DYNAMIC OPTIMISATION OF WATER ALLOCATION FOR HYDROPOWER AND AGRICULTURAL PRODUCTIVITY IN A SRI LANKAN RESERVOIR SYSTEM UNDER FUTURE CLIMATE VARIABILITY

Wijesundara Mudiyanselage Suraj Tharuka

248078X

Degree of Master of Engineering in
Water Resources Engineering and Management

Department of Civil Engineering

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Supervised by

Dr H. G. L. N. Gunawardhana

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

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

Department of Civil Engineering
University of Moratuwa
Sri Lanka

March 2026

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ABSTRACT

Dynamic Optimisation of Water Allocation for Hydropower and Agricultural Productivity in a Sri Lankan Reservoir System under Future Climate Variability

At the global scale, increasing climate-driven hydrological variability is undermining the reliability of historical reservoir operating rules and intensifying competition between hydropower and irrigation, particularly in monsoon-dominated regions, as highlighted by the Inter-Governmental Panel on Climate Change (IPCC) Sixth Assessment Report. This study develops and applies a dynamic, machine learning–based framework to optimise water allocation between hydropower generation and agricultural irrigation in the Samanalawewa–Walawe reservoir system in Sri Lanka under current and near-future climate variability. The work addresses the growing conflict between energy and irrigation demands, compounded by increasingly variable monsoonal inflows, recurrent droughts, and the limitations of conventional rule-curve and programming-based reservoir operation methods in handling nonlinear, uncertain hydrological regimes. The methodology integrates three main components: (i) a daily rainfall–runoff model for the Samanalawewa sub-catchment developed in the Hydrologic Engineering Center–Hydrologic Modeling System (HEC-HMS); (ii) a machine learning module in which a Physics-Informed Neural Network (PINN) and a Long Short-Term Memory (LSTM) network are trained to simulate daily storage change based on the full reservoir water balance and are comparatively evaluated; and (iii) a Python-based dynamic water allocation model that embeds the best-performing ML architecture to generate daily irrigation and hydropower releases, subject to operational rule constraints. The HEC-HMS model reproduces historical inflows with Nash Sutcliffe Coefficient (NSE) values of 0.74 and 0.75, an acceptable Mean Ratio of Absolute Error (MRAE), and realistic flow-duration characteristics, indicating reliable representation of monsoon-driven runoff processes. Under normal hydrological conditions, both LSTM and PINN achieve high predictive skill for daily storage change (NSE $\approx$ 0.87–0.92), but under hybrid datasets including extreme events, the LSTM exhibits smoothed peaks and reduced accuracy (testing NSE $\approx$ 0.67), whereas the PINN maintains higher robustness (testing NSE $\approx$ 0.80) and superior mass-balance consistency, as shown by lower residual variance and more physically plausible parameter sensitivities. The dynamic allocation model, driven by observed inflows and climate-conditioned inputs, yields an optimised storage trajectory that remains consistently below the historically observed storage while satisfying minimum irrigation and hydropower thresholds, revealing a persistent surplus of about 30 MCM that can be reallocated to enhance irrigated area or energy production and reduce spill and evaporation losses. Future inflow and evaporation scenarios for 2021–2040 are generated by coupling downscaled CNRM-CM6-1 precipitation and temperature projections under two Shared Socioeconomic Pathways (SSPs), SSP2-4.5 and SSP5-8.5, with the calibrated HEC-HMS and an LSTM-based evaporation model, while irrigation and hydropower demands are projected using data-driven models conditioned on climate signals. Future projections (2021–2040) reveal that, while SSP2-4.5 maintains comparatively smooth inflow and release patterns, SSP5-8.5 produces sharper inflow peaks, longer low-inflow recessions, and more episodic hydropower and irrigation releases, indicating a clear shift from seasonally regulated storage dynamics to a highly variable, event-driven operational regime.

Keywords: climate change, HEC-HMS, LARS-WG, LSTM, multipurpose reservoirs, PINN, water balance

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ABM	-	Agent-Based Modelling
AI	-	Artificial Intelligence
ANNs	-	Artificial Neural Networks
CEB	-	Ceylon Electricity Board
CMIPs	-	Coupled Model Intercomparison Projects
CN	-	Curve Number
CNRM-CM6	-	Centre National de Recherches Météorologiques - Climate Model 06
DDDP	-	Discrete Differential Dynamic Programming
DP	-	Dynamic Programming
DRC	-	Dynamic Rule Curves
EAs	-	Evolutionary Algorithms
ECHAM5	-	European Centre Hamburg Climate Model version 5
FIDP	-	Fuzzy-Interval Dynamic Programming
FLP	-	Fuzzy Linear Programming
GAs	-	Genetic Algorithms
GCA	-	Grey Correlation Analysis
GCMs	-	Global Climate Models
GIS	-	Geographical Information System
GNDP	-	Gin–Nilwala Diversion Project
GPR	-	Gaussian Process Regression
GWh	-	Gigawatt hour
HEC-HMS	-	Hydrologic Engineering Centre's Hydrologic Modelling System
HEC-ResPRM	-	Hydrologic Engineering Centre-Prescriptive Reservoir Model
HEC-ResSim	-	Hydrologic Engineering Center-Reservoir System Simulation
IAM	-	Integrated Assessment Models
ID	-	Irrigation Department
IM1	-	First Inter-Monsoon
IM2	-	Second Inter-Monsoon

IMOPSO	-	Improved Multi-Objective Particle Swarm Optimisation
IWO	-	Invasive Weed Optimisation
KIS	-	Kalthota Irrigation Scheme
LARS-WG	-	Long Ashton Research Station Weather Generator
LP	-	Linear Programming
LSTM	-	Long Short-Term Memory
MAE	-	Mean Absolute Error
MASL	-	Mahaweli Authority of Sri Lanka
MCDM	-	Multi-Criteria Decision Making
MCM	-	Million Cubic Meters
MIKE	-	DHI MIKE Hydrological Modelling System
ML	-	Machine Learning
MODSIM	-	MODSIM River Basin Management Model
MOLP	-	Multi-Objective Linear Programming
MPC	-	Model Predictive Control
MSE	-	Mean Squared Error
MW	-	Megawatt
NEM	-	Northeast Monsoon
NLP	-	Non-Linear Programming
NSE	-	Nash–Sutcliffe Efficiency
OWMP	-	Open Water Management Program
PaML	-	Physics-aware Machine Learning
PBIAS	-	Percent Bias
PEPF	-	Percentage Error in Peak Flow
PIDL	-	Physics-Informed Deep Learning
PINNs	-	Physics-Informed Neural Networks
PSO	-	Particle Swarm Optimisation
QEPANET	-	EPANET-based Water Network Optimisation Tool
QP	-	Quadratic Programming
RCMs	-	Regional Climate Models
RCP	-	Representative Concentration Pathways

RMSE	-	Root Mean Squared Error
SCS	-	Soil Conservation Service
SD	-	System Dynamics
SMA	-	Soil Moisture Accounting
SOBEK	-	Deltares SOBEK Integrated Hydraulic Modelling Suite
SSP	-	Shared Socioeconomic Pathways
SVMs	-	Support Vector Machines
SWAT	-	Soil and Water Assessment Tool
SWM	-	Southwest Monsoon
VIC	-	Variable Infiltration Capacity
WEAP	-	Water Evaluation and Planning System
WMO	-	World Meteorological Organisation

CHAPTER 1

1 INTRODUCTION

1.1 General

Water scarcity is an increasing global concern that is driven by factors such as pollution and poor management, impacting both wet and dry regions (Chakkaravarthy, 2019). Rather than being solely the result of physical water shortages, ineffective management is often the primary cause (Molden, 2020). In wet regions, inadequate storage and distribution systems lead to shortages, particularly during dry seasons. The imbalance between natural freshwater availability and human demands contributes to various social, economic, and political challenges, including poverty and ecosystem degradation (Gleick & Cooley, 2021). As a result, inefficient water conservation during the wet season reduces water availability for irrigation during dry periods (Beça et al., 2023).

Addressing this crisis requires the implementation of sustainable water management strategies, such as improving water-use efficiency, desalination, and water reuse, while also considering associated environmental and health concerns (Gleick & Cooley, 2021). This highlights the need for reservoirs to store excess water from rainy periods for use when it is most needed. Reservoirs are a fundamental component of water resource systems, providing a reliable and secure supply for domestic, industrial, and agricultural purposes while supporting economic development and livelihood sustainability (He et al., 2024).

As an added benefit, they also serve as a key source for hydropower generation, providing a sustainable energy solution. Reservoirs must maintain an adequate level of service by ensuring sufficient water releases to meet demand while also minimising the risk of prolonged and severe water shortages (Bakker, 2012; Cuvelier et al., 2018). A recent estimate showed that the total global storage capacity of reservoirs and dams ranges between 7,000 and 8,000 km³ (Lehner et al., 2011). In addition to the construction of new dams to meet irrigation and water supply demands, the number of hydropower dams is projected to triple globally from approximately 2,000 to nearly 6,000 by 2030 due to increasing electricity demand (Ansar et al., 2014). Furthermore, regions with inadequate water resource infrastructure continue to invest in dam construction as a means of improving quality of life (Muller et al., 2015).

Reservoir management requires balancing conflicting objectives, such as flood control, drought mitigation, hydropower generation, and water supply, while ensuring compliance with storage capacity, outflow regulations, and ecological constraints (Zhang et al., 2020). Improper water resource management has resulted in global conflicts over water allocation, as multiple stakeholders compete for limited water supplies. Conflicts frequently emerge between upstream communities facing displacement from reservoir submersion and downstream communities experiencing changes in flow patterns, water quality, and ecosystems (Jamali et al., 2021). Modifying reservoir operations can alter natural streamflow patterns, negatively impacting aquatic ecosystem biodiversity (Lee et al., 2023). To overcome these challenges, reservoir operating rules, known as 'rule curves', are traditionally implemented to regulate storage levels for flood control and hydropower generation, ensuring optimised water release strategies to enhance energy production and minimise flood risks (Garrote et al., 2023). With growing water scarcity, particularly in multipurpose reservoirs, management strategies should prioritise reducing both the frequency and severity of water shortages while optimising water availability for all users (Gu et al., 2017).

Climate change is considerably impacting hydrologic systems, increasing precipitation in wetter regions while intensifying drought conditions in drier areas (He et al., 2020). These variations affect the temporal and spatial patterns of rainfall, evaporation, and streamflow, thereby influencing reservoir water availability (Kharin et al., 2018). The rising occurrence of severe droughts, marked by extended duration, extensive impact, and high intensity, presents significant challenges to water supply and demand, with some regions projected to face once-in-a-century droughts or unprecedented arid conditions (Choi et al., 2020; Yi et al., 2022). The growing occurrence of extreme droughts, defined by their prolonged duration, extensive impact, and high intensity, presents significant challenges to water supply and demand (Yi et al., 2022).

The adaptation of reservoir operation policies to address uncertainties in future water availability and demand has been extensively studied (Basheer et al., 2023; Herman & Giuliani, 2018; Nourani et al., 2020). Nourani et al. (2020) demonstrated that re-optimising reservoir operations can effectively reduce water supply deficits under climate change scenarios, while Basheer et al. (2023) emphasised that periodic adjustments to operation policies support the efficient management of both engineering and economic objectives amid evolving climate and socio-economic conditions. These risks underscore the urgent need for adaptive water management strategies to maintain water accessibility, quality, and sustainability under shifting climatic conditions (Beça et al., 2023).

To address growing challenges in reservoir water resource management, optimising water allocation is essential. Reservoir operation presents a complex decision-making challenge, requiring a balance between time-dependent conflicting objectives (Dobson et al., 2019). Studies have shown that mathematical modelling for simulation and optimisation can significantly improve reservoir performance (Dobson et al., 2019; Saab et al., 2022; Ziaei et al., 2012). An optimisation model aims to maximise or minimise an objective function within defined constraints, while a simulation model analyses the behaviour of a water system under specific control actions. (Lin & Rutten, 2016). Optimisation problems have traditionally been addressed using Linear Programming (LP) (Lee et al., 2023), Dynamic Programming (DP) (Rani et al., 2020), as well as Quadratic Programming (QP) and Non-Linear Programming (NLP) (Alfieri et al., 2006). Reservoir system simulation can be conducted using hydrological and hydraulic models, including HEC-ResSim, MIKE 11, and SOBEK (Ngo et al., 2007). However, these traditional methods often face limitations in handling complex, dynamic, and uncertain hydrologic conditions. Therefore, novel approaches are needed to enhance decision-making in water resource allocation.

Machine Learning (ML) has become a transformative advancement in hydrology, significantly enhancing the comprehension and prediction of hydrological processes (Hasan et al., 2024). ML algorithms provide effective methodologies for managing complex, high-dimensional datasets while accurately capturing non-linear relationships with the field transitioning into the big data era (Lange & Sippel, 2020). Although challenges such as data heterogeneity and spatiotemporal inconsistencies persist, ML techniques consistently demonstrate superior performance compared to conventional approaches in hydrological research (Saha & Chandra Pal, 2024; Tessey et al., 2025). Recent advancements in machine learning and artificial intelligence have introduced Physics-Informed Neural Networks (PINNs) as a promising tool for water resource optimisation. Unlike purely data-driven models, PINNs integrate physical laws into neural network architectures (Bhasme et al., 2021; Farea et al., 2024), making them particularly effective for hydrological and reservoir modelling (Luo et al., 2024). The application of PINNs in reservoir optimisation presents a novel approach to enhancing predictive accuracy and operational efficiency, especially in water-scarce regions. This study examines regional water management challenges with a specific focus on the Samanalawewa Reservoir in Sri Lanka. It aims to enhance the efficiency of reservoir management by developing an optimised water allocation framework.

To support future water allocation planning under changing climate conditions, this study proposes the development of a rainfall-runoff model for the Samanalawewa reservoir catchment using the Hydrologic Engineering Centre's Hydrologic Modelling System (HEC-HMS). This approach is adopted based on findings from previous studies identified through the literature review, which demonstrate the applicability of HEC-HMS for simulating rainfall–runoff processes in monsoon-influenced catchments. Once calibrated and validated using historical hydrological and meteorological data, this model will be used to simulate future inflow scenarios based on downscaled and bias-corrected climate projections. The use of HEC-HMS for such applications has been widely demonstrated in tropical and monsoon-influenced basins, including in Thailand (Gunathilake et al., 2020), Vietnam (Dau et al., 2020), and Ethiopia (Ayalew et al., 2024). Studies in these regions have shown that HEC-HMS can effectively capture climate-driven variations in seasonal runoff, inflow timing, and volume when forced with projected precipitation datasets. Following this precedent, the proposed model for the Samanalawewa catchment will provide the necessary hydrologic input to evaluate the performance of dynamic reservoir operation strategies under future climate variability. This study aims to optimise water distribution for hydropower generation and agricultural irrigation using a water balance model. Within this process, PINNs will be employed to integrate physical laws into neural network architectures. To achieve this, a hydrologic simulation-based water balance model will be developed to analyse reservoir inflows, storage dynamics, and outflows. Subsequently, a PINN-based optimisation framework will be implemented to enhance real-time water allocation, ensuring an optimal balance between energy production and irrigation needs. Finally, the effectiveness of the optimised strategy will be evaluated by assessing its impact on water use efficiency, hydropower generation, and agricultural sustainability.

1.2 Problem Statement

The reservoir systems in Sri Lanka are subject to rising issues from competing agricultural irrigation and hydropower generation demands, an issue that is further exacerbated by climate variability. The changes in precipitation patterns, rising droughts, and extreme hydrological variability create temporal and spatial disruptions in water availability, making conventional reservoir management strategies ineffective. Traditional optimisation and simulation methods, i.e., linear, nonlinear, and dynamic programming or standard hydrological models, struggle to deal with the nonlinear, dynamic, and uncertain nature of water inflows and demands under future climate states.

Thus, the need for advanced decision-support systems with the ability to simultaneously maximise hydropower production, ensure reliable irrigation supply, and maintain water balance under extreme conditions is urgent. Purely data-driven approaches, e.g., Long-Short Term Memory (LSTM) networks, lack generalizability to unseen extremes and may violate fundamental physical principles like mass conservation. In contrast, physics-informed approaches, e.g., PINNs, present a chance to blend governing hydrological principles with machine learning for enhancing both predictive capability and physical realism. Despite its promise, no studies have applied dynamic, physics-informed optimisation models to balance hydropower and agricultural water allocation under climate-driven uncertainties in tropical reservoir systems. This knowledge gap motivates the present study, with the goal of developing a PINN-based dynamic water allocation model for the Samanalawewa Reservoir that has the potential to improve operational efficiency, ensure agricultural productivity, and be resilient under future climate uncertainty.

1.3 Main Objective

The main objective of this study is to propose optimisation strategies through the development of a dynamic simulation model aimed at enhancing the efficiency of water resource allocation in a selected Sri Lankan reservoir system, addressing future climate variability and balancing the competing demands of hydropower generation and agricultural irrigation.

1.4 Specific Objectives

The specific objectives of this research are,

- To identify a river basin with competing water demands and simulate the water balance of the reservoir system using a suitable hydrologic model.
- To develop a dynamic optimisation model that incorporates real-time data and predictive analytics to allocate water resources effectively between hydropower generation and irrigation.
- To evaluate the performance of the dynamic optimisation model in allocating water for agricultural irrigation and hydropower generation under present and downscaled future climate scenarios.

1.5 Scope and Limitations

This study aims at the Samanalawewa Reservoir in Sri Lanka with the goal of optimising water allocation for agricultural irrigation and hydropower generation under both current and future climate variability. The research integrates a rainfall-runoff model (HEC-HMS) for inflow simulation and a water balance-based optimisation model using PINNs for enhancing the efficiency of reservoir operation. The simulation considers seasonal and inter-annual variability in inflows, storage processes, and outflows and measures water allocation system performance in terms of water use efficiency metrics, hydropower production, and irrigation reliability. Future climate impacts are incorporated using downscaled and bias-corrected precipitation projections to enable the assessment of reservoir operation robustness to extreme events. This work builds on previous research demonstrating the potential of ML models, including LSTM and PINNs, for improving the accuracy and efficiency of water allocation in reservoir systems.

Despite its strengths, the following are the shortcomings of this study. First, the model relies on historical and future climate data, which can create uncertainties in inflow and water allocation projections. Second, the study concentrates on a single-reservoir system, and results may not be transferable directly to multi-reservoir or basin-scale applications without additional calibration. Third, the framework assumes fixed operational constraints and infrastructure, without accounting dynamically for potential future modifications in reservoir design or irrigation policy. Fourth, while PINNs harness physical laws to improve predictive capacity under extremes, training and optimisation entail high computational costs and laborious hyperparameter tuning. Finally, the study focuses on irrigation and hydropower objectives, and environmental, ecological, or socio-economic water needs are not explicitly defined, which can limit the overall assessment of reservoir management.

