall trend is negative and very low. Accordingly, it could be expected to have a considerably low power generation in the next 5 years due to low rainfall.

Table 4-9 Estimated Inflow and Power Generation of Victoria reservoir

Estimated Data			**Historical Data**		
Year	**Estimated Inflow (MCM)**	**Estimated Power (GWhr)**	**Year**	**Historical inflow (MCM)**	**Historical Power (GWhr)**
2021	1646	486	2014	2223	553
2022	1236	457	2015	2098	792
2023	1159	368	2016	956	595
2024	1429	401	2017	1083	306
2025	2211	690	2018	2209	863
Annual Average	1536	480	Annual Average	1714	622
Deficit	10%	23%			

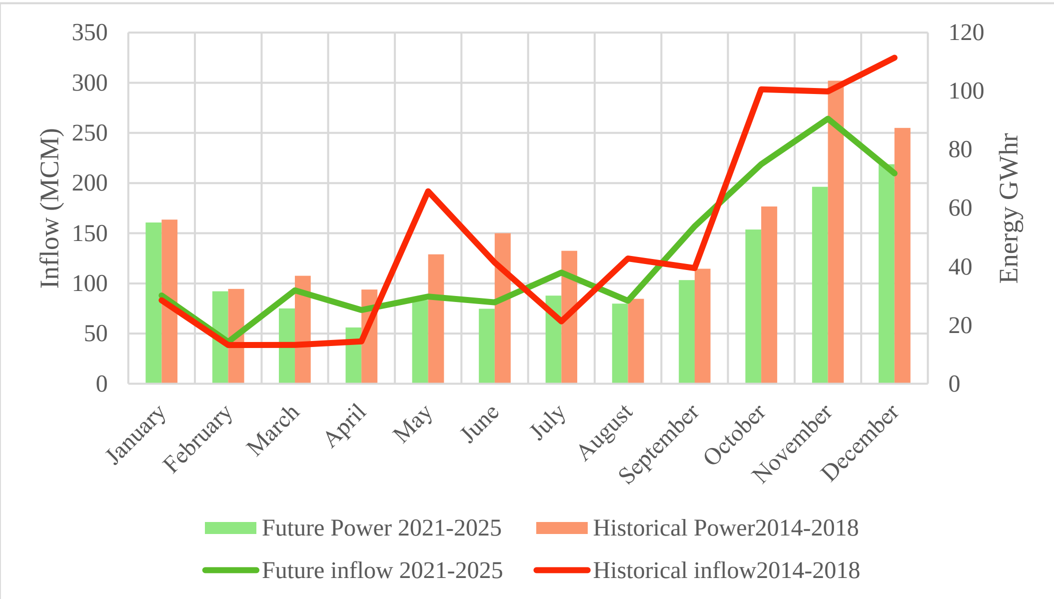


Figure 4-46 Comparison of predicted future monthly Inflow and power generation in Victoria Reservoir

