ASSESSING WATER- USE EFFICIENCY IN THE AGRICULTURAL SECTOR IN THE MALWATHU OYA RIVER BASIN UNDER CHANGING CLIMATE SCENARIOS

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DECLARATION

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Name of Supervisor: Dr. P. K. C. De Silva

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ABSTRACT

ASSESSING WATER- USE EFFICIENCY IN THE AGRICULTURAL SECTOR IN THE MALWATHU OYA RIVER BASIN UNDER CHANGING CLIMATE SCENARIOS

Climate change, conventional agricultural techniques and malfunctioning irrigation systems pose significant challenges to efficient water management in the dry zone of Sri Lanka. Agricultural activities in the dry zone mainly depend upon irrigation reservoirs attached to the hydrodynamics of dry zone basins. Assessing the water use efficiency (WUE) of an irrigation scheme in a water-scarce region is paramount for developing a robust water management strategy considering the escalating impacts of climate change.

Nachchaduwa Irrigation Scheme, situated in the Malwathu Oya basin, Sri Lanka, constitutes the required characteristics of a dry zone irrigation system for this research study about climate change impacts on irrigation supply efficiency. The developed methodology includes two primary components: crop water requirement estimation and irrigation supply estimation. The analysis of crop water requirement estimates revealed distinct seasonal variations. During the Maha season, the crop water demand decreased due to increased rainfall events, with the estimated mean crop water requirement dropping from 1,166.87 mm/season in the base period to 1,076.15 mm/season under SSP 1-2.6 and 1,053.17 mm/season under SSP 5-8.5. Conversely, the Yala season experienced higher water demand under the SSP 5-8.5 scenario with 774.41 mm/season, where the base period requirement is 767.18 mm/season, indicating a 0.9% rise.

The HEC-HMS model has been used to simulate river inflow to the Nachchaduwa Reservoir prior to obtaining the irrigation supply through reservoir operation simulations. Results indicated significant variability in future water availability in the upstream catchment, with a projected mean annual inflow decrease of 8.14% under the SSP 5-8.5 scenario and an increase of 43.16% under the SSP 1-2.6 scenario. The increased variability in inflow highlighted the potential for frequent and severe extreme rainfall events under considered climate scenarios. The two-point hedging rule theory was adopted in reservoir operation simulations for irrigation supply estimation. The annual mean irrigation supply during the base period ranged from 866.56 mm/season to 1,148 mm/season, which shows a decline under the SSP 1-2.6 scenario but increases the variability under the SSP 5-8.5 scenario. These findings manifest the need for resilient irrigation management practices to address future climatic challenges in dry zone irrigation schemes in Sri Lanka.

Keywords: Crop water requirement, HEC-HMS, Irrigation supply, Nachchaduwa Reservoir

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LIST OF ABBREVIATIONS

Abbreviation	Description
AMIP	Atmospheric Model Intercomparison Project
CMIP	Coupled Model Intercomparison Project
DEM	Digital Elevation Model
GCM	Global Circulation Model
GMIS	Global Man-Made Impervious Surface
HEC-HMS	Hydrologic Engineering Center’s Hydrologic Modeling System
HEC-ResSIM	Hydrologic Engineering Center's Reservoir Simulation
HEIFLOW	Hydrological-Ecological Integrated Watershed-Scale Flow
HLMC	High-Level Main Canal
HydroSHEDS	Hydrological data and maps based on Shuttle Elevation Derivatives at multiple Scales
IPCC	Intergovernmental Panel on Climate Change
LLMC	Low-Level Main Canal
MCM	Million Cubic Meters
NIWR	Net Irrigation Water Requirement
NRCS	Natural Resources Conservation Service
NSE	Nash Sutcliffe Efficiency
PBIAS	Percentage Bias
RCM	Regional Climate Model
RCP	Representative Concentration Pathways
RMSE	Root Mean Square Error
RSR	RMSE-Observations Standard Deviation Ratio
SBUH	Soil-Bio-Water-Urban Hydrology
SCS CN	Soil Conservation Service Curve Number
SMA	Soil Moisture Accounting
SRES	Special Report on Emission Scenarios
SRTM	Shuttle Radar Topography Mission
SSP	Shared Socioeconomic Pathways

SWAT	Soil And Water Assessment Tool
UN FAO	United Nations Food and Agricultural Organization
UNFCCC	United Nations Framework Convention on Climate Change
WUE	Water Use Efficiency

CHAPTER 1
INTRODUCTION

1.1 Background

Agricultural water demand occupies 70% of global freshwater consumption, allocating only the remaining 30% for municipal and industrial water consumption (Kilemo, 2022). Changes in precipitation patterns, rising temperatures, and increased evaporation rates pose significant challenges to the effective utilisation of water. Therefore, freshwater resources are already stressed and demand efficient water-use approaches to cope with the ever-growing water requirements for agriculture due to the increasing population.

The concept of water use efficiency (WUE) is paramount in the fields of Irrigation Engineering and agriculture to achieve sustainable water management. WUE has been defined differently in the fields of Irrigation Engineering and agriculture. Within the domain of Irrigation Engineering, WUE is defined as the ratio of crop water consumption to the supplied water amount of a designated spatial boundary (Odhiambo & Kranz, 2011). This perspective highlights the efficiency of irrigation systems in supplying water to crops, emphasising the need for efficient water distribution and consumption. WUE in agricultural practices is defined as the mass of crop yield per one-meter cube of consumed water volume (Hoover et al., 2023). This view emphasises the importance of maximising crop productivity while conserving consumed water by optimising water management practices.

Considering the crucial impact of climate change on agricultural production and water management practices, evaluating the WUE under changing climatic conditions requires a rigorous study. According to the United Nations Framework Convention on Climate Change (UNFCCC), "Climate Change" refers to the natural climate variability observed over analogous periods attributed directly or indirectly to human activities that alter the composition of the global atmosphere (United Nations, 1992). The impacts of climate change constitute an increasing threat to the availability and reliability of water resources. Over the years, the hydrological cycle has been disrupted by changes in precipitation patterns, rising temperatures, and an increase in the frequency of extreme weather events (Hagemann et al., 2013). This has worsened water scarcity and variability in many parts of the world. These alterations impact human populations and natural ecosystems, posing severe threats to water management and conservation initiatives. Moreover, climate change affects the amount and quality of water available, affecting ecosystems, agriculture, industry, and drinking water supplies (Whitehead et al., 2015).

Implementing techniques and methods to lessen the adverse effects of changing climatic conditions on agricultural production involves climate change adaptation in agriculture and irrigation. Farmers confront difficulties such as changed precipitation patterns and an increase in the frequency of extreme weather events as climate trends become more unpredictable (Muthuwatta et al., 2017). In response to increasing the resilience of agricultural systems, adaptation initiatives concentrate on strengthening water conservation methods, diversifying crop types, implementing climate-smart agricultural technologies, and strengthening further water management strategies (Yoshikawa et al., 2014).

Crop water requirement determines the irrigation supply and depends on climate variables, including temperature, precipitation, relative humidity and sunshine hours, which are affected by climate change (Surendran et al., 2015). The concept of crop water requirement is fundamental to agricultural water management since it specifies the volume of water required to compensate for evapotranspiration losses from cultivated areas. Evapotranspiration comprises the transpiration of water through plant tissues and the direct evaporation of water from soil surfaces (Pereira, 1998). The parameters, including crop type, growth stage, rainfall, and soil properties, affect the water required for continuous development and productivity (Yoshikawa et al., 2014). In addition, determining the crop water requirements enables optimising irrigation scheduling, conserving water resources, and mitigating the risks of water scarcity or excess.

Studies assessing climate change impacts on irrigation systems are essential for comprehending the complex relationships that alter agricultural water management with climate change (Banihabib et al., 2016; Vano et al., 2010). These studies evaluate how climate change might affect socioeconomic variables, crop yield, and water availability. Impact assessments assess anticipated changes in crop water requirements and irrigation efficiency, which help to determine the adaptation strategies that will improve water management techniques, boost infrastructure resilience, and optimise irrigation schedules (Song et al., 2016; Zhang et al., 2012). These studies capture the broader socioeconomic and environmental effects of climate change on agriculture by selecting specific study regions characterised by different climate conditions, water requirements, and land use.

Despite numerous studies on WUE and climate change adaptation in agriculture, there remains a research gap in understanding how dry zone irrigation schemes respond to changing climatic conditions and the effectiveness of adaptive strategies in enhancing water use efficiency. In this context, WUE can be selected as an indicator to evaluate the efficiency of irrigation supply defined by irrigation rules under changing climate conditions.

1.2 Problem Statement

The growing effects of climate change cause significant challenges to agricultural water management in dry zone regions, where water resources are already scarce. Determining the response of dry zone irrigation schemes to climate change is crucial for developing effective adaptation strategies to maintain expected agricultural productivity. WUE is an effective indicator for assessing the efficacy of water management strategies established by irrigation rules within the irrigation scheme, particularly in meeting the varying crop water requirements controlled by shifting climatic patterns. In this background, there is a need for comprehensive research to determine the WUE of a dry zone irrigation scheme under changing climate scenarios captured by Global Circulation Models (GCMs).

1.3 Scope of the Study

The scope of the study involves conducting a comprehensive literature review to develop a methodology to assess the WUE of the Nachchaduwa Irrigation Scheme in Malwathu Oya basin, Sri Lanka. The estimation of WUE involves estimating crop water requirements and irrigation supply for the irrigation schemes considered. A thorough hydrological study on the Malwathu Oya basin should be conducted to capture the river inflow to the Nachchaduwa Reservoir, which supplies the irrigation demand of the Nachchaduwa Irrigation Scheme. The scope of the study further involves developing a reservoir operation model to obtain the irrigation releases. The above-mentioned steps will be conducted for historical and future time frames using observed and projected climate data to assess the impacts of climate change.

1.4 Aim and Objectives

The main aim of the research is to assess the WUE of the Nachchaduwa Irrigation Scheme in the Malwathu Oya basin of Sri Lanka under changing climate scenarios. The specific objectives of the study are,

1. To estimate the crop water requirement of the Nachchaduwa Irrigation Scheme using optimum evapotranspiration estimation method
2. To simulate the reservoir inflow to the Nachchaduwa Reservoir using a hydrological model
3. To simulate the actual irrigation supply from the Nachchaduwa reservoir to the downstream irrigation scheme using a reservoir operation model
4. To assess the impacts of climate change on irrigation supply and irrigation requirement under changing climate scenarios

1.5 Arrangement of the Thesis

This thesis comprises six chapters that systematically address the research topic through the outlined aim and objectives in Chapter one. Chapter two comprehensively reviews the literature related to the research topic and context. Chapter three describes the methodology, which consists of study area investigation, irrigation water requirement estimation, reservoir operation modelling, irrigation supply estimation, bias correction of climate estimates, and obtaining climate change projections. Chapter four presents the results of accuracy assessments of bias correction of GCM estimates, hydrological modelling using the HEC-HMS software package, and irrigation releases obtained through reservoir operation modelling. Chapter five discusses the abovementioned results, focusing on crop water requirements, reservoir inflow, and irrigation supply. Chapter six outlines the study's conclusions, recommendations and limitations. In conclusion, extracted references from the literature are presented.

CHAPTER 2
LITERATURE REVIEW

2.1 Introduction

This chapter outlines alternative approaches and perspectives to the research problem. Water management in the dry zone of Sri Lanka is prone to water scarcity threatened by climate change (Arachchige et al., 2011). Therefore, efficient management of water resources in the dry zone had been a timely requirement. Recent researchers have developed water usage plans for dry zone basins to sustain the agricultural water demand (Myuran, 2009). However, studies have not been conducted recently to assess the water use efficiency in paddy agriculture. To assess the water use efficiency in the study area, a water balance study should incorporate the hydrological aspects, reservoir operations and irrigation water use. The growing population, climate change, accelerated urbanisation, and conventional water management practices are contributing to the aggravation of this threat (Arachchige et al., 2011). It is crucial to comprehend the dynamics of these challenges to develop effective strategies to guarantee water availability for agriculture and other essential uses in this region.

Considering the vulnerability of water resources to the adverse effects of climate change, there is an emerging necessity to integrate climate change impact assessments into the decision-making procedures of irrigation practices. The literature often highlights the increasing awareness of the necessity for proactive water resource management techniques in response to changing climatic conditions and rising demand (Shibuya et al., 2007). Despite the requirement for sustainable water management in arid regions, there is a lack of thorough research to analyse the relationship between water usage efficiency and climate characteristics. The aforementioned research gap is addressed through this study, presenting an opportunity for a better understanding of the intricate relationship between climatic variables and the efficient use of water resources.

Recent efforts by other researchers to address this topic have highlighted several key challenges and considerations. Water allocation and transfer policies cannot be effectively formulated using traditional water management practices, regardless of their value for irrigation design and management. Return flows that re-enter the water supply, including seepage and runoff from irrigation, are frequently overlooked by these theories (Keller & Keller, 1995). Therefore, based on traditional estimates, efforts intended to increase water efficiency might not result in actual water savings.

Rosenberg et al. (2003) concluded that the significant changes in temperature and precipitation patterns across the entirety of the United States are indicated by climate change projections derived from the HadCM2 GCM. According to that study, 1 ℃ to 4 ℃ of warming is anticipated by 2030, accompanied by increasing evaporation rates. The seasonal hydrologic cycle, evapotranspiration, and water yield are impacted by these changes in the climate, which affect the study area's water security and supply. Rising temperatures cause changes in the timing and availability of water supplies, early snowmelt, and increased evapotranspiration. These effects highlight the significance of recognising and adjusting water management practices to changing climatic conditions.

The concept of WUE holds significant importance in sustainable agriculture and water resource management. WUE is an indicator used within the field of irrigation engineering and agriculture to assess the effectiveness of water utilisation. In the field of Irrigation Engineering, WUE refers to the ratio between consumed and supplied water volume to a considered spatial boundary, often referred to as Irrigation Efficiency (IE) (Odhiambo & Kranz, 2011). In contrast, agricultural practices present WUE as a quantitative correlation between the volume of water delivered to a crop field and the resulting yield (Hoover et al., 2023).

Gosain et al. (2005) introduced a new IE index that integrates critical factors such as irrigation return flow and direct contributions of groundwater to crop evapotranspiration. This study introduces a comprehensive method for evaluating basin-scale IE. Significant concerns regarding the quantification of IE in regions with intense surface water-groundwater interactions are addressed. Using a distributed ecohydrological model known as the Hydrological-Ecological Integrated Watershed-Scale Flow (HEIFLOW), the methodology estimates the dynamics of groundwater, surface flow, irrigation return flow, and actual evapotranspiration in response to climate variables. This method permits comprehension of the spatiotemporal characteristics of IE and the ways in which it may be affected by climate change under particular scenarios, such as RCP 4.5.

In contrast, Fors (2022) calculates actual evapotranspiration using the Soil and Water Assessment Tool (SWAT) model, calibrated using remotely sensed evapotranspiration data. IE is approximated with a high spatial resolution (250 m) by considering the daily time step of actual evapotranspiration and water balance within each grid cell. This method offers a high degree of spatial resolution, and its primary objective is to quantify IE in accordance with the actual water consumption within grid cells.

The conventional WUE concepts frequently employed in Irrigation Engineering are reviewed by Odhiambo and Kranz (2011), who have introduced effective irrigation water use efficiency, which discusses the importance of return flow in WUE assessments. This perspective emphasises the limitations of conventional efficiency metrics and the significance of return flows in policymaking. Eq. (2-1) presents the relationship between governing factors for WUE (Xiong et al., 2021).

$$\mathrm{WUE} = \frac{ET_c - P_e - GW_{et}}{IRR - F_{rf}} \tag{2-1}$$

In Eq. (2.1), ET_c is actual evapotranspiration, $GW_{et}$is percolation, IRR is irrigation water supply and F_{rf} is return flow. Governing factors for WUE mentioned in Eq. (2-1) are comprehensively discussed in Chapter 2.2 to Chapter 2.5.

2.2 Crop Water Requirement

Crop water requirement refers to the amount of water needed to compensate for evapotranspiration losses from the agricultural fields. The crop's water demand fluctuates across time and space, as the evapotranspiration demand varies with climate and crop conditions. Crop water requirement is often referred to as crop evapotranspiration (ET_c) under optimal plant development conditions (Ali, 2010).

Factors affecting Crop Water requirements are,

- Type of crop
- Stage of the crop (cultivate or growing)
- Leaf area leaf type, stomatal behaviour
- Root length
- Root density

Crop water requirement for a given crop, for the whole growing season, is estimated using Eq. (2-2), where ET_o is reference evapotranspiration, K_c is crop coefficient, t is time interval in days and m is days to physiological maturity from sowing or transplanting.

$$ET_c = \sum_{t=0}^{m}(ET_0 \times K_c) \tag{2-2}$$

2.2.1 Reference Evapotranspiration (ET_o)

ET_o estimates and crop coefficients for different stages of crops are widely used to estimate the crop water requirement in irrigation engineering practices. A hypothetical grass surface of 0.12 m in height, a surface resistance of 70 sm^{-1} and an albedo of 0.23 is considered as the reference surface, which is actively growing and completely covering the ground (Allen & Pereira, 1998).

In this study, UN FAO's Penman-Monteith method (Allen & Pereira, 1998) and Hargreaves method (Hargreaves et al., 1982) were utilised for the computation of reference evapotranspiration and the most optimum method was selected. Due to its physical-based approach, the Modified Penman-Monteith (MPM) method is a reliable and extensively utilised technique to estimate reference crop evapotranspiration. The high data demand of the MPM approach for evapotranspiration estimation is a hindrance, especially in regions with few meteorological stations and extensive datasets. The availability of data on air temperature, wind speed, humidity, and solar radiation is doubtful, particularly in underdeveloped nations. Satellite estimates of relative humidity, sunshine hours and wind speed were extracted from recently developed data portals for satellite estimates. The formula for the MPM is given by Eq. (2-3),

$$ET_0 = \frac{0.408\Delta(R_n - G) + \Upsilon\frac{900}{T+273}U_2(e_s - e_a)}{\Delta + \Upsilon(1 + 0.34u_2)} \tag{2-3}$$

where ET_0 is reference evapotranspiration, R_n net radiation at the crop surface, G is soil heat flux density, T is mean daily air temperature at 2 m height, u_2 is wind speed at 2 m height, e_s

is saturation vapour pressure, e_a is actual vapour pressure, Δ is slope vapour pressure curve and Υ is psychrometric constant.

Hargreaves formula is an empirical formula that requires minimum, maximum, and average temperature and location parameters as input parameters to calculate reference evapotranspiration. The Hargreaves method provides a simple and easily understandable approach for determining reference evapotranspiration governed by Eq. (2-4),

$$\mathrm{ET_0} = 0.0022 * R_A * d_T^{0.5} * (T + 17.8) \qquad (2\text{-}4)$$

where d'_T is the difference between the mean monthly maximum and minimum temperatures for the month of interest, T is the mean air temperature, and R_A is the mean extra-terrestrial radiation given by Eq. (2-5),

$$R_A = 15.392 \times d_r \times (w_s \times sinf \times sind + cosf \times cosd \times sinw_s) \qquad (2\text{-}5)$$

where d_r is the relative distance from the Earth to Sun, w_s is sunset hour angle in radians, f is the latitude of the location, and d is solar declination.

2.2.2 Crop Coefficient (K_c)

The crop coefficient incorporates the effect of traits that differentiate an average field crop from the grass reference, which has a consistent appearance and complete ground cover. K_c is affected by the crop's changing features throughout the growing season (Khan et al., 2021). Figure 2-1 depicts the variation of K_c during different growth stages.

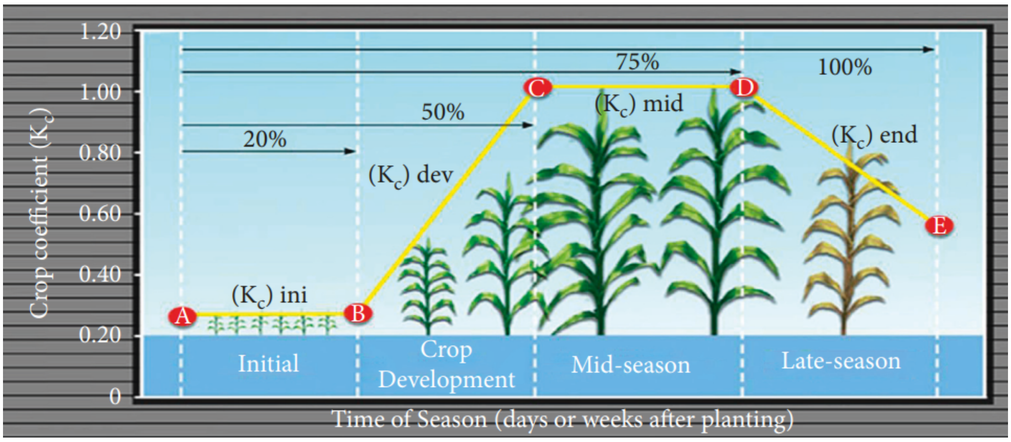

Figure 2-1: Effect of Crop Growth Stage on K_c

Source: Khan et al. (2021)

The following factors also affect the crop coefficient,

1. Crop height: The crop height influences the aerodynamic resistance term, Ra, of the FAO Penman-Monteith equation and the turbulent transfer of vapour from the crop into the atmosphere.
2. Albedo (reflectance) of the crop-soil surface: The albedo is affected by the fraction of vegetation covered and soil surface wetness. Albedo of the crop-soil surface influences

the net radiation of the surface, Rn, which is the primary source of the energy exchange for evaporation.

3. Canopy resistance: The resistance of the canopy to transfer vapour is affected by leaf area, leaf age and condition, and the degree of stomatal control. The canopy resistance influences the surface resistance.
4. Climate: Higher values of K_c are expected in more arid environments and high winds. More humid climates and lower wind speeds will have lower values for K_c.
5. Soil evaporation: The crop coefficient incorporates variations in crop transpiration and soil evaporation between field crops and the reference surface. When the crop is small and barely shades the ground after irrigation or rainfall, the effect of evaporation is more severe. K_c is greatly influenced by how often the soil surface is moist under these low-cover situations.

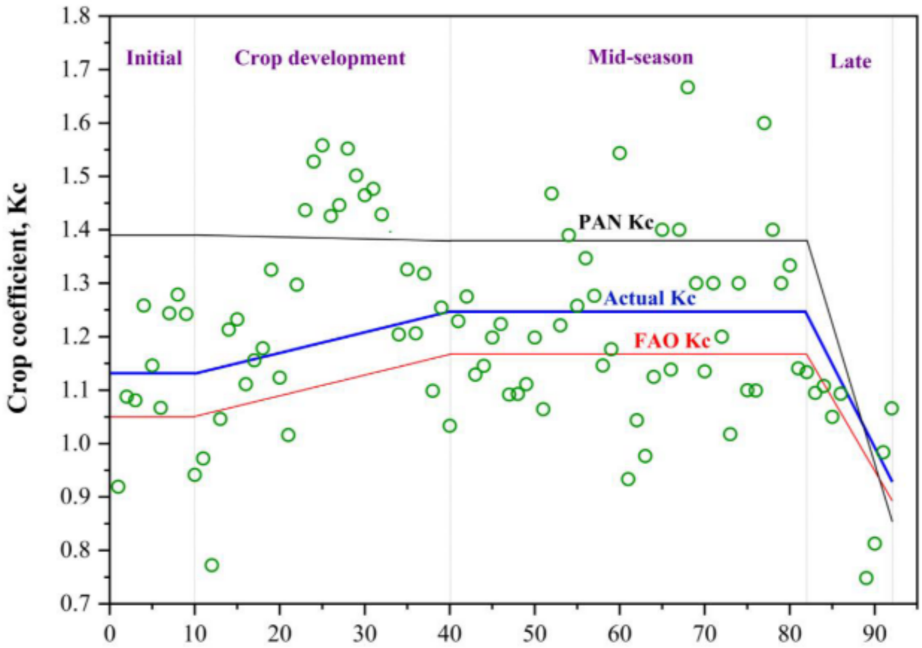

Figure 2-2: Crop Coefficient of Paddy

Source: Kumari et al. (2022)

Figure 2-2 compares the actual K_c values for paddy with K_c values obtained using indirect methods such as the FAO-56 method and pan evapotranspiration method (Allen, 2017; Kumari et al., 2022). K_c values of the FAO method have been obtained considering the actual evapotranspiration estimated by the modified paddy lysimeter and the reference evapotranspiration estimated by the modified Penman-Monteith method.

2.3 Net Irrigation Water Requirement (NIWR)

The amount of water required for crop water consumption during the growing period and the amount of water required to maintain the soil moisture at 60% during the land preparation and cropping period is defined as the NIWR (Yoshikawa et al., 2014). Paddy cultivation maintains soil moisture at 100% of the field capacity. Eq. (2-6) holds the relationship for NIWR, which considers crop evapotranspiration and calculates the additional irrigation water required to meet the crop's water needs by deducting effective rainfall d soil moisture depletion, using:

$$\mathrm{NIWR}_{nc} = \sum(K_c \times ET_0) + P - R_e \tag{2-6}$$

where P represents soil moisture depletion, and R_e represents effective rainfall.

2.3.1 Effective Rainfall

The amount of rainfall that contributes to crop growth after losses through surface runoff, deep percolation and lateral subsurface flow is defined as effective rainfall. Ponrajah (1984) defined empirical equations (Eq. (2-7) and Eq. (2-8)) to estimate effective rainfall to be used in the local context, constituting two independent equations for lowlands and highlands.

Lowland: $P_e = 0.67 \times (R - 1)$ $[P_{e,\,max} = 27$ cm & $P_e = 0$ for $R \leq 2.5$ cm$)$ (2-7)

Highland: $P_e = 0.67 \times (R - 0.25)$ $[P_{e,\,max} = 7.5$ cm & $P_e = 0$ for $R \leq 2.5$ cm$)$ (2-8)

In Eq. (2-7) and Eq. (2-8), P_e represents effective rainfall, and R represents average daily rainfall.

2.3.2 Irrigation Scheduling

Irrigation scheduling involves supplying the appropriate amount of water at the appropriate time. The amount of water to apply depends on the moisture storage of soil, the moisture level at which irrigation is to begin, the depth of the root zone, the presence of any other water sinks besides plants (such as salt leaching), the depth of the water table, the presence of sub-surface drainage facilities, the effectiveness of the irrigation system, and so on (Gu et al., 2020).

Many scholars have advocated for the possible benefits of timing irrigations using climatic data. Fischbach and Somerhalde (1974) used amounts equivalent to the daily ET_o peak (7.52 mm/day) and 0.75, 0.50, and 0.33 of the daily peaks at a frequency ranging from 1.5 to 7 days. They found that the amount of water equivalent to 0.5 of the peak ET_o rates produced the maximum yield across all frequencies examined. Table 2-1 presents required submergence levels for varying growth stages of paddy.

Table 2-1: Depth of Submergence at Different Stages

Stage of Crop Growth	Depth of Submergence (cm)
Before puddling	5-10
During Puddling	2-3
Sowing to the tillering stage	2-3
Tillering to flowering	2-3
Twenty days after flowering	Withhold irrigation

Different submergence depths are required at different crop growth stages to maximise yield potential and water use efficiency. The usual range of submergence depths before puddling is 5 to 10 cm, guaranteeing sufficient soil moisture for germination and early growth. Irrigation depths drop to 2-3 mm during puddling and the sowing that follows to the tillering stage, reflecting the crop's decreased water requirements. Similarly, irrigation depths stay between 2 and 3 mm from the tillering to flowering phases to support crop growth and prevent waterlogging. In conclusion, irrigation is stopped for 20 days after flowering to avoid excessive water stress and encourage proper grain filling. This approach for irrigation scheduling aligns with water application to the unique requirements of the crop at every stage of growth.

2.4 Irrigation Supply Estimation

In dry zone irrigation schemes in Sri Lanka, the irrigation demand is predominantly met through irrigation reservoirs, making accurate estimation of irrigation supply crucial. To achieve this, modelling the operations of these reservoirs is essential, which in turn depends on precise inflow time series data. Conducting a thorough hydrological study to obtain the river inflow to the reservoir is, therefore, a critical component of this process. This approach ensures the development of reliable inflow time series, which are fundamental for simulating reservoir operations accurately. By capturing the variability in river inflow influenced by seasonal changes and climatic variations, the study will enable the prediction of water availability for irrigation purposes.

2.4.1 Hydrological Modelling

Hydrological models provide simplified representations of the hydrological cycle and are extensively employed as tools in the formulation of long-term strategies for integrated water resource planning and management. Hydrologic models can be classified based on their capabilities and limitations. Chow et al. (1988) classified hydrological models as physical and mathematical models. A physically based model is a mathematical representation of an actual phenomenon, including the catchment's physical processes (Devia et al., 2015). Scale and analogue models are subcategories that can be further distinguished among physical models. A scale model represents the natural system that preserves the connections between crucial system components. Analogue models base their representation of the process under study on analogous approaches.

Mathematical models are developed using logical programming languages and mathematical concepts to depict the spatial and temporal aspects of the hydrological cycle (Jajarmizadeh et al., 2012). Mathematical models can be classified as deterministic or stochastic (Shaw et al., 2010). Deterministic models define outcomes according to predetermined relationships between states and occurrences, disregarding stochastic variation. Conversely, a stochastic model can produce unique output values from a solitary set of random inputs.

Deterministic models can be categorised into three broad categories: lumped, distributed, and semi-distributed (Cunderlik, 2003). Lumped models consider the catchment as a whole, whereas state variables represent basin-wide averages (Beven, 2001). Distributed models represent the catchment as a grid, and water fluxes are transferred from one cell to the next as water drains through the basin (Xu, 2002). The process of parameterising distributed models requires a substantial quantity of data. The absence of sufficient data can limit the comprehension of hydrological basins using a fully distributed model (Geethalakshmi et al., 2008).

A semi-distributed model integrates the advantages of both spatial representations and the requirement of limited data resources. The partitioning of the catchment area into smaller sub-basins allows the semi-distributed model to account for spatial variability to the required extent. Considering the above facts, HEC-HMS developed by the US Army Corps of Engineers had been selected for hydrological modelling of the Malwathu Oya river basin, which is more physically based in comparison with the lumped model but requires a lesser amount of data than the fully distributed model.