1.6 Significance of the Research

This study has specific scientific, operational, and policy significance in water resource management under climate variability. By combining PINNs with a water balance model based on hydrological simulation, it provides an effective means of optimising reservoir water allocation between the competing hydropower generation and agricultural irrigation. As opposed to traditional methods, which have a tendency of utilizing stationary rule curves or purely data-driven models, the proposed approach ensures physical consistency, predictability, and sensitivity to extreme hydrologic events, which overcomes the limitations of traditional methods.

The study has three significant implications. First, it enhances the efficiency of reservoir operation as it enables water managers to dynamically assign resources based on real-time prediction and expected inflows, hence reducing water shortages and increasing energy production reliability. Second, it supports the attainment of agricultural sustainability by optimising irrigation scheduling and meeting crop water requirements despite changing or extreme climatic conditions. Third, by incorporating climate projections into reservoir management, the study enables climate-resilient water planning by creating usable information for policymakers and stakeholders to make informed decisions in the face of uncertainty. Moreover, the framework designed in this study can serve as a transferable methodology to other monsoon and tropical multipurpose reservoir systems, enabling broader application of machine learning integrated with hydrological principles. The study therefore bridges the gap between modern computational intelligence techniques and water resource management practice, offering scientific contributions and operational value in water resource management under future climate variability.

1.7 Structure of the Thesis

This thesis is structured into eight chapters, each designed to systematically present the research process and findings. Chapter 1 introduces the study, outlining the research background, objectives, and significance, while establishing the problem and scope of the research. Chapter 2 provides a detailed literature review, highlighting key studies and theoretical frameworks that inform the development of the research methodology. In Chapter 3, the methodology is discussed, explaining the data collection methods, model development, and integration of machine learning techniques for water allocation optimisation. Chapter 4 focuses on the data checking and analysis procedures used to ensure the reliability of the collected data for both the hydrological and machine learning models. Chapter 5 presents the model development and applications, detailing the integration of machine learning models and the dynamic optimisation framework for water management. The results of the study are presented in Chapter 6, showcasing the performance of the models under different scenarios. Chapter 7 provides a discussion of the results, offering interpretations and insights into the findings and their implications for reservoir management. Finally, Chapter 8 concludes the thesis by summarising the major findings, contributions to the field, and providing recommendations for future research and practical applications in water resource management.

CHAPTER 2

2 LITERATURE REVIEW

This chapter synthesizes existing knowledge on water resource management challenges in multipurpose reservoir systems, with particular attention to hydropower generation, agricultural irrigation, and competing sectoral demands. The review further examines traditional reservoir operation approaches, including rule-curve methods and optimisation techniques, before exploring emerging machine learning applications in hydrology, such as data-driven modelling, Physics-Informed Neural Networks (PINNs), and Long Short-Term Memory (LSTM) networks.

2.1. Chapter Introduction

Water resource management has become a central global concern in the twenty-first century due to the escalating impacts of climate change, population growth, and anthropogenic pressures on freshwater systems. Across both developed and developing regions, intensifying droughts, erratic precipitation patterns, and rising temperatures are disrupting the hydrological cycle, resulting in significant variability in streamflow, reservoir inflow, and water storage capacity. These changes threaten agricultural productivity, hydropower generation, and domestic water supply, underscoring the urgent need for efficient and adaptive management frameworks that can ensure long-term water security.

Traditional reservoir operation frameworks, often based on static rule curves or historical flow assumptions, are unable to address the increasing uncertainty and temporal variability of inflows. This non-stationarity, defined by shifting rainfall regimes and rising evapotranspiration rates, poses critical challenges to maintaining the delicate balance between reservoir storage, releases, and competing water demands. For example, recent projections indicate that small perturbations in rainfall or temperature can produce disproportionately large changes in river discharge and reservoir inflow, thereby destabilising established operating schedules (Ashofteh et al., 2013). Consequently, many regions that historically enjoyed water abundance are now experiencing seasonal scarcity and operational stress within multipurpose reservoir systems.

Balancing multiple and often conflicting objectives, such as hydropower production, irrigation supply, flood control, and environmental preservation, further compounds the complexity of water resource management. In many basins, hydropower operations prioritise maximising energy generation, while agricultural sectors demand sustained irrigation releases to support food security. These competing objectives can lead to severe trade-offs, especially during prolonged droughts or peak demand periods. As highlighted by (Beça et al., 2023), efficient reservoir operation must simultaneously account for energy reliability, irrigation scheduling, and ecological flow maintenance. However, under future climate scenarios characterised by greater extremes, maintaining such an equilibrium is increasingly difficult without advanced analytical and decision-support tools.

To address these emerging challenges, the field of water resource engineering has witnessed a significant methodological transformation, from traditional optimisation techniques to adaptive, dynamic, and data-driven frameworks. Historically, reservoir operation relied on mathematical approaches such as Linear Programming (LP), Nonlinear Programming (NLP), and Dynamic Programming (DP). While these techniques effectively modelled deterministic systems, they lacked the flexibility to account for stochastic climatic and hydrological variability. Modern research emphasises the integration of simulation–optimisation frameworks and hybrid models that combine process-based hydrologic simulations (e.g., SWAT, HEC-HMS, HEC-ResPRM) with optimisation algorithms and machine learning components (Beça et al., 2023). These approaches improve reservoir resilience by dynamically adjusting operation policies in response to evolving inflows and climatic projections.

At the same time, adaptive reservoir management, which involves real-time decision-making guided by probabilistic forecasts and system feedback, has gained prominence as an effective response to climate uncertainty. Bozorg-Haddad et al. (2022)

emphasised the role of system dynamics modelling in capturing feedback among climatic, hydrologic, and human systems, enabling water managers to simulate and test the impacts of various policy scenarios. Their findings show that integrated management frameworks, which blend physical modelling with data-driven approaches, enhance both operational performance and sustainability outcomes.

In this context, the evolution toward intelligent, machine–learning–based optimisation represents a paradigm shift in reservoir management. Data-driven techniques such as LSTM networks and PINNs are increasingly applied to forecast inflows, optimise releases, and maintain physical consistency in system behaviour. By fusing hydrologic theory with computational intelligence, these methods offer a robust pathway for decision-making under uncertainty, bridging the gap between predictive modelling and real-world operational control.

2.2. Water Resource Management Challenges

This section examines the key dimensions of reservoir management complexity, focusing on reservoir water balance dynamics, hydropower generation requirements, agricultural irrigation demands, and the trade-offs arising from competing water uses in multipurpose systems.

2.2.1. Reservoir Water Balance and System Dynamics

The reservoir water balance represents a fundamental component of water resources management, describing the relationship between inflows, storage, and outflows that dictate the temporal and spatial distribution of available water releases and inputs which are Precipitation ($P(t)$), Natural Inflow ($I(t)$), Irrigation Releases ($IR(t)$), Power Releases ($PR(t)$), Seepage ($SL(t)$), Evaporation ($E(t)$), Leakage Losses ($L(t)$), and Gross Storage ($S(t)$) at intervals between each day. This dynamic equilibrium is mathematically expressed through the mass balance Equation (1):

$$\frac{d(S(t))}{dt} = P(t) + I(t) - IR(t) - PR(t) - SL(t) - L(t) - E(t) \tag{1}$$

This equation provides the backbone for both deterministic and stochastic hydrological modelling, forming the basis for decision-making in irrigation scheduling, hydropower generation, and drought management. System dynamics frameworks allow the inclusion of time-dependent variables, such as population growth, industrial demand, and policy intervention, into reservoir water balance models. These models integrate mass balance equations with causal feedback structures to simulate the effects of decisions across multiple time horizons, offering insight into long-term resilience and adaptive capacity under uncertainty.

Nascimento et al. (2021) contributed to operationalizing reservoir dynamics by integrating telemetry-based real-time data with machine learning for spill forecasting in hydropower plants. Their model combined hydraulic control principles with predictive algorithms (Random Forest and Multilayer Perceptron), achieving 99% accuracy in forecasting spill events. This approach establishes a dynamic feedback loop: data assimilation → forecast → operational adjustment → updated state, which mirrors the system dynamics feedback process. Such predictive control ensures safety, maximises hydropower yield, and maintains the balance between inflow and outflow even under rapidly changing hydrological conditions.

Optimisation plays an important role in balancing competing reservoir objectives while maintaining water balance consistency. Nicklow et al. (2010) highlighted the role of Evolutionary Algorithms (EAs), notably Genetic Algorithms (GAs), in optimising nonlinear and multi-objective water management systems. GAs simulate the process of natural evolution, iteratively refining operational strategies to maximise objectives such as water supply reliability, energy production, and ecological flow maintenance. Their population-based and iterative structure aligns conceptually with system dynamics, where each generation represents a new state of the reservoir system responding to variable hydrological inputs.

Building on this, Yang et al. (2019) introduced a Multi-Criteria Decision-Making (MCDM) model coupled with Improved Multi-Objective Particle Swarm Optimisation (IMOPSO) and Grey Correlation Analysis (GCA) to rank and select optimal reservoir operation schemes under uncertainty. By integrating hydrological simulations with MCDM tools, they developed a feedback-based optimisation process that captures interdependencies between hydrological, economic, and ecological objectives. This framework enhances the capacity of reservoir models to adapt dynamically to hydrological variability and uncertainty, making it particularly suitable for complex, multipurpose systems like Samanalawewa.

Shevah (2019) emphasised that water balance is not solely a matter of inflows and outflows; it is constrained by environmental degradation, water scarcity, and the overexploitation of natural resources. His analysis of the Middle East water systems showed that chronic over-withdrawal, pollution, and climate-induced variability disrupt both the hydrological cycle and ecosystem equilibrium. He proposed an integrated strategy combining reuse of treated effluents, desalination, and demand management to maintain a sustainable balance between natural inflows and anthropogenic withdrawals. This perspective reinforces the need for water balance modelling frameworks that account not only for hydrological and operational parameters but also for environmental safety and sustainability, especially under rising water scarcity pressures.

2.2.2. Hydropower Generation

Hydropower remains the backbone of Sri Lanka's renewable energy sector, contributing significantly to national electricity generation and socio-economic development. As a country with a long history of water resource utilisation, Sri Lanka has relied heavily on hydropower since the early 20th century, harnessing its river basins for both energy and irrigation purposes. However, as demand for water across sectors increases, hydropower operations now face growing challenges of optimisation, efficiency, and sustainability.

Development and Current Status of Hydropower in Sri Lanka

Sri Lanka's hydropower development dates back to 1895, with the establishment of early mini-hydro plants serving tea estates, followed by the commissioning of the Aberdeen–Laxapana project in 1950, the country's first large-scale grid-connected hydropower plant (Fernando, 2014). The formation of the Ceylon Electricity Board (CEB) in 1969 marked the beginning of systematic hydropower planning and operation across river basins. Successive large-scale schemes, including the Kelani

River Basin projects (335 MW) and the Mahaweli Development Programme, which developed Victoria (210 MW), Randenigala (122 MW), and Rantembe (50 MW), expanded hydropower generation capacity while supporting irrigation and rural electrification.

By the early 2000s, hydropower accounted for approximately 64% of total installed capacity (1,135 MW), but with more than 55% of its economically viable potential already harnessed, further expansion opportunities became limited. Consequently, Sri Lanka's energy mix began transitioning toward thermal and renewable sources, although hydropower continues to play a critical role as the country's primary renewable energy source and peak-load stabiliser (Morimoto, 2013). The introduction of small hydropower (<10 MW) has diversified the generation portfolio, with over 400 MW of small-hydro potential identified. As of the late 2010s, the policy direction has emphasised the integration of hydropower within a diversified and climate-resilient energy system, underpinned by the Sri Lanka Energy Sector Development Plan and sustainability-driven evaluation frameworks (Morimoto, 2013).

Hydropower Optimisation Studies in Sri Lanka

Scientific and engineering efforts to optimise hydropower operations in Sri Lanka have evolved over several decades. The Hydropower Optimisation Study (JICA, 2004) represented a landmark national-level initiative that applied Dynamic Programming (DP) to optimise water release and reservoir operation across major basins, including the Mahaweli and Walawe systems. This study demonstrated that optimisation could enhance generation efficiency significantly; for instance, revising rule curves increased annual power output at Samanalawewa by 1.3% and at the Victoria–Randenigala–Rantembe cascade by 3.6%.

Subsequent research has advanced toward multi-objective frameworks integrating hydropower with irrigation and environmental flow requirements. A work by (Morimoto, 2013) proposed a responsible hydropower development framework, balancing economic benefits against environmental and social costs through multi-criteria regression models. This integrated approach highlighted the importance of incorporating sustainability indicators, resettlement impacts, biodiversity loss, and cost-effectiveness into future hydropower expansion and rehabilitation planning.

Hydropower Generation in the Walawe River Basin

The Walawe River Basin, located in southern Sri Lanka and covering approximately 2,442 km^2, represents one of the country's most complex and strategically significant multi-purpose water systems. The basin features two major reservoirs: Samanalawewa (278 MCM), primarily for hydropower and partial irrigation, and Udawalawe (208 MCM), serving mainly irrigation with secondary hydropower (Smakhtin & Weragala, 2005). Together, these reservoirs store nearly 486 MCM of water, regulating flows for both energy production and irrigation across the basin's command areas.

A hydrological study by Smakhtin and Weragala (2005) showed that regulation by these reservoirs significantly alters downstream hydrology, reducing flood peaks while maintaining higher base flows during dry seasons. Such alterations, though beneficial for irrigation stability, have also impacted wetland ecosystems and downstream water quality. Modelling efforts using SWAT and spatial interpolation techniques confirmed that land use changes and reservoir regulation together influence inflow variability and, by extension, hydropower performance.

The Samanalawewa Hydropower Station, commissioned in 1992 with an installed capacity of 120 MW and average annual generation of 390 GWh, is the key energy component of the Walawe system (Laksiri et al., 2005). Approximately 25% of its inflow is diverted to irrigation via controlled releases and seepage losses, demonstrating the interdependence between the energy and agricultural sectors in this basin (Molle et al., 2005). Optimisation and simulation models have shown that controlled irrigation scheduling can increase both irrigation reliability and hydropower output by 8–10%, while unregulated withdrawals reduce energy yield by up to 20%.

The Samanalawewa Hydropower Scheme

The Samanalawewa Hydropower Scheme has been the focus of several detailed studies exploring system optimisation, trade-offs, and policy implications. Weragala et al. (2007) quantified the economic trade-offs in the basin, showing that water allocated to hydropower produces up to five times higher economic value per cubic meter than irrigation water. Their results emphasised the potential of priority-based water allocation models, such as those implemented in the WEAP framework, to balance energy and irrigation needs dynamically.

Further research by Weragala (2010) expanded on these findings using a network flow simulation model to explore competing water demands under various scenarios. The model demonstrated that prioritising irrigation over hydropower improved supply reliability by 21%, with less than a 0.5% reduction in total hydropower output. Future climate projections under the ECHAM5 model indicated a 25% increase in rainfall by 2050, potentially boosting hydropower generation by 43% while reducing irrigation demand by 3–16%. These results underscore the need for adaptive and integrated reservoir operation strategies to capitalise on climate-driven hydrological shifts.

Recent developments, such as the Gin–Nilwala Diversion Project (GNDP), further highlight the policy direction toward inter-basin transfers to stabilise reservoir inflows in the Walawe Basin. The GNDP aims to supply additional inflows to Muruthawela and Chandrika Wewa, indirectly enhancing Udawalawe and Samanalawewa's operational reliability. Such initiatives exemplify Sri Lanka's strategic movement toward basin-wide hydropower–irrigation integration within the national water–energy–food nexus framework.

2.2.3. Agricultural Irrigation

Reservoirs play a critical role in sustaining agricultural productivity, particularly in regions where rainfall variability and drought conditions limit reliable water supply. By capturing and storing surface runoff during wet seasons, they provide a vital source of irrigation water during dry periods, supporting food security and rural livelihoods globally (Lebon et al., 2022).

Reservoirs are commonly used to convert variable natural flows into steady water supplies for agricultural use. The DAHM-Reservoir agro-hydrological model has demonstrated that small and medium-sized reservoirs can effectively balance inflows and withdrawals, allowing irrigation to remain stable despite seasonal rainfall fluctuations (Lebon et al., 2022). In semi-arid and monsoonal environments, small reservoirs and tank systems serve as decentralised irrigation sources, improving local water access and agricultural resilience. However, the collective operation of these systems can significantly alter the hydrological cycle, emphasising the need for integrated catchment-scale management (Casadei et al., 2019).

Efficient reservoir management ensures water reliability for irrigation while mitigating losses through evaporation and seepage. Studies in South Korea have highlighted that effective reservoir drought response planning and carryover storage management are critical for early-season irrigation reliability (Bang et al., 2017). Moreover, optimisation models combining hydrological and decision-making components, such as the Open Water Management Program (OWMP), have achieved less than 5% relative error in simulating daily runoff and water requirements, demonstrating strong potential for efficient irrigation scheduling (Kim et al., 2004).

In Iran's Tajan irrigation network, simulation–optimisation models integrating genetic algorithms and water balance equations have been applied to optimise conjunctive use between reservoirs and irrigation canals. The results showed that adaptive operation could reduce canal withdrawals by up to 30%, demonstrating the capacity of reservoir-canal coordination to enhance water-use efficiency (Ebrahimian et al., 2020).

Climate change significantly impacts the hydrological behaviour and performance of agricultural reservoirs. In a large-scale analysis of 400 reservoirs across South Korea, inflows remained generally higher than irrigation demands due to rising rainfall trends, but reservoir resilience declined in the past 15 years, particularly in southwestern regions (Ahmad et al., 2022). Such trends indicate that while climate-induced increases in precipitation may temporarily benefit water storage, variability and increased evaporation rates could compromise long-term irrigation reliability.

Beyond hydrological and engineering perspectives, reservoirs also shape social equity and benefit distribution within farming communities. For example, in Indonesia's Geyongan Village, reservoir construction enhanced irrigation equity and productivity, particularly during droughts, yet disparities persisted between upstream and downstream farmers (Salim et al., 2024). Similarly, socio-hydrological studies from Tunisia highlight that while small reservoirs support supplemental irrigation and local resilience, their limited storage and poor institutional support constrain their potential for large-scale intensification (Ogilvie et al., 2019).