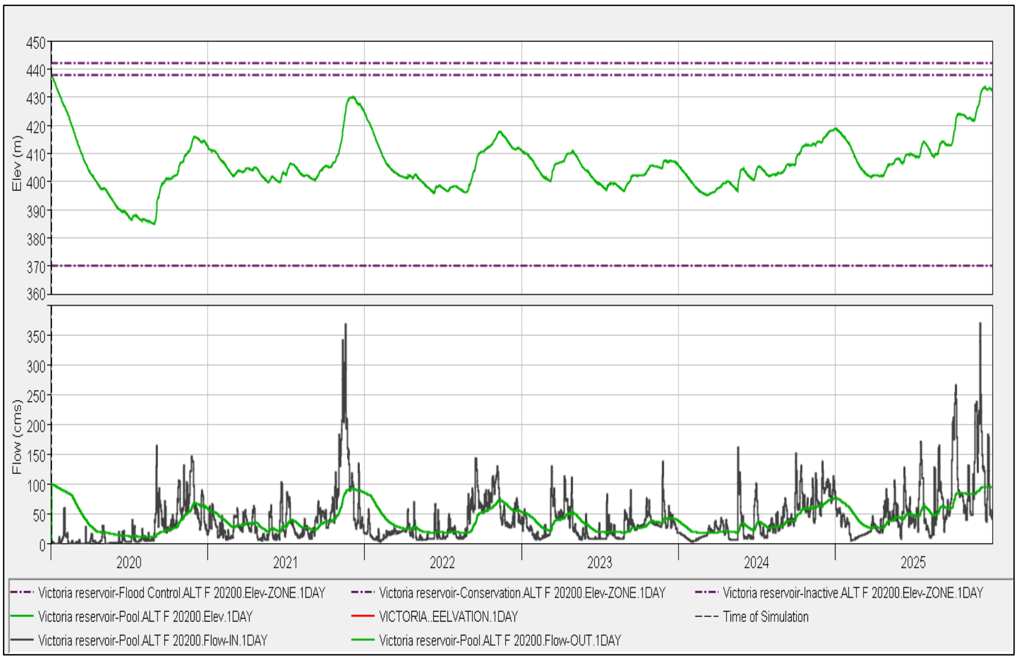


Figure 4-47 Estimated Pool elevation variation over next five years

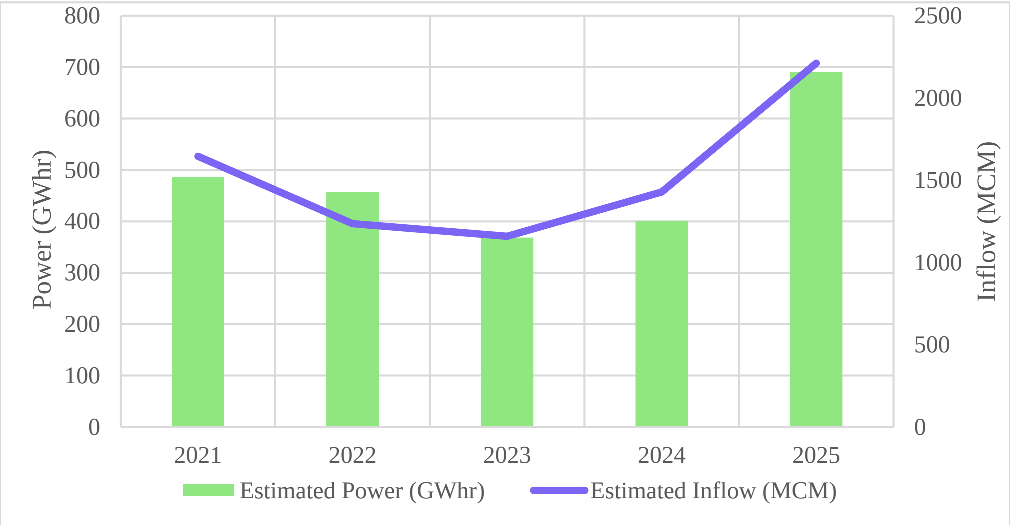


Figure 4-48 Predicted Power Generation and Inflow variation over next five years

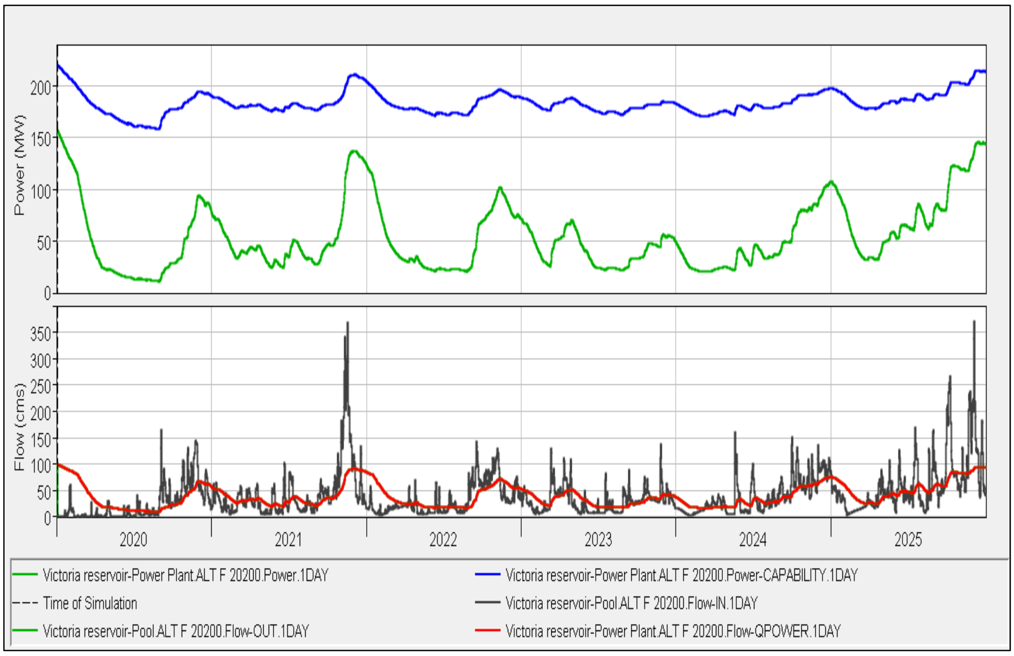


Figure 4-49 Variation of reservoir Operation - Year 2020-2025

5 DISCUSSION

Mahaweli basin is the major river basin in Sri Lanka which contributes to Hydropower generation, Irrigation, drinking water supply, fishing industry and tourism industry as well. The Mahaweli Development project was implemented in 1970s to get the maximum usage of the Mahaweli basin mainly focusing on irrigation and hydropower generation. Mahaweli river is serving to a greater extent for hydropower sector and irrigation sector by supplying water requirement for those industries. There are five major reservoirs in the Mahaweli basin which belong to the Mahaweli Authority of Sri Lanka (MASL) and the power plants operated with those reservoirs are controlled by the Ceylon Electricity Board (CEB). Initially, 100% of power requirement of the country was supplied from hydropower generation. However, presently this situation has changed due to the uncertainty of water availability throughout the year which results in an inadequacy of hydropower to fulfil the total demand and hence other sources are also used to generate power such as thermal, solar, coal, etc.

Other sources such as thermal and coal are non-renewable, not sustainable and not eco-friendly and incur a higher operational cost. But hydropower generation is sustainable, low cost in operation, eco-friendly and renewable. In Sri Lanka, the major power generation method is hydropower other than thermal and other sources. But due to decreasing rainfall, the hydropower generation is decreased and power generation from other power sources is increased. At the beginning of the year 2016, the hydro storage is about 86% and in the previous year, it is about 98% due to the decrease in rainfall in the year 2016 (Annual Report, CEB, 2016). This figure shows how much hydro storage is reduced due to a decrease in rainfall.

The hydropower generation totally depends on rainfall in the catchment. During the dry period, the hydropower generation is less while during the rainy season, the reservoirs are spilling. This is the issue in hydropower generation and it should be better water management practices and reservoir operation procedures should be introduced to optimize the power generation. Further predicting of future rainfall and power generation are also important to identify the critical periods of power generation.

5.1 Data Checking and Filling Missing Data

This study is basically based on rainfall data and reservoir operational data. The analysis of the hydrological model with the use of raw rainfall data and reservoir operational data will lead to less reliable and less meaningful analysis since those data may possess a significant number of missing data or errors (Hasana & Croke, 2013). Accordingly, the recorded rainfall data and reservoir operational data should be subjected to the data checking process and the necessary corrections should be done for data errors and missing data. In this study, the regression method was used to estimate the missing rainfall data and data errors were corrected by visual checking and considering other stations rainfall data.

Missing rainfall data were filled using the regression method considering the correlation of each station. The single mass curve and double mass curves were plotted for each rainfall stations to identify the consistency, homogeneity and correlations of each station. Daily Rainfall data were collected from 7 stations for 30 years from the year 1981 - 2010. Among those seven stations, Hope Estate and Polgolla stations were missing a considerable amount of daily rainfall data (>10%) while other stations were missing few amounts of daily rainfall data (<10%). Therefore, those missing data were filled with regression method with respect to the data of other rainfall stations data which has high correlation to the particular rainfall station.

Reservoir operational data of Victoria reservoir were also checked for data accuracy by plotting daily inflow, reservoir water level, power generation and power discharge data over time. It was observed that few inflow data were recorded as negative values since the inflow to the reservoir was not measured by a stream gauge device. The inflow was obtained by carrying out the water balance at the end of the day. The storage was obtained from an elevation capacity curve which was not updated recently. Further, the power discharge was not measured and it was obtained considering the maximum discharge rate of tunnel and power generated hours. But this maximum discharge rate may be varied (<20%) with the opening of wicket gates of the powerhouse. Therefore, there are issues in the accuracy of power discharged volume, storage and inflow volume of Victoria reservoir. The negative values of inflow volumes were corrected considering the average inflow of nearby days. The outliers of power generation were corrected considering the power discharge amount of a particular date.