2.4.2 Hydrologic Engineering Center's Hydrologic Modeling System (HEC-HMS)

The Hydrologic Engineering Center's Hydrologic Modelling System (HEC-HMS), developed by the United States Army Corps of Engineers, is a physically based and deterministic model. It is generally utilised in a lumped or semi-distributed way and possesses the necessary characteristics for distributed hydrological modelling (USACE, 2016).

HEC-HMS has been used for a variety of purposes, including flood forecasting (Bhuiyan et al., 2017), post-fire response analysis (Cydzik et al., 2009), stormwater management (McEnroe, 2010), and climate impact assessment (Meenu et al., 2013). HEC-HMS can simulate both continuous and event-based hydrological phenomena. In HEC-HMS, the soil moisture accounting algorithm (SMA) and deficit-constant methods are the only methods that account for the loss processes. The watershed is represented by the HEC-HMS with the SMA algorithm using five layers and twelve parameters. The parameters are surface depression storage, canopy interception storage, soil storage, infiltration rate, tension zone storage, soil percolation rate, storage depth, storage coefficient and percolation rate for shallow and deep groundwater layers.

2.4.2.1 Canopy Storage

The interception of rainwater by vegetation constitutes canopy interception (Hydrologic Engineering Center, 2000). The surface structure of the vegetation and weather conditions determine the canopy storage capacity. Earth surface receives excess rainfall after the canopy storage capacity is filled. Table 2-2 presents recommended canopy interception values.

Table 2-2: Canopy Storage According to Vegetation Type

Vegetation Type	Value (mm)
General vegetation	1.27
Grasses and deciduous trees	2.03
Trees and coniferous trees	2.54

2.4.2.2 Surface Storage

The volume of water held on the earth's surface is known as surface storage or surface depression storage (Hydrologic Engineering Center, 2000). After the canopy storage is filled, excess water travels to the earth surface. From the remaining water, some amount infiltrates, and some evaporates as it is kept on the land's surface.

According to the average slope obtained from the digital elevation model (SRTM 90 m) of the basin, maximum surface storage varies between 12 mm and 50.8 m. Table 2-3 presents surface storage capacities of different surface cover types (Sardoii et al., 2012).

Table 2-3: Surface Storage According to Surface Cover

Description	Slope (%)	Surface Storage (mm)
Paved impervious areas	NA	3.2 – 6.4
Steep, smooth slopes	>30.0	1.0
Moderate to gentle slopes	5.0-.30.0	12.7- 6.4
Flat, furrowed land	0.0- 5.0	50.8

2.4.2.3 Impervious Percentage

The imperviousness percentage controls the amount of water penetrating soil layers, and high impervious percentage values contribute to the peaks of the hydrograph (Hydrologic Engineering Center, 2000). Initial values for impervious percentage values for the study were obtained through impervious surface percentage maps (10 m spatial resolution) provided by the Global Man-made Impervious Surface (GMIS) dataset from Landsat, V1 (2010). Initial impervious percentage values for the model were improved by calibration.

2.4.2.4 Transform Method

HEC-HMS provides several methods for transforming rainfall data into runoff data, including the SCS (Soil Conservation Service) method, the SCS CN (Curve Number) method, the SBUH (Soil-Bio-Water-Urban Hydrology) method and the Clark Unit Hydrograph method (Hydrologic Engineering Center, 2000).

Clark Unit Hydrograph is derived from a synthetic unit hydrograph, which involves the explicit representation of the processes of translation and attenuation (Halwatura & Najim, 2013). These two phenomena are crucial in converting excess rainfall into a runoff hydrograph. T_c (time of concentration) and R (storage coefficient) are the hydrograph parameters required to compute the Clark Unit Hydrograph in HEC-HMS.

One way to quantify how quickly a stream reacts to runoff-causing rainfall is to look at its lag time (L) or T_c. These factors are the most critical inputs for estimating peak flow during flood conditions in ungauged watersheds. T_c is the time required for runoff to travel from the hydraulically most distant point in the watershed to the outlet. R is utilised in the linear reservoir that accounts for storage effects. A dimensionless ratio can be defined as the storage coefficient divided by the sum of the time of concentration and storage coefficient.

In this study, the Natural Resources Conservation Service (NRCS) method was used to calculate initial values for T_c (Eq. (2-9)). The NRCS method uses a dimensionless unit hydrograph derived from a curve number (CN), which measures the runoff-producing potential of a watershed.

$$T_c = \frac{L}{0.6} \tag{2-9}$$

$$L = \frac{l^{0.8}(S+1)^{0.7}}{1900Y^{0.5}} \tag{2-10}$$

$$S = \frac{1000}{CN} - 10 \tag{2-11}$$

Abbreviations used in Eq. (2-9), Eq. (2-10), and Eq. (2-11) are *L, CN, l, r* and *S,* which represent lag in hours, curve number, flow length, average land slope percentage, and maximum potential land slope, respectively.

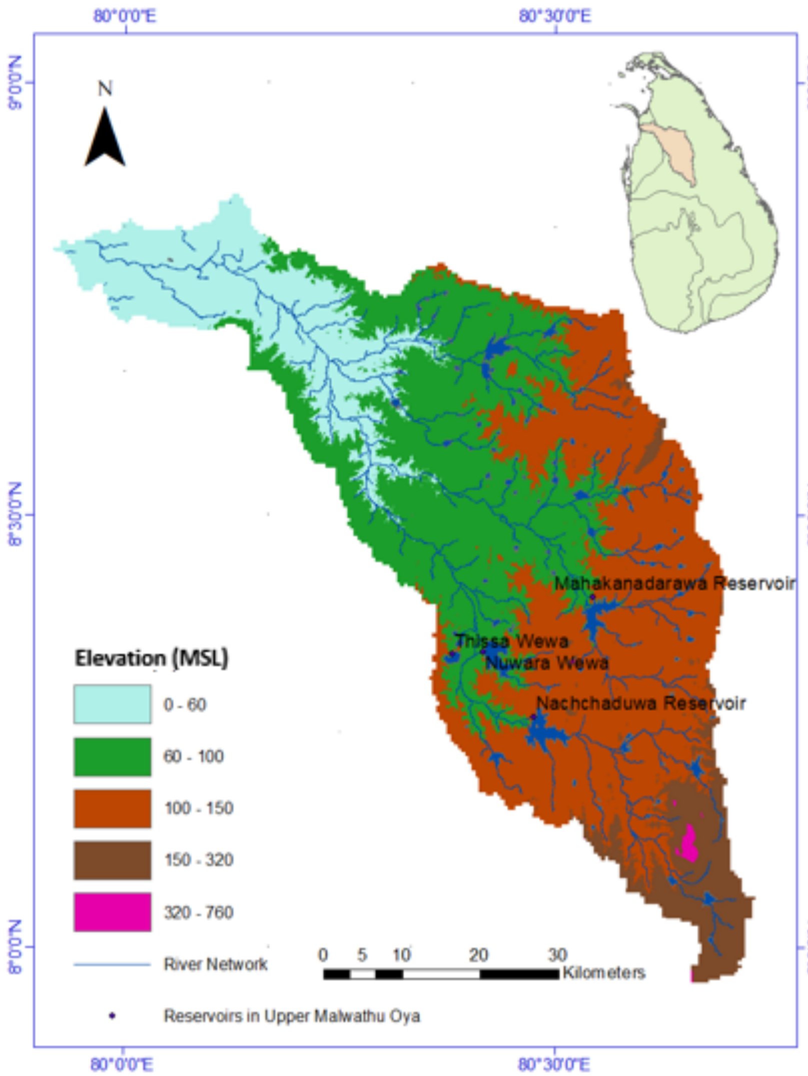

Figure 2-3: Digital Elevation Map of Malwathu Oya Basin

Figure 2-3 represents the DEM developed using ArcMap 10.8. The length of the stream and average watershed slope were extracted from the USGS hydroSHEDS 90 m resolution Digital Elevation Model (DEM). To improve the model accuracy, the author could not use 30 m resolution DEM provided by USGS hydroSHEDS because ArcMAP 10.8 or HEC-HMS software could not delineate a continuous stream for Maha Oya for 30 m resolution DEM.

2.4.2.5 Loss method

Actual infiltration calculations are performed using the loss method in HEC-HMS. Among the 12 loss methods provided by HEC-HMS, researchers often use the Soil Moisture Accounting (SMA) method (Bekele et al., 2021; Kamran & Rajapakse, 2018).

The SMA method utilises three layers to represent the continual variations in soil moisture content throughout the vertical profile of the soil. The groundwater strata are not intended to depict aquifer dynamics; instead, they are intended to illustrate shallow inter-flow interactions. The soil layer is separated into a tension zone and an upper zone. Only soil water from the upper zone percolates, whereas water in the tension zone resists percolation. Water percolates from upper and lower groundwater (Sardoii et al., 2012).

2.4.2.6 Baseflow method

Subsurface flow simulations are performed using the baseflow simulation in HEC-HMS. The linear reservoir method was used in this study to couple with the SMA method.

The linear reservoir baseflow method uses a linear reservoir to model the baseflow recession after a storm event. Infiltration or percolation computed by the loss method is connected as the inflow to the linear reservoirs. It can be used with one, two, or three reservoirs. Partition fractions are used to split the inflow to each of the reservoirs. The inflow is multiplied by the partition fraction to determine the inflow going to each reservoir.

Parameters related to the SMA and linear reservoir methods are further discussed in the methodology, and optimum parameter values to represent the watershed are obtained through model calibration.

2.4.2.7 Performance Evaluating Objective Functions

The objective functions presented by Eq. (2-12) to Eq. (2-14) were used to calibrate and validate the HEC-HMS model. (Shrestha et al., 2017). Table 2-4 presents the performance ranges according to the objective function results.

1. Coefficient of Correlation (R^2)

$$R^2 = \left(\frac{n \sum Q_i Q_i' - \sum Q_i \ \sum Q_i'}{\sqrt{n(\sum Q_i^2) - (\sum Q_i)^2} \times \sqrt{n(\sum Q_{i\,1}'^2) - (\sum Q_i')^2}} \right)^2 \tag{2-12}$$

2. Nash –Sutcliffe Efficiency (NSE)

$$\text{NSE} = 1 - \frac{\sum_{i=1}^{n} (Q_i - Q_i')^2}{\sum_{i=1}^{n} (Q_i - \bar{Q_i})^2} \tag{2-13}$$

3. Root Mean Square Error (RMSE)

$$\text{RMSE} = \sqrt{\frac{\sum_{i=1}^{n}(Q_i - Q_i')^2}{N}} \quad (2\text{-}14)$$

Abbreviations used in Eq. (2-12), (2-13) and (2-14) are *n, Q,* Q_i' and *N,* representing number of data points in time series, simulated discharge, observed discharge and number of observations respectively.

Table 2-4: Objective Function Value Ranges

Performance rating	**RMSE**	**NASH**	**R^2**
Very good	0.00 < RMSE < 0.75	0.75 < NSE ≤ 1.00	0.75 < R^2 ≤ 1.00
Good	0.75 < RMSE < 1.00	0.65 < NSE ≤ 0.75	0.65 < R^2 ≤ 0.75
Satisfactory	1.00 < RMSE < 2.00	0.50 < NSE ≤ 0.65	0.50 < R^2 ≤ 0.65
Unsatisfactory	2.00 < RMSE	NSE ≤ 0.50	R^2 ≤ 0.50

2.5 Climate Projections

According to the UNFCCC, "Climate Change" refers to the natural climate variability observed over analogous periods attributed directly or indirectly to human activities that alter the composition of the global atmosphere (United Nations, 1992). Further, the Intergovernmental Panel on Climate Change (IPCC) defines climate change as the alterations in the variability of climate characteristics over an extended duration, generally spanning decades (IPCC, 2012).

Increasing temperatures, altered precipitation patterns, and more frequent and severe weather events manifest in climate change. This substantially impacts ecosystems, agriculture, biodiversity, and human populations. Sea-level rise, intensified droughts, heat waves, and increased inundation are some of the global effects of climate change.

Increased greenhouse gas emissions, such as carbon dioxide (CO_2), methane (CH_4), and nitrous oxide (N_2O), as a consequence of industrial processes, deforestation, and fossil fuel combustion, are the primary causes of contemporary climate change. These emissions cause an increase in global temperatures by trapping heat in the atmosphere.

2.5.1 Future Rainfall Estimates

Assessing climate change impacts has become crucial in understanding and mitigating its effects. A fundamental aspect of this assessment is obtaining climate variables, including rainfall and temperature, which helps predict how climate change will impact various regions in the abundance of observed data. These estimates are derived from complex climate models developed considering many factors, such as greenhouse gas emissions, oceanic currents, and atmospheric circulation patterns (Hagemann et al., 2012). By analysing these estimates, researchers can gain insights into potential changes in precipitation that may lead to alterations in water availability, ecosystem dynamics, and even social and economic systems (Eccles et al., 2019; Nijssen et al., 2001).

Generating accurate future rainfall estimates requires sophisticated methodologies integrating various data sources and modelling techniques, such as General Circulation Models (GCMs) and Regional Climate models (RCMs). GCMs and RCMs simulate the interactions between the atmosphere, oceans, land, and ice, providing projections of climate variables, including rainfall, under different greenhouse gas emission scenarios (Hagemann et al., 2013). Even though RCMs provide high-resolution, region-specific projections that offer valuable insights into potential changes in rainfall patterns than GCMs, there was no RCM for South Asian or Asian regions under newly introduced climate change scenarios (Mishra et al., 2020).

The estimates provided by the climate model give insights into potential ecological, societal, and economic changes under a range of emissions trajectories related to different levels of greenhouse gas emissions and their resulting atmospheric concentrations, often discussed as climate change scenarios (Mesgari et al., 2022; Peng & Li, 2021). Researchers can explore potential outcomes by examining future rainfall patterns within distinct climate change scenarios. In addition, other stakeholders interacting with environmental sciences can make informed choices about mitigation and adaptation strategies, considering the uncertainties associated with different emissions trajectories (Banihabib et al., 2016).

2.5.2 Climate Change Scenarios

The scientific community has generated future emission scenarios to assess the future climatic reaction. The Intergovernmental Panel on Climatic Change (IPCC) created the Special Report on Emission Scenarios (SRES) to modify previous scenarios based on new data and advances in scientific understanding of the climatic response to emissions. In recent years, the evolution of climate models and scenario frameworks has brought a shift in the preferred choices for assessing the impacts of climate change. The following scenarios are often used in research related to climate change impact assessments (Nakicenovic et al., 2000).

Socio-economic and emission scenarios provide a platform for climate researchers to describe how the world would evolve concerning changes in socio-economy, technology, emissions of greenhouse gases and air pollutants, energy and land use. Under particular scenarios, climate change impacts can be assessed, and mitigation measures could be proposed and implemented in the contexts of each field. Table 2-5 provides a summary of frequently used climate scenarios for recent research.

Table 2-5: Recent Climate Change Scenarios

Special Report on Emissions Scenarios (SRES) (Shen et al., 2014) (B1, A1B, A2)			
Represent different socioeconomic pathways and greenhouse gas emissions trajectories, including various possible futures based on varying levels of globalisation, population growth, and technology.			
Representative Concentration Pathways (RCPs) (van Vuuren et al., 2011)			
Scenario	RCP 2.6	RCP 4.5	RCP 8.5
Greenhouse gas emissions	Very low	Medium-low mitigation (very low baseline)	High baseline
Agricultural area	Medium for cropland and pasture	Very low for cropland and pasture	Medium for cropland and pasture
Air pollution	Medium-Low	Medium	Medium-High

Other researchers concurrently generated a new set of alternative future socioeconomic development pathways, termed shared socioeconomic pathways (SSPs), describing the plausible alternative trends in the evolution of society and natural systems during the 21st century on a global and regional scale (O'Neill et al., 2014) (Figure 2-4). The ultimate objective of the scenario process is to generate integrated scenarios that include socioeconomic and environmental conditions affected by climate change and climate policy (Kriegler et al., 2012).

The SSPs are specified initially by defining qualitative narratives describing broad development pathways hypothesised to produce the desired combinations of challenges to mitigation and adaptation, then sketching qualitative trends in key SSP elements, and finally quantifying those elements deemed most helpful to represent in quantitative form (O'Neill et al., 2017).

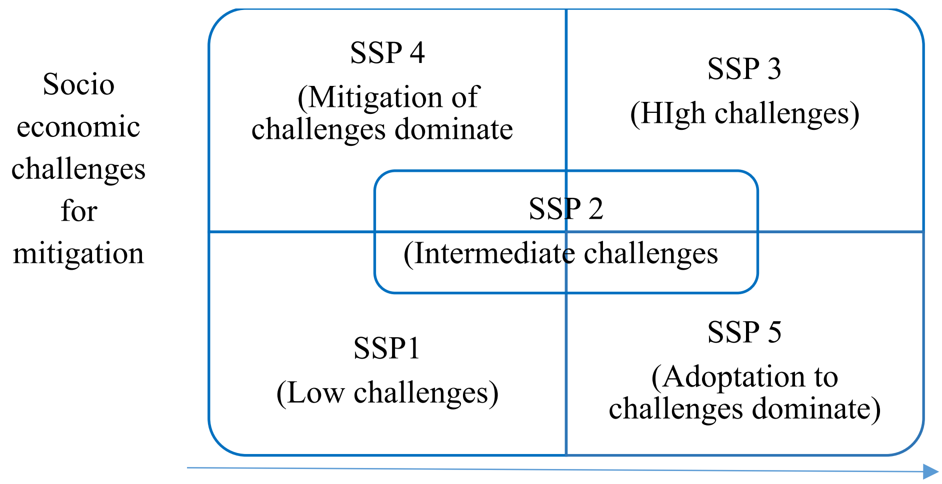

Figure 2-4: Socioeconomic Challenges and Adaptation Aspects Under SSP Scenarios

This study considers scenarios corresponding to Shared Socioeconomic Pathways (SSPs) integrated into Representative Concentration Pathways (RCPs) to assess the impacts of climate change. The overall scenario process aims to produce integrated scenarios that include socioeconomic and environmental conditions affected by climate change and climate policy (O'Neill et al., 2014). The scenarios considered are as follows,

I. SSP126 (SSP 1 + RCP 2.6): A green development pathway
II. SSP245 (SSP 2 + RCP 4.5): An intermediate development pathway
III. SSP585 (SSP 5 + RCP 8.5): A high development pathway

Historical rainfall estimates from 1900 to 2014 and projected rainfall estimates from 2015 to 2100 corresponding to the SSP 1-2.6 and SSP 5-8.5 are only available in one GCM developed by CNRM with daily and 50 km temporal and spatial resolutions, respectively. Data can be downloaded from the ESGF data portal provided by the World Climate Research Programme.

2.5.3 General Circulation Models (GCMs)

Coupled Model Intercomparison Project provides access to different climate models under similar backgrounds while creating a platform to compare each other according to varying conditions (Peiffer et al., 2020). Coupled Model Intercomparison Project has evolved up to phase 6 now and has been analysed through the Intergovernmental Panel on Climate Change (IPCC) Sixth Assessment Report (Intergovernmental Panel on Climate Change (IPCC, 2022). The evolution of the Coupled Model Intercomparison Project through different phases as below.

I. CMIP1: commenced in 1996 and transferred the primary aims of the Atmospheric Model Intercomparison Project (AMIP) to coupled models: assessing and analysing the performance of atmospheric GCMs to simulate the current climate (Touzé-Peiffer et al., 2020)
II. CMIP2: Introduced in 1997, model simulations of climate change under a 1% per year CO2 increase were compared (Touzé-Peiffer et al., 2020)
III. CMIP3: Climate projections under different emission scenarios included (Touzé-Peiffer et al., 2020)
IV. CMIP5: Simulations attempt to address the significant concerns of diverse communities (Touzé-Peiffer et al., 2020)

Coupled Model Intercomparison Project estimates are compared with observed climate data to assess the performance of GCM (Peng & Li, 2021).

CERFACS.CNRM-CM6-1-HR is the only model to estimate daily resolution for SSP5-8.5 and SSP1-2.6 scenarios. CERFACS.CNRM-CM6-1-HR provides relatively accurate results for rainfall while it provides the most reliable estimates for minimum, maximum and average temperatures (Figure 2-5).

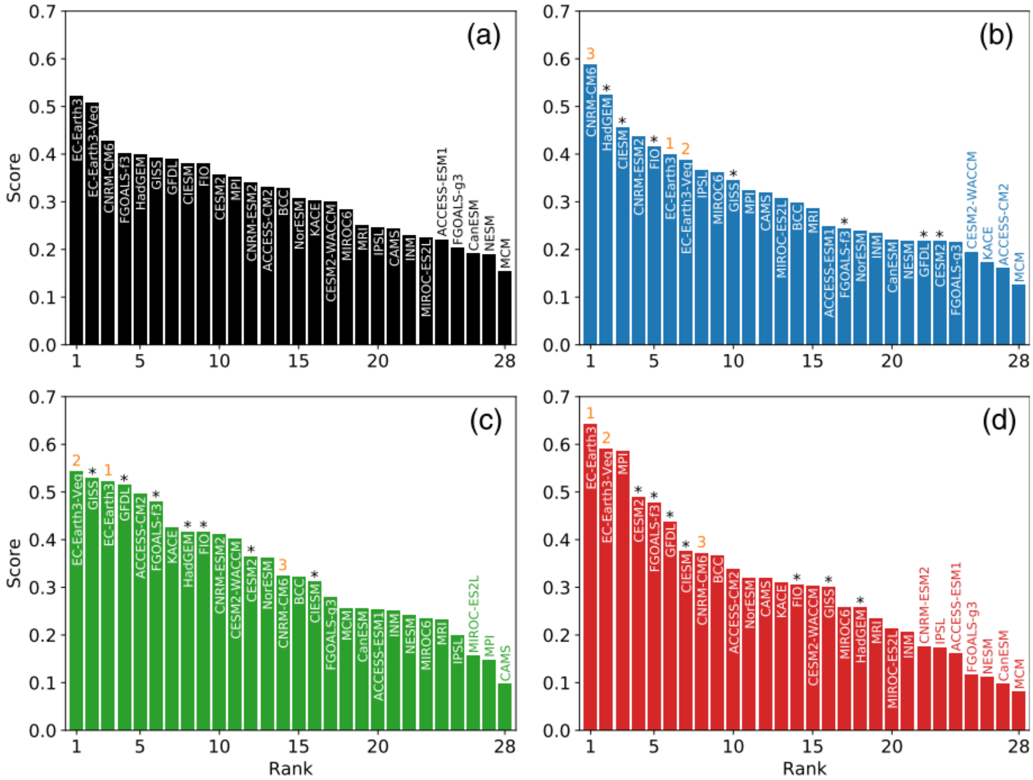

Figure 2-5: GCMs' Scores and Ranks: (a) final; (b) near-surface temperature; (c) precipitation; (d) 850-hPa wind. In variable scores diagrams, the final top 3 is notified in orange numbers; the final top 10 models are marked with an asterisk (Desmet and Ngo-Duc, 2022)

2.5.4 CERFACS.CNRM-CM6-1-HR Model Details

The GCM model is referenced as CERFACS.CNRM-CM6-1-HR is a high-resolution climate model developed by the Centre National de Recherches Météorologiques (CNRM) in collaboration with the Centre Européen de Recherche et de Formation Avancée en Calcul Scientifique (CERFACS) (Voldoire & Aurore, 2019). The CNRM model is a part of the sixth phase of the CMIP, featuring enhanced spatial resolution compared to its predecessors, enabling more detailed simulations of atmospheric, oceanic, and terrestrial processes. Table 2-6 presents the GCM model properties of CERFACS.CNRM-CM6-1-HR GCM.

Table 2-6: GCM Model Properties

Data type	Precipitation
Country of Origin	France
Climate change scenarios	SSP1-2.6, SSP5-8.5
Project	CMIP6
Spatial resolution	50 km
Temporal Resolution	Daily

2.6 Bias Correction of GCM

Bias correction is required to rectify systematic differences between GCM or RCM estimates and actual observations (Hakala et al., 2019). Due to the coarser spatial resolution and inherent limitations in representing specific atmospheric processes, GCMs often exhibit systematic biases compared to observed data. Further, unresolved sub-grid scale orography and related convective parameterisation, unrealistic large-scale response to climate change and invariant biases over time are the various sources within GCMs causing systematic biases (Cannon et al., 2015; Hakala et al., 2019). Recognising and rectifying these systematic errors is crucial for obtaining reliable climate projections that accurately reflect real-world conditions.

One of the significant advantages of bias correction is its positive impact on hydrological simulations. Therefore, rectifying the biases, manifest as deviations in mean climate variables or improper simulation of extreme events, will help obtain accurate hydrological projections for extreme climate events (Pastén-Zapata et al., 2020). This enhances the accuracy of streamflow predictions, which are critical for water allocation, flood forecasting, and reservoir operation modelling (Brekke et al., 2009; Eccles et al., 2019).

Multiple methods are available in the literature for bias correction, each addressing different aspects of GCM biases. Linear scaling, local intensity, power transformation, variance, and quantile mapping methods are frequently used for bias correction in recent literature (Teutschbein & Seibert, 2012). Quantile mapping, a widely used technique, involves adjusting GCM quantiles to match observed quantiles by preserving the distributional characteristics of observed data. Recent research studies have utilised different correction approaches under the quantile mapping framework, including gamma mapping and delta change method (Teutschbein & Seibert, 2012).

2.6.1 Gamma Mapping Method

Gamma mapping introduces scale and shape parameters, allowing multiplicative and additive adjustments to the climate model outputs. This approach offers greater flexibility in correcting biases by allowing shifts in the distribution's location (mean) and scale (variability). The quantile mapping method based on gamma mapping has been proven effective for bias correction of precipitation estimates in previous studies (Block et al., 2009; Ines & Hansen, 2006). Therefore, bias correction of rainfall estimates was conducted using the Gamma mapping-based Quantile Mapping method in this study. Figure 2-6 presents a graphical representation of the quantile mapping bias correction approach.

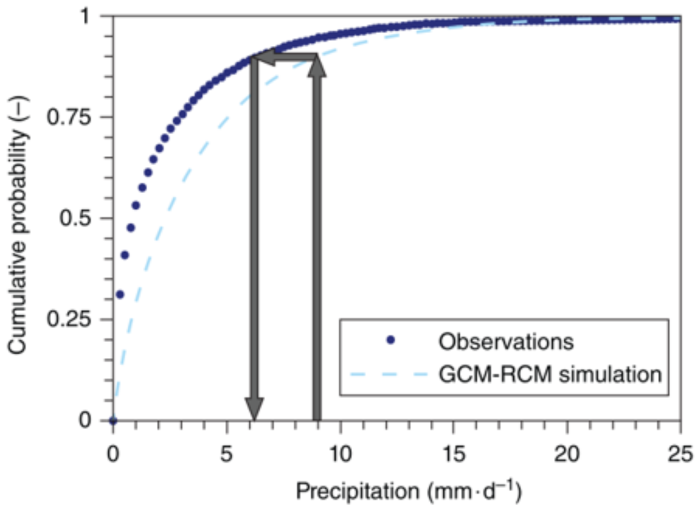

Figure 2-6: Graphical Representation of Gamma Mapping-based Bias Correction (Hakala et al., 2019)

Eq. (2-15) and Eq. (2-16) present inverse probability distribution functions for bias correction using the gamma mapping method. During bias correction, the probability distribution curve of GCM estimates is projected to the probability distribution curve of observed data of the corresponding quartile.

$$P^*_{contr}(d) = F_\gamma^{-1}(F_\gamma(P_{contr}(d)|\alpha_{contr,m}, \beta_{contr,m})|\alpha_{obs,m}, \beta_{obs,m}) \qquad (2\text{-}15)$$

$$P^*_{scen}(d) = F_\gamma^{-1}(F_\gamma(P_{scen}(d)|\alpha_{contr,m}, \beta_{contr,m})|\alpha_{obs,m}, \beta_{obs,m}) \qquad (2\text{-}16)$$

Abbreviations used in Eq. (2-15) and Eq. (2-16) are P^*_{contr}, P^*_{scen}, μ_m, α, β, and obs represent bias-corrected historical precipitation estimate, bias-corrected future precipitation estimate, mean monthly location parameter for Gaussian distribution, shape factor for skewness, scale factor for spread and observed value, respectively.

2.6.2 Delta Change Method

The delta change method involves calculating the differences (delta changes) between future climate model projections and observed historical data for specific quantiles. These estimated changes are then applied as multiplicative scaling factors to adjust the future projections (Cannon et al., 2015). Eq. (2-17) and Eq. (2-18) present mathematical formulation of delta change-based quantile mapping bias correction.

$$P^*_{contr}(d) = P_{obs}(d) \qquad (2\text{-}17)$$

$$P^*_{scen}(d) = P_{obs}(d)\left[\frac{\mu_m(P_{scen}(d))}{\mu_m(P_{contr}(d))}\right] \qquad (2\text{-}18)$$

According to the records from the Irrigation Department of Sri Lanka, daily seepage volumes are assumed to be 0.05% of reservoir storage. In this study, upstream river inflow to the reservoir is estimated using a hydrological model, which can be used to calculate the surface and subsurface runoff contributing to the river runoff.

2.7 Reservoir Operations

Climate change directly impacts water resource availability, quality, and distribution. The changing precipitation patterns and increasing evaporation rates create significant challenges to conventional water management strategies. The shortages in water issues have the potential to escalate, leading to substantial impacts on several sectors, such as agriculture, industry, and domestic consumption (Vano et al., 2010).

The reservoir hydrology and related reservoir operations are vulnerable to climate change, depicting changes in reservoir water level, seasonal water availability, and energy production may be impacted by altered inflows, evaporation rates, and shifting runoff patterns (Guo et al., 2019). Managing reservoirs effectively to respond to changing climate conditions has become essential.