Reservoir-based agriculture must also account for environmental consequences such as eutrophication, nutrient loading, and evaporative losses. A study of seven irrigation reservoirs in Greece revealed high nutrient concentrations and eutrophication risks, particularly during the dry season, driven by fertiliser runoff from nearby farms (Chamoglou et al., 2018). Conversely, technological innovations like shade-cloth covers in Spain's agricultural reservoirs reduced evaporation by up to 85%, enhancing water retention and quality by limiting algal blooms (Martinez-Alvarez et al., 2010).

2.2.4. Competing Demands in Multipurpose Reservoirs

Multipurpose reservoirs are designed to meet various water demands, including irrigation, hydropower generation, flood control, water supply, and ecological maintenance. However, fulfilling these multiple objectives simultaneously often creates significant operational conflicts, particularly in regions with seasonal hydrological variability and increasing competition for limited water resources. The efficient management of such reservoirs therefore requires balancing different, and often opposing, priorities within the constraints of available water storage, downstream requirements, and environmental considerations. These challenges are becoming more critical under the influence of climate variability and socio-economic development, which intensify the uncertainty surrounding water inflows and demands (He et al., 2020; Zhang et al., 2020).

The competing demands for water within a multipurpose reservoir system primarily arise from the different timing and magnitude of water requirements across sectors. Hydropower generation, for example, depends on maximising turbine discharges to meet electricity demands, whereas irrigation requires steady and predictable water releases aligned with cropping cycles. These divergent needs often result in trade-offs that reduce system efficiency if operations are not optimised. In Sri Lanka, this issue is most evident in river basins where reservoirs serve dual purposes, such as the Mahaweli and Walawe systems. Studies have shown that irrigation withdrawals can reduce firm hydropower generation by up to 20%, while prioritising energy production during dry periods can severely constrain water availability, thereby affecting agricultural productivity and rural livelihoods (Molle et al., 2005; Smakhtin & Weragala, 2005).

The Walawe River Basin offers a clear example of the complex trade-offs involved in multipurpose reservoir management. This basin contains the Samanalawewa and Udawalawe reservoirs, which operate in cascade to support both hydropower generation and irrigation supply for over 12,000 hectares of agricultural land. Research by Molle et al. (2005) revealed that despite being designed for dual purposes, operational practices in the basin have historically prioritised irrigation, with water releases from the Udawalawe Reservoir often taking precedence over power generation schedules. Conversely, hydropower operations at Samanalawewa can cause flow fluctuations that do not always align with downstream irrigation demands, leading to periods of both excess and deficit water delivery. Such mismatches illustrate the inherent difficulty of maintaining a dynamic balance between energy and agricultural objectives without a unified management strategy.

Several studies have attempted to address these challenges through quantitative modelling and optimisation frameworks. Weragala et al. (2007) used a network flow simulation model to analyse competing water uses in the Walawe Basin and demonstrated that prioritising irrigation improved system reliability by 21% while reducing hydropower output by less than 0.5%. Similarly, Weragala (2010) developed a comprehensive basin-wide optimisation model that incorporated hydropower, irrigation, and environmental flow objectives, concluding that improved reservoir coordination could increase total system yield by up to 15%. These findings highlight the potential of adaptive and conjunctive operation policies to enhance basin-wide efficiency.

Beyond energy and irrigation, multipurpose reservoirs must also accommodate social and environmental water needs. Smakhtin and Weragala (2005) emphasised that the regulation of flows from the Samanalawewa Reservoir altered the natural hydrological regime, reducing flood peaks but increasing dry-season base flows. While this benefited agriculture by stabilising the downstream water supply, it also disrupted wetland ecosystems and aquatic habitats. Hence, reservoir management strategies must extend beyond economic optimisation to incorporate ecological sustainability and community welfare, ensuring that benefits are equitably distributed among stakeholders.

Globally, similar challenges are reported in large river systems such as the Mekong and the Tekeze, where hydropower maximisation has conflicted with irrigation and fisheries management (Zhang et al., 2020). To address these competing objectives, researchers have adopted multi-objective optimisation techniques, including dynamic programming, evolutionary algorithms, and multi-criteria decision-making (MCDM) models (Garrote et al., 2023). These methods provide structured approaches for evaluating the trade-offs among objectives, allowing for more flexible and adaptive reservoir operations that respond to changing hydrological conditions.

In recent years, the development of system dynamics models and data-driven optimisation approaches has further advanced the ability to manage multipurpose reservoirs effectively. These models simulate the interactions between the water, energy, and agricultural sectors, enabling policymakers to assess the long-term impacts of operational decisions under uncertainty (Farea et al., 2024). Machine learning techniques, including PINNs, are emerging as powerful tools capable of integrating physical laws with large datasets to optimise real-time water allocation in complex systems. Such techniques can enhance decision-making by dynamically adjusting reservoir releases based on hydrological forecasts and system feedback, providing a robust framework for climate-resilient water resource management.

In Sri Lanka, the need for integrated and adaptive management is particularly urgent as hydropower reservoirs face increasing stress from agricultural expansion and climate-induced hydrological variability. The experience from the Walawe Basin demonstrates that achieving an optimal balance between competing demands requires a shift from static rule-curve operations toward dynamic, simulation-based optimisation frameworks. This evolution not only improves operational efficiency but also supports sustainable water governance by ensuring that hydropower generation, agricultural productivity, and environmental conservation are managed as interconnected components of a single resource system.

2.3. Traditional Reservoir Management and Optimisation Approaches

Effective reservoir operation has historically relied on structured rule-based systems and mathematical optimisation techniques to balance water availability with competing demands. Traditional approaches were primarily designed under assumptions of stationarity and relatively predictable hydrological regimes. These methods include rule curves derived from historical records, simulation-based operational analysis, and deterministic optimisation techniques such as linear and nonlinear programming.

2.3.1. Rule Curve-Based and Simulation Methods

Rule curve-based reservoir management has historically served as the foundation for operational decision-making in multipurpose water systems. These methods rely on predefined storage–release relationships, which prescribe reservoir release volumes based on water levels and seasonal inflow expectations. They were developed to maintain reliability for flood control, irrigation, hydropower generation, and water supply while ensuring safety and consistency in operations. However, these static rules often fail to account for inter-annual variability, climate-induced hydrologic shifts, and competing user demands.

Simulation models were introduced to overcome these limitations by mimicking the hydrological and operational processes of reservoirs under varying inflow and demand conditions. Tools such as HEC-ResSim, MODSIM, WEAP, and WEAP21 enable time-based simulation of inflows, storage, and releases while incorporating constraints related to reservoir geometry, turbine capacity, irrigation demands, and ecological flows (Hatamkhani & Moridi, 2019). These models can represent the temporal evolution of storage and hydrological feedback mechanisms, providing decision-makers with a dynamic understanding of system behaviour (Zomorodian et al., 2018).

Despite their advantages, simulation models remain predictive rather than prescriptive; they analyse system performance under assumed operating rules but cannot independently determine the most efficient operating strategies. Moreover, their reliance on deterministic hydrological inputs limits adaptability to climate uncertainty and multi-objective trade-offs. Early studies such as (Karamouz & Houck, 1987) bridged this gap by integrating simulation with regression-based operating rules, setting the stage for modern hybrid models that combine simulation efficiency with optimisation capability.

2.3.2. Traditional Optimisation Techniques

Optimisation models were introduced to enhance reservoir operations by maximising or minimising an objective function (e.g., energy production, irrigation yield, or shortage minimisation) within operational and hydrological constraints. The earliest approaches, based on Linear Programming (LP) and Dynamic Programming (DP), represented the cornerstone of traditional reservoir optimisation (Lee et al., 2023). LP models, with their simplicity and computational efficiency, were widely used for steady-state reservoir optimisation, while DP allowed for time-dependent decision-making, accounting for stage-wise variations in inflows and storage (Karamouz & Houck, 1987).

However, these methods faced challenges of dimensionality and nonlinearity, particularly in multi-reservoir systems with nonlinear hydropower generation relationships or stochastic inflows. To address this, researchers adopted Nonlinear Programming (NLP) and Quadratic Programming (QP) formulations, allowing for more realistic modelling of head–storage–power relationships (Alfieri et al., 2006). For multi-objective systems, Multi-Objective Linear Programming (MOLP) and Fuzzy Linear Programming (FLP) introduced flexibility in balancing conflicting goals such as irrigation reliability, hydropower maximisation, and ecological sustainability (Dabhade & Regulwar, 2021).

Recent studies have further expanded traditional frameworks to handle uncertainty and adaptability. Suo et al. (2022) introduced a Fuzzy-Interval Dynamic Programming (FIDP) approach, which incorporates both temporal variability and parameter uncertainty into optimisation, producing more robust water allocation strategies. Similarly, Wu et al. (2024) combined Discrete Differential Dynamic Programming (DDDP) with Invasive Weed Optimisation (IWO) to develop an enhanced M-IWO-ODDDP algorithm for multi-reservoir hydropower scheduling under water-level constraints. The model improved hydropower generation by nearly 4% and reduced spillage losses, demonstrating the efficiency of hybrid dynamic programming for complex cascade systems.

The evolution of optimisation also includes hybrid techniques that merge LP and NLP, as in the Hybrid LP–NLP Hydropower Optimisation model by Dogan et al. (2021), which significantly reduced computation time while maintaining physical accuracy in power generation modelling. Collectively, these advances demonstrate a shift from deterministic, single-objective models toward flexible, uncertainty-aware, and multi-objective optimisation paradigms capable of addressing the interconnected water–energy–food–ecosystem nexus.

2.3.3. Integrated Simulation and Optimisation Frameworks

As hydrological systems grew in complexity, traditional optimisation techniques alone proved inadequate for addressing the interlinked hydrological, ecological, and socio-economic dynamics of multi-reservoir systems. This led to the emergence of integrated simulation–optimisation frameworks that couple hydrological simulation models with optimisation algorithms, enabling dynamic, feedback-driven decision-making (Zomorodian et al., 2018).

Early examples, such as Karamouz and Houck (1987), used iterative optimisation–simulation–regression cycles to refine reservoir operating policies under stochastic inflow conditions. Later, Tian et al. (2021) advanced this concept by combining the SWAT hydrological simulation with Genetic Algorithm (GA)-based optimisation, adapting water allocation to projected climate and land use changes. Similarly, Hatamkhani and Moridi (2019) coupled WEAP simulations with Particle Swarm Optimisation (PSO) to optimise hydropower plant capacities and water levels across a multi-reservoir watershed, resulting in significant energy and economic efficiency gains.

Recent developments emphasise multi-objective, multi-reservoir optimisation within integrated systems. Dabhade and Regulwar (2021) used Fuzzy Linear Programming to balance hydropower and irrigation objectives while maintaining environmental flows, achieving an 87% satisfaction level among competing objectives. Sorachampa et al. (2020) linked HEC-ResSim simulations with PSO for hydropower optimisation across the Nam Ngum cascade in Laos, achieving an 11% increase in total generation compared to rule-curve operations. Peretti et al. (2025) introduced a metaheuristic framework integrating hydraulic simulation (QEPANET) with economic optimisation, successfully reducing irrigation energy costs by 14% and increasing hydropower revenue by 11%.

These studies highlight that simulation–optimisation coupling allows real-time adaptability, data assimilation, and multi-scale decision-making. Contemporary frameworks integrate System Dynamics (SD), Agent-Based Modelling (ABM), and Machine Learning (ML) techniques (Zomorodian et al., 2018) to capture feedback between hydrological and human systems. The most advanced iterations incorporate climate adaptation (Tian et al., 2021) and long-term policy evaluation (Karimi & Ardakanian, 2010) illustrating a paradigm shift toward resilient, adaptive, and data-informed reservoir operation strategies.

Overall, integrated simulation–optimisation frameworks represent the current frontier in reservoir management, bridging the gap between traditional optimisation models and modern intelligent systems such as PINNs. These approaches not only enhance operational efficiency but also ensure ecological integrity and socio-economic sustainability, a balance essential for the next generation of reservoir management systems.

2.4. Machine Learning Applications in Hydrology

Machine Learning (ML) has transformed modern hydrological modelling by enabling data-driven representation of highly nonlinear, multi-scale, and stochastic processes that are difficult to capture using traditional physically based models. Hydrological systems, governed by complex interactions among precipitation, evapotranspiration, soil moisture, and runoff, pose challenges due to parameter uncertainty and limited data availability. ML algorithms, particularly those employing neural networks and hybrid physics-guided frameworks, have shown remarkable ability to learn temporal–spatial relationships from observational and simulated data, providing a powerful complement to process-based modelling approaches (Shen & Lawson, 2021).

The following subsections review the main advancements in data-driven, physics-informed, and hybrid neural-based models, with special attention to their application in reservoir operation, hydropower optimisation, and water resource management.

2.4.1. Data-Driven Modelling in Water Resources

Data-driven hydrological models rely on the direct mapping of input–output relationships using historical data without explicitly solving governing physical equations. Early applications utilised Artificial Neural Networks (ANNs) and Support Vector Machines (SVMs) for streamflow, rainfall–runoff, and reservoir inflow forecasting (Shelke et al., 2023). These approaches outperformed linear regression and rule-based models in capturing nonlinear hydrological behaviour, particularly for short-term flood and inflow prediction.

The emergence of LSTM networks and their variants revolutionised time-series forecasting by overcoming the limitations of vanishing gradients in recurrent networks. Studies on flood and streamflow prediction demonstrated that LSTM models could accurately forecast river discharge peaks and timing with higher stability and lower error compared to conventional ANNs. Similarly, Renteria-Mena and Giraldo (2024) showed that multivariate LSTMs integrating precipitation, river stage, and flow variables achieved >0.95 correlation for multi-station water level forecasting in Colombia.

For groundwater and reservoir applications, LSTM and hybrid models have achieved significant predictive accuracy. Solgi et al. (2021) applied LSTM to forecast aquifer levels using in-situ piezometric data from the Edwards Aquifer (Texas), obtaining $R^2 > 0.99$ across multiple forecast horizons. Bo et al. (2025) extended this capability by developing a Hybrid HP-LSTM model combining the Hodrick–Prescott filter with LSTM to remove short-term noise and enhance long-term trend prediction in karst groundwater systems. The HP-LSTM achieved a 70–80% reduction in RMSE compared to standard LSTM models.

Data-driven approaches have also proven effective for reservoir inflow estimation and capacity prediction. Dai et al. (2022) introduced an attention-enhanced LSTM model for predicting the storage capacity of Huanggang Reservoir, improving accuracy by

3% relative to baseline models. These findings collectively demonstrate that data-driven ML techniques offer high predictive power for hydrological forecasting, especially where physical process representation is uncertain or incomplete.

2.4.2. Physics-Informed Neural Networks (PINNs)

Despite the success of purely data-driven models, their lack of physical interpretability and extrapolation capability remains a major limitation. To address this, PINNs integrate the governing equations of hydrological systems, such as mass continuity, momentum, and energy balance, directly into the neural network's loss function. The method, first popularised by Raissi et al. (2019), enforces physical consistency by minimising both data-driven loss and the residuals of differential equations, thereby ensuring adherence to conservation laws even under data scarcity (Farea et al., 2024).

PINNs have shown exceptional promise in hydrology for modelling reservoir storage dynamics, groundwater flow, and river hydrodynamics. Latif (2021) applied a PINN-based water balance model to simulate storage and water losses in the Klang Gate Reservoir, Malaysia, successfully capturing nonlinear storage–loss relationships under dynamic inflow and evaporation conditions. Luo et al. (2024) further enhanced PINN architectures to simulate hydrodynamics in complex river networks, incorporating junction constraints and physical penalties that improved training convergence by 90% without sacrificing PDE-level accuracy.

Recent studies have introduced distributed and spatiotemporal extensions of PINNs. Zhong et al. (2024)developed a Distributed Physics-Informed Deep Learning (PIDL) hydrological model that discretised catchments into sub-basins coupled via differentiable routing, enabling hydrological state estimation in ungauged regions. Similarly, Karniadakis et al. (2021) and Zhao et al. (2024) classified emerging PINN variants such as Bayesian PINNs, Adaptive PINNs, and Transfer PINNs, which incorporate uncertainty quantification and domain generalisation, key features for climate-resilient water management.

Moreover, Physics-aware Machine Learning (PaML) has emerged as a broader framework that unifies data-driven and physics-embedded learning paradigms. Xu et al. (2023) outlined four categories, Physics-Guided, Physics-Informed, Physics-

Embedded, and Hybrid Physics-Aware Learning, culminating in the HydroPML platform, which merges process-based hydrological models with deep learning surrogates for real-time and physically consistent predictions. These innovations position PINNs and their derivatives as transformative tools for next-generation hydrological modelling.

2.4.3. Long Short-Term Memory Networks (LSTMs)

The LSTM network, introduced by Hochreiter and Schmidhuber (1997), has become the dominant architecture for hydrological time-series forecasting due to its ability to capture long-term dependencies. LSTMs have been extensively used for streamflow, reservoir inflow, groundwater, and flood forecasting, often outperforming physical and statistical models.

In flood prediction, LSTM networks provided superior peak discharge forecasting compared to linear and ANN models (Le et al., 2019). In river basins such as the Morava (Serbia), LSTM achieved R^2 values exceeding 0.93, outperforming process-based models for daily and hourly discharge forecasting (Leščešen et al., 2025). Sabzipour et al. (2023) compared LSTM against a physically based distributed hydrological model in a Canadian snowmelt-dominated basin and reported that LSTM captured runoff dynamics more accurately with less computational effort.

For reservoir management, modified architectures such as Attention-LSTM (Dai et al., 2022) and Hybrid HP-LSTM (Bo et al., 2025) have advanced model precision for multi-input forecasting tasks, including storage and capacity prediction. In groundwater systems, Solgi et al. (2021) demonstrated that LSTM can model aquifer behaviour solely from historic water-level data without external forcing inputs, highlighting its suitability for data-scarce regions.

Multivariate approaches further extend LSTM applicability. Renteria-Mena and Giraldo (2024) developed a multivariate LSTM for water level forecasting that simultaneously modelled multiple stations, enabling inter-basin correlation analysis and improved hydrological realism. These developments affirm LSTM's status as the foundation of data-driven hydrological modelling, providing the stepping-stone toward hybrid and physics-integrated approaches.

2.4.4. Applications of Machine Learning for Reservoir Optimisation and Control

Reservoir optimisation traditionally relies on linear, nonlinear, and dynamic programming; however, such methods often struggle with high-dimensional, nonlinear, and uncertain systems. ML techniques, particularly neural-based and hybrid optimisation frameworks, have emerged as powerful alternatives for reservoir operation and decision support.