5.2 Rainfall Trend Analysis

Rainfall trend analysis was carried out to identify the rainfall trend in the future and trend magnitude. Mahaweli upper catchment is divided into eight sub-catchments and trend analysis was performed for each sub-catchment. It shows that the trend is negative from June to September which months give low rainfall while the high rainfall months shows a positive trend. The dryer periods getting dryer further and wetter periods getting wetter in future. Therefore, this creates a reduction in inflow to the reservoir and hence a water deficiency to generate the power in the dry period. In the rainy season, there is a surplus in storage.

The trend was analyzed using Mann Kendall test assuming there is monotonic variation (upward or downward). The trend magnitude was estimated using Sen's Slope method. The R software was used with related packages to perform the Mann Kendall test and Sen's Slope method.

The modified Mann Kendall test was used to identify the trend as the basic Mann Kendall Test produced a P-value which is out of the acceptable margins (5%). Since normally the confidence level is considered as 95% hence the P-value should be less than 5% (Drápela & Drápelová). Block Boot Strap (BBS) method is used as the modified Mann Kendal test which was analyzed the trend with user-defined confidence level, simulation times and length of blocks. In this method, the trend was analyzed by making of data blocks and the model was simulated with the given number of simulation times (Khaliq, Ouarda, Gachon, Sushama, & St-Hilaire, 2009). Therefore, it was more accurate and the trend could be analyzed within the given confidence level. The magnitude of the trend was estimated by finding the parameters of the function of the rainfall trend. SEN ZYP package was used to find the intercept of the graph and the increment was given by the BBS method. The monthly average rainfall data were fed to the R software as a dependent variable and years were given as the independent variable such that monthly rainfall is a function of years. Then future monthly average rainfall was predicted using the generated equations for each catchment. These generated future rainfall data were fed to the HEC HMS model as rainfall data to generate the future inflow to the Victoria reservoir.

The estimated future rainfall trend future mean annual rainfall of Mahaweli upper catchment was compared with the projected precipitation for year 2030 and 2050 which was modeled based on regional climatic model. The predicted mean annual rainfall is approximately followup the projected precipitation. But there are concerning about the deviations with projected precipitation. They are the future rainfall was estimated with monthly data and return periods shall be taken in to account.

5.3 Hydrological Model in HEC HMS

Hydrological model was created on HEC HMS to estimate the catchment runoff and then inflows to the reservoirs. Three reservoirs in the upper catchment of the Mahaweli basin namely Kothmale, Polgolla and Victoria reservoir were taken into account. Reservoir operations were not considered in the HEC HMS model as the HEC HMS model was developed to find out the catchment runoff only. But in calibration, the downstream releases of each reservoir were considered to match the inflows to each reservoir. The lag time, CN value and base flow parameters are the most sensitive parameters of the model. Lag time, CN values and base flow parameters were adjusted such that the modelled and observed data were approximately equal. Then the model performances were evaluated by estimating the error of modelled data by Root Mean Square Error (RMSE) method and NSE method. The model calibration was done until it produces the RMSE and NSE values within the acceptable range for modelled output data. Further, the performances of generated modelled data were graphically evaluated by plotting flow duration curves and plotting output put data with observed data over time. After calibration of the model, the validation was performed for another 5 years from 2006 to 2010.

The observed inflow data were obtained from Mahaweli Authority which is not measured data. The inflow data were calculated for reservoirs by performing a water balance for the particular reservoir considering available reservoir capacity and outflows for a particular date. It is observed that some of the inflow data were recorded as negative values since the water balance couldn’t be done accurately due to the following shortcomings.

The elevation capacity curve is not updated for the present condition and the reservoir capacity may be decreased by at least 5-10% due to sedimentations. Therefore, the actual storage may be less than the recorded data

There is no accurate method to measure the power release volume or flow rate. The same outlet is used for power release and irrigation release from the reservoirs, but only the volume used for power generation was recorded. Therefore, no record of irrigation releases. There are no stream gauges installed near the reservoir inlets to measure the inflows to the reservoir. Due to low surface runoff in the catchment, small CN values and high lag times were used for the model.

The future inflow values were estimated from the HEC HMS model with generated future rainfall data from Mann Kendall test and Sen's slope method. The generated inflows followed the same pattern of rainfall. This gives low inflow values in February, March, May, Jun, July August months while other months give considerably high inflow values.

Since the predicted rainfalls were obtained as the monthly average value from Mann Kendall and Sens Slope test results, the HEC HMS model has to be performed for monthly data. Accordingly, the HEC HMS model was calibrated and validated for monthly data for 2001 – 2005 and 2006 – 2010 respectively. The monthly data were fed to the HEC HMS model through a DSS file. The lag time was increased such that the monthly rainfall data affects to the whole month. Accordingly, the lag times were adjusted such that the calibrated inflow values corresponded with actual inflow values.