Accurate prediction of reservoir hydrology and operations is essential for the efficient and sustainable management of water resources. Data-driven models and climate simulations based on scenarios are crucial in forecasting future inflows, reservoir levels, and energy generation. These predictions offer valuable insights for making proactive decisions and minimising potential dangers.

In recent years, researchers have addressed the challenges in integrating reservoir operation for irrigation, particularly in the context of hydrological uncertainty. Various comprehensive models have been formulated to optimise irrigation decisions over different timescales, including short, intermediate, and long-term. These models were considered to manage supply and demand in an uncertain or stochastic environment. According to the literature, a prominent concern of recent research studies was identifying steady-state strategies or reservoir operation rules for multipurpose reservoirs and optimisation of the agricultural yield of irrigation reservoirs (Mujumdar & Ramesh, 1997).

The researchers have used different modelling approaches for reservoir operation modelling, including the reservoir optimisation models and simulation models (Uysal et al., 2016). Among them, HEC-ResSIM has been identified as the most effective simulation model capable of simulating operations of a network of reservoirs (Chandel et al., 2023). A notable characteristic of this method is its incorporation of an extensive number of variables into simulations, significantly enhancing the precision compared to various alternative simulation approaches (Baraa et al., 2016).

The Hydrologic Engineering Center's Reservoir Simulation (HEC-ResSIM) software models the reservoir operations. Reservoir operation simulations can be applied for downstream flood management, optimum hydropower generation and management of surrounding water management practices, including management of water availability in nearby reservoirs and tanks (Klipsch and Hurst, 2021). A real-time reservoir operation model can be developed using HEC-ResSIM to provide optimal reservoir releases to compensate for irrigation demand while maintaining water levels for the survival of flora and fauna (Mujumdar & Ramesh, 1997). The HEC-ResSIM model is highly efficient in representing the actual reservoir functions, allowing the definition operations of outflow control structures based on physical dimensions and release operations based on demand management (Jebbo & Awchi, 2019).

Multiple guidelines and several simulation and optimisation models have been proposed for optimal operations, including zonal rules and standard operating policies as the most straightforward approaches. Reservoir rules are crucial for optimising reservoir performance, balancing numerous objectives, and increasing resistance to climatic unpredictability and dry conditions (Dash et al., 2022). Incorporating these requirements in modelling improves scenario analysis, allowing for the assessment of different management decisions and evaluating their impact on reservoir operations within the context of long-term water resource planning (Srinivasan & Kumar, 2018).

Reservoir operation for irrigation is crucial in effective water resource management in a river basin consisting of irrigation reservoirs (Song et al., 2016). A reservoir water balance study should be conducted to evaluate the performance of the reservoir and identify the irrigation period, interruption period, and flood control period (Song et al., 2016). Reservoir operations differ according to the type of cultivation, crop water requirement, regional weather conditions, characteristics of the irrigation network and the operators' experience (Song et al., 2016).

Critical components of reservoir water balance are upstream inflow, irrigation water supply, and reservoir rule, which are linked to spillway flow and irrigation supply. Reservoir storage governs the reservoir water balance indicated by Eq. (2-19) as,

$$S_i = S_{i-1} + Q_i + R_i - IWS_i - E_i - PS_i - SS_i \tag{2-19}$$

where S_i represents the reservoir storage of day i, S_{i-1} is the reservoir storage of day $i\text{-}1$, R_i is the rainfall of day i, IWS_i is irrigation water supply, E_i is reservoir surface evaporation, SR_i is reservoir release from spillway and SS_i is reservoir seepage of day i.

CHAPTER 3

METHODOLOGY

The methodology of this study is structured to evaluate the WUE of the Nachchaduwa Irrigation Scheme in the Malwathu Oya basin, Sri Lanka, under varying climate scenarios. The research was initiated with a comprehensive literature review to establish a methodology to address the research problem. The methodology comprises two primary components: estimating the crop water requirement of the irrigation scheme and estimating the irrigation supply from the reservoir.

The feasible evapotranspiration estimation method was selected from the literature considering the availability of data to estimate the crop water requirement. Due to the limited data availability within the study area, the Hargreaves method was used for ET_o estimation. Crop water requirement estimations were obtained by coupling the Hargreaves method with guidelines from the Irrigation Department of Sri Lanka for effective rainfall and percolation estimation. ET_o estimates were compared with remotely sensed ET_o estimates to ensure accuracy.

Irrigation supply estimation involved hydrological modelling to obtain the river inflow and reservoir operation modelling to obtain irrigation releases. The hydrological modelling component will involve developing a hydrological model using the HEC-HMS to capture the hydrological processes of the Malwathu Oya basin validated through actual river discharge observations of Malwathu Oya. This step is critical for assessing the water availability for irrigation under different climate scenarios since inflow time series contribute to the reservoir operation model, which simulates actual irrigation supply to downstream schemes.

Bias-corrected GCM estimates were utilised to generate irrigation supply and demand projections under changing climate scenarios. Considering the feasibility, accuracy, and adaptability of the GCM model to the South Asian region, the GCM model was selected from the literature for updated climate scenarios defined by the IPCC. Bias correction of GCM estimates was conducted to ensure monsoonal climate variability. Results were obtained in daily time steps, and an analysis was conducted for cultivation seasons.

By integrating these models and methodologies, the study aims to provide a robust assessment of the WUE, capturing both historical and projected climate data to understand the impacts of climate change on irrigation practices. By defining WUE as the ratio of crop water usage to applied irrigation water, the study offers a nuanced evaluation of current irrigation practices. The outcomes will highlight the critical role of reservoir operations in water management and offer valuable insights for developing effective adaptation strategies to maintain agricultural productivity in dry zone regions under climate change.

3.1 Methodology Statement

Addressing the significant challenges created by climate change to agricultural water management in dry zone regions, where water resources are already scarce, is crucial. This research focuses on the Nachchaduwa Irrigation Scheme in the Malwathu Oya basin, Sri Lanka, aiming to determine the WUE under changing climate scenarios. A comprehensive literature review was conducted to develop the methodology to achieve the research objectives outlined, which involves estimating crop water requirements of the Nachchaduwa Irrigation Scheme, generating river inflow to the Nachchaduwa Reservoir, and developing a reservoir operation model to determine irrigation releases. These steps were followed for both historical and projected climate conditions to assess the impacts of climate change.

3.2 Methodology Flowchart

The methodology developed to achieve the objectives of the research study is illustrated in Figure 3-1.

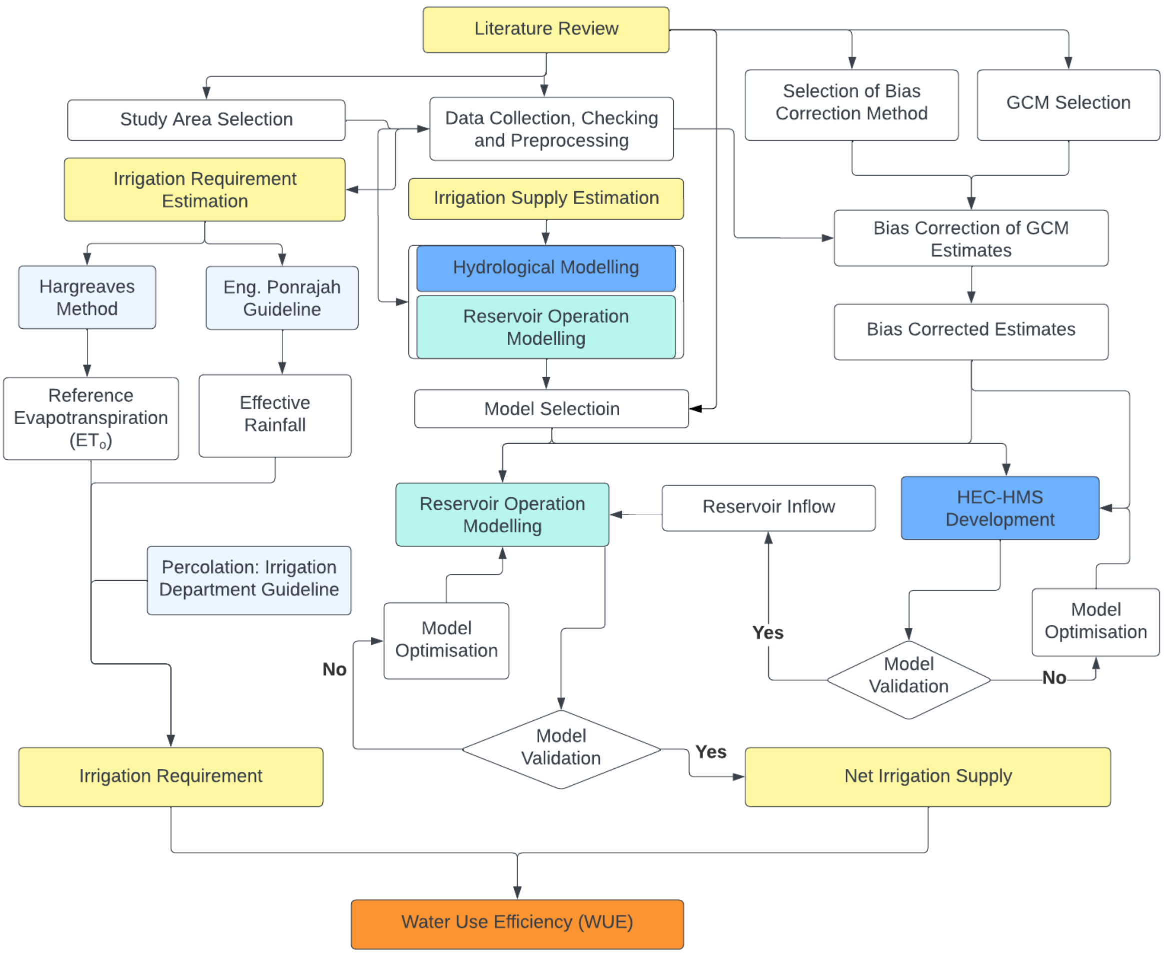

Figure 3-1: Methodology Flowchart

3.3 Study Area

Malwathu Oya basin is the second largest river basin in Sri Lanka, with an approximate catchment area of 3,187 km^2. The river originates from Ritigala hills and flows to the sea at Arippu in Mannar district. The main river is 164 km in length. Malwathu Oya basin is predominantly drained by two major tributaries, Malwathu Oya and Kanadara Oya, which flow through the North Central and North provinces of Sri Lanka. Two major tributaries confluence around Thanthirimale creating Aruvi Aru River which flows through the Northwestern Province of Sri Lanka.

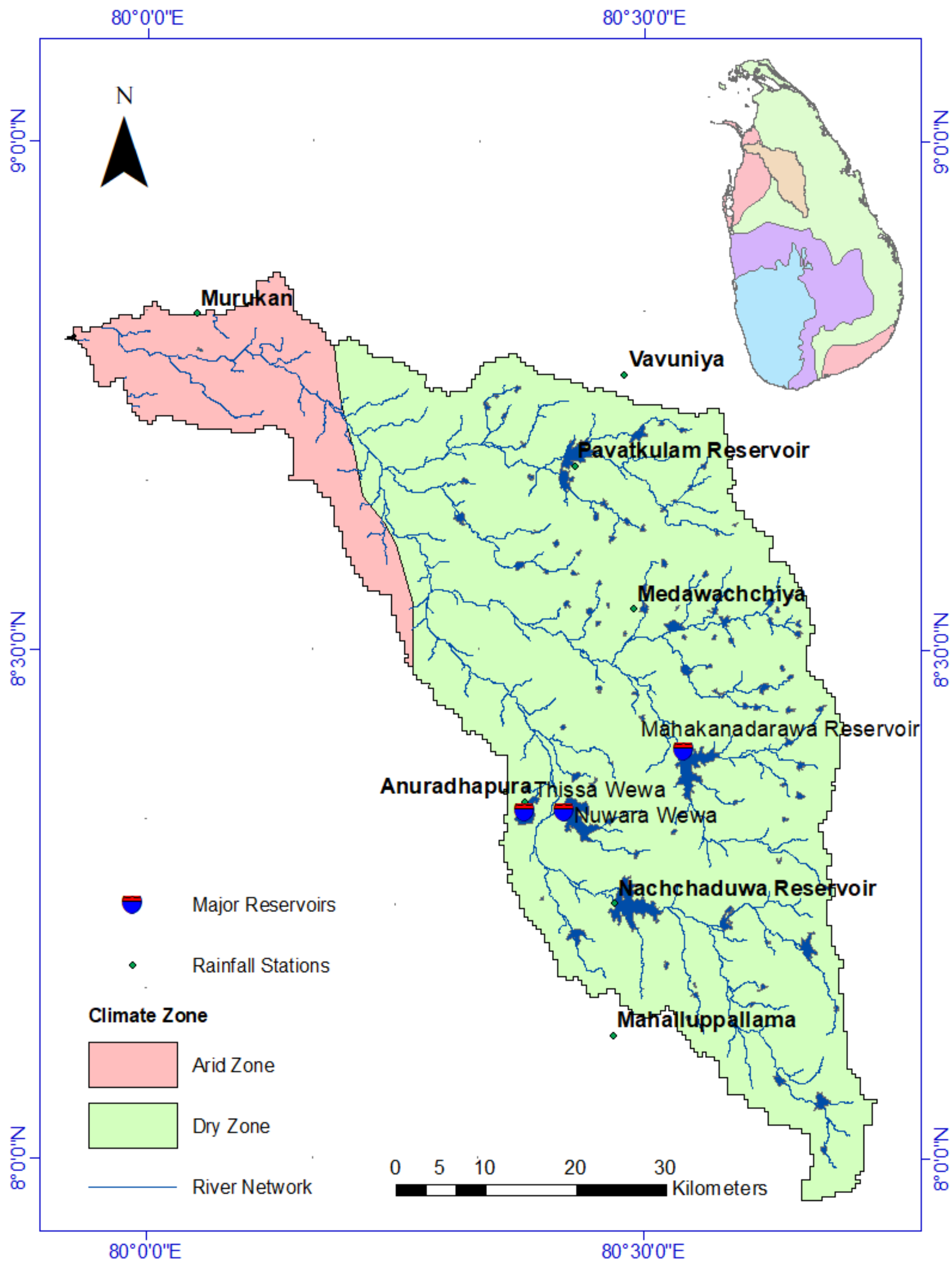

Figure 3-2: Major Reservoirs and Meteorological Stations inside the River Basin

The study area belongs to the Tropical Savannah climate category according to the Kopen-Geiger climate classification (Kottek et al., 2006), with an average annual temperature of 28.4 °C and mean annual precipitation of 1,341 mm (Saase et al., 2020). According to the local climate zone classification, Malwaathu Oya belongs to dry and arid climate zones (Figure 3-2). Malwathu Oya basin receives rainfall from Northeast, Southwest and two inter-monsoon seasons with durations of October to January, May to September, March to April and October to November, respectively. The dry climate causes high evaporation rates, especially from May to September. Dry periods and droughts are common phenomena in the study area (Saase et al., 2020).

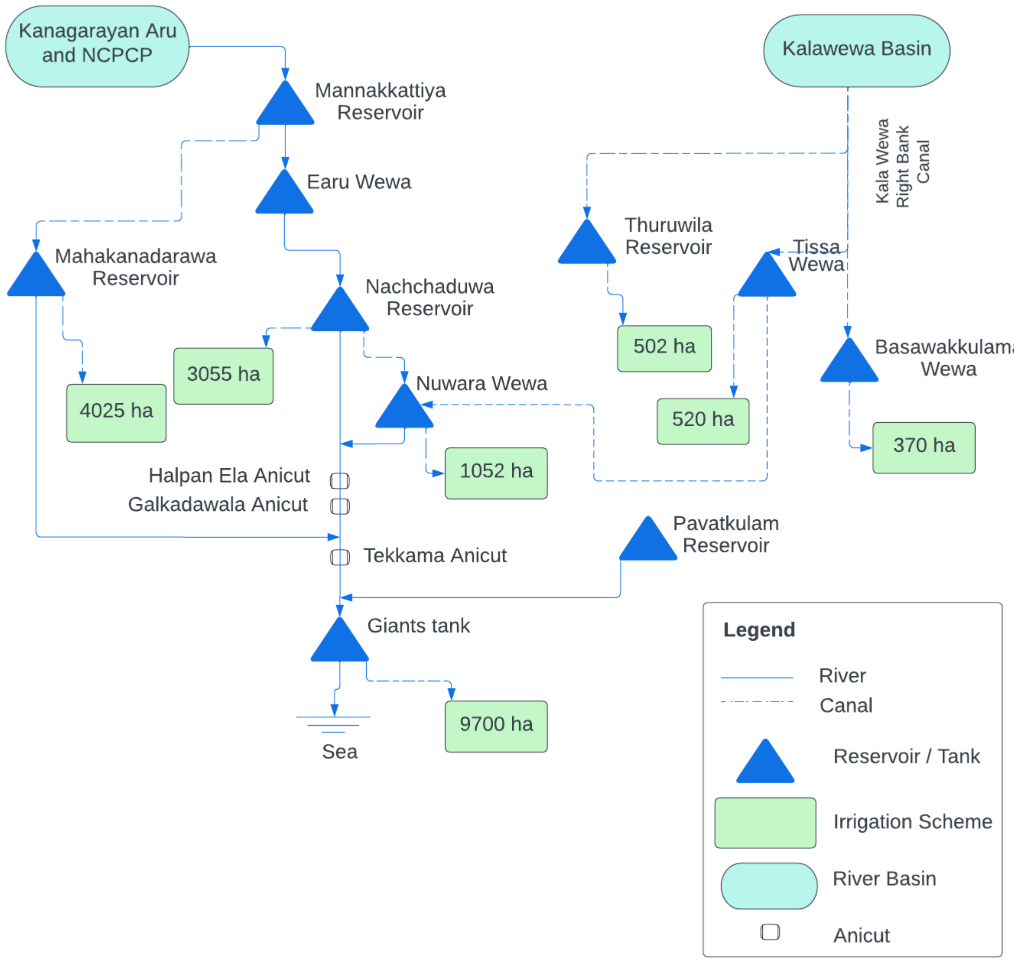

Figure 3-3: Reservoir Network of Malwathu Oya Basin

Agricultural activities in the dry zone mainly depend on a sophisticated water management system due to inadequate water yield, where the average annual rainfall is less than 1,200 mm (Subramaniam Sivakumar, 2019). The water management system consists of reservoirs connected by spillways and diversion canals, which are structured as a cascade system (Jayatilaka et al., 2003). According to the size of the reservoir and the irrigatable area, reservoirs in Sri Lanka are categorised into major, medium, minor, and micro tanks (Murray, 2000). The upstream catchment from the

Kappachi River gauging station consists of four major reservoirs, including Nachchaduwa Reservoir, Mahakanadarawa Reservoir, Nuwara Wewa, and Thissa Wewa (Figure 3-3).

The Nachchaduwa Irrigation scheme of Malwathu Oya basin was selected to conduct this study. It is situated upstream of Nachchaduwa Reservoir, which is one of the ancient tanks in Sri Lanka. It receives water augmentation from the Mahaweli system through the Kalawewa Feeder Canal and its catchments. The spillways of the Nachchaduwa tank are located on the right bank. There is no command area on the right bank, though there are two feeder canals to Nuwara Wewa, one of which is the natural stream with gate facilities, and the sluice of the other is attached to the spillway.

There are two main canals on the left bank: the High-Level Main Canal (HLMC) and the Low-Level Main Canal (LLMC). There is only one LB sluice, which is divided into two canals just downstream of the sluice (Figure 3-4). At the station 14.5 km from the HL Main Canal, the Tissa Wewa feeder canal from Kalawewa RB Canal joins, and the HL Main Canal functions as the feeder canal. The maximum command area of the Nachchaduwa scheme is 29.04 km^2. Since the canals are single-band canals, the HL Main Canal alignment follows the contour line of the landscape, which has necessitated many curves.

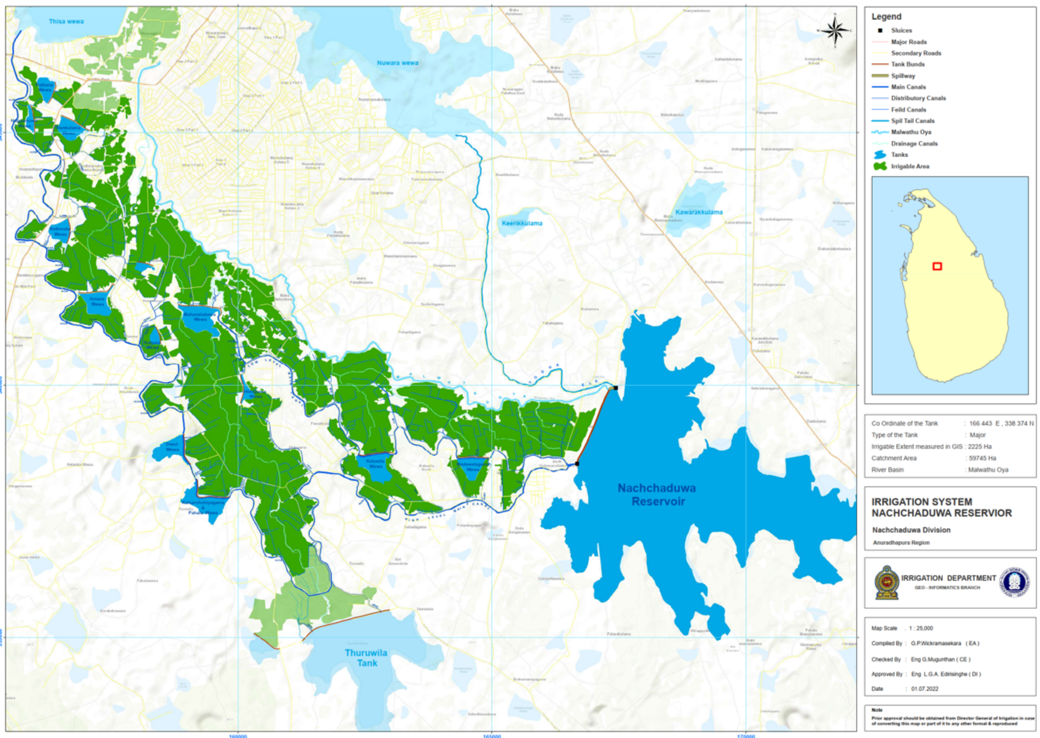

Figure 3-4: Nachchaduwa Irrigation Scheme

Source: Irrigation Department of Sri Lanka

According to the Mahaweli Development Authority reports, paddy is cultivated for 100% and 50% from the Nachchaduwa irrigation scheme during the Maha and Yala cultivation seasons, respectively.

3.4 Irrigation Water Requirement Estimation

Crop water requirement for a given crop for the whole growing season is governed by Eq. (2-2). This study used the CROPWAT model to determine the irrigation water requirement developed by the Land and Water Development Division of FAO (FAO, 1992). Estimation of reference evapotranspiration, crop water requirement and irrigation scheduling are the significant functions of the CROPWAT model. It can be further utilised to estimate irrigation efficiencies under varying water supply conditions (Heng et al., 2002). Reference evapotranspiration (ET_o) was estimated using the Hargreaves method, considering the lesser data requirement and the feasibility of conducting the study for future scenarios. Eq. (2-4) provides the Hargreaves equation for ET_o estimation.

In order to obtain actual evapotranspiration rates (ET_a), reference evapotranspiration estimates should be projected to actual crop conditions, incorporating K_c. Eq. (2-2) governs crop water requirements for paddy for the growing season. In addition to the crop water requirement, which mainly depends upon temperature variations, rainfall and soil moisture depletion should be considered while determining the irrigation requirement. Eq. (2-6) presents a formula for estimating net irrigation water requirements.

Ponrajah (1984) defined empirical equations to estimate effective rainfall to be used in the local context. Eq. (2-7) and Eq. (2-8) constitute independent equations to estimate effective rainfall for lowlands and highlands.

3.4.1 Data Collection

Data requirements for the estimation of net irrigation requirement constitute climate data of the study area, soil data of irrigation scheme, crop data corresponding to paddy and data governing the submergence depth of paddy at different growth stages presented by Table 3-1 and Table 3-2. Crop data of paddy required for crop water requirement estimation are extracted from the recent studies conducted for the study area or similar geographical and climate conditions and presented in Table 3-3.

Table 3-3 and Table 3-4, respectively.

Rainfall data and temperature data were collected from the Meteorological Department of Sri Lanka. Due to the unavailability of consistent observed data sets for relative humidity, wind speed at 2 m from the surface and sunshine duration, satellite estimates provided by the NASA power project were considered for this study.

Table 3-1: Climate Data for the CROPWAT Model

Data Type	**Longitude (Dec. Deg)**	**Latitude (Dec. Deg)**	**Source**	**Resolution (Dec. Deg)**
Minimum, Maximum, Average Temperature	80.38°	8.35°	Meteorological Department	-
Relative humidity			NASA POWER Projects Data Access Viewer v2.0.0	$0.50^{\circ} \times 0.83^{\circ}$
Wind Speed at 2 m				$0.50^{\circ} \times 0.83^{\circ}$
Sunshine duration				$1.00^{\circ} \times 1.00^{\circ}$
Rainfall			Meteorological Department	-

Soil data were extracted from recent research publications conducted for the study area. Table 3-2 presents soil parameters with the corresponding references required for irrigation water requirement estimation.

Table 3-2: Soil Data for CROPWAT Model

Parameter	**Value**	**Reference**
Available water capacity (mm H_20/m Soil)	120	(Fors, 2022)
Infiltration rate (mm/day)	30	(Fors, 2022)
Drainable porosity (%)	15	(Narmilan & Sugirtharan, 2020)
Maximum water depth (mm)	100	
Maximum Percolation after Puddling (mm/day)	6	
Water availability at planting (mm)	25	

Crop data of paddy required for crop water requirement estimation are extracted from the recent studies conducted for the study area or similar geographical and climate conditions and presented in Table 3-3.

Table 3-3: Crop Data for CROPWAT Model

Parameter	Value	Reference
Rooting depth (m)	0.1-0.9	(Fors, 2022)
Puddling depth (m)	0.3	(Narmilan & Sugirtharan, 2020)
Critical depletion	0.2	
Crop Height (m)	0.6	
Maximum Percolation after Puddling	3.1	

Submergence depths corresponding to different growth stages of paddy are presented in Table 3-4.

Table 3-4: Submergence Depth of Paddy Fields According to the Crop Growth Stage

Stage of crop growth	Depth of submergence (cm)
Before puddling	5-10
During Puddling	2-3
Sowing to the tillering stage	2-3
Tillering to flowering	2-3
Twenty days after flowering	Withhold irrigation

3.4.2 CROPWAT Model Development

Initially, climate data, including minimum, maximum and average temperature and rainfall data, were collected, and accuracy checking was conducted. This data is used to estimate the ET_0 using the Hargreaves method, which calculates ET_0 based on temperature and extraterrestrial radiation. Simultaneously, specific crop data, such as crop type, growth stages, root depth, and crop coefficients, were collected. Figure 3-5 presents the model development procedure of the CROPWAT model.

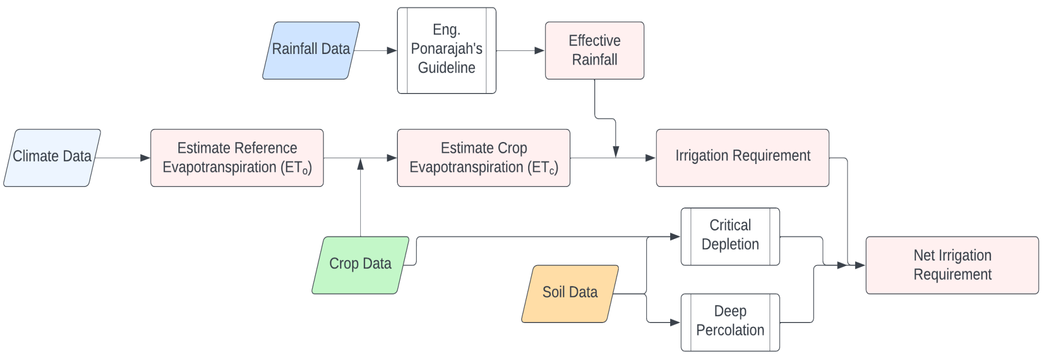

Figure 3-5: CROPWAT Model Development Flowchart

Combining ET_0 and the crop data, the actual crop evapotranspiration (ET_c) was estimated, reflecting the specific water needs of the crop at different growth stages. Ponrajah (1984) determined the effective rainfall, which is the portion of total rainfall available for crop use after accounting for runoff and evaporation. The effective rainfall data is then combined with the estimated ET_c to calculate the irrigation requirement, indicating the amount of water needed from irrigation to meet the crop's water demands after accounting for effective rainfall. Soil data, including soil type, water holding capacity, and infiltration rate, were integrated into the model to refine the irrigation requirement. This involves considering critical depletion, the allowable soil moisture depletion level before irrigation must be applied to avoid crop stress, and estimating deep percolation losses, the water that percolates below the root zone and becomes unavailable to the crop. Table 3-5 presents model parameters representing the irrigation scheme characteristics.

Table 3-5: CROPWAT Model Parameterization

Parameter	Value	Reference
Rooting depth (m)	0.1-0.9	(Fors, 2022)
Puddling Depth (m)	0.3	(Narmilan &
Available water capacity (m)	0.1	(Fors, 2022)
Critical depletion (m)	0.2	(Narmilan & Sugirtharan, 2020)
Crop Height (m)	0.6	
Infiltration rate (mm/day)	30	(Fors, 2022)
Drainable porosity (%)	35	(Narmilan & Sugirtharan, 2020)
Maximum water depth (mm)	250	
Maximum percolation after	3.1	
Water availability at planting (mm)	120	

3.5 Irrigation Supply Estimation

The difference between scheduled and actual irrigation supply can result in various issues that have substantial implications for managing water resources in the agricultural sector. The errors in irrigation scheduling could lead to mistiming, insufficiency, or excessiveness of irrigation supply. Scheduling errors may be further intensified by the unpredictable fluctuations in weather conditions, wherein unforeseen precipitation or protracted aridness may hinder.