Raman and Chandramouli (1996) pioneered a hybrid Dynamic Programming–ANN framework that generalised reservoir release policies, providing near-optimal decisions with lower computational cost. Later studies incorporated Genetic Algorithms (GAs) and Evolutionary Optimisation within reservoir control frameworks to solve multi-objective problems balancing irrigation and hydropower.

Recent advances integrate reinforcement learning and neural optimisation with simulation tools. Warin (2023) demonstrated that neural dynamic programming can approximate Bellman value functions using deep neural networks, enabling efficient reservoir operation under uncertainty. Similarly, Latif (2021) and Luo et al. (2024) showed that PINNs can act as differentiable surrogates for simulation models, allowing joint hydrological prediction and control optimisation.

In Sri Lanka, Ekanayake et al. (2021) applied Gaussian Process Regression (GPR) and Support Vector Regression (SVR) to forecast hydropower generation at the Samanalawewa reservoir, achieving $R^2 = 0.92$ and RMSE = 4.5%, thus demonstrating ML's potential for national-scale energy–water management. These approaches enable dynamic allocation of water between hydropower and irrigation objectives, central to sustainable reservoir management under climate variability.

Overall, ML-based reservoir optimisation frameworks provide adaptive, real-time, and multi-objective decision-support capabilities that are unattainable with traditional rule-curve methods. When coupled with physics-informed modelling, they offer a pathway toward climate-resilient and physically consistent water allocation strategies.

2.5. Hydrological Modelling for Streamflow Estimation

Hydrological modelling plays a fundamental role in water resource assessment and management by simulating the transformation of rainfall into runoff, which forms the primary inflow to reservoirs. The ability to estimate streamflow accurately under varying climatic and land-use conditions is critical for sustainable reservoir operation, flood control, irrigation planning, and hydropower generation. Over the past few decades, numerous hydrological models have been developed to represent the physical processes governing catchment hydrology. These models differ in their spatial representation, data requirements, and process complexity, ranging from empirical and conceptual to fully physically based and data-driven frameworks (Ben Khélifa & Mosbahi, 2021; Chakraborty & Biswas, 2021; Madhushankha & Wijesekera, 2021).

2.5.1. Overview of Hydrological Models

Hydrological models can generally be classified into empirical, conceptual, physically based, and data-driven categories, as given in Table 2-1.

Table 2-1: Available types of hydrological models in the literature

Model Type	Description
Empirical models	Empirical models rely on statistical relationships derived from observed data, offering simplicity but limited transferability.
Conceptual models	Conceptual models, such as the HEC-HMS and HBV, conceptualise the catchment as a series of storage components representing infiltration, surface runoff, and baseflow (Madhushankha & Wijesekera, 2021).
Physically based distributed models	Physically based distributed models, including MIKE SHE, SWAT, and VIC, use detailed spatial input (topography, land use, and soil data) to solve governing equations of water flow and energy balance (Chea & Oeurng, 2018).
Data-driven models	Data-driven models, often based on machine learning algorithms, have recently gained popularity for their ability to learn nonlinear hydrologic responses from large datasets.

Among these, HEC-HMS has emerged as one of the most widely used rainfall–runoff simulation tools worldwide. Its modular structure and flexible process representation make it suitable for diverse hydrological conditions, from tropical monsoon catchments in Sri Lanka to arid and urban environments (Ben Khélifa & Mosbahi, 2021). HEC-HMS represents hydrological processes through a combination of loss models (e.g., SCS Curve Number, Green–Ampt, or Deficit and Constant), transform models (e.g., SCS or Clark Unit Hydrograph), baseflow models (e.g., exponential recession), and routing models (e.g., Muskingum or Lag). This flexibility allows the model to represent both lumped and semi-distributed catchments efficiently (Srinivas et al., 2017).

Furthermore, integration with GIS tools (HEC-GeoHMS) facilitates spatial preprocessing of topography, land use, and soil data, allowing for more realistic sub-basin parameterization (Chakraborty & Biswas, 2021). These capabilities make HEC-HMS particularly valuable in data-limited tropical regions, such as Sri Lanka, where ground-based hydrometeorological networks are sparse but remote-sensing datasets are increasingly available.

Several hydrological models have been developed to simulate rainfall–runoff processes, each with different assumptions, data requirements, and simulation capabilities. Commonly used models include TOPMODEL, TANK, HEC-HMS, MIKE11/NAM, and SWAT, which differ in their simulation structure, required input data, and accessibility. A comparison of these widely used models is presented in Table 2-2.

Table 2-2: The comparison between available hydrological modelling techniques

Criteria	**Model Performance**				
	TOPMODEL	TANK	**HEC-HMS**	MIKE11/NAM	SWAT
Time of simulation	Only event-based	Only continuous	Continuous and event-based	Only continuous	Continuous and event-based
Data requirement	Runs with more data availability	Runs with limited data availability	Runs with limited data availability	Runs with limited data availability	Runs with moderate data availability
Model accessibility	Freely available	Freely available For education purposes	Freely available	Freely available For education purposes	Freely available

These characteristics make HEC-HMS particularly suitable for hydrological modelling in Sri Lankan river basins, where data availability may be limited but reliable simulation of rainfall–runoff processes is essential for water resources planning and reservoir management.

2.5.2. Applications of HEC-HMS for Rainfall–Runoff Modelling

The HEC-HMS, developed by the U.S. Army Corps of Engineers, is one of the most widely used conceptual hydrological modelling tools for simulating rainfall–runoff and streamflow processes (Adams et al., 2010). Designed with flexibility and adaptability, it provides a comprehensive framework for representing precipitation loss, direct runoff, baseflow, and channel routing across diverse hydrological and climatic settings. HEC-HMS can simulate event-based and continuous hydrological processes, including low-flow and extreme flow conditions, making it a valuable tool for both flood forecasting and water resources planning (Anderson et al., 2002).

HEC-HMS integrates multiple hydrological methods within a modular structure, allowing users to select appropriate algorithms to represent catchment processes accurately. These include various loss models (such as SCS Curve Number, Green–Ampt, and Deficit & Constant methods), transform methods (such as Clark or SCS Unit Hydrograph), and baseflow algorithms (including Constant, Exponential, or Recession models).

Due to its adaptability and relative ease of use, HEC-HMS has been extensively applied in climate impact assessment studies to evaluate hydrological responses under changing climatic conditions (Bai et al., 2019). Its framework supports the integration of projected precipitation and temperature data derived from downscaled climate models, making it suitable for long-term water resource assessments and climate resilience planning. Furthermore, its capacity to incorporate spatial data from remote sensing and GIS enhances its applicability in both gauged and ungauged catchments, enabling detailed analysis even in data-scarce regions.

In Sri Lanka, Madhushankha and Wijesekera (2021) successfully applied HEC-HMS to the Baddegama sub-catchment of the Gin Ganga Basin, achieving reliable daily streamflow predictions with RMSE values below 3.5 mm/day and consistent hydrograph fitting. The study demonstrated that the Deficit and Constant loss, SCS Unit Hydrograph, and Exponential Recession baseflow methods produced optimal performance for monsoon-influenced basins.

In India, Shelke et al. (2023) Simulated inflows to the Koyna Reservoir using HEC-HMS v4.8, achieving NSE values between 0.75–0.85 and R^2 around 0.90, validating the model's capacity for reservoir inflow prediction in multipurpose water systems. Similarly, Chakraborty and Biswas (2021) applied HEC-HMS in the Teesta River Basin, an ungauged Himalayan catchment, where the model achieved NSE values between 0.6 and 0.81 and R^2 up to 0.94, illustrating its robustness in mountainous regions.

Beyond South Asia, Chea and Oeurng (2018) successfully simulated monthly flow in the Tonle Sap Basin (Cambodia) using HEC-HMS with NSE = 0.61 and PBIAS = 10.85%, while Ben Khélifa and Mosbahi (2021) applied the model in Tunisia to urban flood estimation, validating peak flow accuracy through comparative assessment with the Rational Method.

These studies collectively demonstrate that HEC-HMS performs reliably under both gauged and ungauged conditions and can reproduce seasonal runoff patterns typical of monsoon climates. Moreover, the model's ability to integrate GIS-derived hydrological parameters and remote sensing data enhances its applicability to catchments with limited field observations, such as the Samanalawewa Reservoir Basin in Sri Lanka.

The HEC-HMS framework has also been extended for reservoir operation analysis when coupled with optimisation models such as HEC-ResSim and HEC-ResPRM. For instance, De Lara et al. (2014) used HEC-ResSim to simulate hydropower generation in the Tucuruí Dam, Brazil, achieving NSE = 0.98 for daily outflows. Similarly, Faber and Harou (2006) employed HEC-ResPRM to optimise releases across the Mississippi Headwaters System, demonstrating the integration potential of hydrological and reservoir models for multi-objective decision-making.

2.5.3. Model Calibration and Validation Techniques

Model calibration and validation are critical steps to ensure the reliability and transferability of hydrological simulations. Calibration involves adjusting model parameters, such as curve numbers, lag times, and baseflow coefficients, until simulated flows match observed data, while validation assesses model performance against independent datasets.

Studies have consistently shown that multi-criteria calibration using both statistical indices and hydrograph comparison produces more robust results (Chea & Oeurng, 2018; Madhushankha & Wijesekera, 2021). Common performance metrics include the Nash–Sutcliffe Efficiency (NSE), Coefficient of Determination (R^2), Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and Percent Bias (PBIAS). For instance, Shelke et al. (2023) achieved NSE > 0.75 and $R^2 \approx 0.90$ after calibrating five historical inflow events for the Koyna Reservoir. Similarly, Chakraborty and Biswas (2021) validated their model with NSE = 0.81 and PEPF < 25%, confirming strong hydrograph agreement even in ungauged basins.

Both manual and automatic calibration methods (e.g., Nelder–Mead simplex or Univariate Gradient optimisation) have been applied successfully in regional studies. Sensitivity analyses commonly identify CN, initial soil moisture, and routing coefficients as the most influential parameters (Chea & Oeurng, 2018). Moreover, studies have highlighted the importance of model robustness testing under future climate projections, as variations in rainfall intensity and antecedent soil conditions significantly affect runoff generation.

Through iterative calibration and multi-year validation, HEC-HMS ensures hydrological consistency and reliability, making it an appropriate model for simulating inflow variability under climate change in Sri Lankan reservoirs. The model's proven accuracy and flexibility, coupled with its compatibility with optimisation algorithms (e.g., PINNs in this study), make it an ideal tool for dynamic reservoir management under uncertain hydrologic regimes.

2.6. Climate Change and Reservoir System Resilience

Climate change is exerting profound and multifaceted impacts on water resources globally, altering precipitation patterns, temperature regimes, and hydrological cycles. These shifts have significant implications for reservoir operation, water allocation, and long-term system reliability. Reservoirs, originally designed under assumptions of hydrologic stationarity, are increasingly challenged by climatic non-stationarity, which manifests as variability in rainfall timing, intensity, and duration, as well as changes in evaporation and inflow behaviour (Bozorg-Haddad et al., 2022; Ward et al., 2013). Building resilience in reservoir systems, therefore, requires the development of adaptive management frameworks that integrate climate projections, hydrologic modelling, and advanced optimisation tools.

2.6.1. Climate Variability and Hydrological Extremes

Global climate change has intensified both the frequency and magnitude of hydrological extremes, including droughts and floods. Rising global temperatures, projected to increase by 1.5–2.0°C by mid-century, are expected to accelerate evapotranspiration, reduce soil moisture, and amplify the hydrological cycle's variability (Masson-Delmotte et al., 2021). Studies indicate that changes in precipitation intensity and seasonal distribution are already observable in many regions, with tropical and subtropical areas being particularly vulnerable (Ward et al., 2013).

In the Sri Lankan context, long-term records indicate a decline of approximately 7% in mean annual rainfall since 1961, combined with increased rainfall intensity during extreme events (Eriyagama et al., 2010). Spatial analysis reveals that while the Southwest monsoon has exhibited minor variability, the Northeast monsoon, vital for dry-zone irrigation, has declined significantly. Simultaneously, consecutive dry days and drought frequency have increased, particularly across the North Central and Eastern provinces, where irrigation and paddy cultivation dominate (Eriyagama et al., 2010). Such climatic alterations have direct repercussions for reservoirs dependent on seasonal inflows, leading to water shortages during the Yala season and increased flood risks during the Maha season.

Globally, similar trends are evident. For example, in the Eastern Nile Basin, Abera et al. (2018) observed substantial interannual fluctuations in precipitation and inflows under RCP4.5 and RCP8.5 scenarios, leading to significant reductions in hydropower reliability. The Lake Urmia Basin in Iran has experienced comparable imbalances, where decreased rainfall and rising evaporation caused reservoir shrinkage, affecting agricultural and ecological systems (Bozorg-Haddad et al., 2022). Collectively, these studies underscore that climate-induced hydrological extremes are disrupting traditional reservoir operation assumptions, necessitating dynamic management strategies.

2.6.2. Impact of Climate Change on Reservoir Operation and Inflows

Changes in precipitation patterns significantly affect reservoir inflow variability, storage capacity utilisation, and operational efficiency. Seasonal shifts in rainfall timing alter both hydropower generation schedules and irrigation water releases, creating challenges for multipurpose reservoir management. Model-based assessments reveal that climate change impacts reservoir operations primarily through two mechanisms:

(1) Altered inflow seasonality, earlier snowmelt, or rainfall peaks shorten storage periods and delay recharge.

(2) Increased evaporation losses, reducing effective storage volumes (Bozorg-Haddad et al., 2022).

For example, Abera et al. (2018) applied the Soil and Water Assessment Tool (SWAT) combined with bias-corrected CORDEX-Africa data to simulate future inflows to the Tekeze Reservoir in the Eastern Nile. Under RCP4.5 and RCP8.5, mean annual inflows were projected to decrease by 7–15%, with hydropower generation declining by 10–13%. Similarly, Ward et al. (2013) demonstrated that under multidecadal variability scenarios, reservoir systems in the U.S. and Asia may experience reliability reductions exceeding 20% unless operational rules are adjusted periodically.

In Sri Lanka, the vulnerability assessment by Eriyagama et al. (2010) highlighted possible declines in reservoir storage reliability, especially within the Mahaweli and Walawe basins, where variations in monsoon onset significantly affect hydropower production and irrigation requirements. Studies predicted that paddy irrigation demand could rise by 13–23% by 2050 under HadCM3 A2 scenarios due to evapotranspiration increases (De Silva et al., 2007). These findings imply that the Samanalawewa Reservoir, which depends heavily on monsoon inflows, may experience similar operational stress under future climate regimes. Therefore, dynamic operating policies integrating seasonal climate forecasts and multi-objective optimisation are necessary to sustain water and energy outputs.

2.6.3. Evaluation of Climate Change Impact and Downscaling Climate Data

Evaluation of Climate Change Effects

Understanding the effects of climate change on hydrological systems requires integrating multiple scientific frameworks that capture interactions between atmospheric, terrestrial, and hydrological processes. Climate change alters precipitation regimes, temperature, and evapotranspiration, directly influencing runoff generation, groundwater recharge, and the overall availability of water resources (El Jeitany et al., 2024). Frameworks such as hydrological models, climate scenario analyses, and integrated assessment models (IAMs) have been widely used to quantify these responses and predict their implications for water management.

Hydrological models, including the Soil and Water Assessment Tool (SWAT) and the Variable Infiltration Capacity (VIC) model, provide process-based simulations that translate climatic inputs into hydrological responses such as flow, soil moisture, and evapotranspiration. When integrated with climate projections, they enable the assessment of potential changes in runoff, drought frequency, and reservoir inflows under future climates. Global Climate Models (GCMs) and downscaled climate data complement these models by providing the necessary meteorological inputs that reflect long-term climate trends and variability. Climate scenario analysis further extends these assessments by exploring alternative emission and socioeconomic trajectories, while Integrated Assessment Models (IAMs) couple physical climate systems with economic and policy dimensions to evaluate mitigation and adaptation pathways.

Global Climate Models (GCMs)

The Earth's climate system responds dynamically to both natural variations and anthropogenic forcing. Global Climate Models (GCMs) serve as physics-based numerical tools that simulate these interactions between the atmosphere, ocean, cryosphere, and biosphere to project future climate conditions (Ashfaq et al., 2022). The Coupled Model Intercomparison Projects (CMIPs), coordinated by the World Climate Research Programme, provide a standardised framework for comparing and evaluating GCM outputs across multiple modelling centres (Eyring et al., 2016).

Since their inception in 1995, CMIP phases have progressively advanced the spatial resolution and physical representation of climate processes. The latest Phase 6 (CMIP6) includes more than 50 GCMs with horizontal grid resolutions of approximately 0.5°, offering improved simulation of atmospheric circulation, cloud microphysics, and monsoon dynamics (Ashfaq et al., 2022). However, despite these improvements, the spatial resolution of GCMs remains inadequate for direct use in basin-scale hydrological studies, where catchment processes typically occur at resolutions of 1–10 km. Thus, downscaling remains indispensable to bridge this scale gap.

The CMIP6 framework provides a wide range of emission and socioeconomic pathways through its Shared Socioeconomic Pathways (SSPs). These scenarios, SSP1-1.9, SSP1-2.6, SSP2-4.5, SSP3-7.0, and SSP5-8.5, represent varying challenges to mitigation and adaptation, from aggressive climate action to fossil-fuel-driven development (Meinshausen et al., 2020). The SSP2-4.5 scenario depicts a stabilisation trajectory with intermediate forcing levels, whereas SSP5-8.5 represents a high-emission scenario with substantial radiative forcing and global warming potential (**Error! Reference source not found.**). Employing both moderate and extreme s cenarios enables researchers to capture the range of plausible climate futures and associated hydrological risks.

Downscaling of GCM Data

While GCMs effectively reproduce global climate behaviour, their coarse resolution limits their applicability for local-scale hydrological modelling. Downscaling is therefore essential for translating GCM-scale information (typically 100–300 km) into high-resolution data that better represents regional climate processes (Bhuvandas et al., 2014). Downscaling methods are broadly categorised into dynamical and statistical approaches, as shown in Figure 2-2 (Jain, 2023).