5.4 Reservoir Operations and Hydropower Generation in HEC ResSim

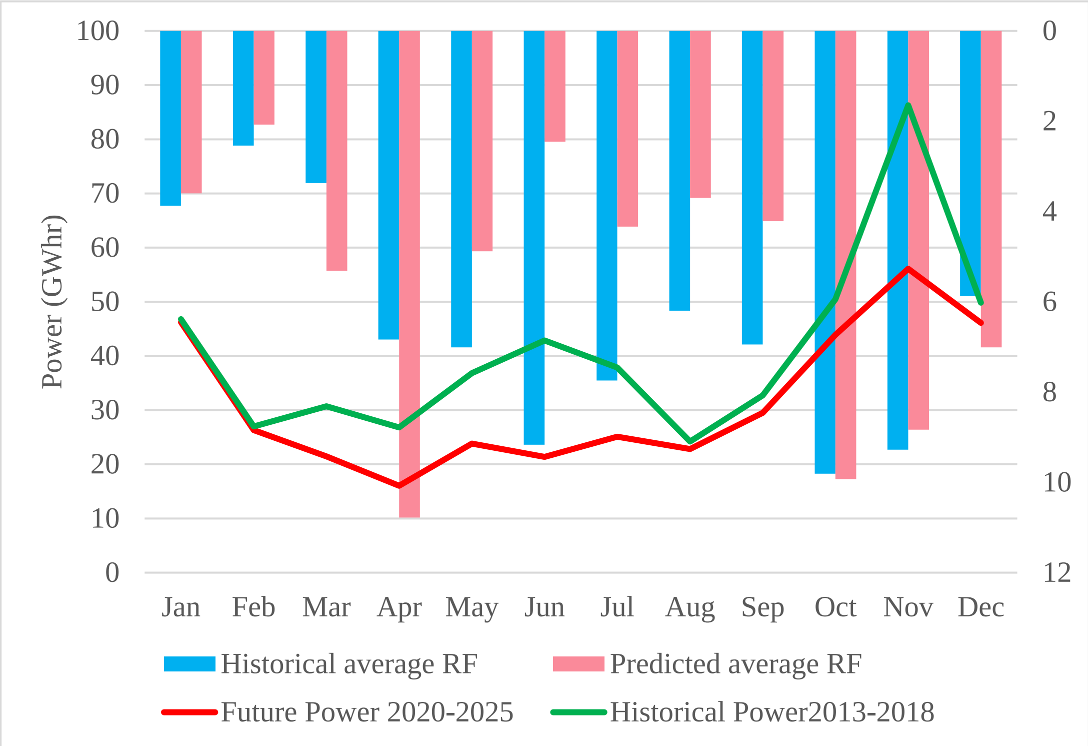
Reservoir operations and hydropower generations of Victoria Reservoir were simulated using the HEC ResSim platform. The watershed model was created corresponding to the physical characteristics of the catchment under watershed model. The reservoir physical properties, operational data of reservoir and power plant were modelled in the Reservoir Network model (Meshkat & Klipsch, 2018). The model was calibrated with the year 2015 data and validated with the year 2016 data. The predicted inflow data were used to obtain the future power generation of the Victoria reservoir from the year

2010 to the year 2025. The efficiency of the power plant was taken as the governing factor to calibrate the model comprising of model power generation with actual operational power generation data.

The power generation depends on the rainfall of the catchment area, inflow to the Victoria reservoir, Reservoir capacity and efficiency of the power plant. The inflows to the Victoria reservoir are downstream release of Polgolla barrage and catchment runoff from sub-basins of Victoria reservoir (Victoria, Hope Estate and Duckwary Estate). Polgolla downstream release depends on upstream reservoirs operations which are Polgolla Diversion, Kothmale and Upper Kothmale operations. Because of the complexity of the reservoir network simulation, only the Polgolla downstream release was considered instead of the reservoir operations of other upstream reservoirs.

The model simulation was performed and compared the predicted power generation with historical power generation data. The power generation in year 2016 was decreased by 28% rather than the year 2015 because the inflow to the reservoir in 2016 was decreased by 55% compared to the year 2015. the inflow in 2016 was decreased due to the considerable reduction in rainfall in the year 2016 rather than the year 2015 (48% compared to the year 2015) (Annual Report, CEB, 2016). Accordingly, these historical records reveal that rainfall of the catchment highly affects the hydropower generation of the particular power plant.

The predicted annual inflow for the next 5 years (year 2021 - 2025) will be 1536.00 MCM and the observed annual inflow for the past 5 years (year 2014 - 2018) was 1714.00 MCM. Therefore, the inflow in the next 5 years is reduced by 10% compared to the period of year 2014 – 2018. The annual Power generation for the past 5 years from the year 2014 – 2018 was 622.00 GWh and for the next 5 years (year 2021-2025), it will be 480.00 GWh (Figure 4-46, Figure 4-47 and Figure 4-48). Therefore, the annual average power generation will be reduced by 23% in the next 5 years compared to the past six years period of the year 2014 – 2018.



The future power generation variation was almost followed the monthly rainfall variation. The power generation was decreased in months of low rainfall events and power generation was increased in months of high rainfall events occurred. Since the overall rainfall trend is negative, the future annual rainfall will be decreased and that

Estimated Data			**Historical Data**		
Year	**Estimated Inflow (MCM)**	**Estimated Power (GWhr)**	**Year**	**Historical inflow (MCM)**	**Historical Power (GWhr)**
2021	1646	486	2014	2223	553
2022	1236	457	2015	2098	792
2023	1159	368	2016	956	595
2024	1429	401	2017	1083	306
2025	2211	690	2018	2209	863
Annual Average	1536	480	Annual Average	1714	622
Deficit	10%	23%			

will lead to a decrease in hydropower generation. Accordingly, it shall be expected considerably low hydropower generation from hydropower plants compared to the present situation. Therefore, the required electrical power would not be satisfied from the hydropower plant and the authorities will have to look forward to the development of other electricity sources.

6 CONCLUSIONS AND RECOMMENDATIONS

6.1 Conclusions

- Data from seven rainfall stations were used to analyse the rainfall trend in the upper Mahaweli basin. The best correlation, high homogeneity and high relative consistency were shown by Kothmale, Sogama, Ambewala and Duckwary station. Watawala and Hope Estate Stations highly deviated and Polgolla station moderately deviated from homogeneity, relative consistency and correlation.
- The rainfall trend was analyzed with Mann Kendall test and it gives that the rainfall trend is negative in the months of May to September and positive trend in other months in all rainfall stations except Hope Estate. Hope Estate shows a positive trend in all months except January. The overall rainfall trend is negative in Duckwary Estate, Sogama, Watawala and Ambewala rainfall stations while a positive rainfall trend is shown by Hope Estate, Polgolla and Kothmale rainfall stations.
- The overall magnitude of the negative trend is higher than that of the positive trend in rainfall stations in Mahaweli upper catchment. Hence the mean annual rainfall reduction for the next 30 years will be 18% and in year 2025 it is reduced by 14%.
- Victoria reservoir gets high daily inflows (more than about 7.8 MCM to a maximum of 130 MCM and average of 5 MCM) during the months of October to January and May to July while other moths get low inflows during the year 2014 to year 2018.
- The rainfall trend is negative in South West Monsoon, Second Inter Monsoon and North East Monsoon while only first inter monsoon follow the positive trend. South west monsoon has high negative trend and the monthly rainfall intensity is low (below 150mm). Hence this season is getting dryer in future
- The first intermediate zone follows positive trend with high monthly rainfall intensity (above 200 mm). he ce this season get more rainfall with increasing

the intensity with time. Second intermonsoon and North Est Mosoon follow up low value negative trend with high rainfall intensity (above 200mm) and low rainfall intensity (below 150mm) respectively.