Figure 3-6 represents the daily irrigation supply to Nachchaduwa Irrigation Scheme from Nachchaduwa Reservoir, and daily evapotranspiration estimates indicate the requirement. Due to the aforementioned reasons, the actual irrigation supply has diverged from the irrigation scheme's estimated irrigation requirement. Hence, this study uses a data-driven model to estimate the irrigation supply.

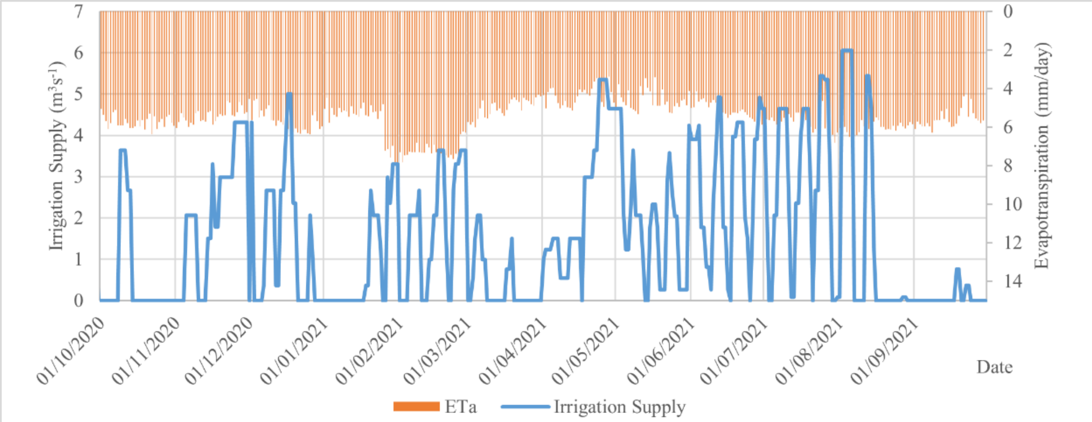

Figure 3-6: Irrigation Release Time Series (2020/2021)

Irrigation supply to the Nachchaduwa irrigation scheme is controlled through Nachchaduwa Reservoir operations considering the irrigation requirement. In order to obtain irrigation supply through reservoir releases, reservoir operations of Nachchaduwa Reservoir should be accurately simulated. The inflows and outflows of the reservoirs mainly govern reservoir operations. A hydrological study was carried out in the study area to estimate the reservoir inflow from the upper catchment to Nachchaduwa Reservoir.

Referring to the literature review conducted, data requirements to conduct a hydrological study include rainfall, streamflow, temperature (minimum, maximum and average), crop water requirement, and reservoir data. The temporal resolution of daily scale data was appropriate for the study, considering the availability of observed data and future estimates from GCMs. World Meteorological Organization (WMO) guidelines were followed to decide the number of data-gathering points within the basin (WMO, 2008).

3.5.1 Data Collection

Daily rainfall and temperature were collected from the Meteorological Department of Sri Lanka and the Irrigation Department of Sri Lanka for the mentioned meteorological stations (Table 3-6) considering the spatial distribution within the river basin. River discharge observations at Kappchchi station were collected from the Irrigation Department of Sri Lanka to calibrate and validate hydrological simulations.

Table 3-6: Data Collection

Data Type	Station	Longitude (Dec. Deg.)	Latitude (Dec. Deg.)	Duration
Rainfall	Pavatkulam	80.43°	8.68°	1990-2021
Rainfall, Temperature	Anuradhapura	80.38°	8.35°	1990-2021
Rainfall	Nachchaduwa	80.47°	8.25°	1990-2021
Rainfall, Temperature	Mahailuppallama	80.47°	8.12°	1990-2021
River discharge	Kappachi	80.27°	8.59°	2005-2021

Reservoir data, including pool properties (area-storage-stage curves, evaporation, seepage), sluice details (sill level, gate size and length of channel) and spill details (type of spill, length, sill level, gate size and number of gates) were used as input data for reservoir operation modelling in HEC-HMS. Irrigation requirements of the primary irrigation schemes were estimated using the CROPWAT model following the procedure explained in the Chapter 3.4.

3.5.2 Data Checking and Preprocessing

Initially, missing data percentages of selected rainfall stations were identified and presented in Table 3-7. Continuity and consistency were checked for rainfall data using the single and double mass curves. Figure 3-7 presents single mass curves of daily rainfall time series of selected rainfall stations within the Malwathu Oya basin.

Table 3-7: Details of Missing Data

Data Type	Station	Missing Data Percentage
Rainfall	Pavatkulam	5%
Rainfall	Mahailuppallama	2%
Rainfall	Anuradhapura	2 %
Rainfall	Nachchaduwa	4 %
Temperature	Anuradhapura	1%
Temperature	Mahailuppallama	1%

Through the plotted single mass curves, correlated (similarly varying time series) rainfall stations were identified to fill the missing data (Figure 3-8 and Figure 3-9).

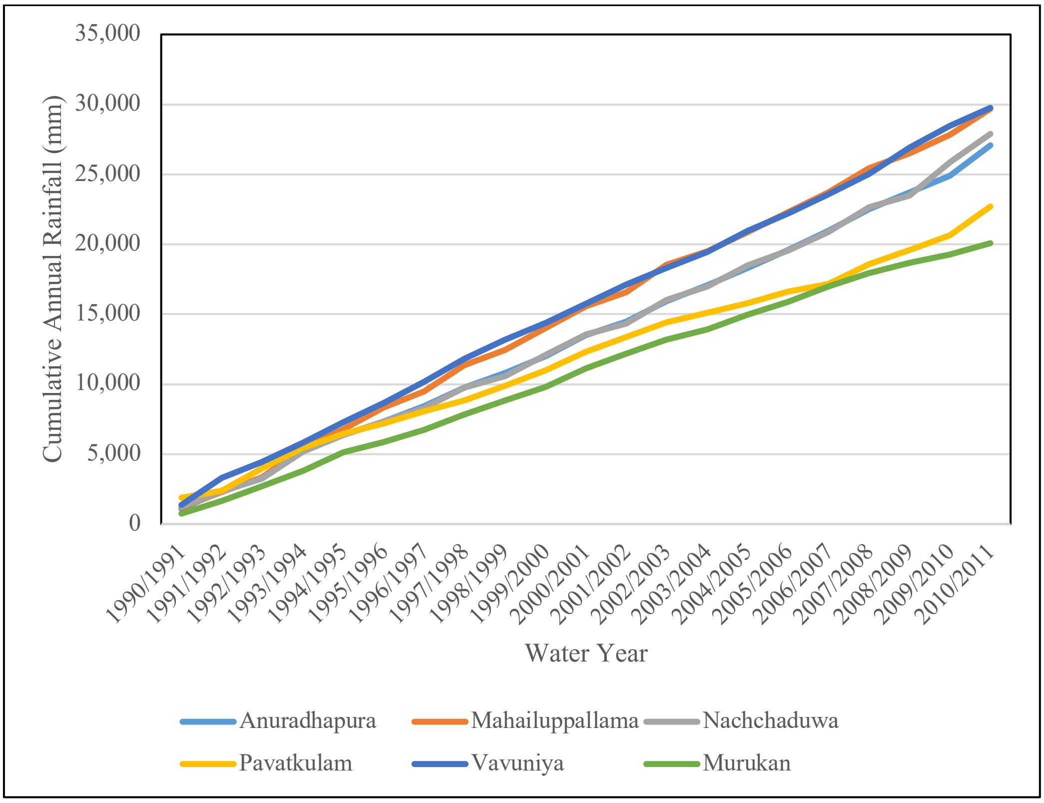

Figure 3-7: Single Mass Curves – Rainfall Data

The continuity and long-term trend of rainfall data were checked using the double mass curve method (Mu et al., 2010). The mass curve method was used to fill the gaps in the rainfall time series because the missing data percentages are below 10% (Figures 3-10 & 3-11).

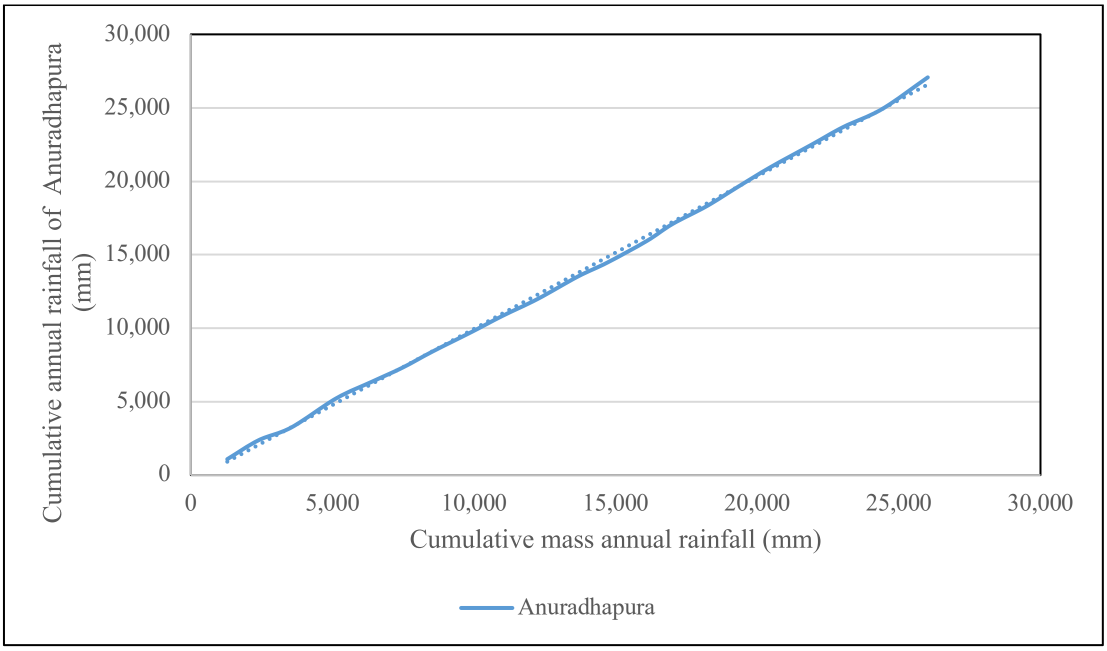

Figure 3-8: Double Mass Curve – Anuradhapura Station Rainfall Data

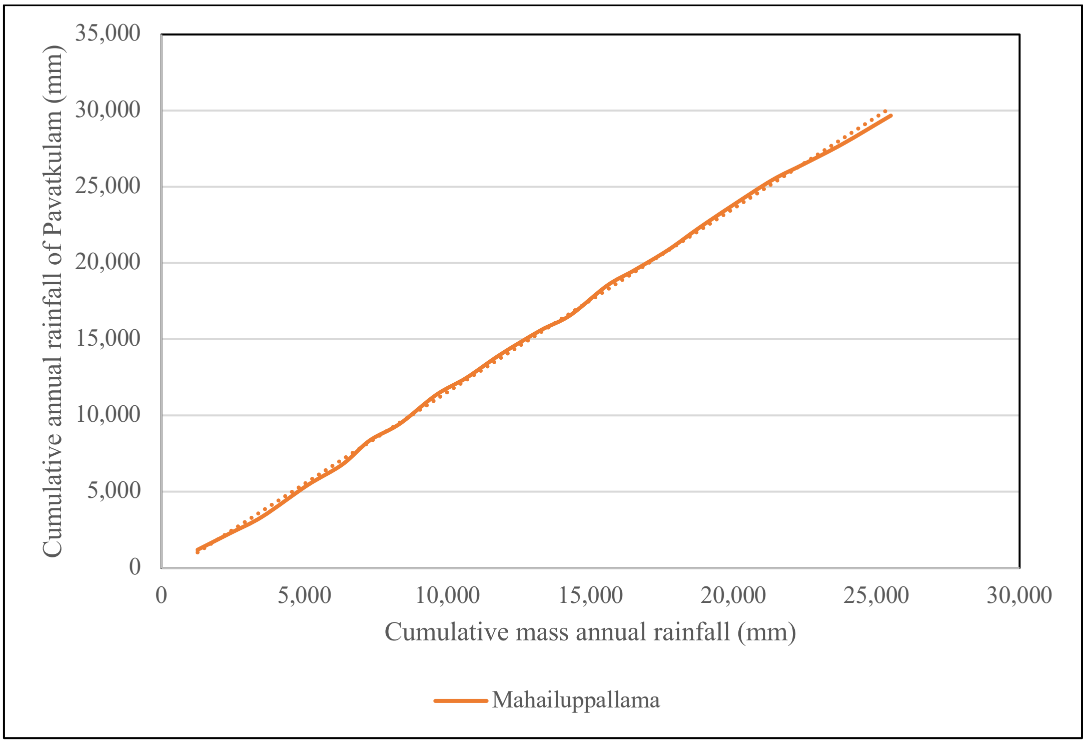

Figure 3-9: Double Mass Curve – Mahailuppallama Station Rainfall Data

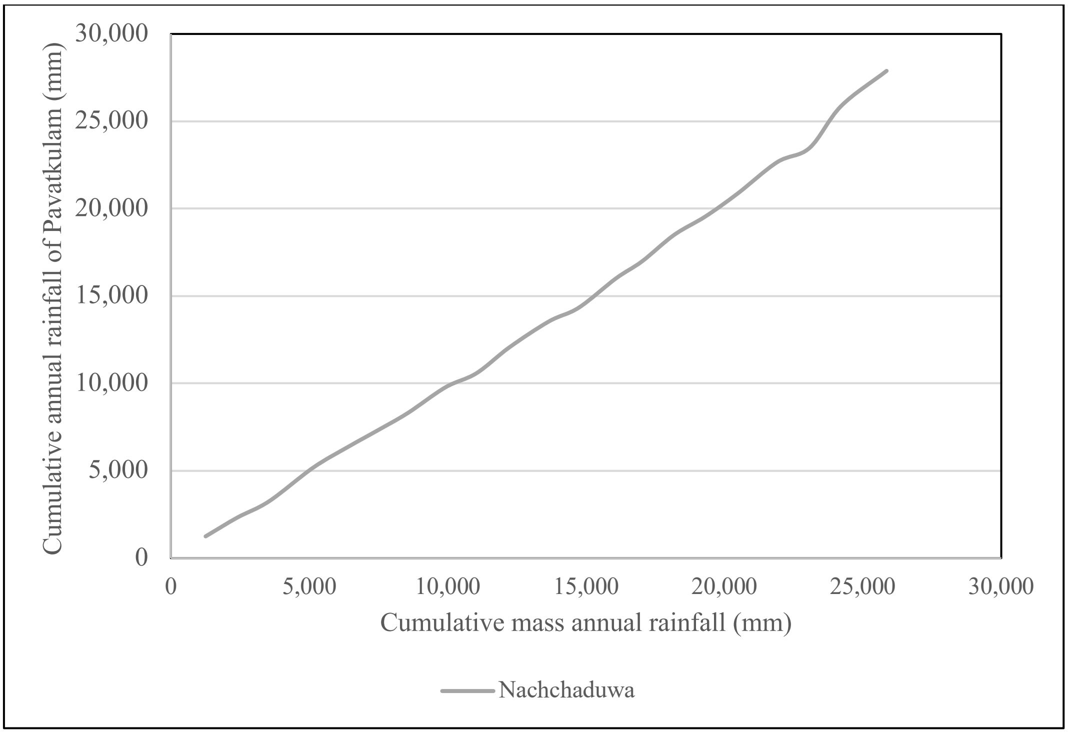

Figure 3-10: Double Mass Curve – Nachchaduwa Station Rainfall Data

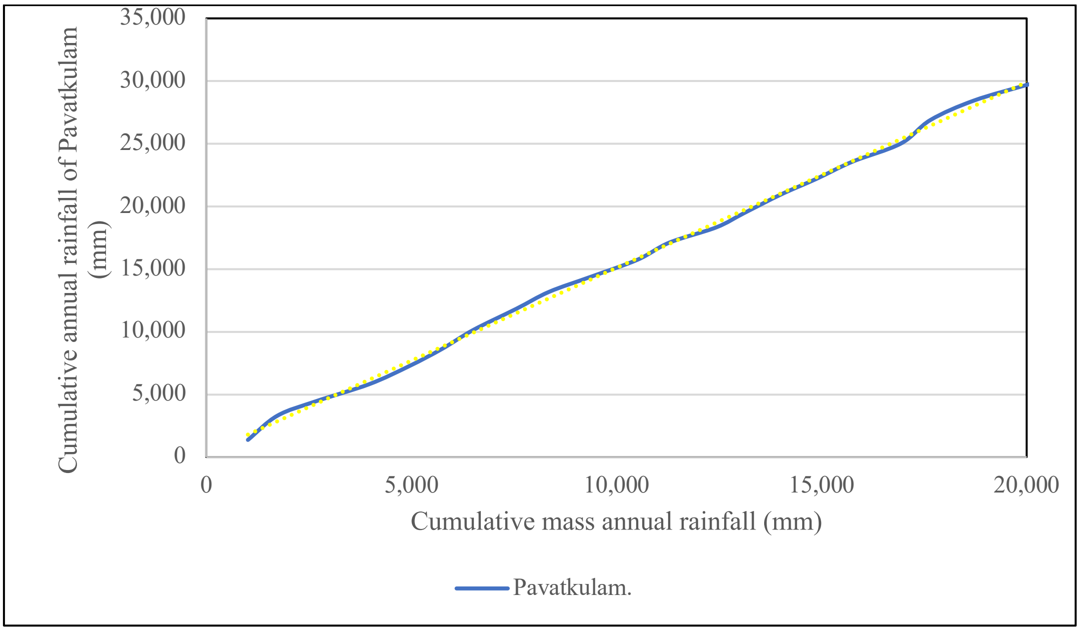

Figure 3-11: Double Mass Curve – Pavatkulam Station Rainfall Data

Sub-basin scale rainfall estimates were required to model the sub-basin scale streamflow response to rainfall. Spatial mean rainfalls of each sub-basin were estimated using the Thiessen polygon method, which is widely used in spatial interpolation. The Thiessen polygon map of the upper catchment from Kappachi station was developed using ArcMap 10.8 (ESRI, USA).

A visual data-checking method was used to check the accuracy of streamflow observations at the Kappachi River gauging station. The compatibility of streamflow data with Thiessen rainfall of the entire basin was checked by tabulating the streamflow along with Thiessen rainfall, presented in Figure 3-12.

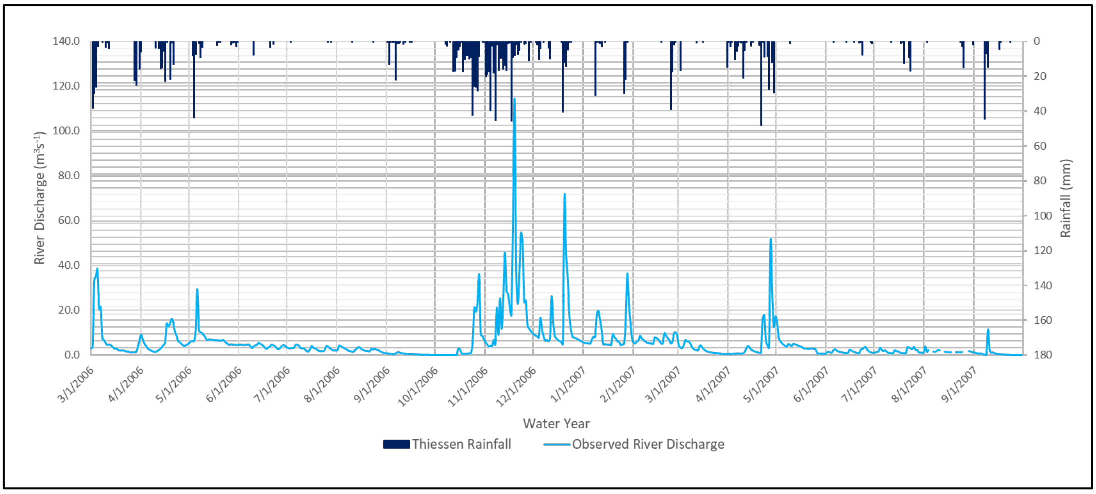

Figure 3-12: Compatibility of river discharge observations at Kappachi gauging station with Thiessen Rainfall

Reservoir operations of major reservoirs were incorporated into the hydrological modelling due to the significant impact on surface runoff of the basin. Properties of major reservoirs in the Malwathu Oya basin presented in Table 3-8 were used as input parameters of reservoir configuration for hydrological modelling.

Table 3-8: Properties of Major Reservoirs in the Malwathu Oya Basin

Property	**Nachchaduwa Resesrvoir**	**Nuwara Wewa**	**Thissa Wewa**	**Mahakanadarawa Reservoir**
Capacity (MCM)	37.1	37.1	3.3	0.0
Catchment area (km^2)	611.0	84.0	5.2	326.0
Dam Length (m)	1,650.0	6,770.0	2,650.0	2,800.0
Dam Height (m)	10.7	10.7	6.4	NA
Whole Supply level (m)	101.7	87.4	91.5	94.8
Storage @ entire supply (MCM)	55.7	44.5	4.3	46.5
Lowest supply level (m)	99.6	82.8	88.1	89.8
Storage @ low supply (MCM)	17.9	7.4	1.0	5.9
Active storage capacity (MCM)	37.8	37.1	37.0	40.6

3.5.3 HEC-HMS Model Development

The model structure of HEC-HMS contains three sections: basin model, climate model and control specifications. The Basin model development process comprised sink filling, terrain reconditioning, drainage preprocessing and stream identification of the study area, was derived using ArcMAP 10.8 software package based on the Digital Elevation Model (DEM) with 90 m spatial resolution obtained from the Shuttle Radar Topography Mission (SRTM) data portal (Farr et al., 2007).

HEC-HMS software provides a reservoir operation simulation tool utilised for this study. Reservoirs and diversion canals inside the upper Malwathu Oya basin were modelled as reservoir and diversion elements, respectively. A considerable component of basin water is used for irrigation through rainwater storage reservoirs in the Malwathu Oya basin. Therefore, water releases for irrigation purposes were estimated using the CROPWAT model developed by the UN FAO (Smith M., 1992). Return flow was assumed to be 31% of the irrigation supply and diverted to the downstream river of the irrigation scheme with a day delay (Gosain et al., 2005).

Reservoir data, including pool properties (area-storage-stage curves, evaporation, seepage), sluice details (sill level, gate size and length of channel) and spill details (type of spill, length, sill level, gate size and number of gates) were used as input data for reservoir operation modelling in HEC-HMS.

HEC-HMS utilises different parameter sets to represent various phases of the hydrological cycle. Canopy and surface storage account for the interception of rainwater by vegetation and the earth's surface storage, respectively. Excess rainwater is transformed into surface runoff using the transform formula. Infiltrated excess rainwater governs the watershed's soil moisture balance over a long period, which is determined by the loss method. Subsurface flow simulations are performed using the baseflow method in HEC-HMS. The Soil Moisture Accounting (SMA) algorithm (loss method) and Clarke Unit Hydrograph (transform) methods were used in this study to couple with the linear reservoir (baseflow) method for a better representation of long-term hydrological processes (Fleming & Neary, 2004). Table 3-9 presents calibrated values of model parameters representing catchment characteristics and different phases of the hydrological cycle.

Table 3-9: HEC-HMS Model Parameterisation

Parameter	**Calibrated value**	**Value from Literature**	**Obtained by**
Surface max storage (mm)	10.0	12.0-50.8	Literature (Fleming & Neary, 2004)
Canopy max storage (mm)	4.0	2.0	
Max infiltration rate (mm/hr)	36.0	13.0-25.0	Literature (Fors, 2022)
Impervious (%)	10.0	40.0-50.0	Literature (Sampath et al., 2015)
Max soil storage (mm)	150.0	120.0	
Soil tension storage (mm)	120.0	60.0	

Parameter	Calibrated value	Value from Literature	Obtained by
Soil percolation rate (mm/hr)	2.5	1.3	Literature (Sampath et al., 2015)
GW1 storage (mm)	200.0	200.0	
GW1 percolation rate (mm/hr)	2.0	27.0	Literature (Mahaweli Water Security Investment Report, 2014)
GW2 percolation rate (mm/hr)	0.5	7.7	
GW1 storage coefficient (hr)	100.0	80.0	Literature (Sampath et al., 2015)
GW2 storage (mm)	15.0	200.0	
GW2 storage coefficient (hr)	30.0	20.0	
Time of concentration (hr)	35.0-165.0	32.0-165.0	SCS lag method (Mckeever et al., 1972.)
Muskingum K	4.0	10.0	Literature (Sampath et al., 2015)
Muskingam X	0.3	0.2	

River discharge data from 2017 to 2021 of the Kappachi River gauging station were used for model calibration and validation. The objective functions mentioned by Equations 2-12, 2-13 and 2-14 were used to evaluate the model performance concerning river discharge observations.

3.6 Reservoir Operation Modelling

Using reservoir operation modelling to estimate irrigation supply necessitates river inflow estimates as an essential input parameter estimated under hydrological modelling. Using reservoir operation modelling to estimate irrigation supply necessitates river inflow estimates as an essential input parameter estimated under hydrological modelling. The reservoir operation model uses mathematical algorithms accompanied by hydraulic principles to optimise water release from the reservoir while balancing competing demands for irrigation, flood control, and environmental considerations.

Considering the literature review, HEC-ResSIM software has been selected to simulate the reservoir operations of the Nachchaduwa reservoir, which can develop optimal release schedules that meet irrigation supply needs while keeping reservoir storage levels within acceptable bounds. Furthermore, sensitivity analysis and scenario testing can be used to determine the effects of various management practices and climate scenarios on irrigation supply reliability by examining historical inflow patterns, hydrological forecasts, and future water demand estimations.

HEC-ResSIM functions by incorporating the principle of reservoir water balance into its operations, whereby simulations of reservoir models are constructed by analysing inflows, outflows, and storage dynamics (Uysal et al., 2016). Critical components of reservoir water balance are demonstrated in Figure . Reservoir storage governs the reservoir water balance indicated by Eq. (2-19).

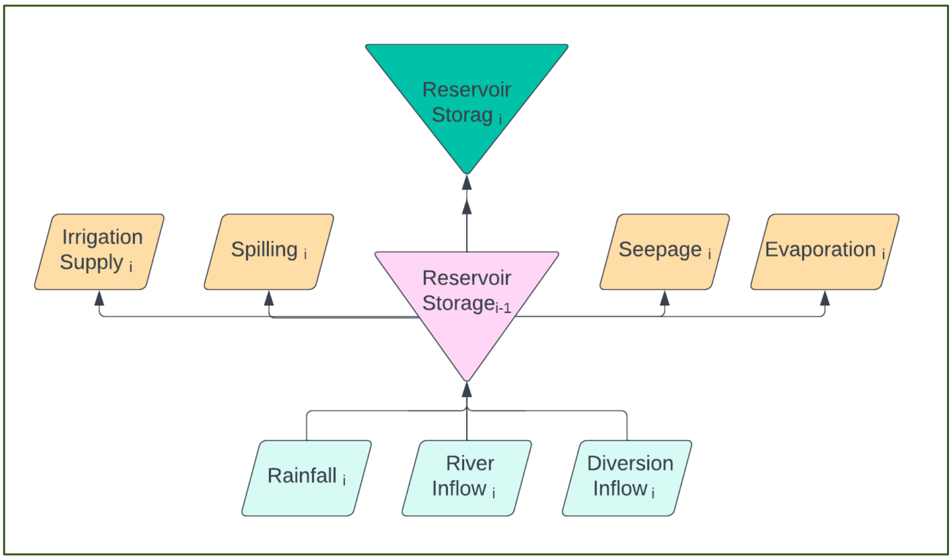

Figure 3-13: Reservoir water balance diagram

The automated water level monitoring system near the dam records daily water level observations of Nachchaduwa Reservoir (Figure 3-14).

Figure 3-14: Automated water level monitoring system at Nachchaduwa Reservoir

The accuracy of the water level observations was conducted using the visual checking method. Initially, the reservoir water level was plotted with upstream catchment rainfall to check the correspondence to rainfall and the continuity of water level data. Figure 3-15. Then, water level data was further checked through the Water level- storage-area rating curve of the Nachchaduwa Reservoir.

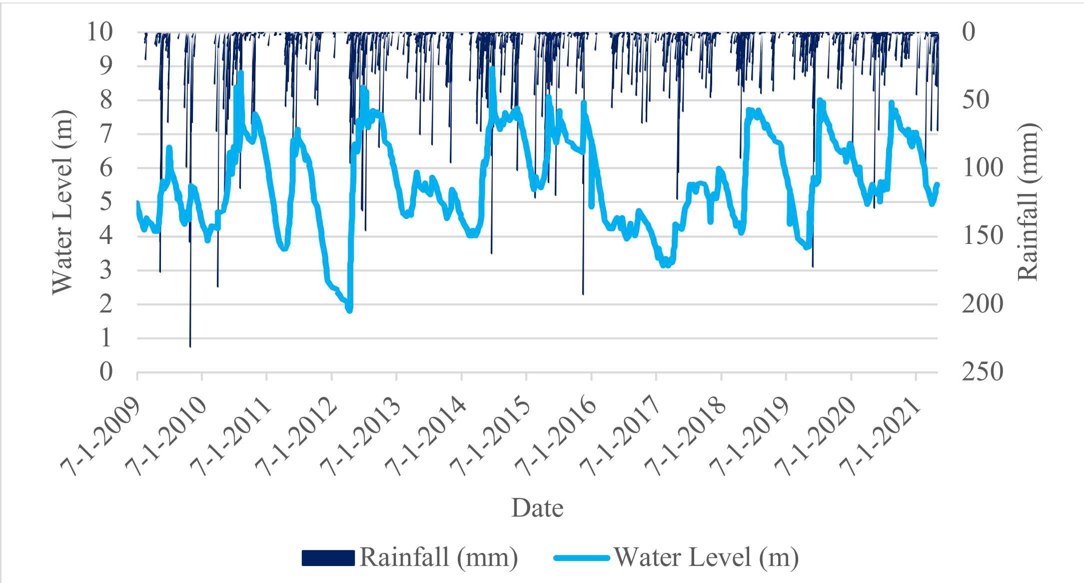

Figure 3-15: Reservoir water level vs upstream rainfall

3.6.1 Model Development

Developing a reservoir simulation model in HEC-ResSIM involves a systematic process, including watershed setup, reservoir network configuration, and simulations (Chandel et al., 2023). In this chapter, the following steps are initiated to construct a comprehensive model for water resource management of the Nachchaduwa reservoir.