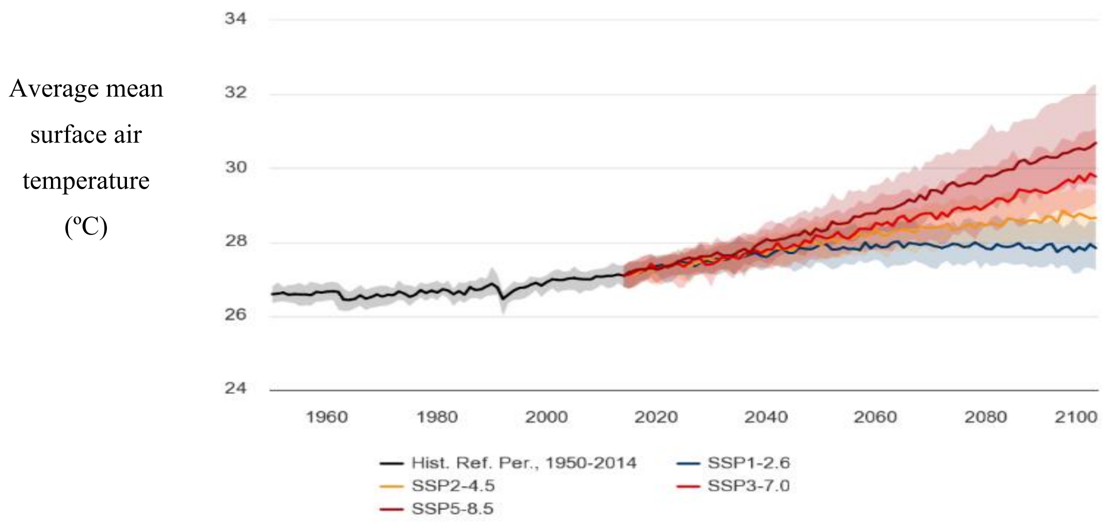


Figure 2-1: Projected variation of the average mean surface air temperature in Sri Lanka in upcoming 100 years

(Source: *World Bank Climate Change Knowledge Portal, 2023*)

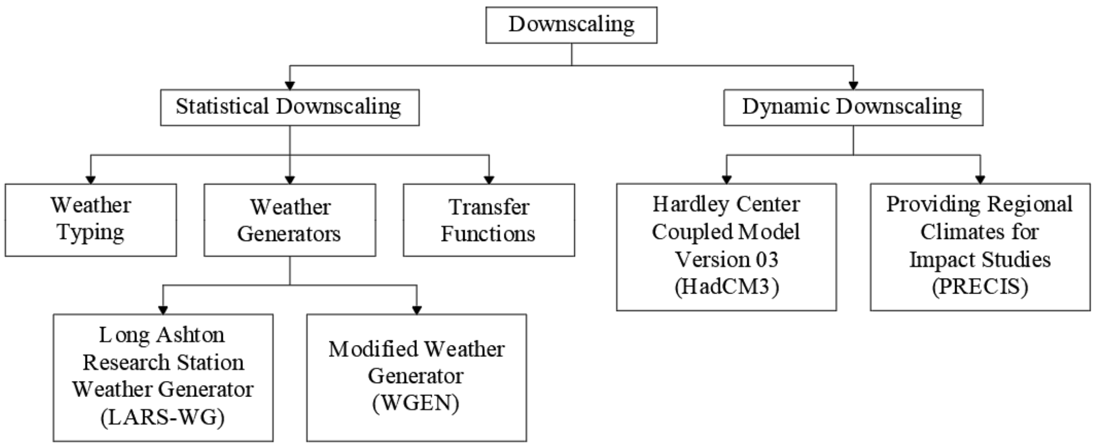


Figure 2-2: Methods of downscaling GCM data and their subcategories

(Source: Jain, 2023)

Dynamical downscaling employs Regional Climate Models (RCMs), which nest high-resolution grids within GCM domains to explicitly resolve mesoscale atmospheric processes, land–atmosphere interactions, and orographic effects. While highly accurate, RCMs require extensive computational resources and detailed boundary conditions. Conversely, statistical downscaling establishes empirical relationships between large-scale predictors (e.g., geopotential height, humidity, wind velocity) and local climate variables (e.g., precipitation, temperature), offering a computationally efficient alternative for generating site-specific projections (Wilby et al., 2002).

Among statistical methods, the Long Ashton Research Station Weather Generator (LARS-WG) has emerged as a robust and widely adopted tool for simulating daily weather sequences under current and future climate conditions. LARS-WG uses semi-empirical probability distributions to stochastically generate precipitation and temperature data that replicate observed climatic variability and seasonal patterns (Hassan et al., 2013). Its strength lies in the capacity to link GCM-derived perturbations to stochastic parameters, enabling the generation of localised future weather series consistent with large-scale projections. Comparative analyses demonstrate that LARS-WG surpasses traditional models such as WGEN in reproducing wet–dry spell frequencies and extreme precipitation events, making it highly suitable for climate impact assessments (Jain, 2023).

2.6.4. Adaptive and Climate-Resilient Water Management Strategies

To ensure sustainability under increasing climate uncertainty, reservoir management must evolve from rigid, rule-based operations to adaptive, climate-resilient frameworks. Adaptive management involves iterative policy updates based on observed and projected hydrological changes, integrating real-time monitoring, forecast-based operation, and scenario planning (Ward et al., 2013).

Approaches such as Dynamic Rule Curves (DRC) and Model Predictive Control (MPC) allow operators to adjust reservoir releases dynamically according to forecasted inflows, minimising the risk of shortages or spillage. Bozorg-Haddad et al. (2022) showed that integrating adaptive rules with system dynamics modelling improved water reliability and ecosystem recovery by over 50% in the Lake Urmia system.

In Sri Lanka, where water resource systems are strongly monsoon-driven, developing climate-resilient operation frameworks is particularly critical. Incorporating machine learning (ML) and PINNs into reservoir management can enhance predictive capabilities by fusing data-driven insights with hydrological principles. Such hybrid models enable real-time optimisation of water allocation among competing sectors (irrigation, hydropower, domestic use) while maintaining system sustainability.

Ultimately, climate-resilient reservoir management combines hydrological simulation, statistical downscaling, and AI-driven optimisation to achieve long-term robustness under uncertain climatic futures. The integration of HEC-HMS simulations with PINN-based optimisation, as proposed in this study, represents a practical implementation of adaptive water management aligned with both scientific advancement and sustainable development goals.

2.7. Chapter Summary

This chapter reviewed the theoretical, methodological, and empirical foundations relevant to modern reservoir management under climatic and operational uncertainty. It highlighted that traditional, rule-based operation frameworks are increasingly inadequate in addressing non-stationary hydrological behaviour driven by climate change, population growth, and competing sectoral demands. The literature emphasises a paradigm shift toward adaptive, data-driven, and multi-objective approaches capable of balancing hydropower generation, irrigation supply, flood control, and environmental sustainability.

The discussion on reservoir water balance and system dynamics demonstrated that inflow variability, evaporation, and feedback mechanisms among hydrological and socio-economic subsystems critically influence storage reliability and release efficiency. System dynamics and optimisation studies revealed that integrated modelling frameworks, combining mass balance, feedback loops, and optimisation algorithms, offer superior adaptability and resilience compared to static operational rules.

In the context of hydropower and irrigation management, Sri Lankan case studies, particularly from the Mahaweli and Walawe basins, showed that coordinated reservoir operation enhances both energy yield and irrigation reliability. However, these systems remain vulnerable to monsoon variability and climate-induced inflow fluctuations, reinforcing the need for adaptive management. Multi-objective and simulation–optimisation frameworks were found effective in mitigating trade-offs among hydropower, irrigation, and ecological flow requirements.

The review of optimisation methodologies traced the evolution from traditional Linear and Dynamic Programming to hybrid and evolutionary algorithms capable of solving nonlinear, high-dimensional water allocation problems. Integrated simulation–optimisation frameworks, which couple hydrological simulations with metaheuristic optimisation, have emerged as powerful tools for multi-reservoir operation under uncertainty.

Advancements in machine learning (ML) and PINNs have further transformed hydrological modelling. Data-driven models, particularly LSTM networks, provide accurate inflow and streamflow forecasting, while PINNs enhance physical consistency by embedding governing hydrological equations into learning architectures. These approaches collectively support intelligent, real-time decision-making for reservoir operation and control.

The chapter also examined hydrological modelling with a focus on the HEC-HMS framework, which remains one of the most reliable rainfall–runoff simulation tools for both gauged and ungauged catchments. Its adaptability, integration with GIS, and compatibility with optimisation and climate projection models make it particularly suitable for Sri Lankan basins.Finally, the section on climate change and reservoir resilience outlined the increasing frequency of hydrological extremes, shifts in rainfall seasonality, and rising evaporation rates that threaten storage reliability and operational efficiency. Statistical downscaling and bias correction methods, especially the LARS-WG model, were identified as vital for generating localised climate inputs for hydrological simulation.

CHAPTER 3

3. METHODOLOGY

This chapter presents the methodological framework adopted to develop and evaluate a dynamic reservoir water allocation system under present and near-future climate conditions. The approach integrates hydrological modelling, machine learning techniques, and rule-based optimisation within a structured computational framework.

3.1. Methodology Flowchart

The overall research methodology adopted in this study was developed to systematically integrate hydrological modelling, machine learning–based dynamic optimisation, and climate change projection for the reservoir water management framework. The complete methodological process is illustrated in Figure 3-1, which presents the logical sequence from problem identification to model evaluation and result interpretation.

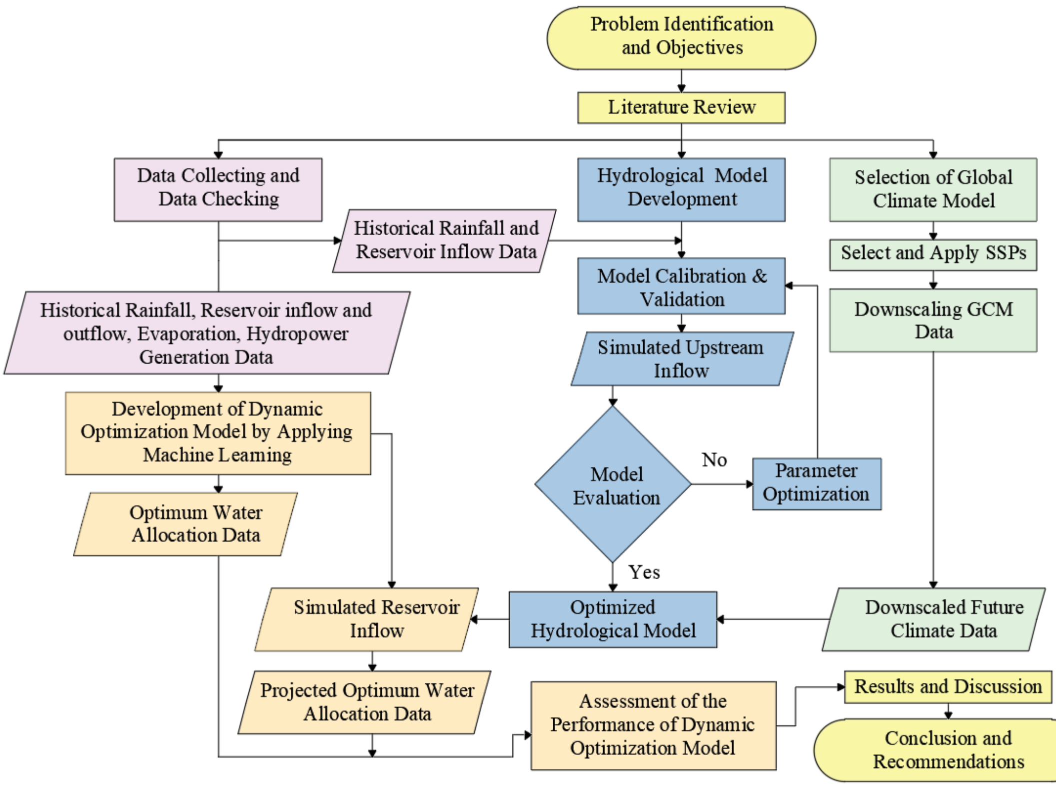


Figure 3-1: The overall methodology adopted for the study

The study was initiated with problem identification and the formulation of specific research objectives based on the observed hydrological and operational challenges within the study area. A comprehensive literature review was subsequently undertaken to establish the theoretical foundation, identify knowledge gaps, and select appropriate modelling techniques and analytical tools relevant to reservoir operation, optimisation, and climate impact assessment.

The methodological framework was divided into three major components:

(1) Development of the dynamic simulation and optimisation model using machine learning,
(2) Development and calibration of the hydrological model (HEC-HMS), and
(3) Downscaling and application of future climate data for reservoir water allocation projections.

The process began with data collection and verification, which included historical rainfall, reservoir inflow and outflow, evaporation, crop water requirement, and hydropower generation records. These datasets were pre-processed and used as input for both the hydrological and machine learning model developments.

In the first component, two machine learning architectures (LSTM and PINNs) were developed to simulate the reservoir water balance dynamically. A comparative evaluation between these two approaches was conducted to determine the most effective model for representing the nonlinear water balance processes under varying hydrological extremes. The best-performing model was subsequently integrated into a dynamic optimisation model implemented in Python to generate the optimum water allocation dataset for the historical period.

Parallelly, a hydrological model of the catchment was developed using HEC-HMS to simulate upstream inflows to the reservoir. The model underwent rigorous calibration and validation using observed hydrometeorological data. Model evaluation was performed through statistical indices (e.g., NSE, R^2, RMSE), and parameters were iteratively optimised until satisfactory performance was achieved. The resulting optimised hydrological model was then used to simulate reservoir inflows under historical and projected climate conditions.

In the third component, future climate projections were incorporated to assess the impact of climate change on reservoir operation. Global Climate Models (GCMs) were selected based on their regional performance and availability of data under multiple Shared Socioeconomic Pathways (SSPs). The selected GCM outputs were subjected to statistical downscaling and bias correction using the LARS-WG weather generator, producing localised daily rainfall and temperature datasets for the study area. These downscaled data were input into the calibrated HEC-HMS model to generate projected streamflow datasets representing future inflow scenarios.

The simulated inflow series were subsequently used as input to the dynamic optimisation model to derive projected optimum water allocation datasets for future periods. Model performance and consistency were then assessed by comparing historical and projected outputs to evaluate potential changes in reservoir behaviour, water availability, and allocation efficiency under climate change. Finally, the methodology concluded with a comprehensive evaluation and interpretation of the model results, leading to recommendations for adaptive reservoir management strategies and climate-resilient water allocation practices.

3.2. Study Area and Data Collection

This section provides a detailed description of the study area and outlines the data acquisition process undertaken for model development, calibration, and validation. Subsections 3.2.1 to 3.2.3 discuss the physical and climatic characteristics of the study area, and the collection and preprocessing of datasets used for the development of the machine learning and hydrological models, respectively.

3.2.1. Study Area

The present study focuses on the Walawe River Basin, located in the southern region of Sri Lanka between latitudes 6°00′–6°40′ N and longitudes 80°30′–81°00′ E (Figure 3-2). The basin covers approximately 2,424 km², extending from the central highlands at elevations exceeding 2,000 m MSL to the southern coastal plains. The river originates near Balangoda in the Sabaragamuwa Province and flows southward for about 138 km before discharging into the Indian Ocean near Ambalantota. This topographic gradient defines distinct climatic and hydrological zones: the upper basin belongs to the wet zone, receiving over 3,000 mm of annual rainfall, while the lower plains fall within the dry zone, with precipitation decreasing to nearly 1,000 mm (Molle et al., 2005; Weragala, 2010).

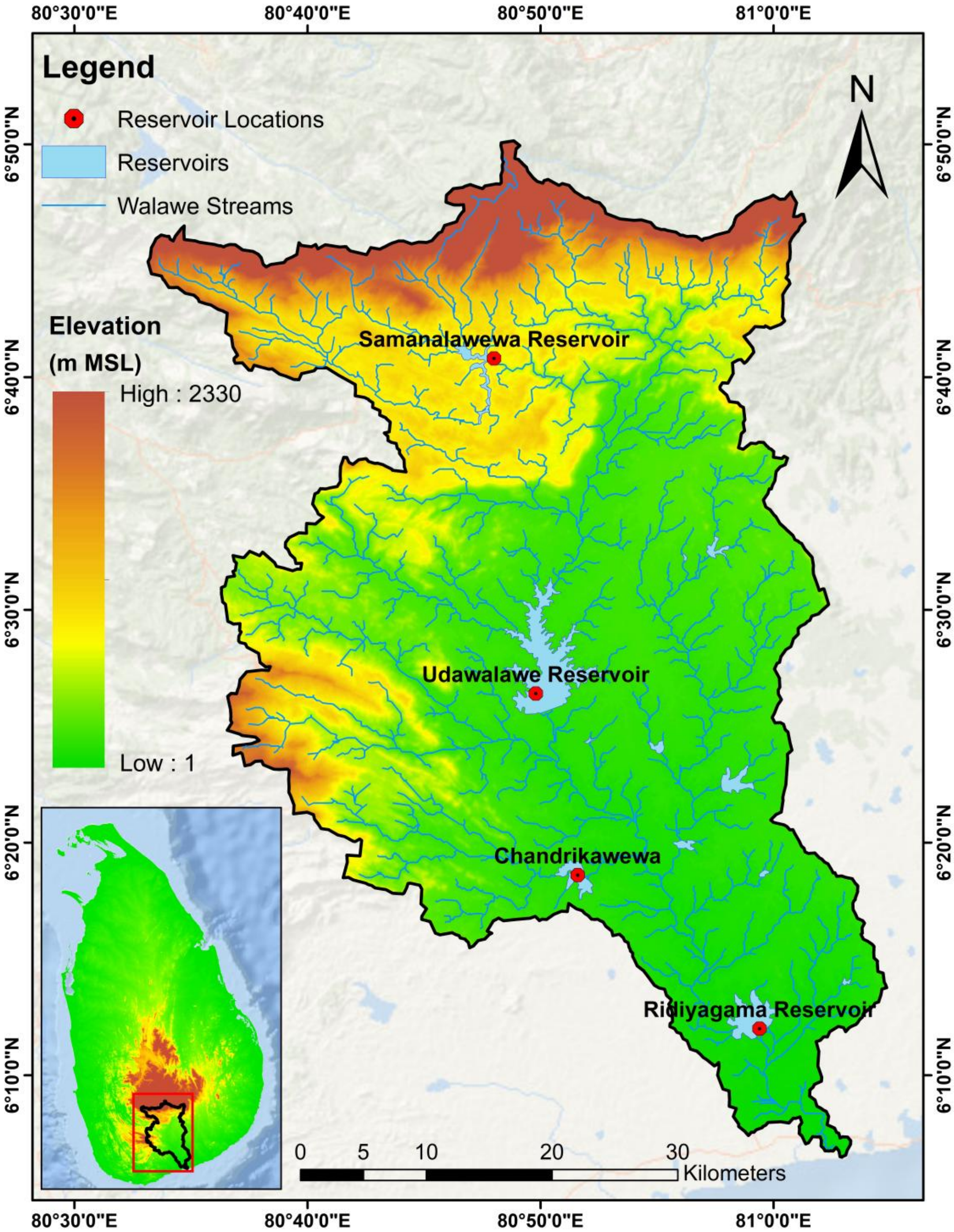


Figure 3-2: The Digital Elevation Map of Walawe River Basin and reservoir locations

The basin's rainfall regime is governed by four seasonal monsoons (Figure 3-3), the Northeast Monsoon (NEM: Dec–Feb), First Inter-monsoon (IM1: Mar–Apr), Southwest Monsoon (SWM: May–Sep), and Second Inter-monsoon (IM2: Oct–Nov), with IM1 contributing the largest rainfall share (~36%) and SWM the least (~17%) (Eriyagama et al., 2010). Mean annual temperature varies from 23–25°C in the highlands to 25–28°C in the lowlands. Average annual discharge is estimated at 1.1 × 10^9 m^3, of which about half contributes to surface runoff, while 7–12% recharges groundwater (Weragala et al., 2007).