- The estimated future inflows show that high daily inflows (more than about 4.6 MCM to a maximum of 40 MCM and average of 4.2 MCM) get during the months of October to January and May to July while other months get low inflows during the year 2021 to year 2025.
- The catchment modelling was performed on HEC HMS to get the inflows to the reservoir. The future inflow for the next 5 years (year 2021 to 2025) shall be decreased by 10% compared to the last five years (year 2014 to 2018) recorded inflow data.
- It is observed that future hydropower generation (year 2021 to 2025) in Victoria reservoir shall be decreased by 23% compared to the last five years (year 2014 to 2018) recorded data.

Based on the identified adverse change in rainfall with a negative trend over time and its quantitative impacts on hydropower generation, necessary measurements should be implemented to optimize the power generation in satisfying the increasing power demand. Since the overall annual rainfall indicates a negative trend, it could be expected that the inflows to the reservoir are not sufficient to fulfil the expected power generation. Accordingly, it is advisable to look for other alternative electricity sources to generate the expected power in the future such as wind power and solar power thus reducing thermal power and coal power considering sustainable development. .

6.2 Recommendations

The rainfall trend in Mahaweli upper catchment area was analyzed with the past 30 years of data from 1981-2010. The trend is negative from June to September which has low rainfall and from September to January, there is a positive trend with high rainfall. This shows that dryer periods getting more dryer while wet periods getting wetter in future. The surface runoff and total inflows to the reservoir follow up the same pattern of the rainfall. Hence the inflows to Victoria reservoir will decrease in dry periods further and it will increase in the rainy season. The water availability for hydropower generation is decreased in dry periods further. But in rainy periods of the year, the rainfall is increased and the storage is increased.

The magnitude of the negative rainfall trend is higher than the positive trend. Hence, it could be expected that decreasing of rainfall is higher than the increasing amount throughout the year. Hence, the overall annual trend of rainfall is negative. Accordingly, in future, the inflows will further reduce and the water availability for hydropower generation will be decreased. In addition to that, the same rainfall trend is shown in all sub-catchments of the three reservoirs in upper catchment of Mahaweli basin. Therefore, the same storage trend could be expected in the three reservoirs of the system. These three reservoirs are in a cascade system which helps to store the surplus water of upstream reservoirs in the rainy season in downstream reservoirs and transfer the required water to downstream reservoirs in the dry period from upstream reservoirs. But as the same trend is occupied in the whole catchment this strategy is not valid any more for this system since in dry periods all reservoirs have low capacity and in rainy seasons all reservoirs are spilling or at FSL level. Accordingly, it is better to increase the capacity of reservoirs to store water in rainy seasons if it is feasible or introduce retention ponds near the reservoirs to store excess water in rainy seasons and to utilize in dry periods for hydropower generation.

When calibrating the inflows in HEC HMS Model, the observed inflow data were taken from Mahaweli Authority which are not measured data. Those inflow data have been derived from Water balance in the reservoir considering the storage, and outflows such as downstream releases and power releases. The capacity curves for these reservoirs have not been updated recently Further it was unable to derive the exact discharge for power releases also. The power discharge rate is recorded as pre-defined specified flow rate which may be deviated from actual discharge according to gate openings at the power plant. Therefore, it is required to improve the data accuracy in operational data.

The monthly rainfall data does not give the ideal distribution of inflows throughout the month since the peak values were not encountered. Accordingly, peak inflows and high-power generation values were not encountered. Hence, it is advisable to use of suitable method to estimate the rainfall trend and its magnitude on a daily basis rather than a monthly basis. Mann Kendall test and Sen’s slope method are not practical to use on a daily basis because if we want to get daily analysis, the test has to be repeated for all 365 days of the year. Since the Mann Kendall and Sens slope test were developed assuming the trend has a monotonic trend, further investigation to verify long term trends are recommended.

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APPENDICES

Appendix: A Estimated Monthly average Rainfall Data for 30 Years - Year 1981 - 2010

Estimated value – Est Observed Value – Ob

Month	Ambewala				Kothmale				Watawala				Sogaama	
	Est	**Ob**	**Est**	**Ob**	**Est**	**Ob**	**Est**	**Ob**	**Est**	**Ob**	**Est**	**Ob**	**Est**	**Ob**
January	140	134	67	77	84	90	75	94	84	97	61	156	174	194
February	59	71	40	49	56	86	41	73	52	63	39	74	55	81
March	95	101	105	105	123	156	105	106	84	97	54	60	104	107
April	138	158	201	206	307	342	262	255	161	182	93	111	165	183
May	154	185	215	254	435	504	224	230	109	115	74	106	119	127
June	225	228	349	335	670	698	247	250	117	132	75	126	144	155
July	166	199	283	267	613	598	241	238	112	108	74	117	145	153
August	158	178	213	226	469	461	168	183	74	87	54	94	114	117
September	189	178	221	237	432	451	201	223	108	114	69	86	169	169
October	211	217	320	329	533	538	284	312	218	227	147	201	282	304
November	191	221	232	255	372	404	310	320	237	250	151	207	285	292
December	183	183	110	125	126	183	138	148	148	171	158	215	249	250

Appendix: B Estimated Monthly average Future Rainfall (Year 2020 - 2050) and Observed Monthly average Rainfall (Year 1981- 2010)

Month	Ambewala		Kothmale		Watawala		Sogaama		Polgolla		Hope Estate		Duckwary Estate	
	Observe	Future	Observe	Future	Observe	Future	Observe	Future	Observe	Future	Observe	Future	Observe	Future
January	134	172	77	82	90	44	94	80	97	95	156	42	193	264
February	71	59	49	56	86	65	73	41	63	69	74	39	81	76
March	100	120	105	197	156	190	105	172	97	206	60	126	107	141
April	158	176	206	396	342	561	255	422	182	256	111	219	183	234
May	185	6	254	219	504	530	230	100	115	38	106	116	127	50
June	228	67	335	187	698	20	250	0	132	57	126	100	155	85
July	199	81	267	265	598	269	238	124	108	7	117	144	153	52
August	178	60	226	174	461	236	183	50	87	45	94	119	117	119
September	178	63	237	222	451	309	223	80	114	35	86	94	169	82
October	217	344	329	459	538	643	312	0	227	263	201	204	304	240
November	221	278	255	349	404	291	320	135	250	216	207	261	292	325
December	183	218	125	212	183	245	148	153	171	259	215	190	250	244

Appendix: C Comparison of Estimated Monthly Future Rainfall and Monthly Historical Rainfall Variation