Watershed delineation involves capturing the topographic features of the watershed, including the connectivity of river streams, canals, and reservoirs, to represent actual water management processes accurately. Figure 3-16 demonstrates the arrangement of the Nachchaduwa Reservoir watershed, indicating inflows and outflows.

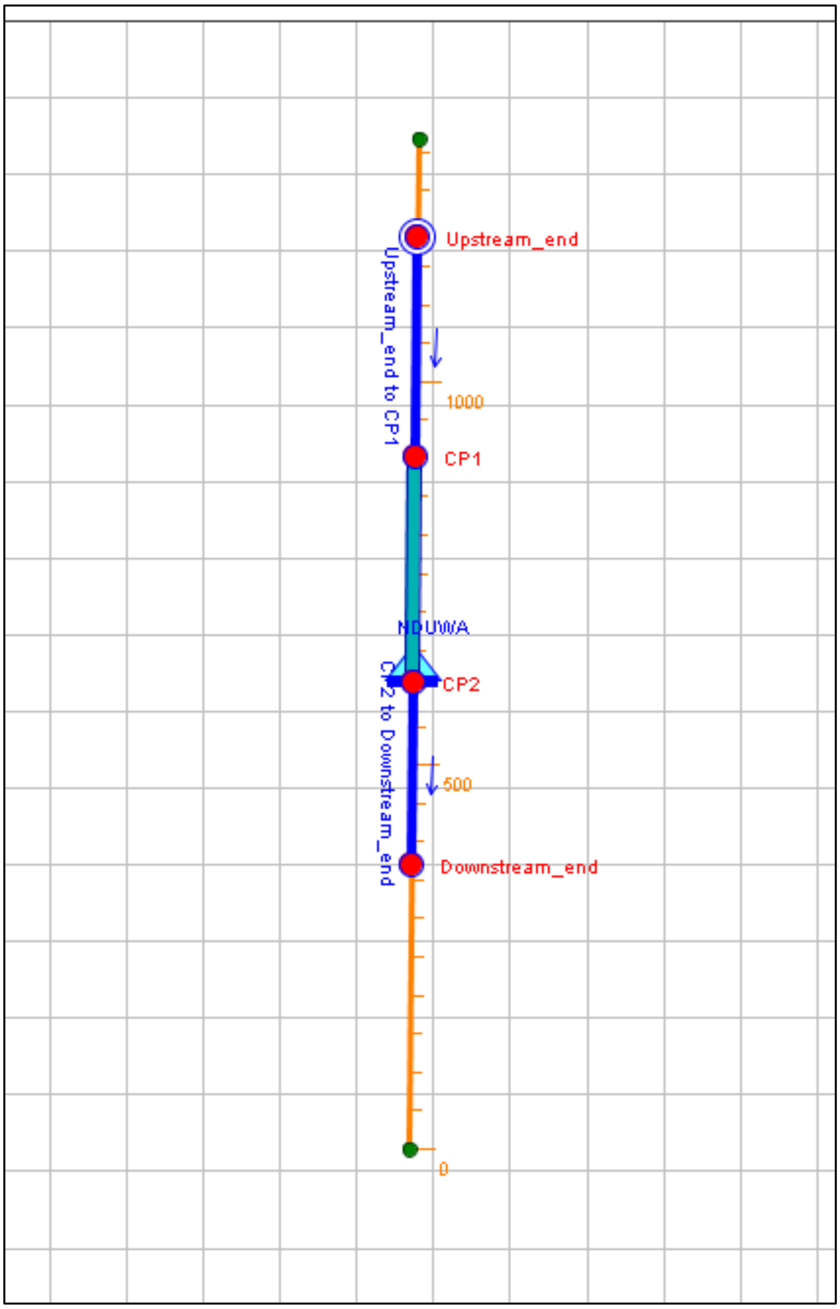

Figure 3-16: Watershed arrangement of Nachchaduwa Reservoir using HEC-ResSIM

Reservoir pool properties, outflow controlling structures, operating rules, and guide curves are defined under the reservoir network development, which features the functions of reservoirs. The reservoir elevation-storage-area function developed by the Irrigation Department of Sri Lanka is given as the premier parameter of the reservoir (Figure 3-17).

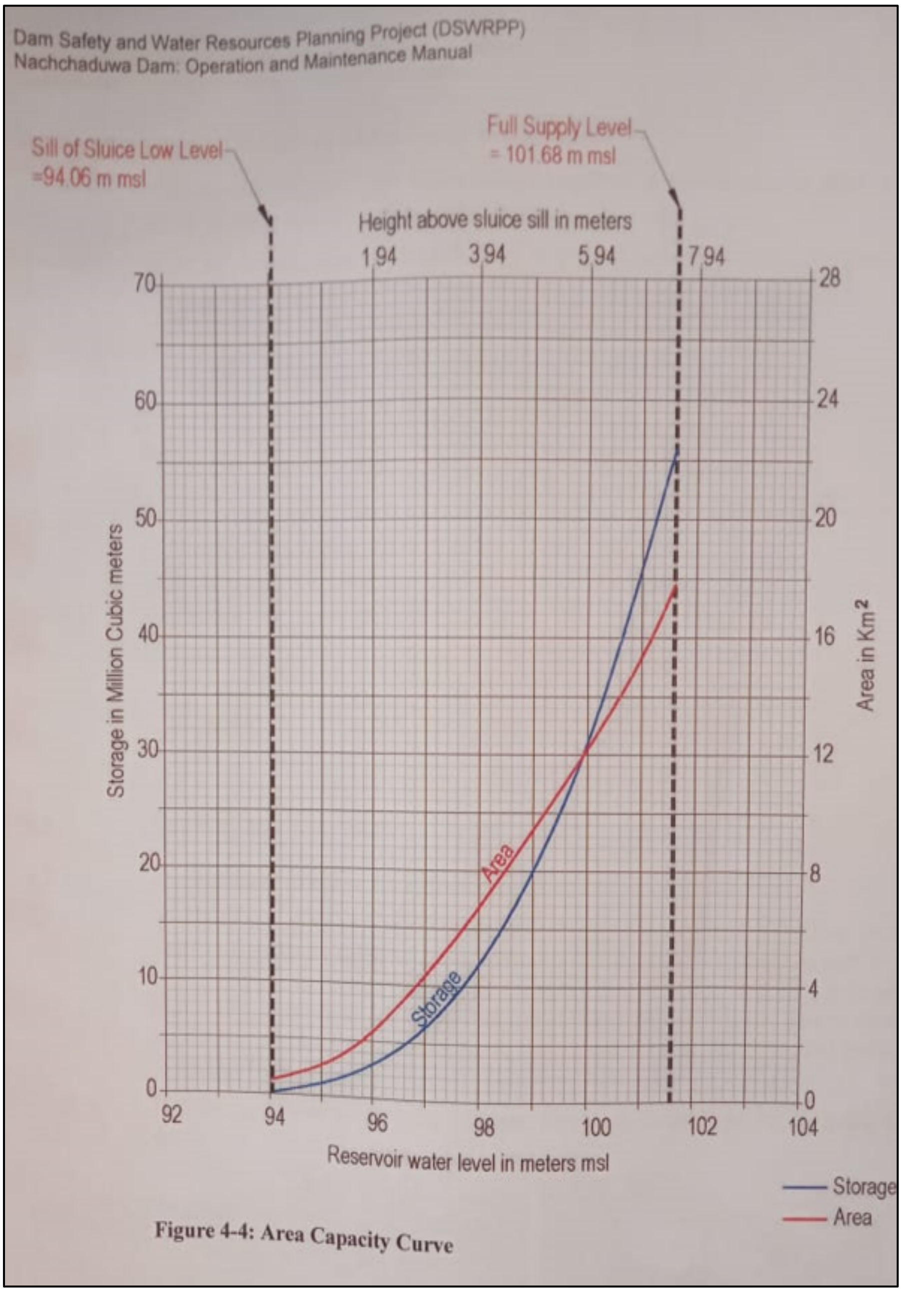

Figure 3-17: Reservoir Elevation-Storage-Area curve of Nachchaduwa reservoir (Nachchaduwa Dam Operation and Maintenance Manual)

Since HEC-ResSIM governs the water management of the reservoir based on reservoir water balance, the water balance equation components were inserted into the model as dependent variables while maintaining the reservoir water level or storage as the independent variable. Seepage and evaporation data were inserted into the model as pool data in tabular format. Monthly seepage was calculated based on the irrigation guidelines of Sri Lanka, which defines monthly seepage as 0.05% from reservoir storage (Ponrajah, 1984). Figure 3-18 presents the daily seepage time series as a function of reservoir elevation.

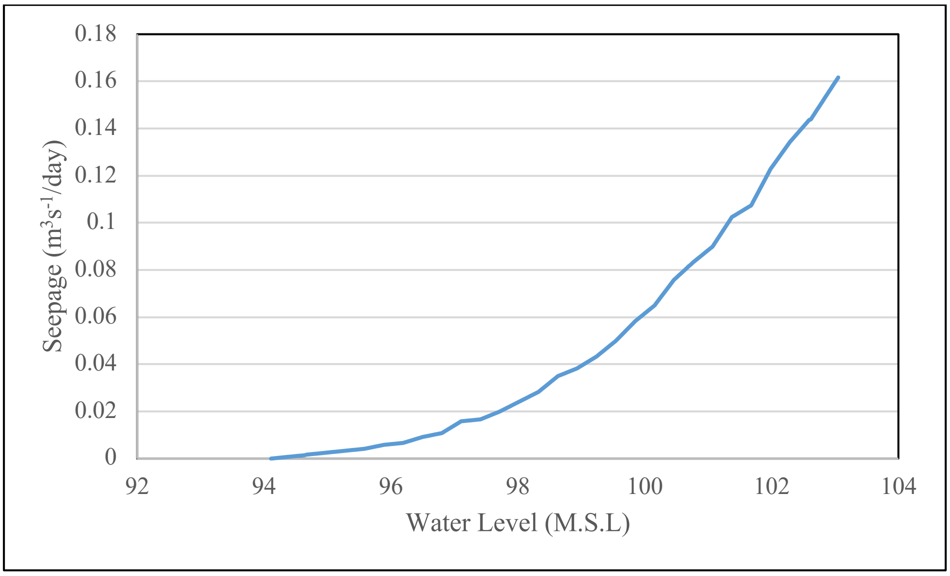

Figure 3-18: Reservoir elevation-seepage curve

Releases from outflow controlling structures are defined based on formulated rule curves that are developed considering hydrodynamics and the physical dimensions of outflow structures. Outflow structures of Nachchaduwa Reservoir are proper bank main spillway, right bank ogee spillway, right bank spillway to Nuwara Wewa, left bank ogee spillway, HLMC gate and the low-level central canal LLMC (gate on the left bank. Outflow structure dimensions and gate specifications are presented in Table 3-10.

Table 3-10: Details of Outflow Structures of Nachchaduwa Reservoir

Right Bank				
Outlet	**Length (m)**	**No. of Gates**	**Skill Level (m)**	**Gate Dimension (m × m)**
Ogee Spillway directed towards mainstream	115.8	-	101.7	-
Controlled gated outlet to mainstream	50.0	6.0	99.4	2.7× 2.3
Controlled gated outlet to Nuwara Wewa	15.0	3.0	97.1	1.2×1.1

Left Bank				
Outlet	**Length (m)**	**No. of Gates**	**Sill Level (m)**	**Gate dimension (m × m)**
High-Level Main Canal (HLMC)	6.0	3.0	95.0	1.2×1.1
Low Level Main Canal (LLMC)	3.6	1.0	92.0	1.2×1.1

Climate responses to reservoir operations and water management were formulated based on the functioning of outflow-controlling structures. The formulation of release curves for different outflow structures is based on findings from the literature review. Discharge from gated outlets was calculated from Eq. (3-1) for varying elevation levels of the reservoir (Swamee, 2009). The sill level of the gated outlet is 99.4 m. According to reservoir water levels from Irrigation Department records, gate opening heights were obtained using Eq. (3-1),

$$Q = 0.864 \times h \times l \times (g \times h_0)^{0.5} \times \left(\frac{h_o - a}{h_o + 15h}\right)^{0.072} \quad (3\text{-}1)$$

where h is the sluice gate opening height, l is the sluice gate length, g is the acceleration due to gravity, h_o is a sluice gate upstream water depth above the sill level, and Q is discharge from the outlet. Release curves for the right bank main sluice and right bank Nuwara Wewa diversion sluice discharges are presented in Figure 3-19 and Figure 3-20.

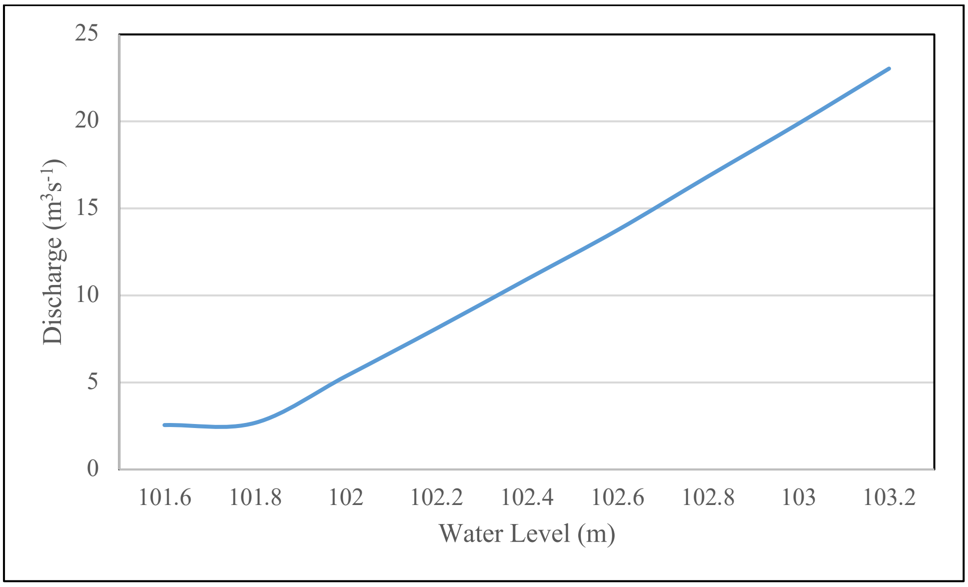

Figure 3-19: Right bank primary sluice release rule curve

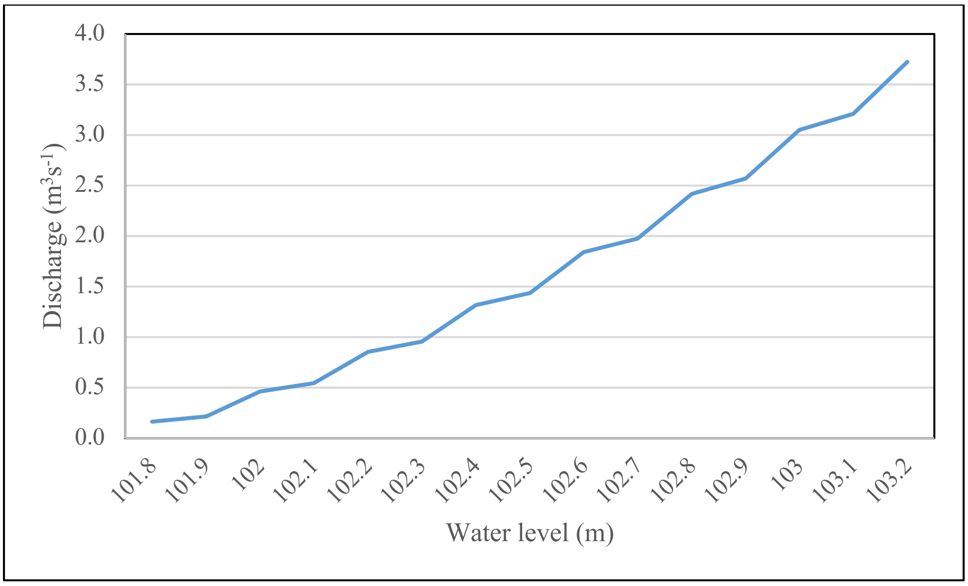

Figure 3-20: Right bank Nuwara Wewa sluice release curve

Discharges from ogee spillways are calculated for varying elevation levels of the Nachchaduwa reservoir using Eq. (3-2),

$$Q = C_d \times L \times (H_e)^{1.5} \tag{3-2}$$

where, C_d stands for discharge coefficient, L is the length of the ogee spillway, and H_e represent the water depth above the spillway crest level (Swamee, 2009). Flood discharge from the right bank ogee spillway to the mainstream and left bank ogee spillway to the left bank downstream are presented by Figure 3-21 and Figure 3-22.

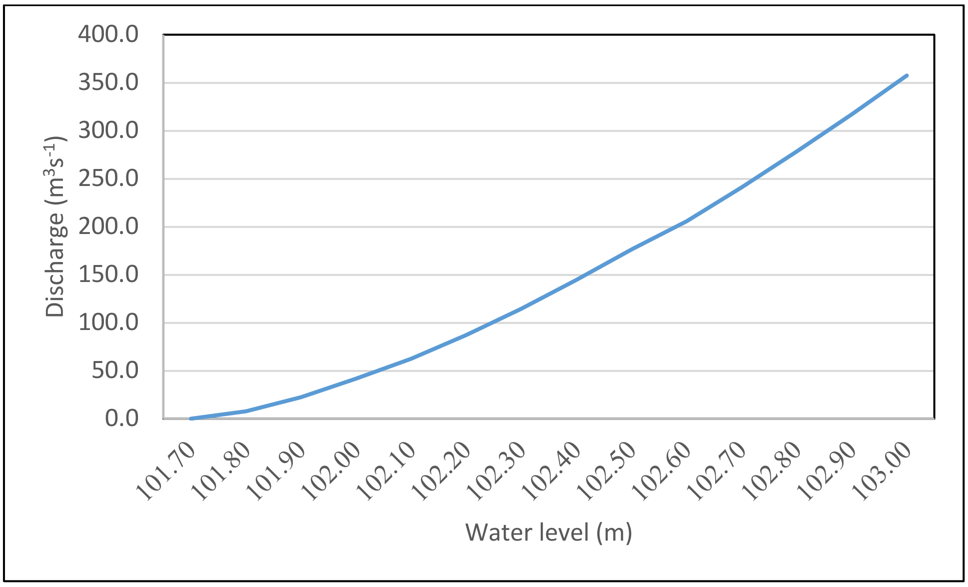

Figure 3-21: Flood discharge curve for right bank ogee spillway

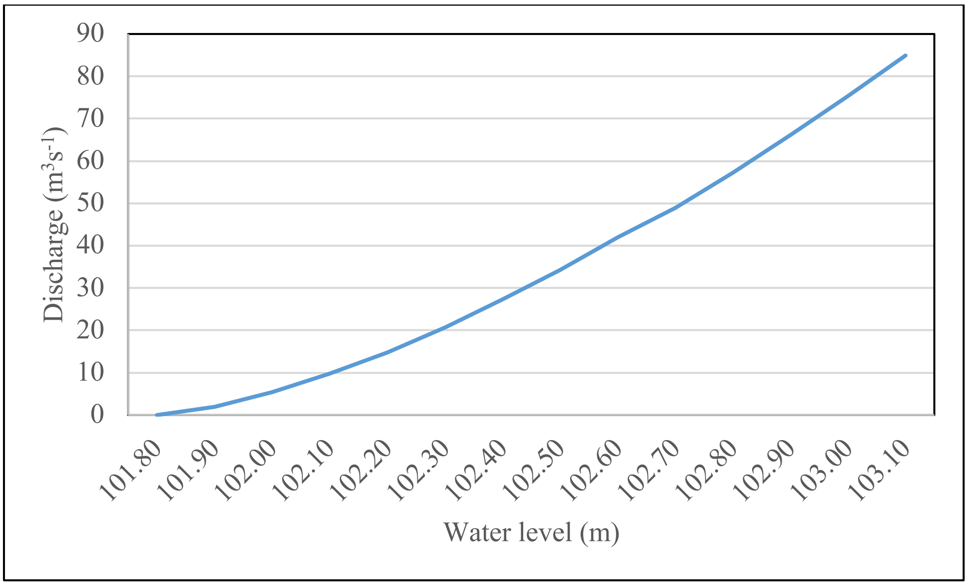

Figure 3-22: Flood discharge curve for left bank ogee spillway

Relative to the main reservoir properties, water level, storage and area, releases from outflow structures are managed through reservoir rules defined to utilise the water for multiple purposes. In order to improve decision-making and optimise the management of water resources, reservoir rules are integrated into reservoir operation modelling. These regulations provide a structured framework governing water releases and withdrawals for regulatory compliance and operational efficacy (Taghian et al., 2014).

Flood, conservation, and inactive zones are the three essential zones. The flood zone addresses flood risk management by directing regulated releases during times of heavy input to avoid flooding. The conservation zone fulfils the water demands by controlling the inflows and outflows of the reservoir. The inactive zone emphasises environmental protection, ensuring that habitats remain undisturbed. According to the Irrigation Department of Sri Lanka, water levels of the flood zone, conservation zone and inactive zone of Nachchaduwa reservoir are 103.0 m, 101.7 m and 94.1 m, respectively.

In order to adopt effective strategies to mitigate the risks of water shortages under extreme drought conditions, researchers have utilised different water management policies considering the impacts of climate change and social and ecological scenarios. Among them, the standard operating policy is the most straightforward rule that aims to fulfil the demand as much as possible (Harboe et al., 1993; Neelakantan & Sasireka, 2013). The major shortcoming of standard operating policy is that it only serves excess water for future delivery. Therefore, the hedging rule is identified as a practical solution, a rationing mechanism intended to reduce the fluctuation of water deficit by assigning a fixed amount of reservoir yield in advance (Dash et al., 2022). In order to evaluate the efficacy of various hedging strategies in protecting reservoir water for immediate and future use, this study examined one-point and two-point techniques, which were investigated to assess their effectiveness in preserving reservoir water. The hedging rule is defined using two inflection points (P1 and P2), described by the water availability and releases at considered points. Water availability in the reservoir is obtained through the reservoir's water balance. Eq. (3-3) to Eq. (3-8) capture the mathematical formulation of hedging rule-based reservoir operations to obtain irrigation releases.

$$IR_{1,t} = \alpha_1 D_t \tag{3-3}$$

$$IS_{1,t+1} = \beta_1 K \tag{3-4}$$

$$IWA_{1,t} = IR_{1,t} + IS_{1,t+1} \tag{3-5}$$

$$IR_{2,t} = IR_{1,t} + \alpha_2 \left(D_t - IR_{1,t}\right) \tag{3-6}$$

$$IS_{2,t+1} = IS_{1,t+1} + \beta_2\left(K - IS_{1,t+1}\right) \tag{3-7}$$

$$IWA_{2,t} = IR_{2,t} + IS_{2,t+1} \tag{3-8}$$

Where *D* is the demand during period *t, K* is the active storage capacity, and $IR_{1,t}$, and $IR_{2,t}$ are one-point and two-point releases. $IWA_{1,t}$ and $IWA_{2,t}$ are the water availabilities and, $IS_{1,t+1}$ and I$IS_{2,t+1}$ are carryover (end-of-period) storages corresponding to the inflection points P1 and P2.

Corresponding releases for the linear hedging rules explained by Eq. (3-9) to Eq. (3-13),

$$R_t = \frac{IR_{1,t}}{IWA_{1,t}} \times WA_{,t}\ ; 0 < WA_{,t} < IWA_{1,t} \tag{3-9}$$

$$R_t = IR_{1,t} + \frac{IR_{2,t} - IR_{1,t}}{IWA_{2,t} - IWA_{1,t}} \times (WA_{,t} - IWA_{1,t})\ ;\ IWA_{1,t} < WA_{,t} < IWA_{2,t} \tag{3-10}$$

$$R_t = IR_{2,t} + \frac{D_t - IR_{2,t}}{D + K - IWA_{2,t}} \times (WA_{,t} - IWA_{2,t})\ ;\ IWA_{2,t} < WA_{,t} < D_t + \mathrm{K} \tag{3-11}$$

$$R_t = D_t \; ; WA_{,t} > D_t + \mathrm{K} \quad (3\text{-}12)$$

$$Seepage\ (ss) = 0.005 \times \frac{Reservoir\ storage}{30} \quad (3\text{-}13)$$

where R_t is the release and $WA_{,t}$ is the water availability during period *t*. Once the release is obtained, the carryover storage, S_{t+1} is calculated using Eq. (3-14) and Eq. (3-15).

$$S_{t+1} = \min(WA_{,t} - R_t, \mathrm{K}) \quad (3\text{-}14)$$

$$Spill = \max(0, WA_{,t} - D_t - K) \quad (3\text{-}15)$$

Conditions for analysis were given under different alternative simulations, and results were obtained prior to conclusions. HEC-ResSIM operates in daily or monthly timestep, and this model is configured to operate under irrigation demands. Model simulations could be verified through observed reservoir release data. The operating timestep was selected based on the availability of the observed data. The simulation process includes estimating storage, surface area, and reservoir elevation.

Irrigation requirement and irrigation supply estimations were conducted for both historical and future time frames to evaluate the impacts of climate change. To ensure accuracy in these estimations, GCM estimates were bias-corrected before being utilised in the crop water requirement estimation, hydrological modelling, and reservoir operation modelling.

3.7 Bias Correction of GCMs

Global circulation models (GCMs) are integrated with hydrological and agricultural models as part of a multidisciplinary methodology to assess the effects of climate change on water availability and irrigation efficiency. Climate projections under hypothetical global trends serve as inputs to hydrological models, which simulate the complex interactions between climate, land surface, and water resources within a specific watershed or river basin. Simultaneously, forecasted climate data are included in agricultural models to evaluate the effects on crop water requirements, irrigation demand, and irrigation efficiency. Assessing the possible effects of climate change on water resources and agricultural systems by combining GCMs with hydrological and agricultural models allows policymakers to make informed judgments about adaptation.

The quantile mapping method based on gamma mapping has been proven effective for bias correction of precipitation estimates in previous studies (Block et al., 2009; Ines & Hansen, 2006). Consequently, this study employed the Gamma mapping-based Quantile Mapping method for bias correction of rainfall estimates.

3.7.1 Gamma Mapping Method

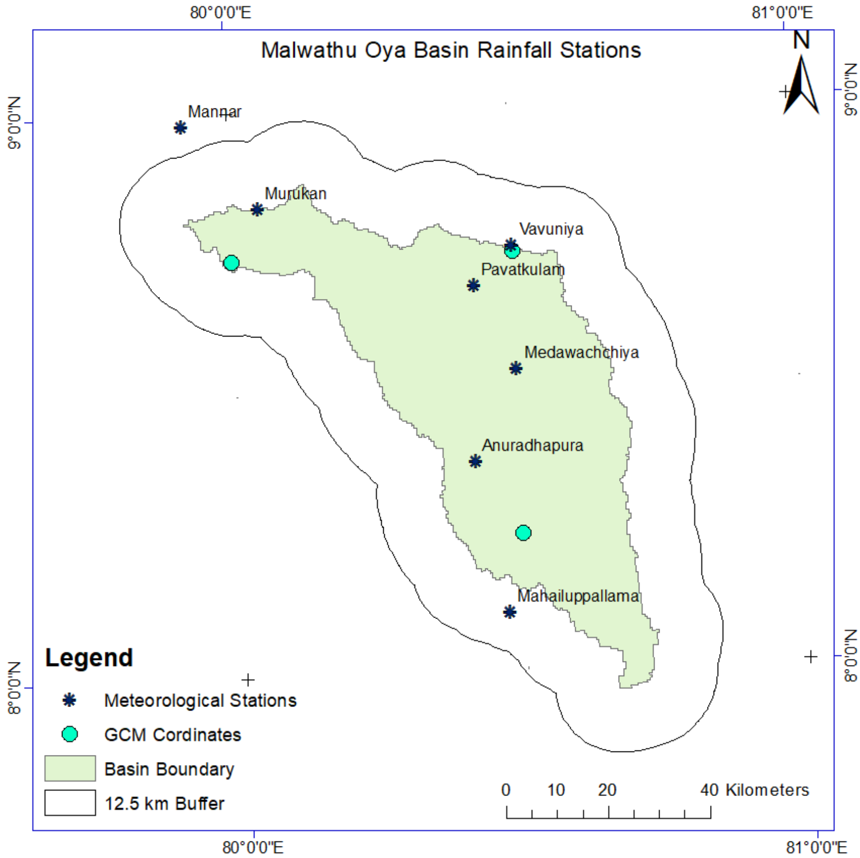

Figure 3-23: Meteorological stations and GCM coordinates in the proximity of the Malwathu Oya basin

The distribution of meteorological stations and GCM coordinates within the proximity of the Malwathu Oya river basin is presented in Figure 3-23. Table 3-11 provides location coordinates for considered meteorological stations and corresponding GCM grid cell center points.

Table 3-11: Meteorological Station and GCM Coordinates

Station	Meteorological Station Coordinate (Dec. Deg.)		Centre of Coordinate of GCM Grid Cell (Dec. Deg.)	
	Longitude	Latitude	Longitude	Latitude
Mahailuppallama	80.47	8.10	80.50	8.24
Vavuniya	80.50	8.75	80.50	8.74
Murunkan	80.05	8.83	80.00	8.74

The mathematical formulation for bias correction of historical and scenario-based rainfall estimates using the gamma mapping method is given by Eq. (2-15) and Eq. (2-16). The above process was conducted for four couples made of four different quantiles of observed data series and GCM rainfall time series. Python environment was utilised to do the bias correction, considering the recent advances in Python, which provide built-in functions for bias correction using the gamma function.

These corrected climate estimates are subsequently incorporated into hydrological and agricultural models to reflect regional variations in climatic impacts on water availability and irrigation efficiency.