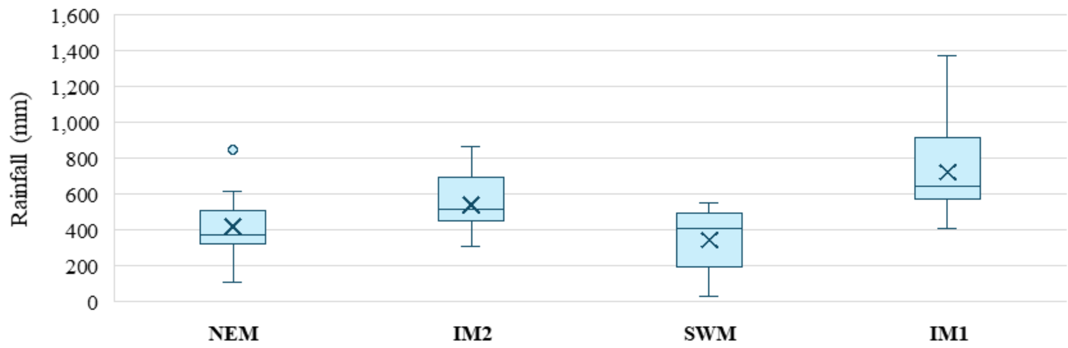


Figure 3-3: The seasonal rainfall variation within the Walawe River Basin area

The Samanalawewa Reservoir is situated on the upper Walawe sub-basin (Figure 3-4) and it was designed primarily for hydropower generation and flood control, with a gross storage capacity of 278 MCM. Water is conveyed through a 5.5 km headrace tunnel to the Kapugala Hydropower Plant, which generates approximately 300 GWh annually and supplies electricity to nearly 300,000 households (Pathiraja & Wijayapala, 2017). The reservoir's operation, however, has been affected by a subsurface leakage of roughly 55 MCM $year^{-1}$, emerging downstream of the right abutment (Molle et al., 2005). This seepage flow, though unintended, now sustains the Kalthota Irrigation Scheme (KIS), providing water for about 865 ha of paddy cultivation and highlighting the interdependence between energy production and agricultural supply.

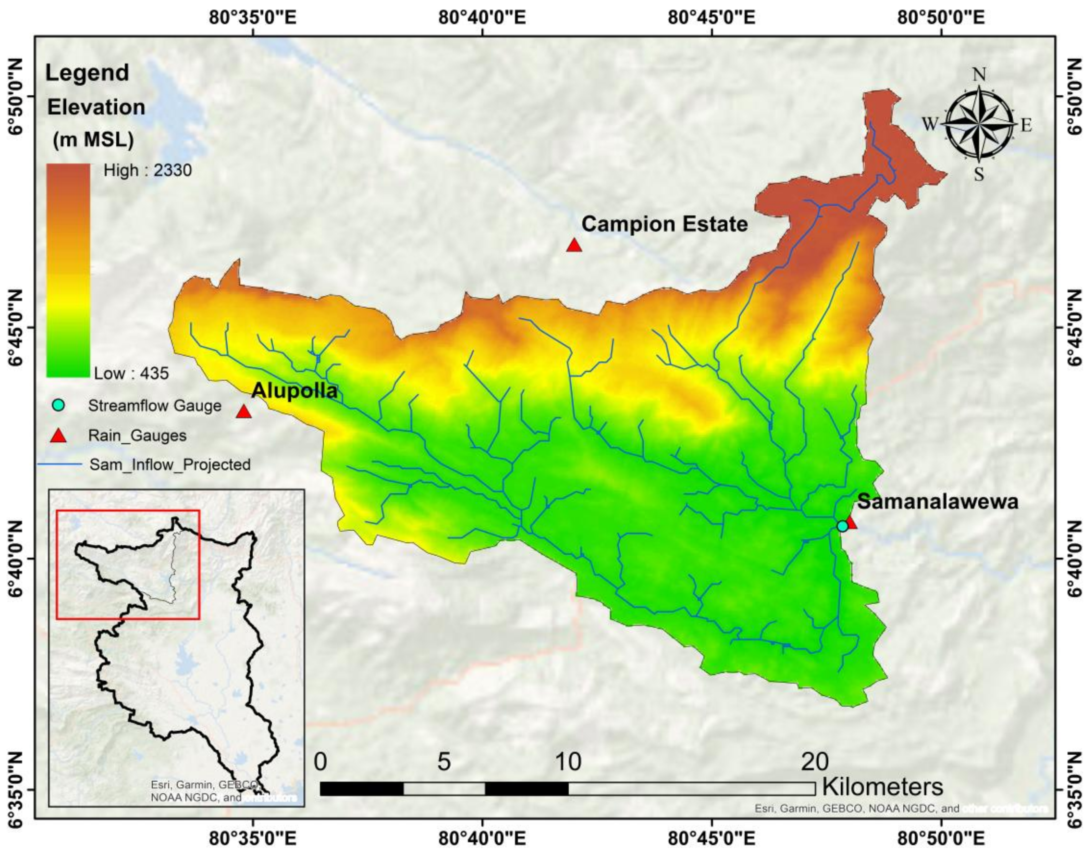


Figure 3-4: The digital elevation map of Samanalawewa sub-catchment area

Downstream, the Udawalawe Reservoir (208 MCM) complements Samanalawewa in a cascade operation, serving both hydropower and irrigation demands within the Walawe Irrigation System, which supports nearly 30,000 ha of agricultural land (Weragala et al., 2007). The integrated Samanalawewa–Udawalawe system (Figure 3-5) represents a complex multi-objective reservoir network, balancing hydropower generation, irrigation releases, and environmental flows under varying monsoonal inputs.

The basin also encompasses numerous small tank cascade systems (STCS), particularly in the Kolonne, Thanamalwila, and Embilipitiya Divisions, which play a vital role in local water retention and drought resilience (International Water Management Institute [IWMI], 2013).

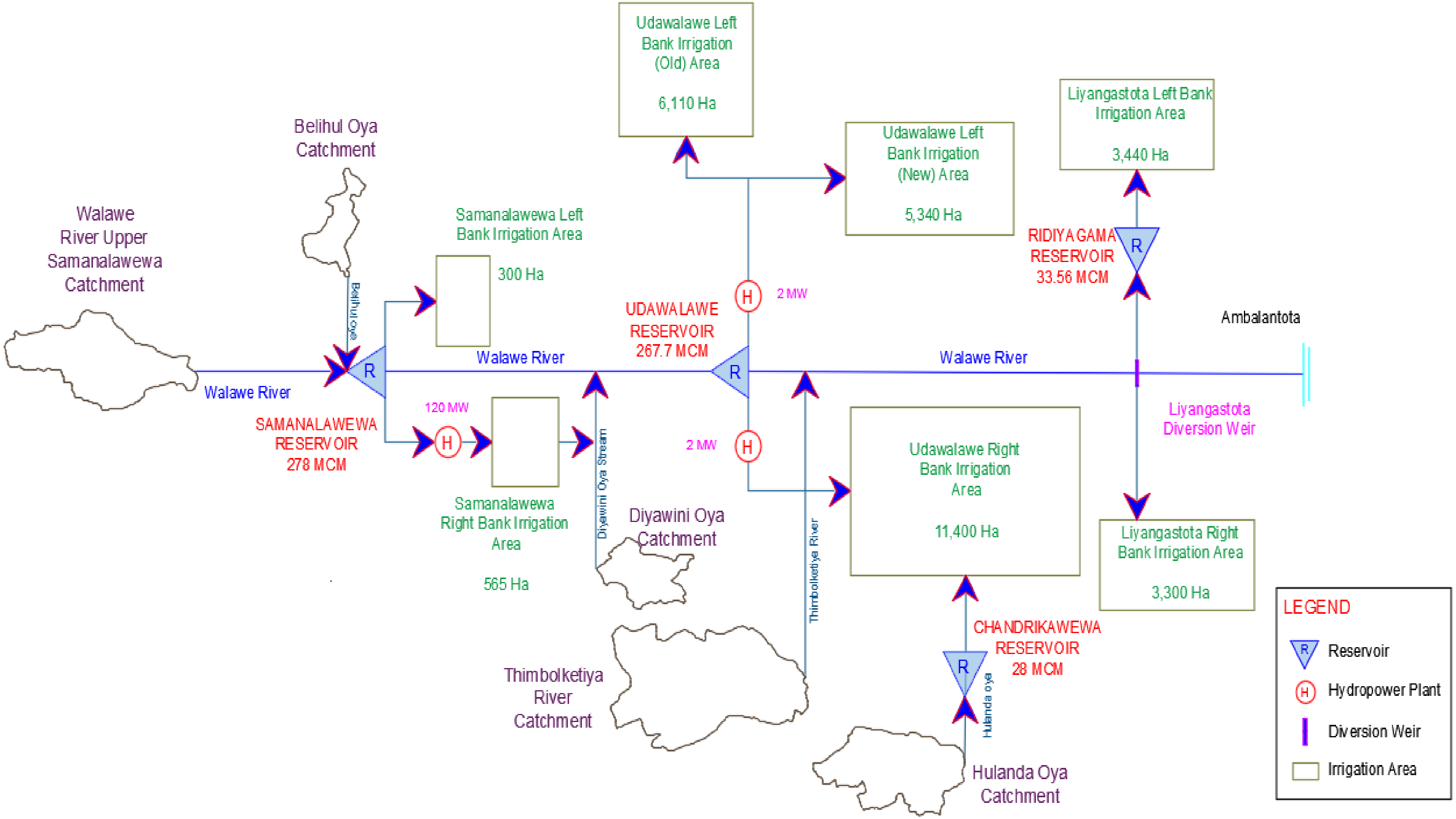


Figure 3-5: A schematic diagram of the water management system for Walawe River Basin

Together, these hydraulic infrastructures underpin a socio-hydrological system where water scarcity, agricultural expansion, and power demand coexist within a context of climatic variability and institutional overlap among the Ceylon Electricity Board (CEB), Irrigation Department (ID), and Mahaweli Authority. Given its distinct climatic gradients, strong monsoonal variability, and competing sectoral demands, the Walawe Basin, particularly the Samanalawewa sub-basin, provides an ideal setting for integrated hydrological and machine-learning-based water management research. This study utilises the basin's long-term hydrometeorological datasets to develop and validate an HEC-HMS-based rainfall–runoff model and to integrate machine learning architectures (LSTM and PINN) for simulating and optimising the reservoir water balance. The basin's exposure to climate-driven hydrological fluctuations further supports the application of downscaled climate projections to assess future water allocation and system resilience under changing climatic conditions.

3.2.2. Data Collection for the Development of Machine Learning Models

For the development and training of the machine learning models, a comprehensive daily time series dataset of the Samanalawewa Reservoir was compiled covering the period January 2005 to January 2022. This dataset includes the key hydrological and operational parameters required for the formulation of the reservoir water balance model: Precipitation (P), Natural Inflow (I), Irrigation Releases (IR), Power Releases (PR), Seepage (SL), Evaporation (E), Leakage Losses (L), and Gross Storage (S), each measured at a daily temporal resolution. The data were obtained from two primary institutional sources, the Mahaweli Authority of Sri Lanka (MASL) and the Ceylon Electricity Board (CEB), which maintain systematic hydrological and operational records for the Samanalawewa Hydropower Scheme.

The collected dataset was subjected to rigorous quality control and preprocessing before model development. Missing or inconsistent entries were corrected using statistical interpolation and cross-validation with adjacent hydrological stations. Outlier analysis was performed to identify extreme values and ensure physical consistency among the hydrological variables. Two distinct datasets were utilised for model training and testing, covering the period 2005–2022. Both datasets were subsequently divided into training (70%) and testing (30%) subsets to support model calibration, validation, and comparative evaluation between the LSTM and PINN architectures. The first dataset (Modified Dataset) represents normal hydrological conditions, developed by filtering out extreme peak events exceeding the 98th percentile of daily storage changes (Figure 3-6a). The second dataset retained all-natural variability within the testing period and retained the same as first dataset for the training period (Hybrid Dataset) to assess model resilience under stress conditions (Figure 3-6b).

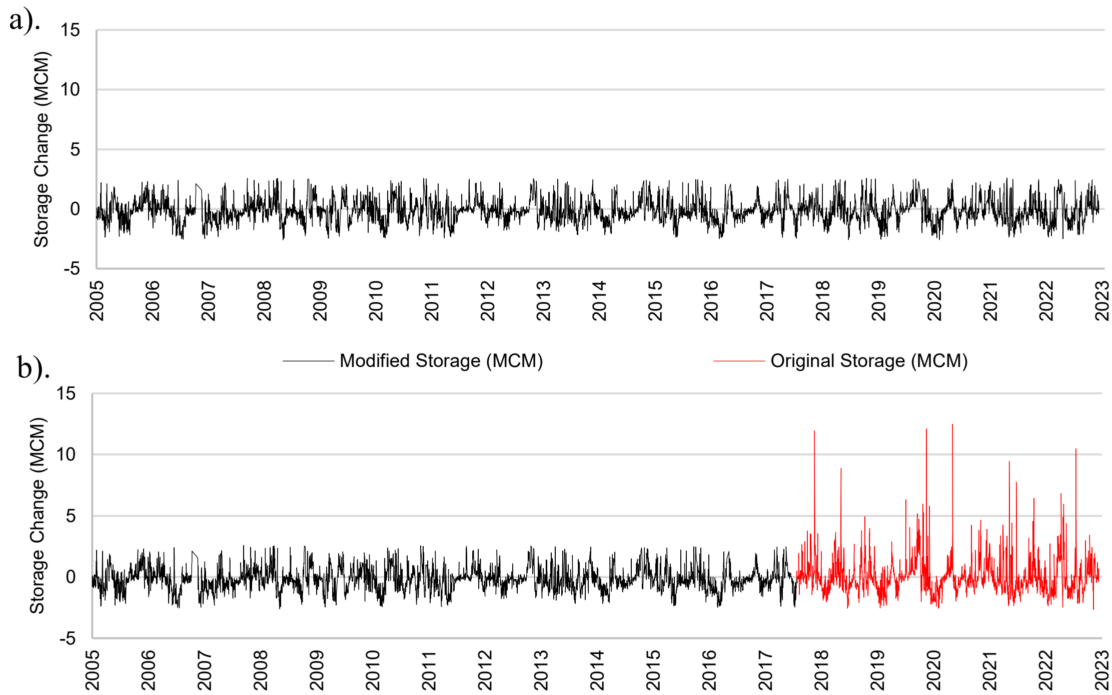


Figure 3-6: The two data series developed for the performance evaluation of Machine learning models (a) the modified data series without peaks for the period from 2005 January to 2023 January (b) the hybrid data series for the period from 2005 January

The resulting data structure enables a robust examination of model capability in simulating reservoir water balance under both normal and extreme operational conditions, forming the empirical foundation for the dynamic simulation model developed in this study.

2.1.1. Data Collection for the Development of a Hydrological Model

To evaluate the potential future impacts of climate variability on reservoir water management, a rainfall–runoff hydrological model was developed using the HEC-

HMS platform. This required the acquisition of comprehensive hydro-meteorological datasets representing both spatial and temporal variability across the Walawe River Basin, particularly focusing on the Samanalawewa sub-catchment.

Daily rainfall and streamflow (inflow) records were obtained from the Sri Lanka Department of Meteorology and the Department of Irrigation for the period 2010 to 2018. The selected rainfall and streamflow gauge stations were distributed strategically to capture the basin's hydroclimatic gradients from the high-elevation wet zone to the downstream dry zone. The details of the selected rainfall and inflow gauges, including their station codes, geographic coordinates, elevation, and record lengths, are presented in Table 3-1 and illustrated spatially in Figure 3-7.

Table 3-1: Selected gauges and their locations

Data type	**Stations**	**Location (UTM Coordinate; WGS84, Zone 44N)**	
		Longitude	**Latitude**
Rainfall Data	Alupolla	453583.06 E	742815.93 N
	Samanalawewa	477895.04 E	738378.70 N
	Campion Estate	466849.27 E	749438.99 N
Reservoir Inflow	Samanalawewa	477895.04 E	738378.70 N

These datasets formed the foundation for the HEC-HMS model calibration and validation phases. The model was configured to simulate daily inflows into the Samanalawewa Reservoir using observed rainfall as the primary input and observed inflows as target outputs. The validated model was subsequently used to simulate future inflow scenarios under downscaled climate projections, thereby linking hydrological responses to future water allocation and reservoir management assessments.