Historical RF - year 1981 – 2010   Future RF   - Year 2021 – 2050

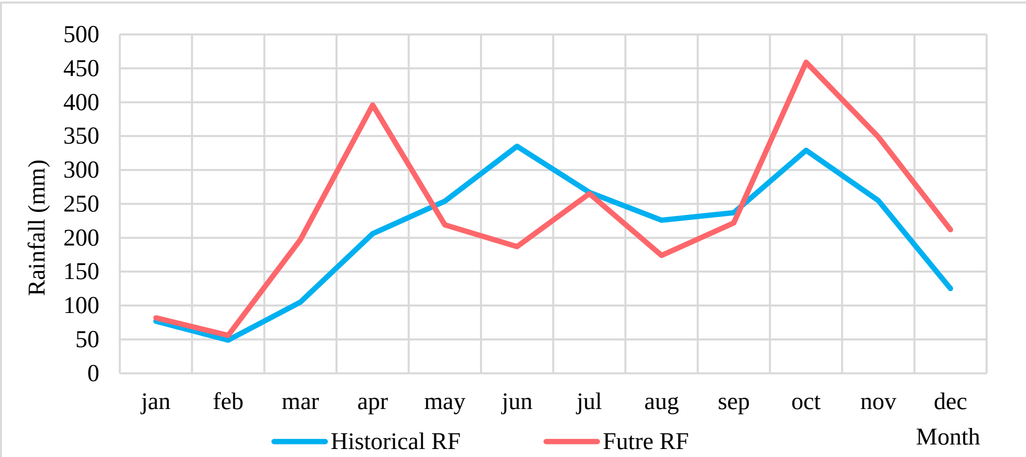


Figure - C - 1 Ambewala Catchment

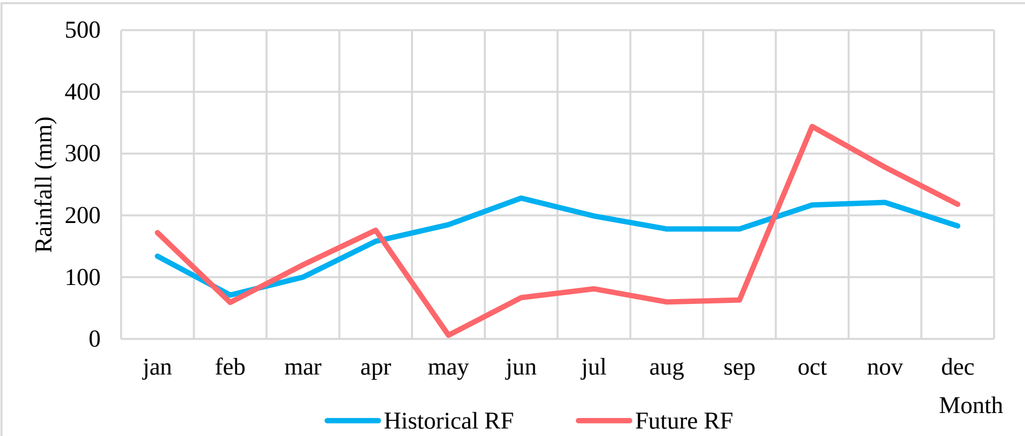


Figure - C - 2 Kothamle Catchment

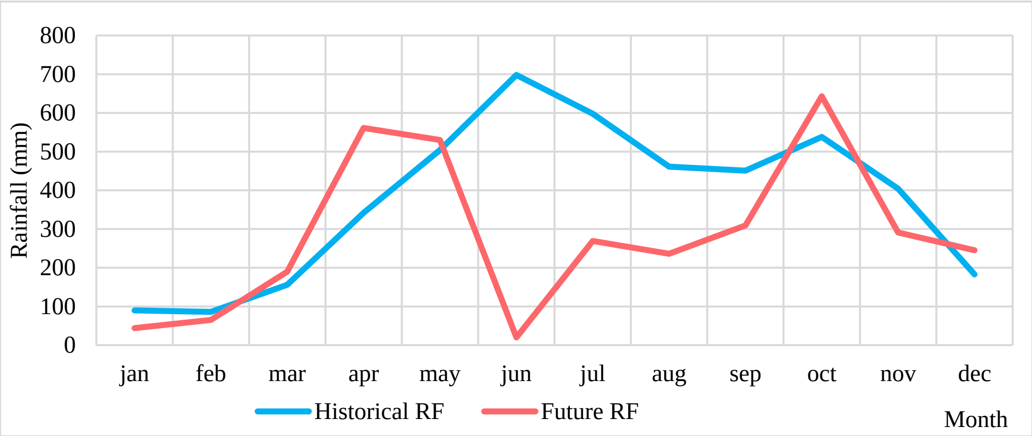


Figure - C –3 Watawala Catchment

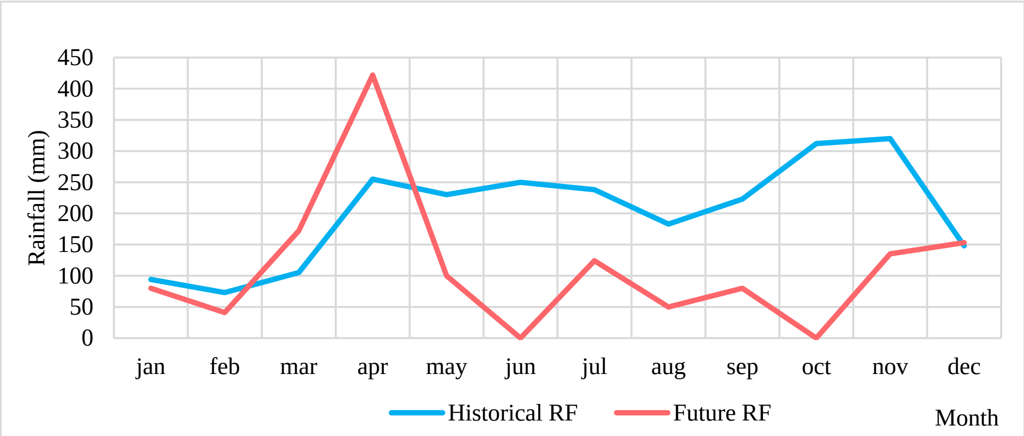


Figure - C - 4 Sogama Catchment

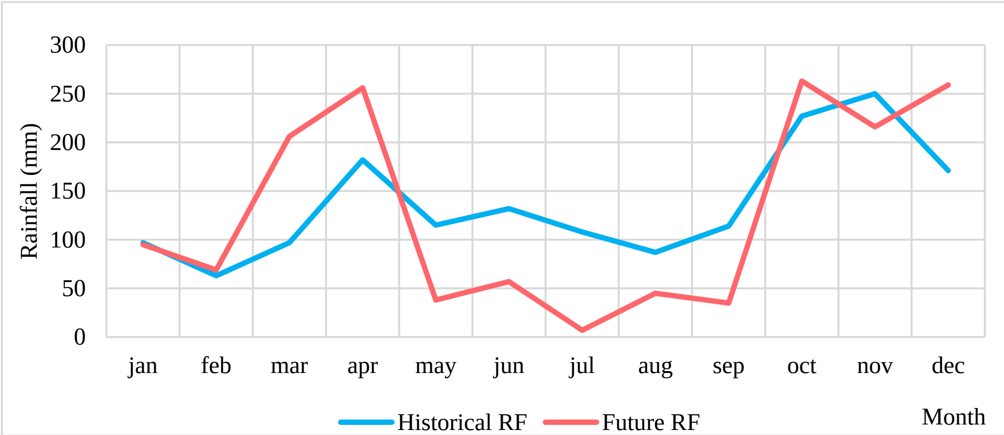


Figure - C - 5 Polgolla Catchment

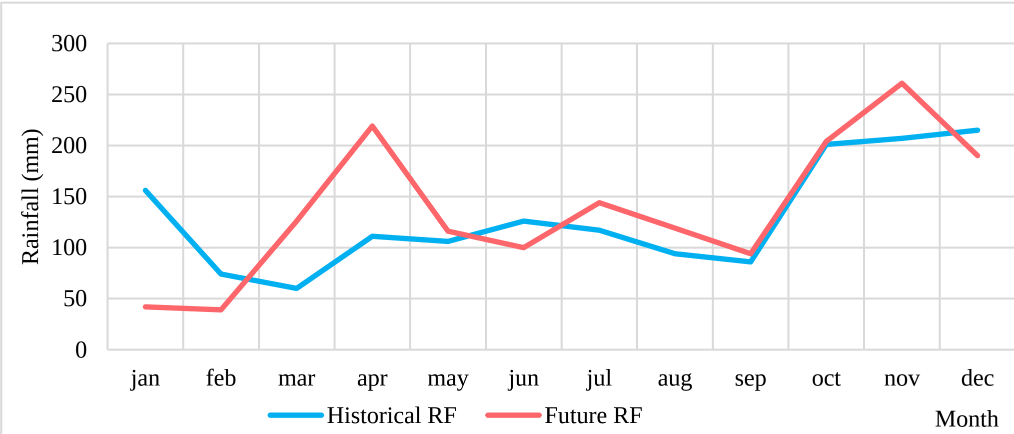


Figure - C - 6 Hope Estate Catchment

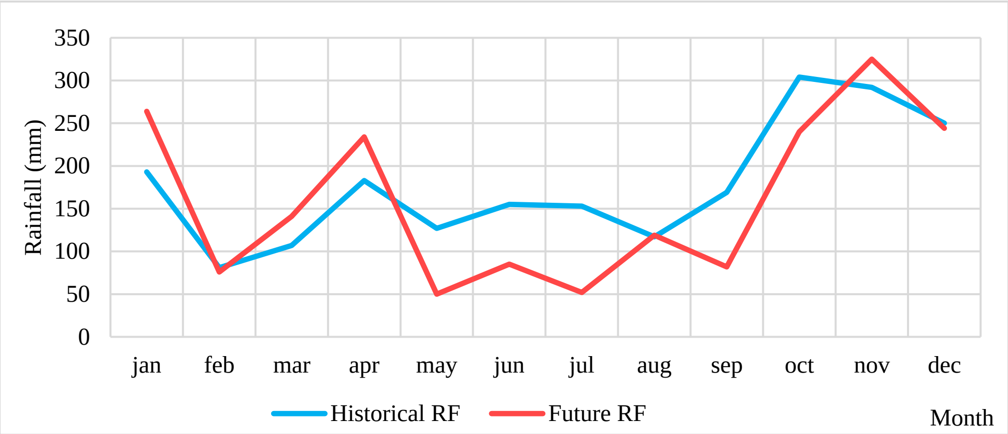


Figure - C - 7 Duckwary Estate Catchment

Appendix : D "R" Script used for Rainfall Trend Analysis

D - *1 Loading packages "Kendall", "Modifiedmk" and "ZYP"*

library(Kendall)

library(modifiedmk)

library(zyp)

D – *2 Assigning variables*

The Excel file name – ZYP1