CHAPTER 4

RESULTS

This chapter explains the results obtained from the methodology employed to evaluate the irrigation water use efficiency within the study area of the Nachchaduwa Irrigation Scheme. Initially, the methodology explains the estimation of irrigation water requirements using the CROPWAT model. The model estimates reference evapotranspiration, crop water requirement, and irrigation scheduling, thereby serving as a fundamental tool for estimating irrigation requirements using the study region's climate, soil, and crop data.

Results of the hydrological assessment of the Malwathu Oya basin were presented after that, which was conducted to estimate the river inflow to the Nachchaduwa Reservoir. The HEC-ResSIM software package has been utilised to simulate the reservoir operations of the Nachchaduwa reservoir, which is crucial for estimating irrigation supply. Sensitivity analysis and scenario testing are crucial elements to evaluate how management strategies and climatic scenarios affect the dependability of irrigation supplies, offering insightful information for decisions about the management of water resources.

In order to assess the impact of climate change on the irrigation supply and irrigation requirements of paddy, GCM estimates were used to project future climate conditions represented by temperature and rainfall. Results of the bias correction process of GCM rainfall estimates using the gamma mapping method presented at the beginning of this chapter before presenting the crop water requirement and irrigation supply estimation results, providing insights into future climate conditions.

4.1 Bias Correction of GCM Estimates

An insight into the accuracy and dependability of climate model outputs in representing basin-wide precipitation patterns can be gained by comparing the raw and bias-corrected estimates with stational rainfall observations at a monthly scale. To correct GCM outputs and reduce systematic biases in the climate model simulations, the quantile mapping approach is used to align the data with historical rainfall records.

4.1.1 Comparison between GCM estimate, bias-corrected GCM estimate and Observed Rainfall

Monthly average rainfall time series are presented using bar charts, which offer a visual representation of the differences between the uncorrected GCM estimates, observed station rainfall, and the bias-corrected estimates, allowing for an evaluation of the performance of the bias correction method. Average monthly estimates are considered for comparison, calculated over the base period spanning from 1991 to 2020, providing a robust basis for assessing the accuracy and reliability of the GCM-derived rainfall estimates before and after bias correction.

This analysis enhances our understanding of the applicability and limitations of bias correction techniques in improving the representation of rainfall variability within the Malwathu Oya basin, thereby facilitating more accurate assessments of future climate impacts on water resources and agricultural systems in the region. Figure 4-1, Figure 4-2 and Figure 4-3 compare average monthly rainfall values for GCM estimates, bias-corrected GCM estimates and observed rainfall. It further illustrates the improvement achieved through the bias correction relative to the GCM estimates.

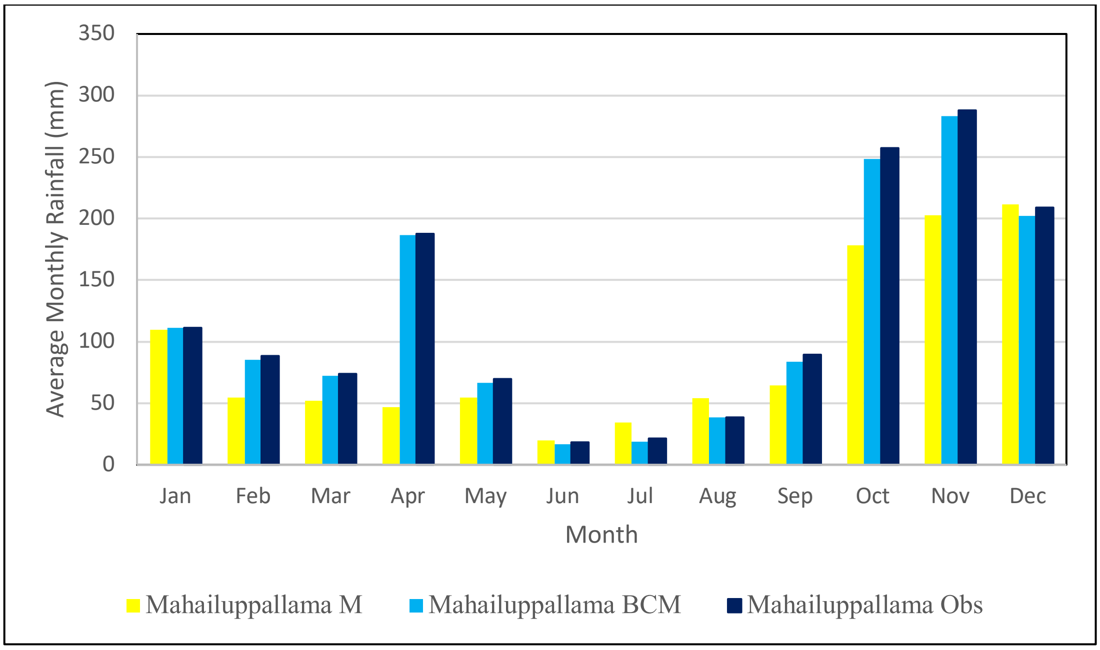

Figure 4-1: Average monthly rainfall estimates of raw GCM model, bias-corrected model and observed data- Mahailuppallama Station

Malwathu Oya basin is situated in the North-Central province of Sri Lanka, where the primary water sources are Second Inter Monsoon from October to November and North-East monsoonal rainfall from December to February. Figure 4-1, Figure 4-2 and Figure 4-3 further highlights that the selected CERFACS.CNRM-CM6-1-HR GCM is capable of capturing monsoonal rainfall characteristics within the river basin.

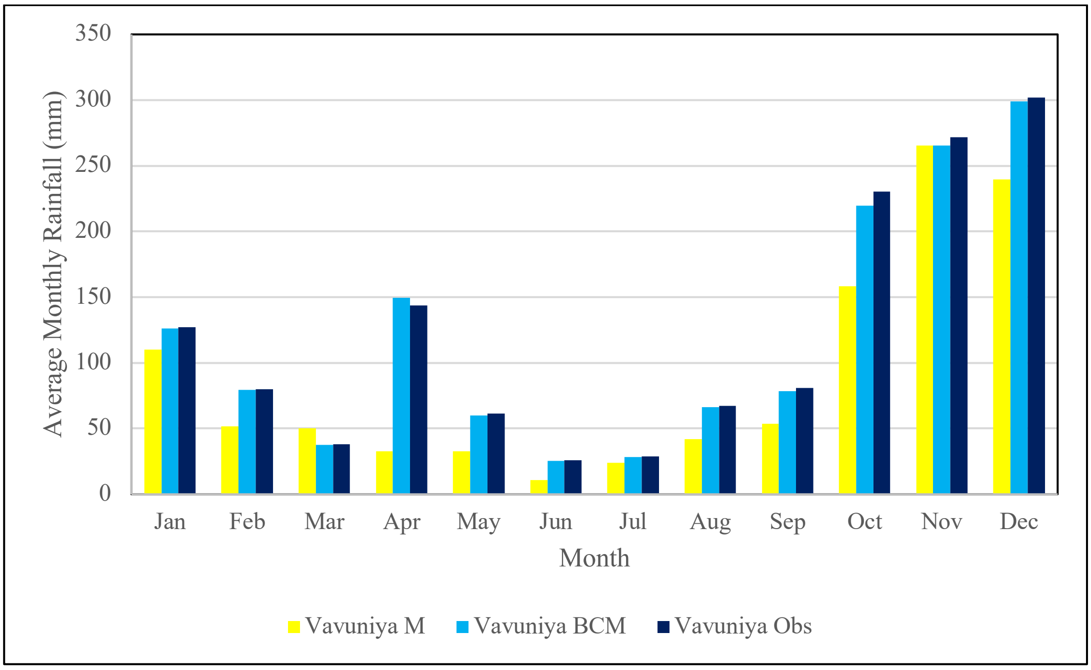

Figure 4-2: Average monthly rainfall estimates of raw GCM model, bias-corrected model and observed data - Vavuniya Station

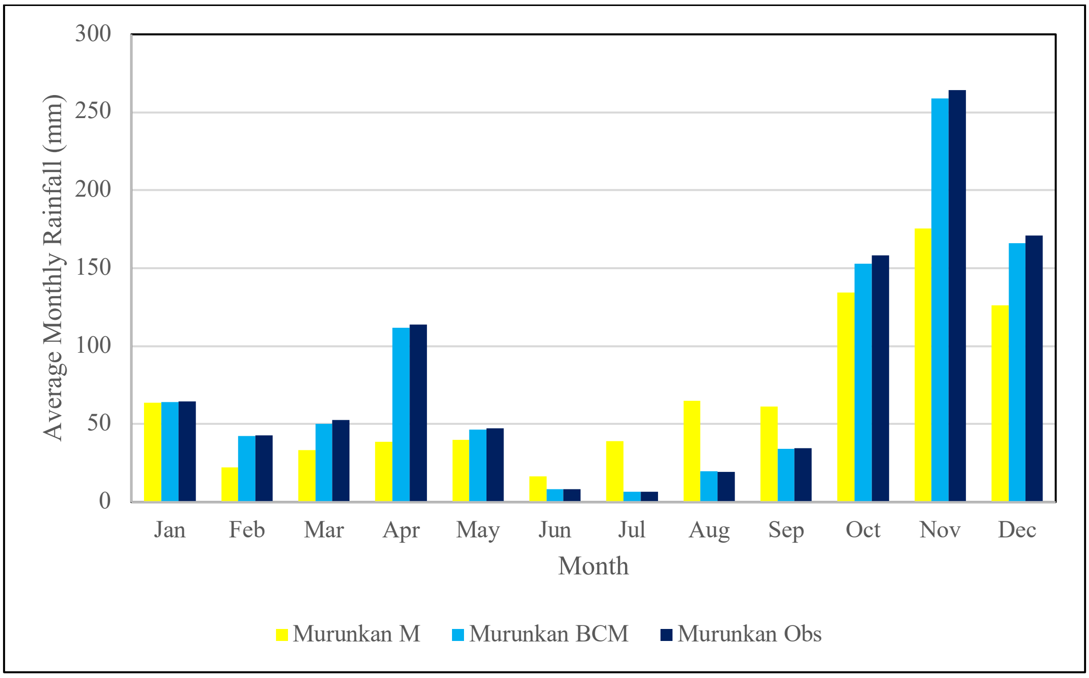

Figure 4-3: Average monthly rainfall estimates of raw GCM model, bias-corrected model and observed data - Murunkan Station

The cumulative distribution function (CDF) plots provide a thorough visual representation of the corrective improvements made by the Quantile Mapping bias correction method by exhibiting the cumulative probability distributions of both the GCM estimations and observed rainfall data. Figure 4-4, Figure 4-5, and Figure 4-6 illustrate the correction improvements followed due to the Quantile Mapping bias correction method, which is conducted considering the four quantiles of cumulative probability distributions of GCM estimates and corresponding observed rainfall data.

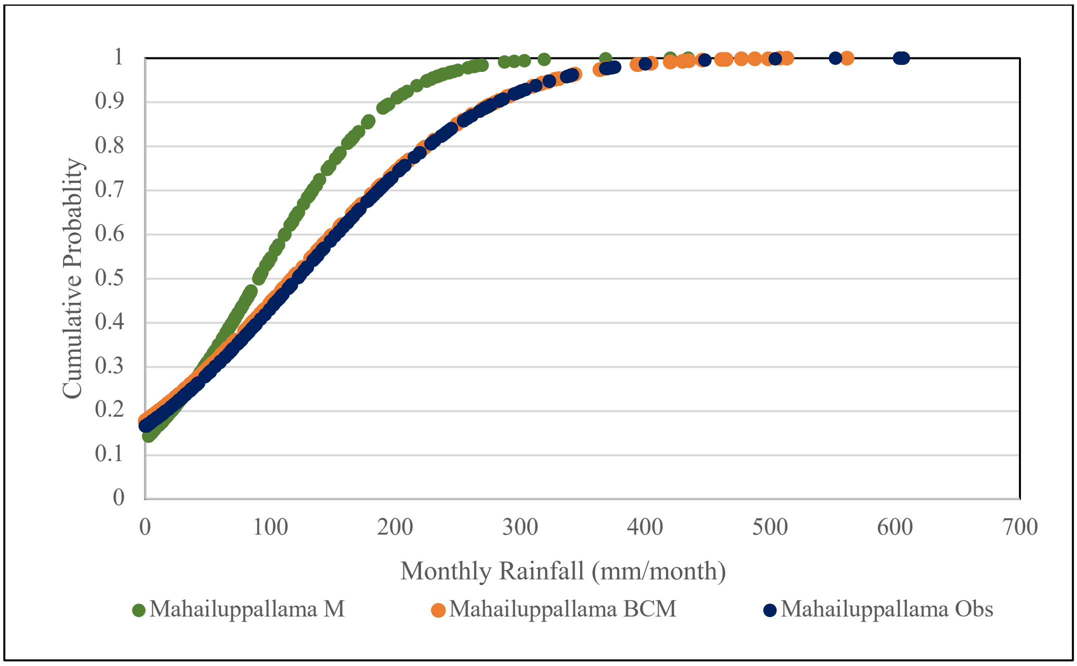

Figure 4-4: Comparison between CDF curves of bias-corrected and observed rainfall data of Mahailuppallama station

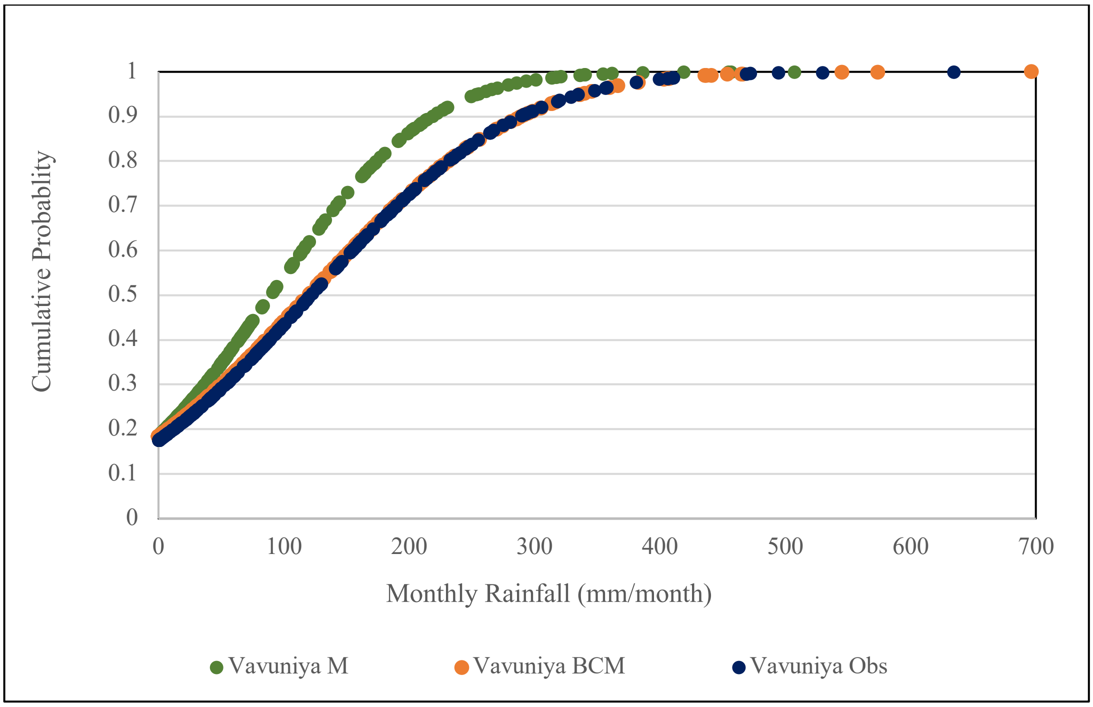

Figure 4-5: Comparison between CDF curves of bias-corrected and observed rainfall data of Vavuniya station

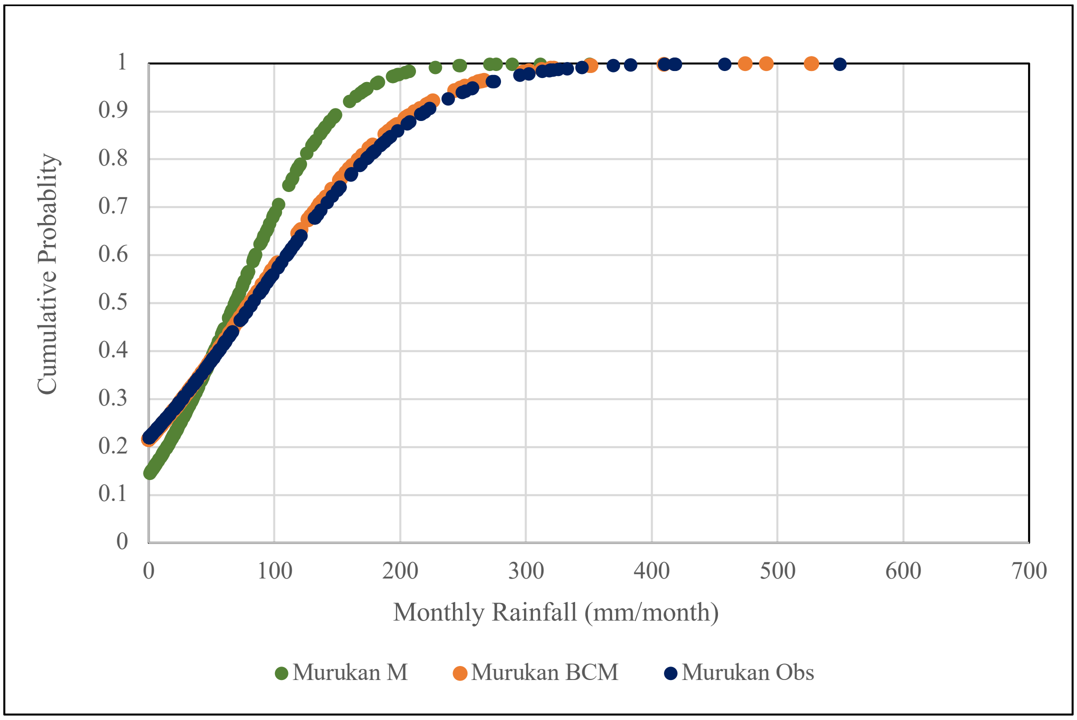

Figure 4-6: Comparison between CDF curves of bias-corrected and observed rainfall data of Murunkan station

Estimates of projected rainfall under the SSP 1-2.6 and SSP 5-8.5 scenarios provide information on possible future climatic paths under various greenhouse gas emissions scenarios and socioeconomic pathways. A future with reduced greenhouse gas emissions, reflecting efforts to slow down global warming and shift to sustainable development, is depicted in the SSP 1-2.6 scenario. On the other hand, the SSP 5-8.5 scenario depicts a future with high greenhouse gas emissions brought on by a prolonged reliance on fossil fuels and insufficient attempts to slow down climate change.

Together with predicted rainfall estimates under two SSPs, SSP 1-2.6 and SSP 5-8.5 scenarios, covering the years from 2015 to 2100, the annual rainfall time series offers a thorough picture of historical rainfall trends throughout the base period of 1991–2014. The annual rainfall time series captures historical precipitation data for the base period (1991-2014), showing increased extreme rainfall patterns over the study period.

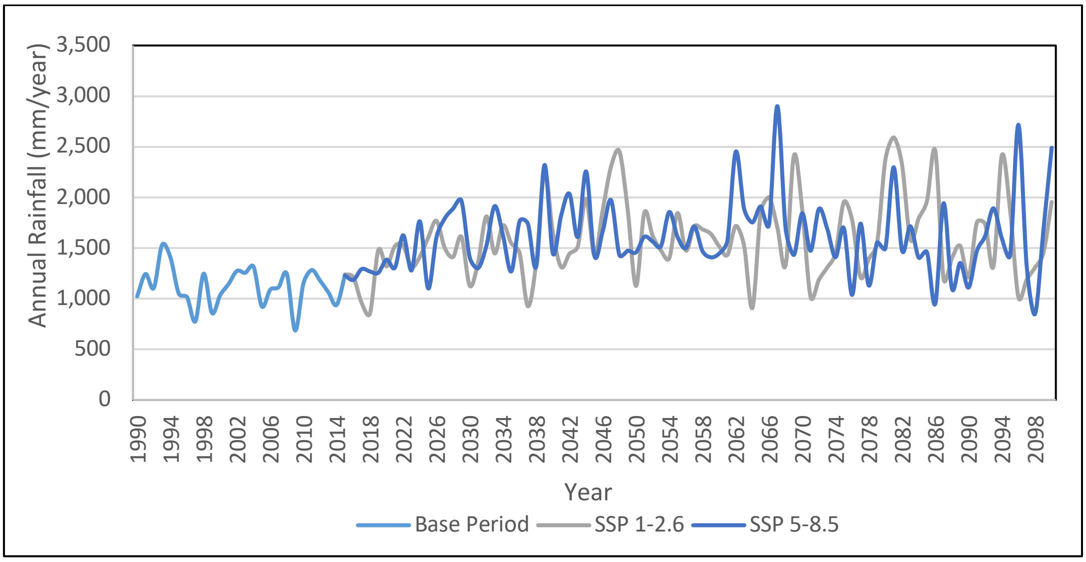

Figure 4-7: Bias corrected Rainfall Estimates – Anuradhapura Station

Figure 4-8, Figure 4-9, and Figure 4-10 present bias-corrected average monthly rainfall estimates for near, mid and far future periods under SSP 1-2.6 and SSP 5-8.5 scenarios for Anuradhapura station, which was utilised to calculate the irrigation requirement and irrigation supply of the Nachchaduwa Irrigation scheme. Average monthly rainfall graphs for the near future period between 2015-2044 depict that the rainfall estimates for SSP 5-8.5 generate higher values relative to SSP 1-2.6 estimates except during the November and December months. Rainfall estimates for the far future window under the SSP 1-2.6 scenario provide higher values except during April relative to the SSP 5-8.5 scenario, highlighting the variation of rainfall capturing capability of CERFACS.CNRM-CM6-1-HR GCM model for the far future under expected climate conditions.

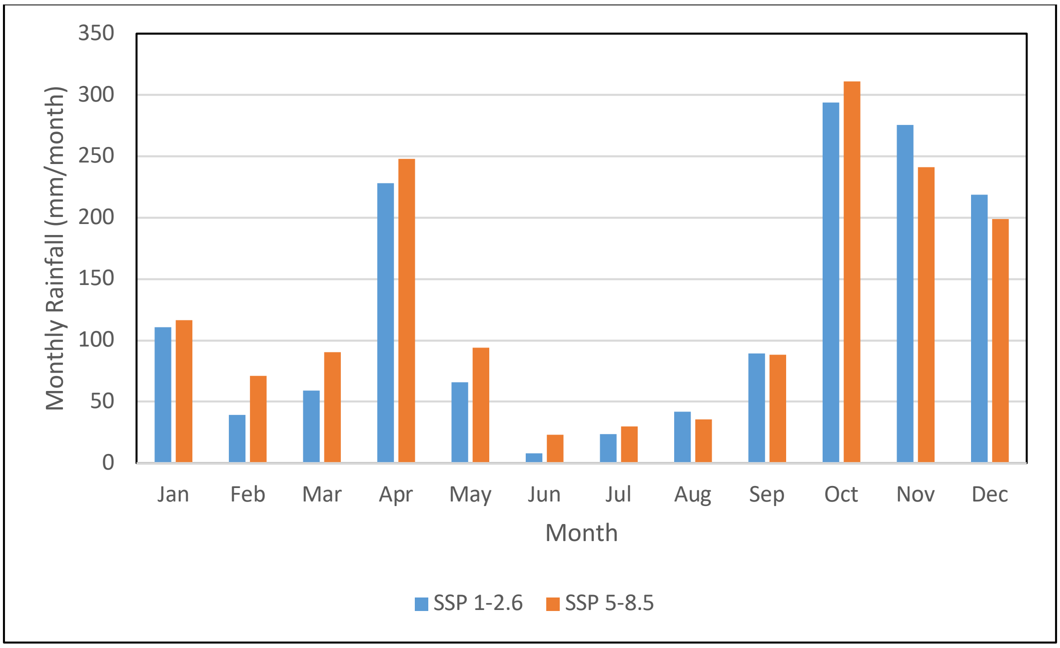

Figure 4-8: Bias-corrected GCM estimates for the near future- Anuradhapura Station

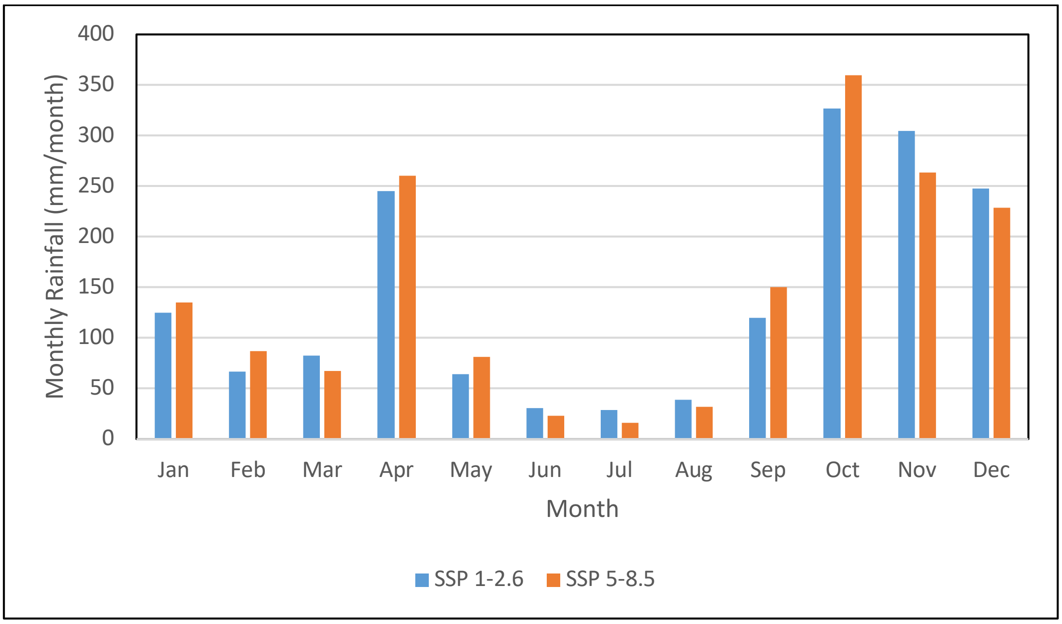

Figure 4-9: Bias-corrected GCM estimates for mid-future- Anuradhapura Station

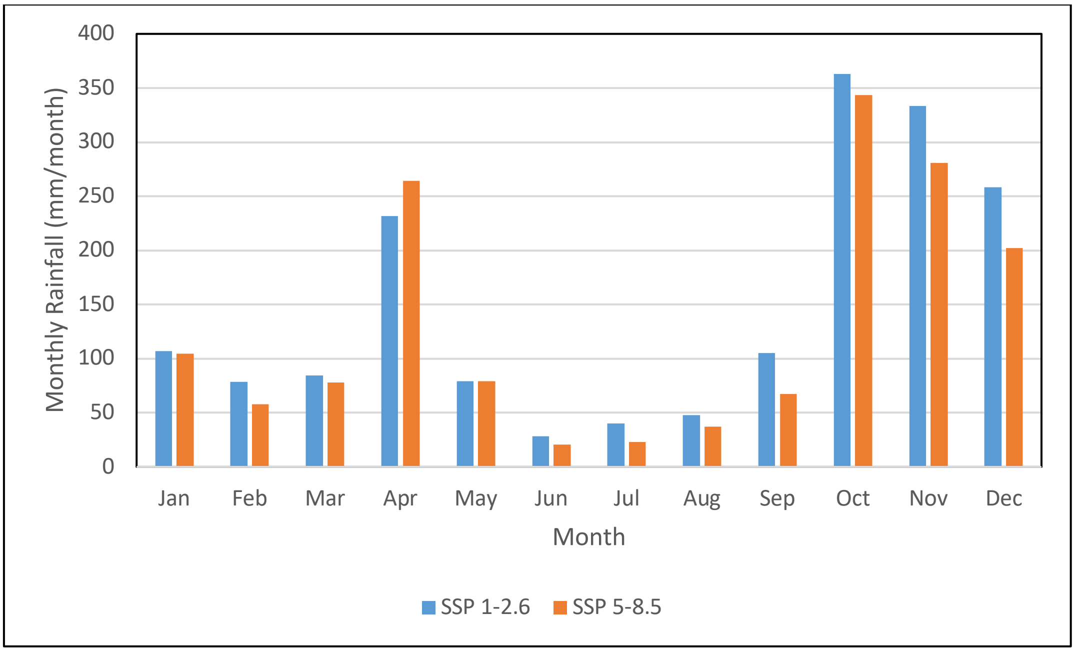

Figure 4-10: Bias corrected GCM estimates for far future- Anuradhapura Station

4.1.2 Comparison between GCM estimate, bias corrected GCM estimate and Observed Temperature

The bar charts illustrate the bias-corrected GCM estimates derived from the CERFACS.CNRM-CM6-1-HR GCM estimates, visually represent the degree of alignment between the model outputs and observed temperature data. Minimum, maximum and average temperature data were bias corrected to estimate potential evapotranspiration.