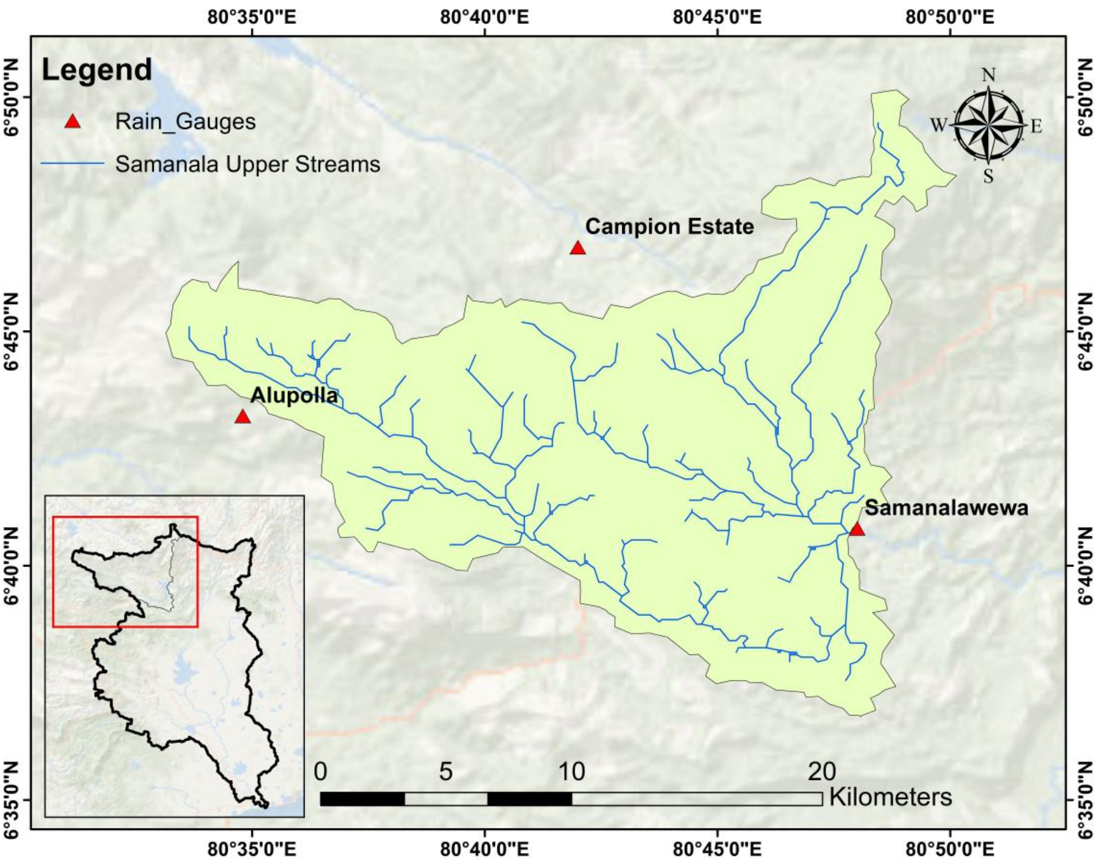


Figure 3-7: The locations of the selected rain gauges for the calculation of Thiessen average rainfall

3.3. Chapter Summary

This chapter presents an integrated methodological framework developed to evaluate and optimise reservoir water management under historical and future climate conditions. The methodology systematically combines hydrological modelling, machine learning–based dynamic optimisation, and climate change projections to support informed reservoir operation and water allocation decisions. The overall research process follows a structured sequence beginning with problem identification and literature review, progressing through data collection, model development, calibration, validation, optimisation, and concluding with performance assessment and interpretation of results.

The methodological framework is organised into three main components. The first component focuses on the development of a dynamic simulation and optimisation model using machine learning techniques. Two advanced architectures, LSTM networks and PINNs, were implemented to simulate reservoir water balance processes under nonlinear and highly variable hydrological conditions. A comparative evaluation was carried out to identify the most effective model, which was then integrated into a Python-based dynamic optimisation framework to generate optimal historical water allocation strategies.

The second component involves hydrological modelling of the Walawa River Basin using the HEC-HMS platform. Historical hydro-meteorological data, including rainfall and streamflow records, were used to develop, calibrate, and validate the rainfall–runoff model. Model performance was evaluated using standard statistical indices such as Nash–Sutcliffe Efficiency, coefficient of determination, and root mean square error. The calibrated hydrological model was subsequently employed to simulate reservoir inflows under both observed and projected climate conditions.

The third component incorporates climate change impacts by applying future climate projections derived from selected Global Climate Models (GCMs) under multiple Shared Socioeconomic Pathways (SSPs). The GCM outputs were statistically downscaled and bias-corrected using the LARS-WG weather generator to produce localised daily rainfall and temperature series. These downscaled datasets were input into the calibrated HEC-HMS model to generate future inflow scenarios, which were then used in the dynamic optimisation model to estimate projected optimal water allocation strategies.

CHAPTER 4

4. DATA CHECKING AND ANALYSIS

This chapter presents the procedures undertaken to ensure the reliability, consistency, and suitability of the datasets used in model development.

4.1. Data Checking and Analysis for the Development of Machine Learning Models

The accuracy and internal consistency of the operational and hydrometeorological data are critical prior to developing predictive machine learning models. Reliable datasets ensure that the trained models accurately represent the reservoir's physical dynamics and improve the precision of subsequent water balance simulations. Therefore, a series of data verification and sensitivity analyses were carried out for the Samanalawewa Reservoir before model development. The following sections describe the Water Balance Satisfaction Check and Storage–Parameter Sensitivity Analysis, which were performed to validate the dataset's integrity and its suitability for machine learning applications.

4.1.1. Water Balance Satisfaction Check

Before initiating model development, it was essential to verify the accuracy and consistency of the collected daily reservoir operation and hydrometeorological data. To achieve this, a simple water balance check was performed using the observed operational variables of the Samanalawewa Reservoir. The dataset comprised all the essential hydro-operational parameters required for the water balance computation, namely, precipitation (*P*), natural inflow (*I*), irrigation release (*IR*), power release (*PR*), seepage (*SL*), evaporation (*E*), leakage (*L*), and gross storage (*S*). This verification ensured that the data were internally consistent and accurately reflected the reservoir's physical behaviour. The fundamental mass balance equation of the reservoir was used to compute the daily change in storage as a function of all inflow and outflow components, expressed as Equation (2):

$$\frac{d\big(S(t)\big)}{dt} = P(t) + I(t) - IR(t) - PR(t) - SL(t) - L(t) - E(t) \tag{2}$$

The observed change in storage, $\Delta S(t)_{LHS}$, was estimated from the difference between two consecutive daily storage values, as shown in Equation (3):

$$\Delta S(t)_{LHS} = S(t+1) - S(t) \qquad (3)$$

The computed change in storage, $\Delta S(t)_{RHS}$, was derived using the complete hydro-operational balance as in Equation (4):

$$\Delta S(t)_{RHS} = P(t) + I(t) - IR(t) - PR(t) - SL(t) - L(t) - E(t) \qquad (4)$$

The consistency between the observed and computed storage changes was statistically evaluated using Nash–Sutcliffe Efficiency (NSE), Root Mean Square Error (RMSE), and the Coefficient of Determination (R^2), given respectively by Equations (5).(6), and (7):

$$NSE = 1 - \frac{\sum_{t=1}^{N}(\Delta S(t)_{LHS} - \Delta S(t)_{RHS})^2}{\sum_{t=1}^{N}\left(\Delta S(t)_{LHS} - \overline{\Delta S(t)_{LHS}}\right)^2} \qquad (5)$$

$$RMSE = \sqrt{\frac{1}{N}\sum_{t=1}^{N}(\Delta S(t)_{LHS} - \Delta S(t)_{RHS})^2} \qquad (6)$$

$$R^2 = \frac{\left[\sum_{t=1}^{N}\left(\Delta S(t)_{LHS} - \overline{\Delta S(t)_{LHS}}\right)\left(\Delta S(t)_{RHS} - \overline{\Delta S(t)_{RHS}}\right)\right]^2}{\sum_{t=1}^{N}\left(\Delta S(t)_{LHS} - \overline{\Delta S(t)_{LHS}}\right)^2 \times \sum_{t=1}^{N}\left(\Delta S(t)_{RHS} - \overline{\Delta S(t)_{RHS}}\right)^2} \qquad (7)$$

where $\Delta S(\bar{t})_{LHS}$and $\Delta S(\bar{t})_{RHS}$are the mean values of the observed and computed storage change series, respectively. The resulting performance indices, NSE = 0.92, RMSE = 0.40 Mm³, and R^2 = 0.92, demonstrated a strong correlation between observed and computed storage variations, confirming excellent dataset integrity and physical consistency. Figure 4-1 illustrates the comparison between the observed and calculated storage changes for the representative year 2013, showing a close match between the two time series.

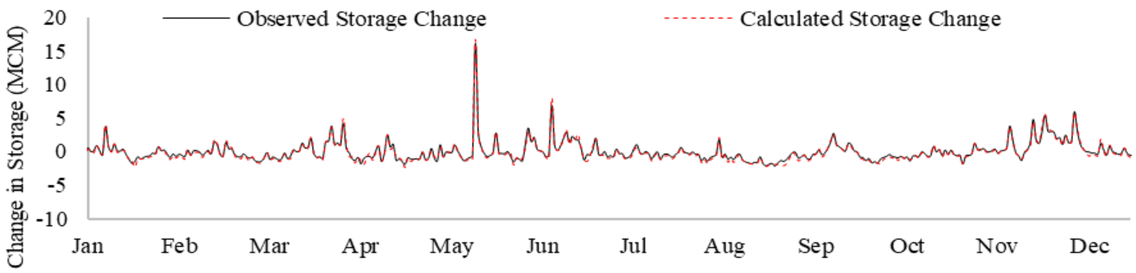


Figure 4-1: Time series plot showing the match between observed and calculated storage changes for the selected year (2013)

These results confirm that the dataset faithfully represents reservoir hydrodynamics and can be confidently used in machine learning model development for reservoir water balance simulation.

4.1.2. Storage–Parameter Sensitivity Check

A sensitivity analysis was conducted to evaluate how fluctuations in individual hydrological and operational parameters affect the reservoir's storage behaviour. This step provides insight into the degree of influence each parameter exerts on storage variation and helps prioritise key variables for inclusion in the machine learning framework. Using the parameters from the water balance model, the storage change (ΔS) was analysed by systematically varying each input parameter, precipitation (P), inflow (I), irrigation release (IR), power release (PR), evaporation (E), seepage (SL), and leakage (L), while keeping the others constant. Each parameter was modified in increments of ±10%, ranging from –50% to +50%, and the resulting changes in reservoir storage were observed.

The analysis revealed a positive correlation between storage change and the inflow-related variables (precipitation and natural inflow). As these parameters increased, reservoir storage also rose due to enhanced catchment runoff and inflow contribution. Conversely, variables representing outflows, namely irrigation release, power release, evaporation, seepage, and leakage, exhibited negative correlations with storage change. Higher water releases and losses led to a corresponding decline in reservoir storage. This relationship highlights the dynamic interaction between inflow and outflow components in governing the storage regime of the reservoir. The sensitivity outcomes align with hydrological expectations and further confirm that the dataset accurately captures physical system responses. Figure 4-2 presents the variation of observed storage change with respect to individual input parameters.

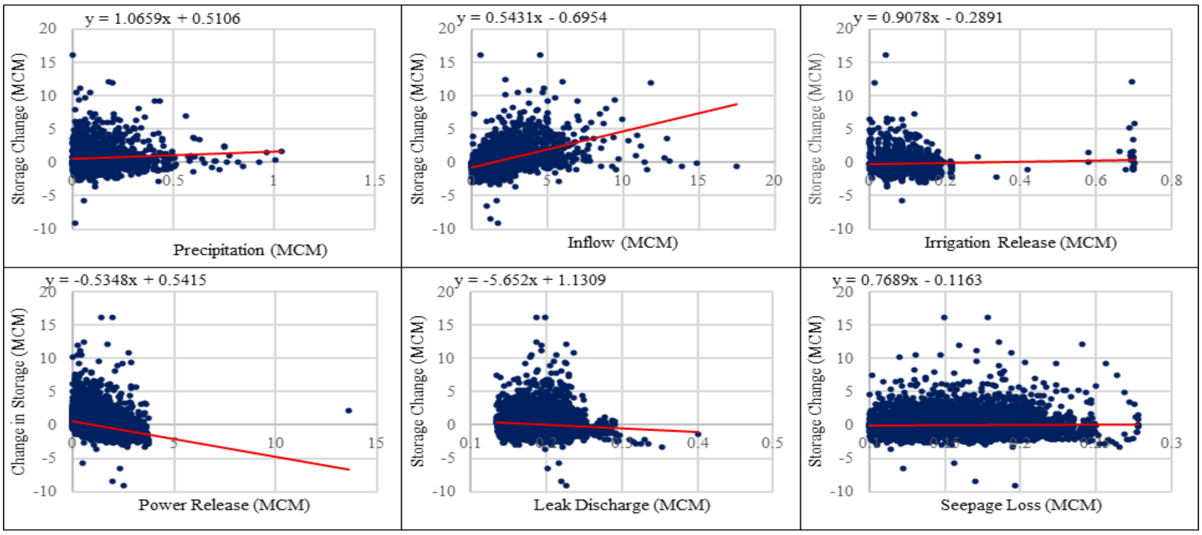


Figure 4-2: Variation of storage change with observed input variables for the water balance

4.2. Data Checking and Analysis for the Development of a Hydrological Model

To ensure the reliability and accuracy of the input data used in the hydrological modelling process, extensive data checking and validation procedures were carried out before model development. The model calibration and validation were performed using an eight-year dataset comprising daily rainfall and daily reservoir inflow observations. Since rainfall in the study area exhibits significant spatial variability due to its complex topography, a representative rainfall dataset was derived by employing the Thiessen polygon method based on measurements obtained from three key rain gauge stations: Alupolla, Samanalawewa, and Campion Estate. The Thiessen polygons were generated using ArcGIS software to determine the relative influence area of each rain gauge within the sub-catchment (Figure 4-3). This method ensures that spatial rainfall variability across the catchment is accurately represented by assigning area-weighted contributions from each station. The computed Thiessen weights for the selected gauges are presented in Table 4-1, which were later used to calculate the weighted average daily rainfall input for the model.

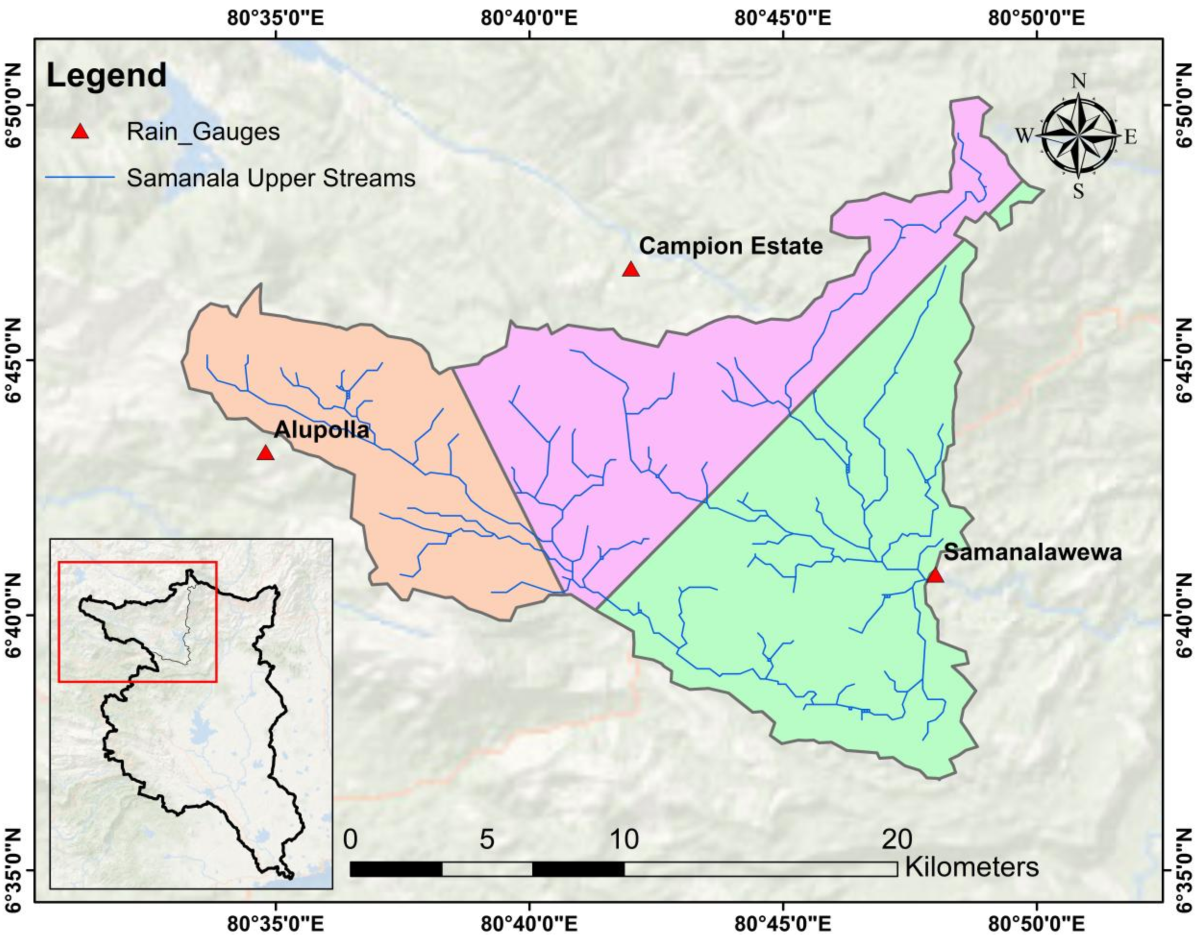


Figure 4-3: The Thiessen polygons that have been plotted for the selected three stations

Table 4-1: Thiessen weightage values used for the selected rain gauge stations

Station	Alupolla	Samanalawewa	Campion Estate
Thiessen weightage	0.24	0.42	0.34

Visual Data Checking

The initial stage of data verification involved a visual inspection of rainfall and streamflow records to identify potential inconsistencies, anomalies, or missing values. By plotting rainfall and corresponding inflow data on the same time axis, patterns were visually compared to assess their logical relationship. Consistent peaks between rainfall and inflow hydrographs typically confirm data reliability, while discrepancies may indicate recording errors, missing data, or issues with timing and gauge calibration (Figure 4-4). This step provided a qualitative understanding of the temporal coherence between rainfall and runoff responses, which is essential for developing a physically consistent hydrological model.

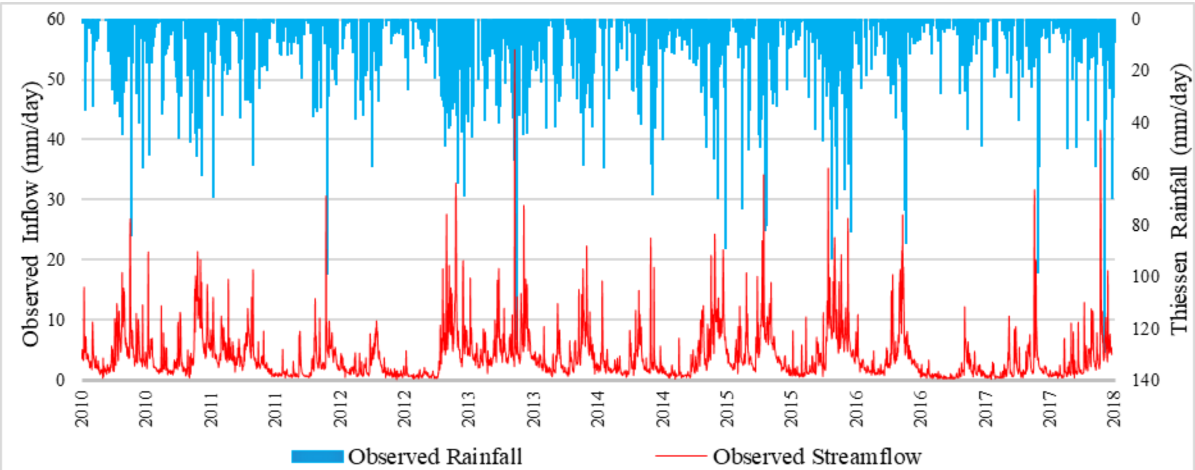


Figure 4-4: Rainfall runoff hydrograph plotted for the visual data checking

Single Mass Curve Analysis

The single mass curve method evaluates the long-term consistency of rainfall data by plotting the cumulative rainfall against time for each gauge station. A straight line on the plot indicates that the station has maintained consistent measurement characteristics over time, while any deviation or change in slope suggests possible alterations in observational practices or data errors. Figure 4-5 presents the single mass curves for the Alupolla, Campion Estate, and Samanalawewa stations. The near-linear relationships observed for all stations confirm the consistency and reliability of the long-term rainfall records used for this study.