Dependent variables - *Months*

y1<-ZYP1$Jan

y2<-ZYP1$Feb

y3<-ZYP1$Mar

y4<-ZYP1$Apr

y5<-ZYP1$May

y6<-ZYP1$Jun

y7<-ZYP1$Jul

y8<-ZYP1$Aug

y9<-ZYP1$Sep

y10<-ZYP1$Oct

y11<-ZYP1$Nov

y12<-ZYP1$Dec

Independent variable - Years

x<-ZYP1$Years

D – *3 Auto correlation for* each month

```
acf(y1,lag.max = 1)
acf(y1,lag.max = 1)$acf
acf(y2,lag.max = 1)
acf(y2,lag.max = 1)$acf
acf(y3,lag.max = 1)
acf(y3,lag.max = 1)$acf
acf(y4,lag.max = 1)
acf(y4,lag.max = 1)$acf
acf(y5,lag.max = 1)
acf(y5,lag.max = 1)$acf
acf(y6,lag.max = 1)
acf(y6,lag.max = 1)$acf
acf(y7,lag.max = 1)
acf(y7,lag.max = 1)$acf
acf(y8,lag.max = 1)
acf(y8,lag.max = 1)$acf
acf(y9,lag.max = 1)
acf(y9,lag.max = 1)$acf
acf(y10,lag.max = 1)
acf(y10,lag.max = 1)$acf
acf(y11,lag.max = 1)
acf(y11,lag.max = 1)$acf
acf(y12,lag.max = 1)
acf(y12,lag.max = 1)$acf
```