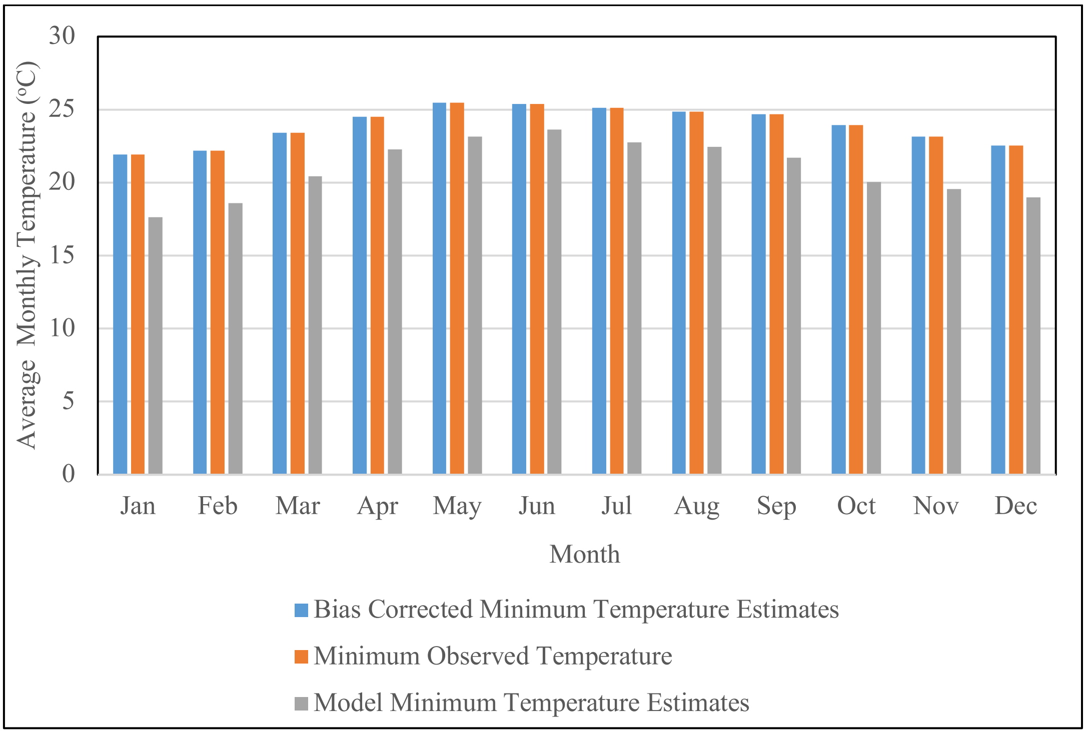

Figure 4-11: Correlation between minimum monthly bias-corrected and observed temperature data- Anuradhapura station

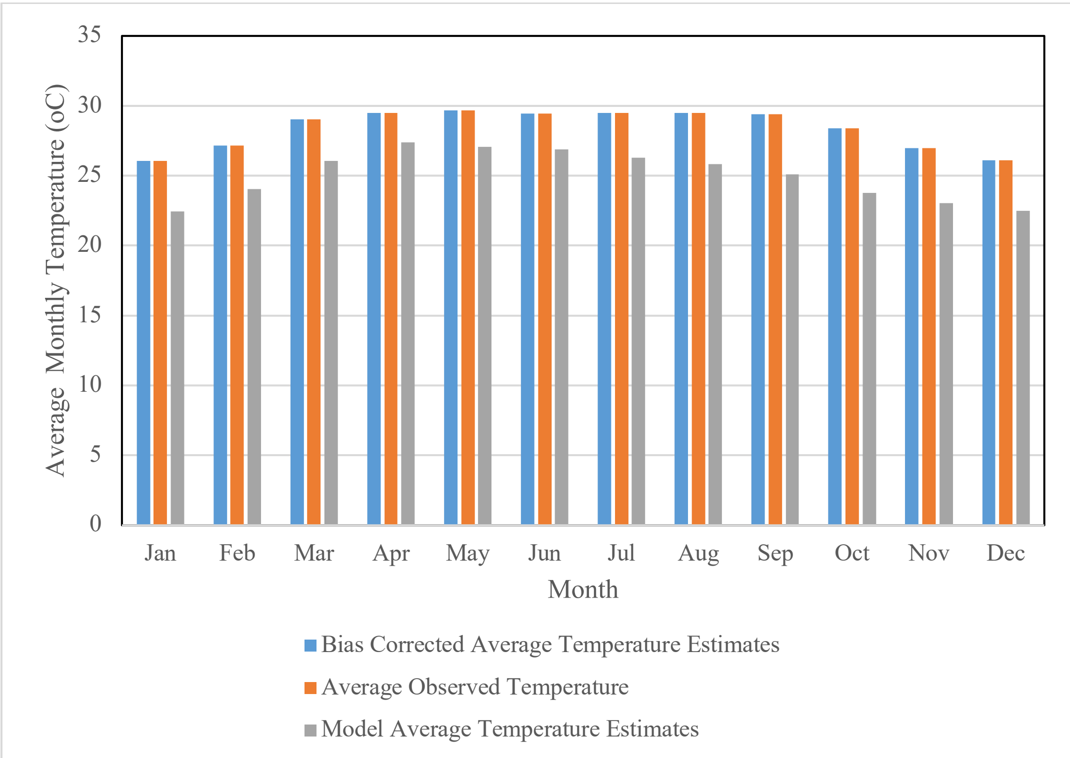

Figure 4-12: Correlation between average monthly bias-corrected and observed temperature data- Anuradhapura station

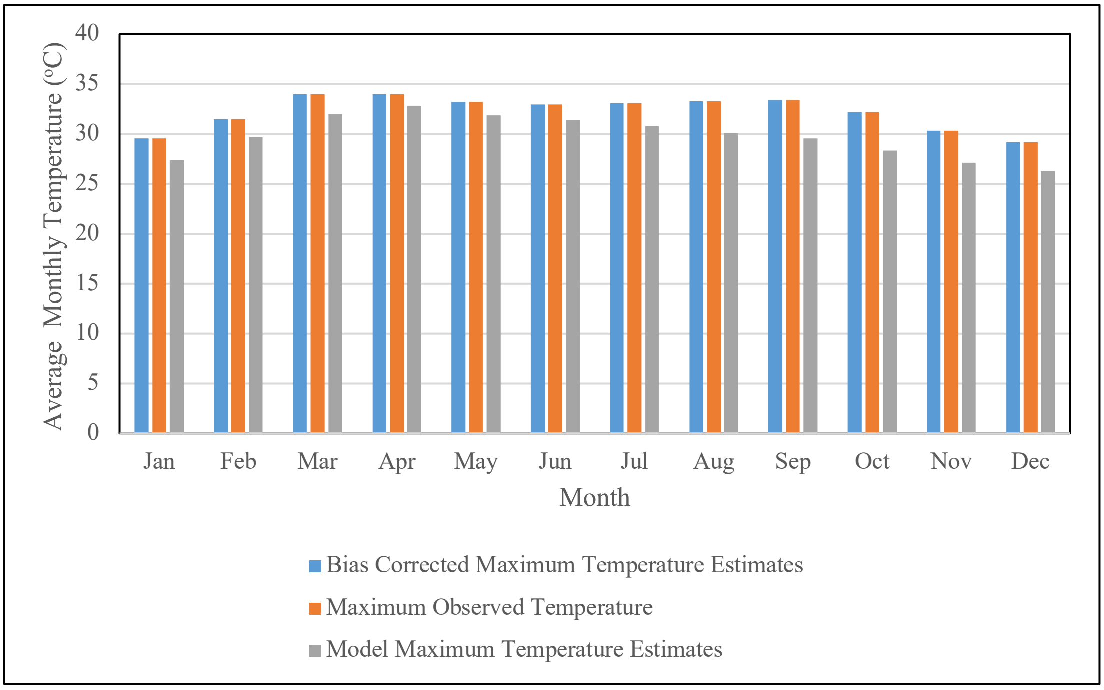

Figure 4-13: Correlation between average monthly bias-corrected and observed temperature data- Anuradhapura station

Figure 4-14 presents the variation of bias-corrected average yearly minimum, maximum and average temperature estimates under SSP 1-2.6 and SSP 5-8.5 scenarios, highlighting that the SSP 5-8.5 scenario provides higher estimates than the SSP 1-2.6 scenario.

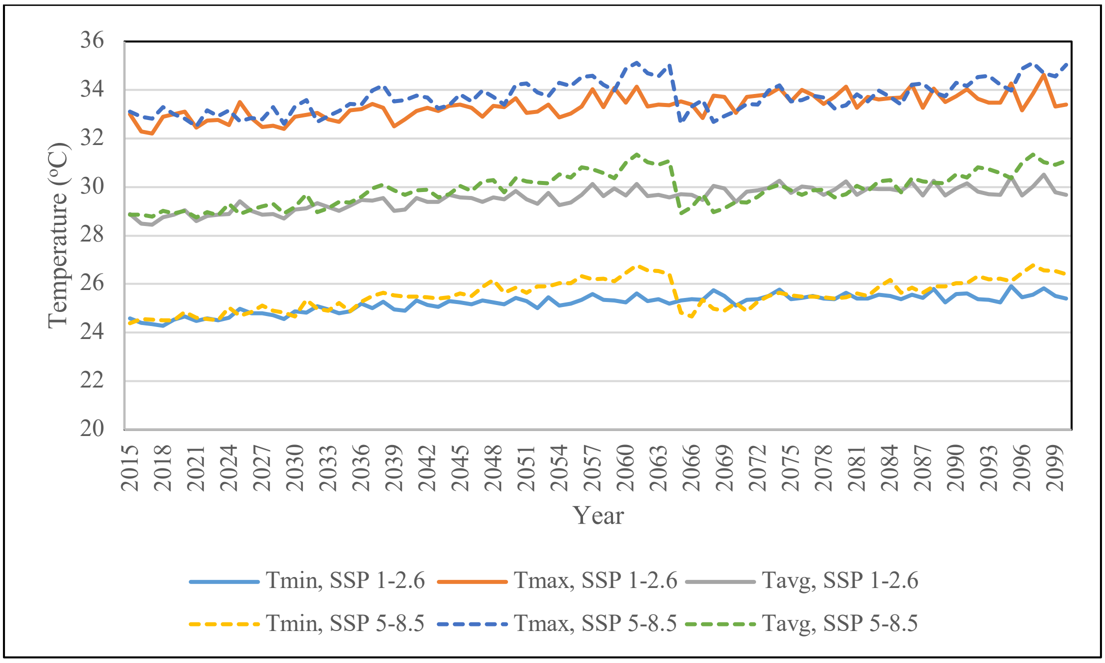

Figure 4-14: Variation of minimum, maximum and average temperature under SSP scenarios

Figure 4-15 presents a variation of potential evapotranspiration under SSP scenarios, which depicts a similar variation pattern to temperature for the near and mid future periods, where the SSP 5-8.5 scenario generates higher evapotranspiration rates. However, evapotranspiration rates of SSP 1-2.6 and 5-8.5 scenarios for the far future vary drastically.

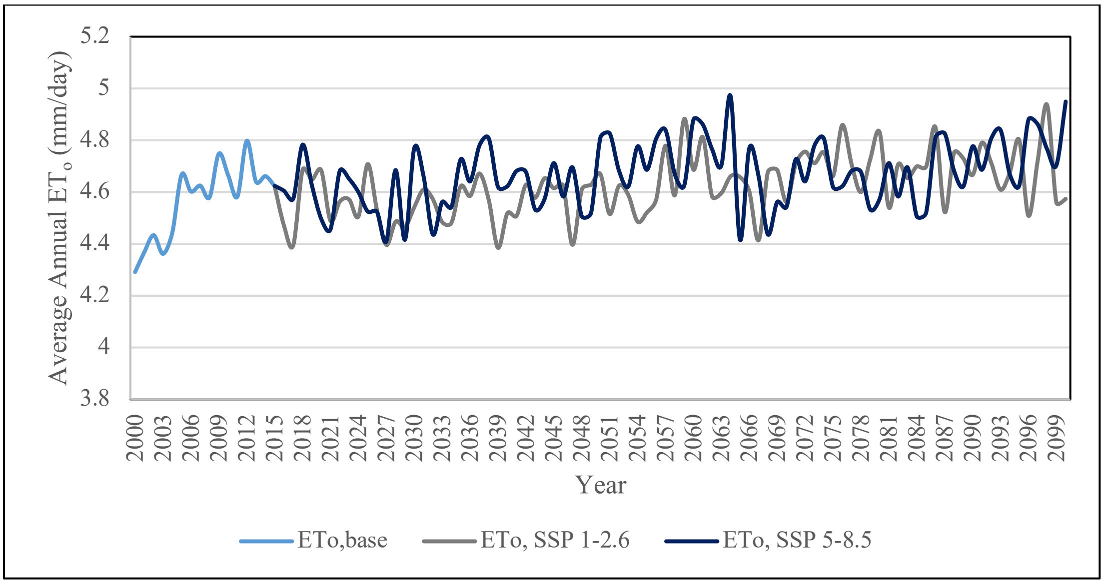

Figure 4-15: Variation of Potential Evapotranspiration estimates under SSP scenarios

Considering the estimated evapotranspiration rates, rainfall estimates, long-term and average percolation rates, irrigation requirements of the Nachchaduwa Irrigation scheme during the Maha and Yala seasons were estimated and presented in Figure 4-16 and Figure 4-17 respectively. Figure 4-16 highlights that the annual irrigation requirement estimated for the SSP 1-2.6 scenario is considerably higher than the estimated amount for the SSP 5-8.5 scenario. Contradictory irrigation requirement estimated under climate predictions depicted by the SSP 5-8.5 scenario provides higher estimates relative to the SSP 1-2.6 scenarios illustrated in Figure 4-17.

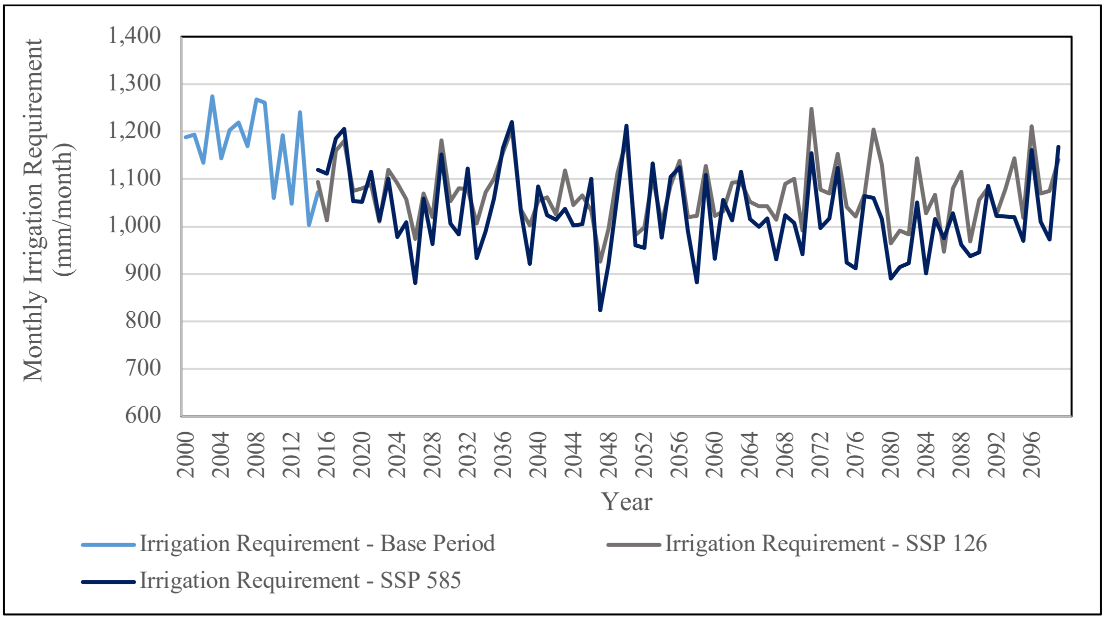

Figure 4-16: Irrigation requirement variation -Maha Season

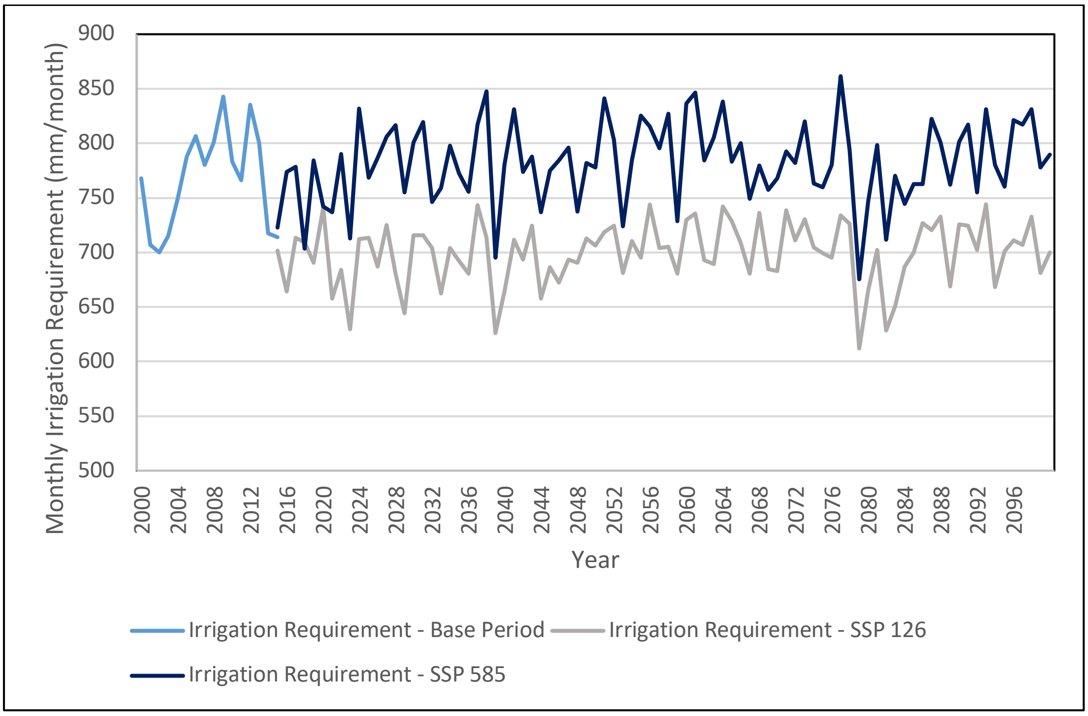

Figure 4-17: Irrigation requirement variation -Yala Season

4.2 HEC-HMS Model Results

Hydrological modelling was conducted to estimate reservoir inflow to the Nachchaduwa reservoir from the upper catchment of the Malwathu Oya basin. To simulate the river inflow dynamics to the reservoir, the model considers several hydrological phenomena, such as correlations between rainfall and runoff, evapotranspiration, and streamflow routing.

4.2.1 Model Calibration and Validation

River discharge observations of Malwathu Oya at the Kappachi river gauging station were used for model calibration and validation. Observed and simulated discharge for two years of calibration period 2017/2018 and 2018/2019 water years are shown in Figure 4-18. Hydrographs for observed and simulated discharge values for two years of the validation period 2019/2020 and 2020/2021 water years are shown in Figure 4-19.

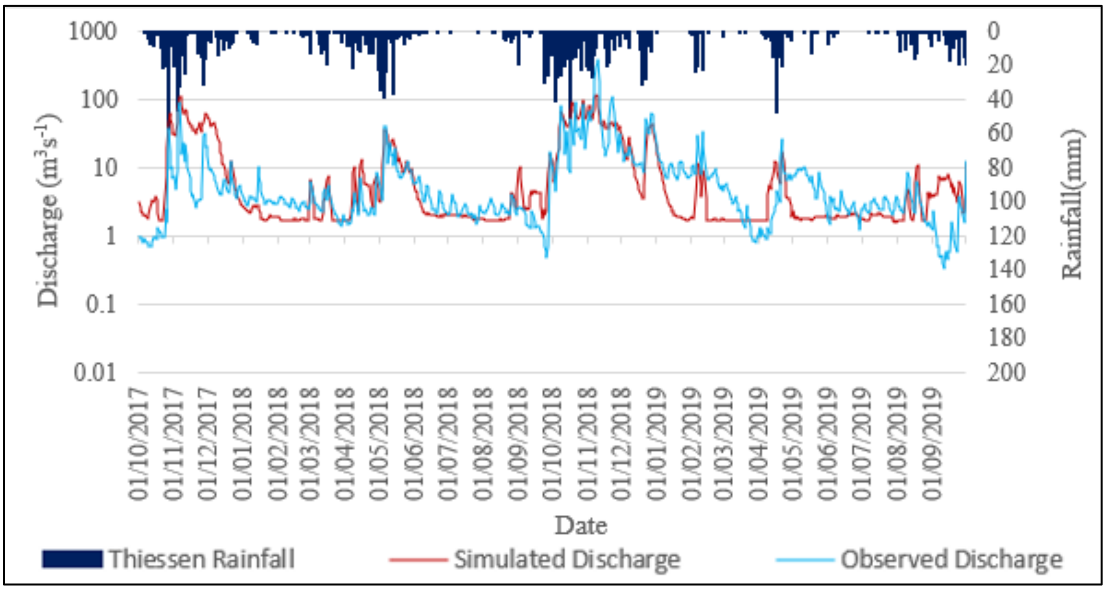

Figure 4-18: Hydrograph for Calibration Period

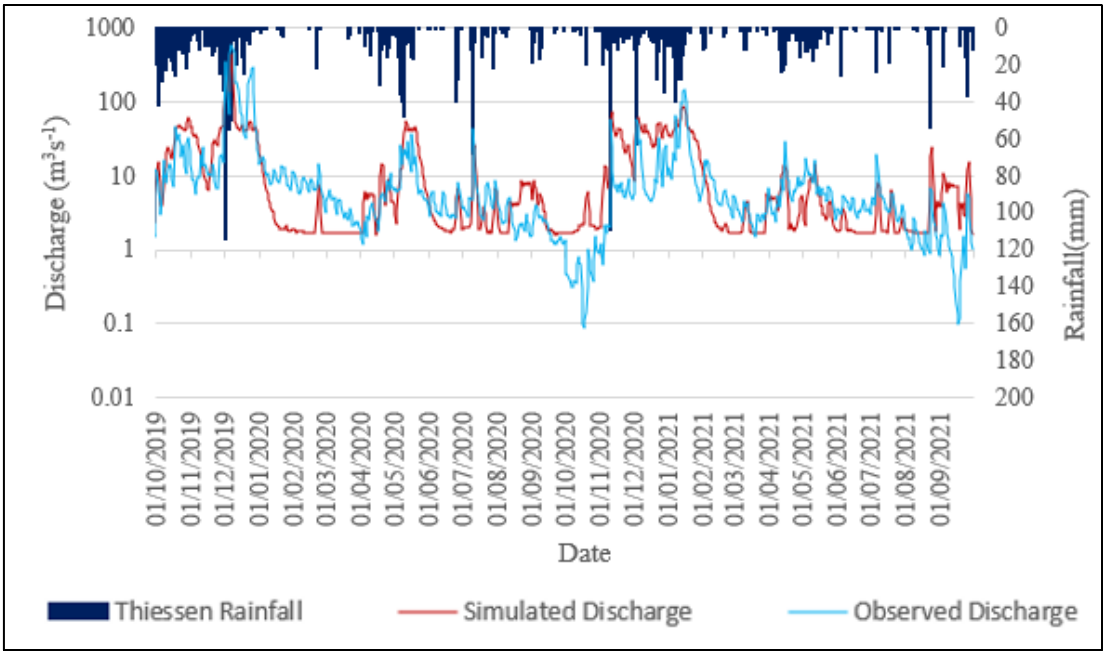

Figure 4-19: Hydrograph for Validation Period

The climate signal represented by Thiessen rainfall is closely followed by the streamflow time series in the Malwathu Oya basin as depicted by flow hydrographs.

In addition, flow hydrographs further highlight the differences between the estimated and observed streamflow during low flow conditions, highlighting the model accuracy under different flow regimes.

The reliability of river runoff simulations was evaluated using performance indicating objective functions at calibration and validation stages. Root Mean Square Error (RMSE), Nash Sutcliff objective function (NSE), and Coefficient of Determination (R^2) objective functions were selected considering their applicability to evaluate percentage difference in simulated and observed values, goodness of fit for peak flow events, and correspondence between observed and simulated values respectively. Model simulations showed satisfactory performance by the objective function values for both calibration and validation periods, as presented in Table 4-1.

Table 4-1: Objective Function Results- Hydrological Model

Performance rating	**RMSE**	**NSE**	**R^2**
Calibration	0.80	0.55	0.58
Validation	0.60	0.60	0.65

As a dry zone basin where a major component of river water is utilised for irrigation purposes, the Malwathu Oya basin is characterised by numerous major, medium, and minor tanks controlling streamflow generation during storm conditions. The upper catchment of the basin comprises five major tanks and uncounted medium and minor tanks, significantly regulating streamflow dynamics.

The impact of incorporating reservoirs in hydrological modelling is evaluated using the runoff coefficient estimated for model simulations conducted for two scenarios: river runoff with major reservoirs and river runoff without significant reservoirs. Runoff coefficient is the ratio between streamflow volume and rainfall volume (Crow et al., 2018). Seasonal average rainfall volumes, streamflow volumes and corresponding runoff coefficients were estimated based on HEC-HMS model results. Table 4-2 shows estimated seasonal average rainfall and streamflow volumes and corresponding runoff coefficients estimated for scenarios mentioned in the methodology.

Table 4-2: Runoff Volumes and Coefficients with Consideration of Significant Tanks

Scenario	**Attribute**	**Maha Season (Million m³)**	**Yala Season (Million m³)**
	Rainfall	2601.99	1524.44
With reservoirs	Cumulative streamflow	477.45	133.15
	Runoff Coefficient	0.18	0.09
Without reservoirs	Cumulative streamflow	918.84	226.17
	Runoff Coefficient	0.35	0.15

River inflow to the Nachchaduwa reservoir simulated using the HEC-HMS model under future climatic scenarios represented by SSP 1-2.6 and SSP 5-8.5 provides a better understanding of the effects of climate change on water availability and reservoir inflow dynamics. The perspectives into the potential alterations in river inflow patterns driven by climatic shifts can be obtained by analysing Figure 2-1 that compares the base period, SSP 1-2.6 scenario, and SSP 5-8.5 scenario. A significantly increasing trend in river discharge was observed for the base period, while the magnitude and frequency of occurrence of extreme rainfall events have significantly improved for SSP 1-2.6 and SSP 5-8.5 scenarios.

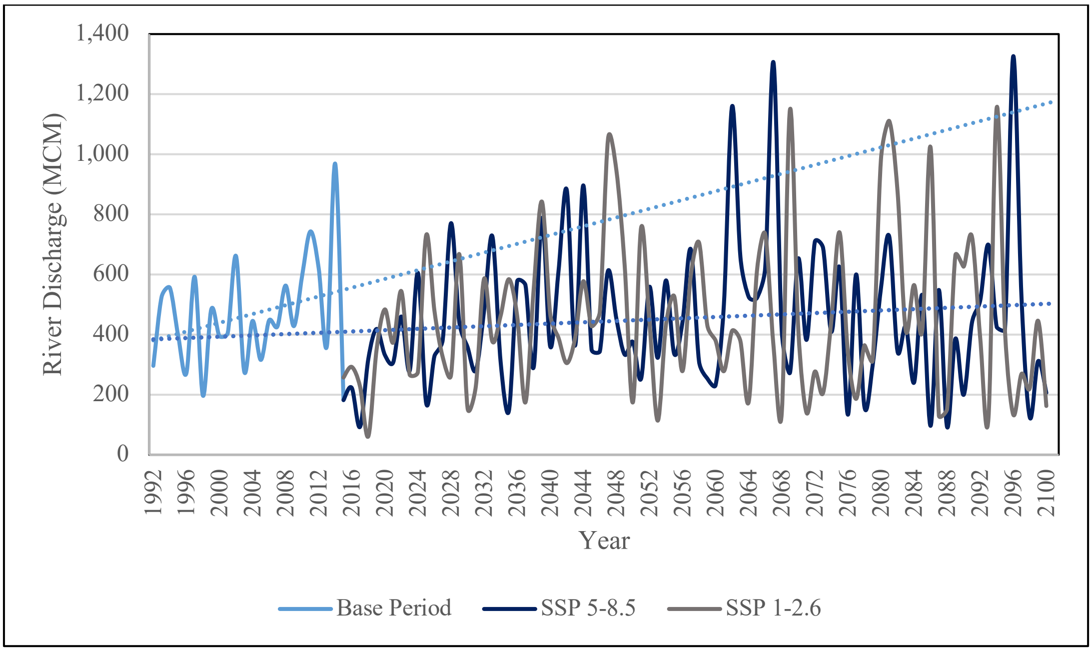

Figure 4-20: Annual river discharge to Nachchaduwa Reservoir under SSP scenarios

River discharge variations at Nachchaduwa Reservoir were analysed using discharge plots extrapolated across various climate scenarios and seasonal farming practices, providing a comprehensive grasp of the hydrological implications of climate change. In agricultural planning and water resource management concepts, it is critical to analyse river inflow to irrigation reservoirs during the course of the Maha and Yala cultivation seasons.

The Maha cultivation season, which is representative of the rainy season and is associated with increased precipitation and river inflow, invites a study of river inflow patterns to take advantage of water storage and use opportunities, particularly when optimising irrigation supply. Similar to the variability of rainfall for the base period, SSP 1-2.6 and SSP 5-8.5 scenarios, river inflow under SSP 5-8.5 provides higher estimates and higher variability than under SSP 1-2.6 depicted in Figure 4-21.