D – 4 Modified Mann Kendall Test

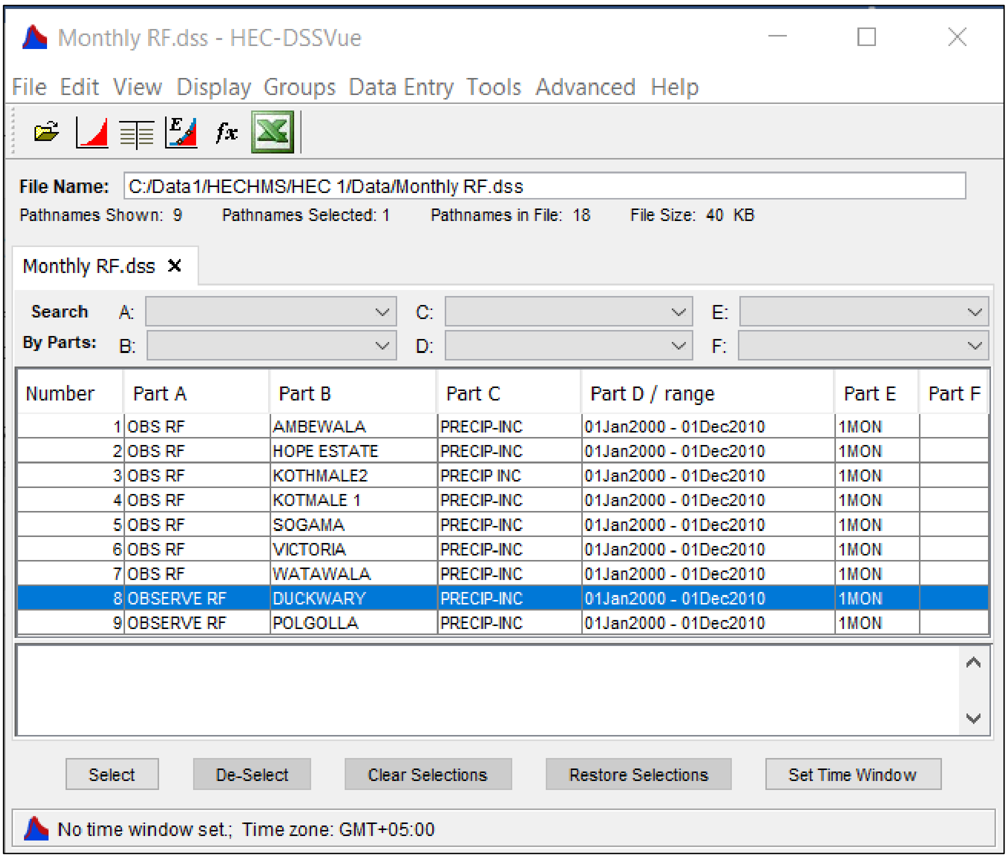
```
bbsmk(y1,ci = 0.95,nsim = 2000,eta = 1,bl.len = NULL)

bbsmk(y2,ci = 0.95,nsim = 2000,eta = 1,bl.len = NULL)

bbsmk(y3,ci = 0.95,nsim = 2000,eta = 1,bl.len = NULL)

bbsmk(y4,ci = 0.95,nsim = 2000,eta = 1,bl.len = NULL)

bbsmk(y5,ci = 0.95,nsim = 2000,eta = 1,bl.len = NULL)

bbsmk(y6,ci = 0.95,nsim = 2000,eta = 1,bl.len = NULL)

bbsmk(y7,ci = 0.95,nsim = 2000,eta = 1,bl.len = NULL)

bbsmk(y8,ci = 0.95,nsim = 2000,eta = 1,bl.len = NULL)

bbsmk(y9,ci = 0.95,nsim = 2000,eta = 1,bl.len = NULL)

bbsmk(y10,ci = 0.95,nsim = 2000,eta = 1,bl.len = NULL)

bbsmk(y11,ci = 0.95,nsim = 2000,eta = 1,bl.len = NULL)

bbsmk(y12,ci = 0.95,nsim = 2000,eta = 1,bl.len = NULL)
```

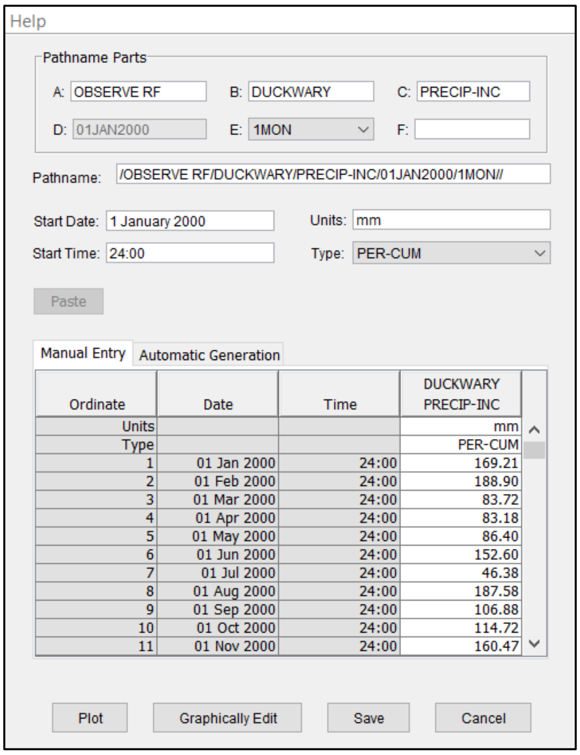
H – 5 Sen Slope – Package” zyp”

```
df=data.frame(x=c(x),y=c(y1))

zyp.sen(y~x,df)

df=data.frame(x=c(x),y=c(y2))

zyp.sen(y~x,df)

df=data.frame(x=c(x),y=c(y3))

zyp.sen(y~x,df)

df=data.frame(x=c(x),y=c(y4))

zyp.sen(y~x,df)

df=data.frame(x=c(x),y=c(y5))

zyp.sen(y~x,df)
```

```
df=data.frame(x=c(x),y=c(y6))
zyp.sen(y~x,df)
df=data.frame(x=c(x),y=c(y7))
zyp.sen(y~x,df)
df=data.frame(x=c(x),y=c(y8))
zyp.sen(y~x,df)
df=data.frame(x=c(x),y=c(y9))
zyp.sen(y~x,df)
df=data.frame(x=c(x),y=c(y10))
zyp.sen(y~x,df)
df=data.frame(x=c(x),y=c(y11))
zyp.sen(y~x,df)
df=data.frame(x=c(x),y=c(y12))
zyp.sen(y~x,df)
```

Appendix : E HEC DSS File – Importing Monthly Rainfall Data





The findings, interpretations and conclusions expressed in this thesis are entirely based on the results of the individual research study and should not be attributed in any manner to or do neither necessarily reflect the views of UNESCO Madanjeet Singh Centre for South Asia Water Management (UMCSAWM), nor of the individual members of the MSc panel, nor of their respective organizations.