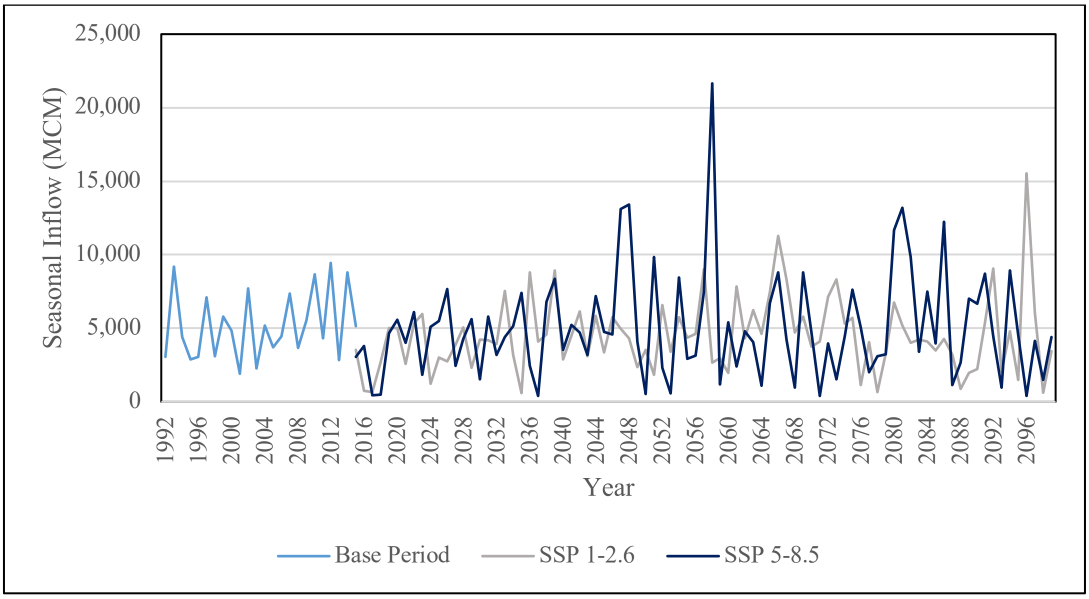

Figure 4-21: Seasonal river inflow to Nachchaduwa Reservoir under SSP scenarios - Maha Season

The Yala cultivation season, which is representative of the dry season and is characterised by reduced river inflow and increased irrigation requirements, requires a careful evaluation of anticipated changes in river inflow dynamics to determine water availability for crop cultivation. Compared to Maha seasonal river inflow volumes, Yala seasonal river discharge volumes are considerably low and show different variability in climate scenarios. During the Yala season, the SSP 1-2.6 scenario generates higher estimates than the SSP 5-8.5 scenario, while the maximum annual discharge volume during the 85 years has been reduced by 48.51%.

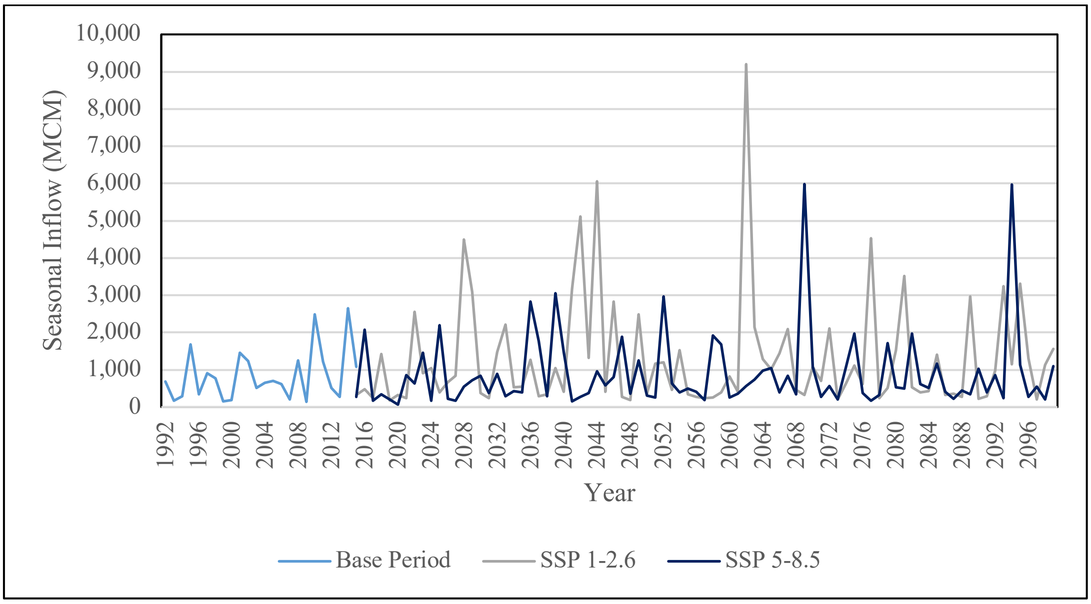

Figure 4-22: Seasonal River inflow to Nachchaduwa Reservoir under SSP scenarios - Yala Season

4.3 Reservoir Operation

The chapter presents the results of reservoir operation modelling developed to reduce water shortages during severe drought conditions. Irrigation releases were estimated using the two-point hedging rule principle, allowing the amendment of the reservoir storage rules and supplying irrigation requirements under reduced deficit.

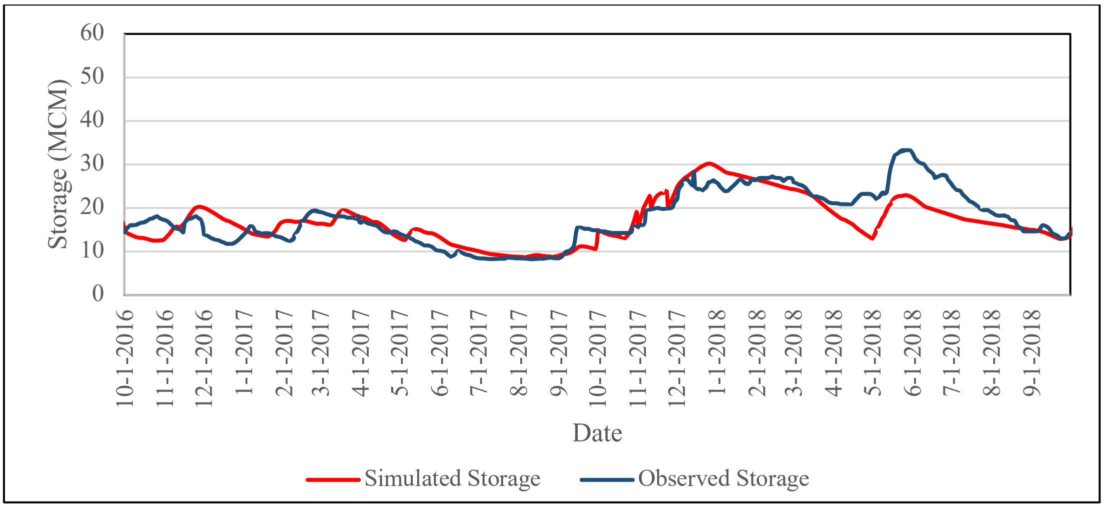

Figure 4-23: Observed vs Simulated reservoir storage for the calibration period

Figure 4-24 compares simulated and observed reservoir storage during the validation period of 01/10/2018 to 30/09/2020.

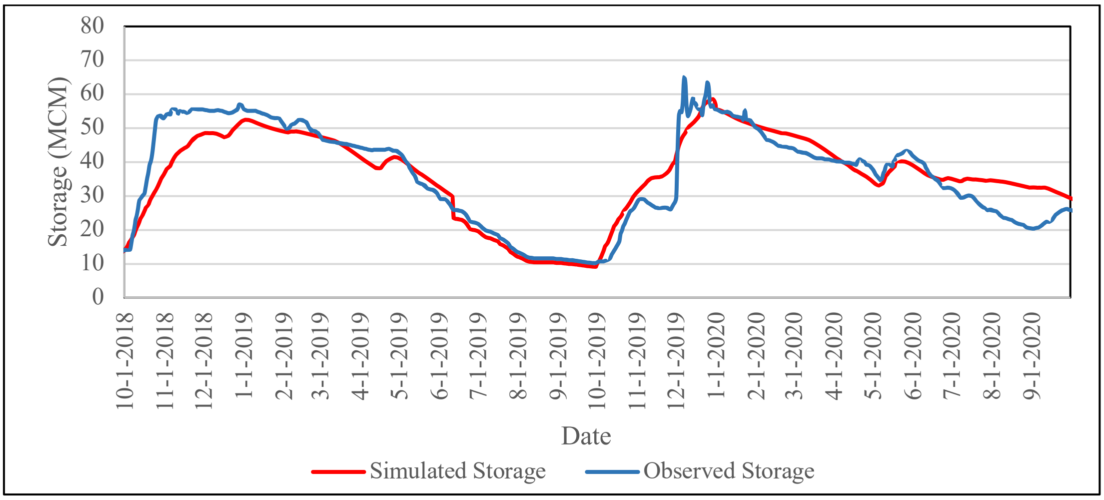

Figure 4-24: Observed vs Simulated reservoir storage for the validation period

The simulation results provided valuable insights into the performance of different hedging strategies under varying climatic and hydrological conditions. Using objective functions, including RMSE-observations standard deviation ratio (RSR), Nash-Sutcliffe Efficiency (NSE), coefficient of determination (R^2) and percentage bias (PBIAS), model performance for calibration and validation were evaluated. Figure 4-23 presents a comparison of simulated reservoir storage and observed reservoir storage during the calibration period of 01/10/2016 to 30/09/2018. Reservoir operation simulations indicated good to satisfactory performance according to the objective function evaluations for both calibration and validation periods, as presented in Table 4-3.

Table 4-3: Performance Rating of Reservoir Operation Modelling

Duration	**NSE**	**R^2**	**RSR**	**PBIAS**
Calibration	0.641	0.658	0.599	-0.043
Validation	0.750	0.752	0.387	-0.004

Incorporating reservoir inflow simulations, rainfall and temperature projections under SSP -2.6 and SSP 5-8.5 scenarios, reservoir operations for future scenarios were estimated to analyse the impact of climate change. Figure 4-25 presents reservoir annual cumulative reservoir storage volumes for SSP 1-2.6 and SSP 5-8.5 scenarios during base (2000-2014), near future (2015-2044), mid future (2045-2074) and far future (2075-2100) periods. Reservoir storage volumes for the SSP 5-8.5 scenario generate higher values than the SSP 1-2.6 scenario. In addition, Figure 4-25 highlights that the annual average storage volumes for future periods have considerably increased relative to base period estimates.

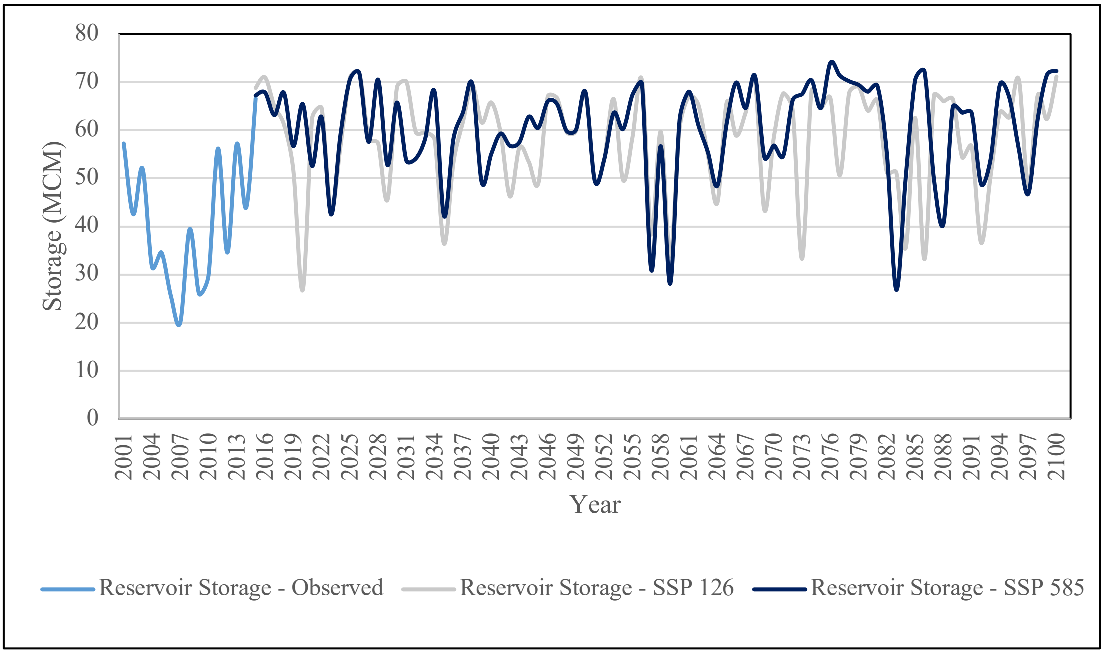

Figure 4-25: Varying reservoir storage volumes for future scenarios

Considering the varying irrigation requirements and significant changes in climate conditions during the Yala and Maha cultivation seasons, an analysis of irrigation supply estimates was conducted separately for the two seasons. Figure 4-26 presents that Maha cultivation seasonal irrigation supply estimates for future scenarios have decreased compared to base period estimates due to increased water availability caused by higher rainfall values depicted in Figure 4-7.

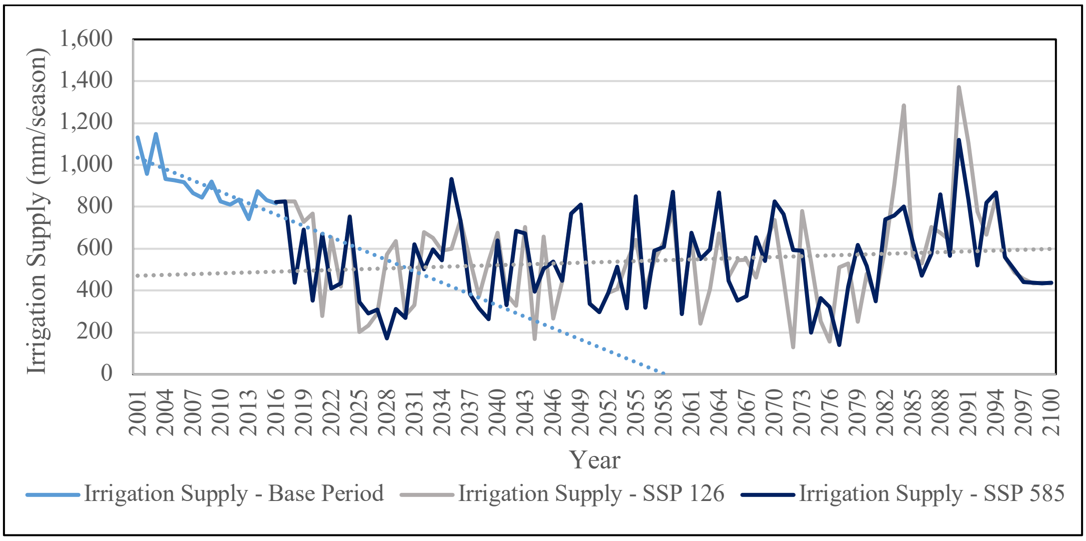

Figure 4-26: Cumulative irrigation supply during Maha Season

Controversy: Yala cultivation seasonal irrigation supply does not imply a trend in variability. Further, Figure 4-27 depicts the turbulent variation of irrigation supply, which is characterised by close peaks and valleys. Regardless of reduced cultivated area and cropping period (135-day and 105-day paddy are cultivated during Maha and Yala cultivation seasons, respectively), irrigation supply estimates for future scenarios vary in the window of 200-800 mm/season for both cultivation seasons.

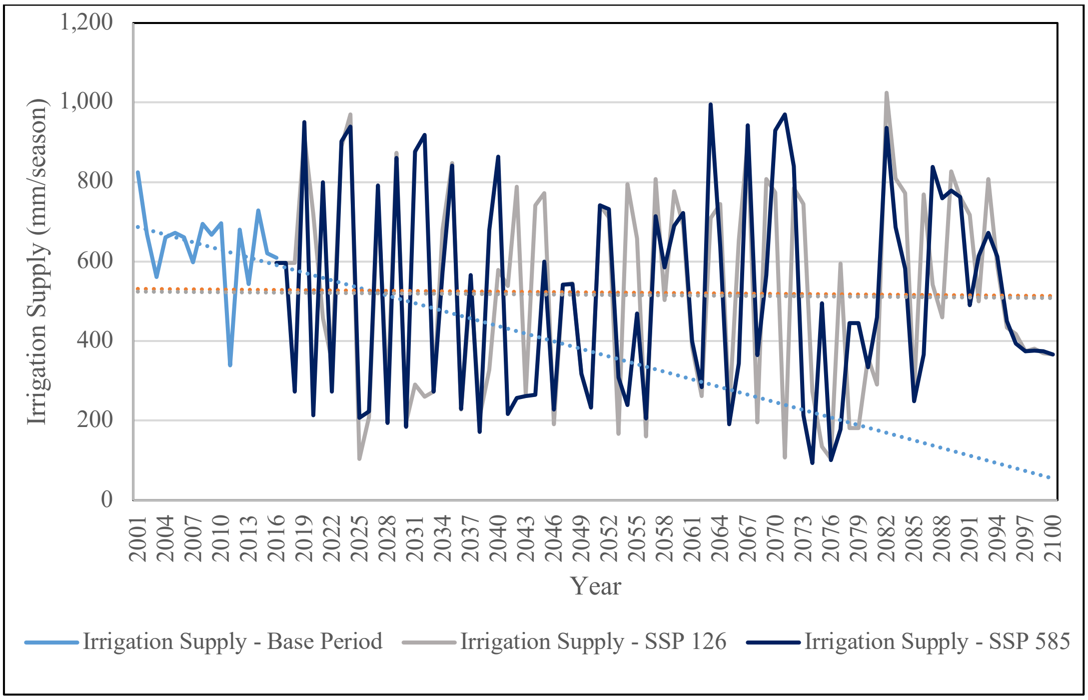

Figure 4-27: Cumulative irrigation supply during the Yala Season

CHAPTER 5

DISCUSSION

The sustainability and efficiency of irrigation schemes are challenged due to ever-growing water demand, changing climatic conditions, and conventional irrigation systems. Assessing irrigation efficiency is paramount in evaluating the performance of water management strategies for existing water scarcity. Nachchaduwa Irrigation Scheme, situated in the Northcentral Province of Sri Lanka, facilitates background to conduct a case study to evaluate irrigation efficiency amidst challenging climate conditions and water demands.

The discussion chapter is arranged to address the objectives of this research study, which aimed to assess the water use efficiency of the Nachchaduwa irrigation scheme under changing climate scenarios. The main aim of this research was achieved by following specific objectives,

1. To estimate the crop water requirement of the Nachchaduwa Irrigation Scheme using an optimum evapotranspiration estimation method
2. To simulate the reservoir inflow to the Nachchaduwa Reservoir using a hydrological model
3. To simulate the actual irrigation supply from the Nachchaduwa reservoir to the downstream irrigation scheme using a reservoir operation model
4. To assess the impacts of climate change on irrigation supply and irrigation requirement under changing climate scenarios

5.1 Crop Water Requirement of Nachchaduwa Irrigation Scheme

In Sri Lanka, during the Maha season, 135-day paddy is cultivated, and during the Yala season, 105-day paddy is cultivated. Regardless of the crop water requirement for the extended period during the Maha season, the crop water requirement during the Yala season is considerably high due to inadequate water availability in irrigation reservoirs. Crop water requirement variation for the Maha season during the base period shows a decreasing trend due to frequent rainfall events from the northeast monsoon. Figure 4-16 and Figure 4-17 depict more reduction in crop water requirement for future scenarios relative to the base period, which is expecting severe higher rainfall events during the Maha cultivation season.

Overall, crop water demand during the Maha season under SSP 1-2.6 is higher compared to SSP5-8.5, depicted in Figure 4-15. The projected changes in ET_o can explain this counterintuitive result. While SSP1-2.6 projects an increase in rainfall during the Maha season, it also anticipates a rise in ET_o due to increasing temperatures. This combination of contributors has caused an increment in crop water requirement under SSP scenarios during the Maha season. Across considered climate scenarios, seasonal crop water requirement estimates were evaluated in terms of near (2015-2044), mid (2045-2074) and far (2075-2100) future durations. Specifically, the mean crop water requirement of Maha season during the base period is 1,166.87 mm/season, which decreases to 1,076.15 mm/season for SSP 1-2.6 and further to 1,053.17 mm/season in SSP 5-8.5. Correspondingly, the standard deviation decreases from 79.61 in the base period to 56.56 in SSP 1-2.6 and 82.88 under SSP 5-8.5, reflecting percentage decrements of approximately 28.95% and 14.01%, respectively, indicating higher fluctuations for future scenarios.

Conversely, Yala seasonal crop water requirements show a significant increment under SSP 5-8.5 compared to SSP 1-2.6, which follows a similar trend to the base period. Since crop water requirement estimates depend on climate variables, these observations provide further evidence that climate projections under SSP 5-8.5 provide realistic estimates compared to 2010s' decadal climate characteristics. Under SSP scenarios, the mean crop water requirement during the base period is 767.18 mm/season, which increases to 774.41 mm/season, representing percentage increments of 0.9%. This indicates potential challenges associated with increased water demands in the future. This upward trajectory in mean values is accompanied by a corresponding increase in maximum irrigation requirements, suggesting more significant variability in irrigation needs, especially under more extreme climate scenarios.

In conclusion, the observed trends and variability patterns highlight the complexities and uncertainties inherent in crop water requirements under climate change. These results would challenge decision-making and implementing strategies for water management.

5.2 Reservoir Inflow to Nachchaduwa Reservoir

Water availability in the Malwathu Oya basin is predominantly controlled by the reservoirs and tank cascade systems. Hence, the impact of reservoirs on streamflow simulation was evaluated. Neglecting the reservoir operations in hydrological modelling for a reservoir-rich river basin would result in overestimates in streamflow. The HEC-HMS software package is suitable for modelling watersheds with limited data resources, while distributed hydrological modelling requires more data resources and effort to calibrate the models.

The hydrological model was developed only considering the four major reservoirs in the upper Malwathu Oya basin. Medium and minor reservoirs and tank cascade systems were not considered due to a lack of data and complexity. Hence, performance-indicative functions show satisfactory values for model calibration and validation. Further, the Nachchaduwa Reservoir water is extracted to fulfil irrigation and industrial requirements. Therefore, the runoff coefficient calculated for both scenarios represents shallow river runoff conditions.

Statistics on reservoir inflow variations from the base period (1992-2014) to the anticipated scenarios under SSP 5-8.5 and SSP 1-2.6 from 2015 to 2100 have important implications for reservoir operations of Nachchaduwa Reservoir. To identify deviations from normative conditions due to changing climates, the base period discharge plot provides a fundamental point of reference that clarifies historical river inflow dynamics. The average yearly inflow to the reservoir during the base period (1992–2014) was 481.70 MCM, with a standard deviation of 204.36 MCM. Even though the high variability of river inflow estimates due to frequent extreme climate events has neutralised the trend for future scenarios, river discharge simulations for the historical period (1992-2014) depict an increasing trend with a gradient of 7.30.

The resulting estimates for mean inflow reveal different patterns under the SSP 5-8.5 and SSP 1-2.6 scenarios. The mean annual inflow decreases to around 442.91 MCM under the SSP 5-8.5 scenario (2015–2100), representing a decrease of approximately 8.14% from the base period. However, the inflow variability increases significantly as the standard deviation increases to 314.68 MCM, providing evidence of more extreme and frequent rainfall events.

The mean annual inflow under SSP 1-2.6 increased significantly to 689.55 MCM between 2015 and 2100, representing an increase of about 43.16% over the base period. Similarly, the standard deviation increases and reaches 305.78 MCM. River discharge simulations for SSP 1-2.6 ensure a more promising future for water availability. The quantified statistics showing the variability provide a basis for understanding the possible impacts of climate change on the river discharge to Nachchaduwa Reservoir.

5.3 Irrigation Supply from the Nachchaduwa Reservoir

The reservoir operation simulation of Nachchaduwa Reservoir was conducted using a water balance model based on the two-point hedging rule principle to control irrigation supply and water detention. The one-point technique (HR1) involves releasing a predetermined percentage of demand during the current period, whereas the two-point technique (HR2) changes release based on current demand and the difference between current and previous period releases. Considering the good to satisfactory model performance rating for calibration and validation explained in Tables 4-3, irrigation supply estimates were extracted from reservoir operation simulations.

The annual cumulative irrigation supply estimates fluctuate in the range of 866.56 mm/season to 1,148 mm/season for the base period, which declines to the range of 810.81 MCM to 832.14 mm/season during the near future period under SSP 1-2.6 scenario. Further, the variability rises under SSP 5-8.5, and mean cumulative estimates vary more noticeably, from 278.01 mm/season to 873.59 mm/season. The estimates of irrigation supplies exhibit increasing variability during mid and far-future timeframes. The mean cumulative estimates for the mid-future and far-future under the SSP 1-2.6 scenario show a significant increase over the base period, ranging from 658.84 mm/season to 1,372 mm/season. Under the SSP 5-8.5 scenario, irrigation supply estimates are variable but generally tend to be lower, ranging from around 198.66 mm/season to 1,120 mm/season. These patterns demonstrate the variability of irrigation supply estimates for climate projections under SSP scenarios.

Analysis of irrigation supply estimates was conducted in terms of Yala and Maha cultivation seasons for SSP 1-2.6 and SSP 5-8.5 scenarios. Yala and Maha cultivation seasonal irrigation supply estimates depict a similar decreasing trend with different high and low ends during the base period. Yala seasonal supply estimates during the base period vary from 339.11 mm/season to 824.51 mm/season, while for Maha season, estimates vary between 741.21 mm/season to 1,148 mm/season. According to the Maha seasonal estimates presented in Figure 4-26, SSP 1-2.6 projections generate higher estimates relative to SSP 5-8.5 for the near and mid future. Similar to irrigation requirements and river inflow variations for future scenarios, Yala seasonal estimates fluctuate intensely. In conclusion, the analysis of irrigation supply estimates for Yala and Maha cultivation seasons demonstrates complex variability, highlighting the requirement for effective water management strategies.

CHAPTER 6

CONCLUSIONS, LIMITATIONS AND RECOMMENDATIONS

6.1 Conclusions

The research aimed to assess the WUE of the Nachchaduwa Irrigation Scheme under changing climate scenarios, focusing on achieving objectives that address the challenges posed by climate variability on crop water requirement and water availability of a dry zone irrigation scheme. The conclusion chapter is structured in terms of objectives outlined at the beginning of the research, providing insights into the overall findings of the study.

The analysis of crop water requirement estimates revealed significant seasonal variations in crop water demand, influenced by different SSP climate scenarios. During the base period, the Maha seasonal crop water requirement showed a decreasing trend due to increased extreme rainfall events. In contrast, the Yala seasonal water demand showed an increasing trend. Yala seasonal crop water demand is significantly higher for the SSP 5-8.5 scenario than the SSP 1-2.6 scenario, indicating the critical impacts of climate change. These findings highlight the requirement of unique water management strategies for each cultivation season.

In order to obtain irrigation supply through reservoir operations, river inflow to the Nachchaduwa Reservoir was simulated using a hydrological model. The HEC-HMS software was employed to model the watershed, considering the major reservoirs in the upper Malwathu Oya basin. The study demonstrated that climate change and the functions of reservoir networks within the basin significantly impact river inflows. The SSP 5-8.5 scenario shows a decrease in mean annual inflow and increased variability, while the SSP 1-2.6 scenario projected a substantial increase in river inflow to the reservoir. These results provide a robust understanding of water availability in the Malwathu Oya basin, illustrating more frequent and severe extreme river discharge events for SSP 1-2.6 and SSP 5-8.5 scenarios.

The irrigation supply from the Nachchaduwa Reservoir to the downstream irrigation scheme was simulated using a reservoir operation model based on the two-point hedging rule principle. The model's performance, validated through calibration, indicated good results. The simulation results showed fluctuating irrigation supply estimates, with a general decline for the near future under the SSP 1-2.6 scenario and increased variability under the SSP 5-8.5 scenario. Further, the Maha seasonal irrigation supply estimates demonstrated a decreasing trend for the near future under SSP 1-2.6, while the Yala season exhibited enhanced fluctuations and increased variability, especially under SSP 5-8.5.

In conclusion, the study to assess the impacts of climate change on irrigation supply and irrigation requirements under SSP scenarios revealed that climate projections under the SSP 5-8.5 scenario represent more severe climate events than SSP 1-2.6, demonstrating the potential challenges for decision-making in agricultural water management. In addition, findings emphasise the critical need for adaptive seasonal water management strategies that consider future climate variability to ensure the sustainability of Sri Lanka's dry zone irrigation systems.

6.2 Limitations of Study

Major limitations and constraints faced during the research were due to the need for extensive data sources to capture the overall water balance of the Malwathu Oya basin. Extracting river discharge estimates for reservoir operation simulations at the upstream location would pose inherent drawbacks due to varying catchment characteristics between the upper Malwathu Oya subbasin, Kanadara Oya sub-basin and upstream catchment of Nachchaduwa Reservoir. Even though the upstream basin from the Kappachi river gauging station consists of 2,077.03 km^2 of basin area, which requires observations from one river gauging station for model calibration and validation according to world meteorological guidelines, river discharge estimates of upstream locations may not accurately capture temporal dynamics of the upstream watershed same as at Kappachi gauging station.

Another limitation was the uncertainty inherent in climate projections given by bias-corrected GCM estimates for SSP 5-8.5 and SSP 1-2.6 scenarios. These uncertainties, particularly regarding the frequency and intensity of extreme weather events, significantly affect the projected crop water requirements and reservoir inflow estimates. As a result, accurate prediction of future water availability and irrigation demand becomes challenging. Understanding these limitations is crucial for interpreting the study's findings and guiding future research to address these gaps, enhance model accuracy, and develop more robust water management strategies under changing climate scenarios.

6.3 Recommendations

Recommendations for future work can be categorised into crop water demand estimation, hydrological modelling, and reservoir operation modelling. With the availability of accurate data on soil properties, land use and climate variables, spatially distributed crop water demand estimations would allow researchers to conduct a more comprehensive analysis. With the availability of high-resolution remotely sensed data products for actual evapotranspiration estimates, distributed crop water requirement estimations obtained through theoretical techniques could be validated.

The hydrological model of the Malwathu Oya basin was developed considering only the major reservoirs within the basin due to data constraints. These simplifications may not fully capture the intricacies of the entire watershed, potentially leading to discrepancies between the model results and actual conditions. It is recommended that data collection of medium reservoirs within the Malwathu Oya basin be conducted with the objective of incorporating medium reservoir functions into hydrological modelling through data-driven techniques, which allows for the handling of more data with a wider scope.

Due to the complexities involved in reservoir operations of Nachchaduwa Reservoir, conventional reservoir operation models could not capture the overall water balance during severe climate events. This study was conducted using a data-driven model, which was manually adjusted to look back at the reservoir's storage after an extreme climate event. To address these challenges, a machine learning-based reservoir operation model could be adopted to identify reservoir storage after extreme climate events and train the model to respond accordingly.

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