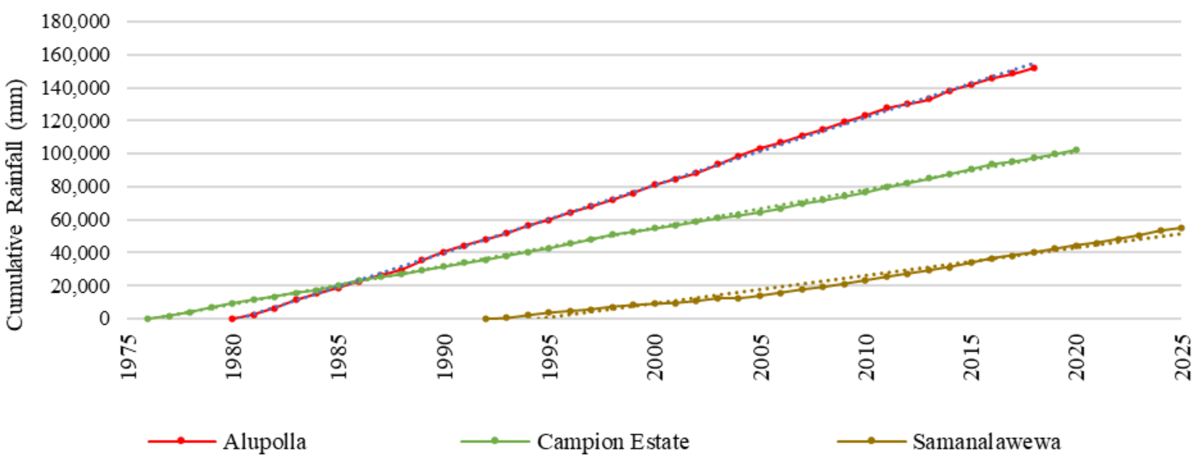
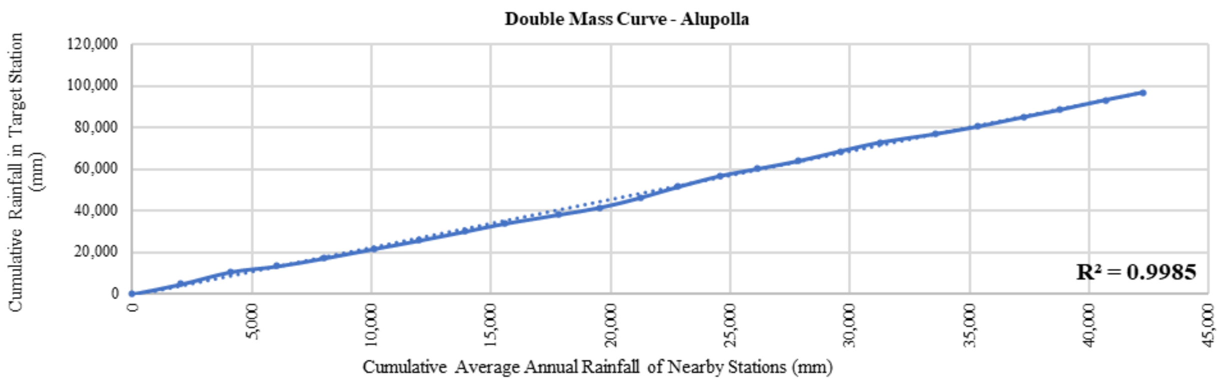
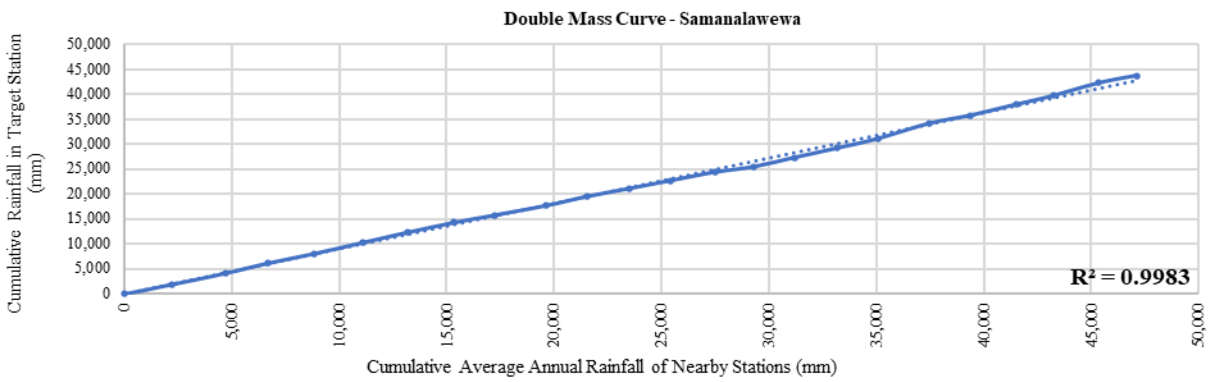


Figure 4-5: Single mass curves plotted for the selected rain gauge stations

Double Mass Curve Analysis

The double mass curve method provides a cross-verification of rainfall data between neighbouring stations. It involves plotting the cumulative rainfall of a target station against the average cumulative rainfall of surrounding stations. A consistent linear trend indicates homogeneity across the dataset, whereas any break in the slope implies inconsistency, potentially caused by gauge relocation, environmental changes, or instrument malfunction. For the selected three stations, the double mass curves displayed excellent linearity with R^2 values greater than 0.99, as shown in Figure 4-6, confirming strong correlation and data coherence among the stations.





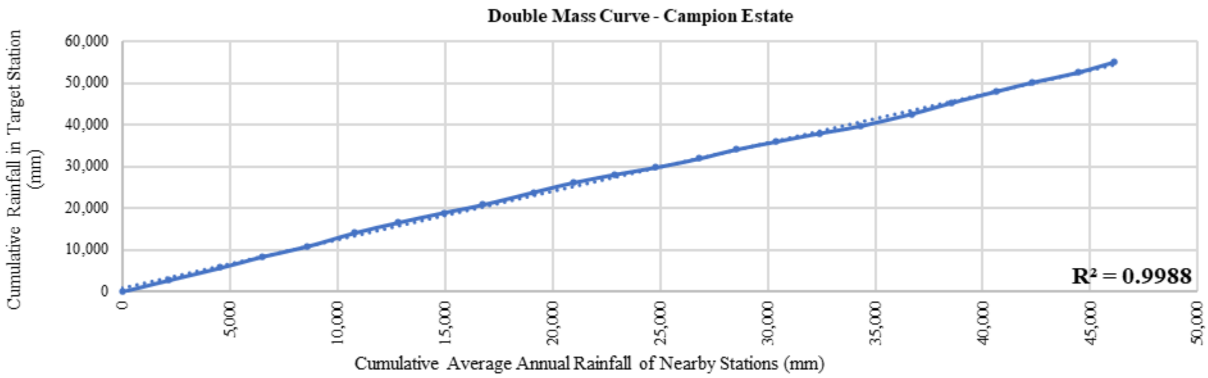


Figure 4-6: Double mass curves plotted for each rainfall gauge selected

In certain instances, missing rainfall observations were identified within the dataset. To address these data gaps, the nearest station patching method was applied. This approach utilises data from nearby gauges exhibiting similar rainfall trends to estimate missing values. Following WMO (2008) guidelines, this method was only applied when missing data represented less than 10% of the total dataset for a given station. The missing values were estimated using the slope ratio method, where the slope of the single mass curve for the station with missing data was compared with that of the reference station. The ratio between these slopes was then used to scale the reference station data, ensuring that the patched values maintained consistency with the local rainfall regime.

The comprehensive analysis combining visual inspection, single and double mass curve evaluations, and patching of missing data confirmed that the rainfall dataset is both consistent and homogeneous. The strong linearity ($R^2 > 0.99$) of the double mass curves and the absence of significant deviations in single mass curves indicate that the rainfall stations maintained reliable measurement practices over the analysis period. Therefore, the derived Thiessen-weighted rainfall dataset was deemed suitable for use as input to the HEC-HMS hydrological model for simulation, calibration, and validation processes

4.3. Chapter Summary

This chapter presents a comprehensive data checking and analysis framework implemented to ensure the accuracy, consistency, and reliability of hydrometeorological and operational datasets before their use in machine learning and hydrological modelling. Given the sensitivity of reservoir water balance simulations to data quality, rigorous verification procedures were applied to confirm that the datasets accurately represent the physical behaviour of the Samanalawewa Reservoir system and are suitable for predictive modelling applications.

For the development of machine learning models, a detailed water balance satisfaction check was first conducted using observed daily operational and hydrological data. The reservoir mass balance equation was applied to compute storage variations based on precipitation, inflow, irrigation release, power release, evaporation, seepage, and leakage. The computed storage changes were compared against observed storage variations, and the consistency between the two was evaluated using statistical performance indicators, including Nash–Sutcliffe Efficiency, Root Mean Square Error, and the coefficient of determination. The strong agreement between observed and calculated storage changes confirmed excellent internal consistency and validated the physical integrity of the dataset.

A storage–parameter sensitivity analysis was subsequently performed to assess the influence of individual hydrological and operational variables on reservoir storage behaviour. Input parameters were systematically varied within a defined range while holding others constant, allowing the identification of dominant drivers of storage variability. The analysis revealed positive correlations between storage and inflow-related variables, such as precipitation and natural inflow, while outflow-related variables, including irrigation release, power release, evaporation, seepage, and leakage, exhibited negative correlations. These results aligned with hydrological expectations and further verified the dataset's physical realism.

The chapter also details data checking procedures undertaken for hydrological model development. Rainfall and inflow datasets were subjected to visual inspection to detect inconsistencies, anomalies, or missing values. Spatial rainfall variability within the catchment was addressed using the Thiessen polygon method, ensuring area-weighted representation of rainfall inputs. Long-term consistency of rainfall records was evaluated using single mass curve analysis, while double mass curve analysis was employed to assess homogeneity and cross-station coherence. High linearity and strong correlation among rainfall stations confirmed data reliability.

Where minor data gaps were identified, missing rainfall values were estimated using the nearest station patching method in accordance with established guidelines. Overall, the integrated application of statistical evaluation, sensitivity analysis, visual inspection, and mass curve techniques confirmed that the datasets are consistent, homogeneous, and suitable for subsequent machine learning simulations and hydrological modelling.

CHAPTER 5

5. MODEL DEVELOPMENT AND APPLICATIONS

This chapter presents the development and implementation of the modelling framework designed to optimize reservoir water allocation under current and projected climate conditions. It details the construction of the hydrological model, the integration of machine learning techniques for reservoir water balance simulation, and the formulation of the dynamic water allocation model.

5.1. Integration of Machine Learning for Reservoir Water Balance

The integration of machine learning (ML) techniques into reservoir water balance modelling represents a significant advancement in improving prediction accuracy and operational adaptability. This study developed and evaluated two ML architectures, a PINN and an LSTM network (Figure 5-1), to simulate daily reservoir storage dynamics under varying hydrological conditions. The objective was to identify the model that best replicates physical water balance behaviour while maintaining robustness under both normal and extreme flow regimes.

5.1.1. Development of PINN Model for Reservoir Water Balance

To embed physical hydrological principles into the learning framework, a PINN was developed to simulate daily reservoir storage changes ($\Delta S(t)$). Unlike purely data-driven models, the PINN integrates the reservoir water balance equation directly into its loss function, thereby constraining the model to generate physically consistent predictions even under extreme conditions.

The model incorporated eight key input features, precipitation ($P(t)$), inflow ($I(t)$), irrigation release ($IR(t)$), power release ($PR(t)$), seepage ($SL(t)$), leakage ($L(t)$) and evaporation ($E(t)$), representing the governing terms of the water balance. The PINN was implemented using a deep residual architecture comprising three hidden layers with 256, 128, and 64 neurons, respectively. Layer normalisation (Ba et al., 2016), LeakyReLU activation (Maas, 2013), and L2 regularisation (Heaton, 2018) were applied to stabilise learning and prevent overfitting, while a skip connection between the first and third layers improved gradient propagation and convergence. A custom composite loss function was designed to balance physical accuracy and statistical performance. It combined physics loss to enforce mass balance consistency, a proxy NSE term to capture hydrological realism, and MSE to minimize numerical error, ensuring that the model produced physically consistent and statistically reliable predictions (Raissi et al., 2019). The model was trained using the Adam optimiser (learning rate = 0.0005) for 1,000 epochs with early stopping (patience = 100) and gradient clipping to enhance stability. Model performance was evaluated using RMSE, MAE, NSE, and R^2, with the best model weights selected based on validation loss. The predicted results were inverse transformed to physical magnitudes and decomposed to verify consistency with observed hydrological processes.

5.1.2. Development of LSTM Model for Reservoir Water Balance

To capture nonlinear temporal dependencies in the reservoir water balance, an LSTM model was developed using the TensorFlow–Keras framework (Chicho & Sallow, 2021). Eight hydrological input variables, identical to those used in the PINN model, were normalised using the MinMaxScaler to enhance training stability. A seven-day input sequence was used to represent short-term temporal dependencies critical for reservoir inflow–storage relationships. The model architecture consisted of two stacked LSTM layers with 64 and 32 units, respectively, followed by layer normalisation and ReLU activation for nonlinearity. Dropout layers (rates = 0.3 and 0.2) were applied to prevent overfitting, followed by a Dense output node producing daily storage change predictions. The model was compiled using the Adam optimiser (learning rate = 0.001) and trained for 150 epochs with early stopping (patience = 20) and batch size = 32. A custom hybrid loss function combining MSE and NSE (Kratzert et al., 2019) was defined as Equation (8):

$$Loss = 0.2 \times MSE - 0.8 \times NSE \quad (8)$$

This formulation balances numerical accuracy with hydrological realism, ensuring accurate replication of both average and peak flows. Model evaluation was conducted using RMSE, MAE, R^2, and NSE metrics on both training and testing datasets (Equations (9), (10), (11), and (12)).

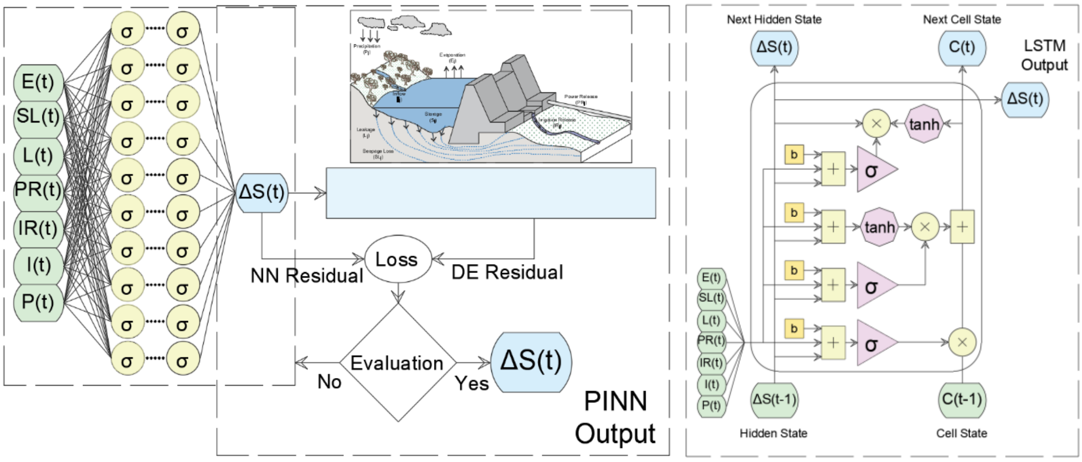


Figure 5-1: A simple schematic diagram of PINN and LSTM architectures

$$NSE = 1 - \frac{\sum_{t=1}^{N}(\Delta S(t)_{Obs.} - \Delta S(t)_{Sim.})^2}{\sum_{t=1}^{N}\left(\Delta S(t)_{Obs.} - \overline{\Delta S(t)_{Sim.}}\right)^2} \tag{9}$$

$$RMSE = \sqrt{\frac{1}{N}\sum_{t=1}^{N}(\Delta S(t)_{Obs.} - \Delta S(t)_{Sim.})^2} \tag{10}$$

$$R^2 = \frac{\left[\sum_{t=1}^{N}\left(\Delta S(t)_{Obs.} - \overline{\Delta S(t)_{Sim.}}\right)\left(\Delta S(t)_{Sim.} - \overline{\Delta S(t)_{Obs.}}\right)\right]^2}{\sum_{t=1}^{N}\left(\Delta S(t)_{Obs.} - \overline{\Delta S(t)_{Sim.}}\right)^2 \times \sum_{t=1}^{N}\left(\Delta S(t)_{Sim.} - \overline{\Delta S(t)_{Obs.}}\right)^2} \tag{11}$$

$$MAE = \frac{1}{N}\sum_{t=1}^{N}|\Delta S(t)_{Obs.} - \Delta S(t)_{Sim.}| \tag{12}$$

where $\Delta S(t)_{Obs.}$ and $\Delta S(t)_{Sim.}$ are the daily storage change values of the observed and simulated time series.

5.1.3. Performance Evaluation and Comparison of Machine Learning Models

Both the PINN and LSTM models were evaluated for predictive performance, generalisation, and adherence to hydrological principles (Figure 5-2). Statistical indicators, including RMSE, MAE, NSE, and R^2, were computed for both normal and extreme datasets. Model optimisation was achieved through iterative tuning of network hyperparameters, including neuron count, layer depth, learning rates, and dropout ratios for the LSTM, and residual weighting, layer width, and regularisation coefficients for the PINN.

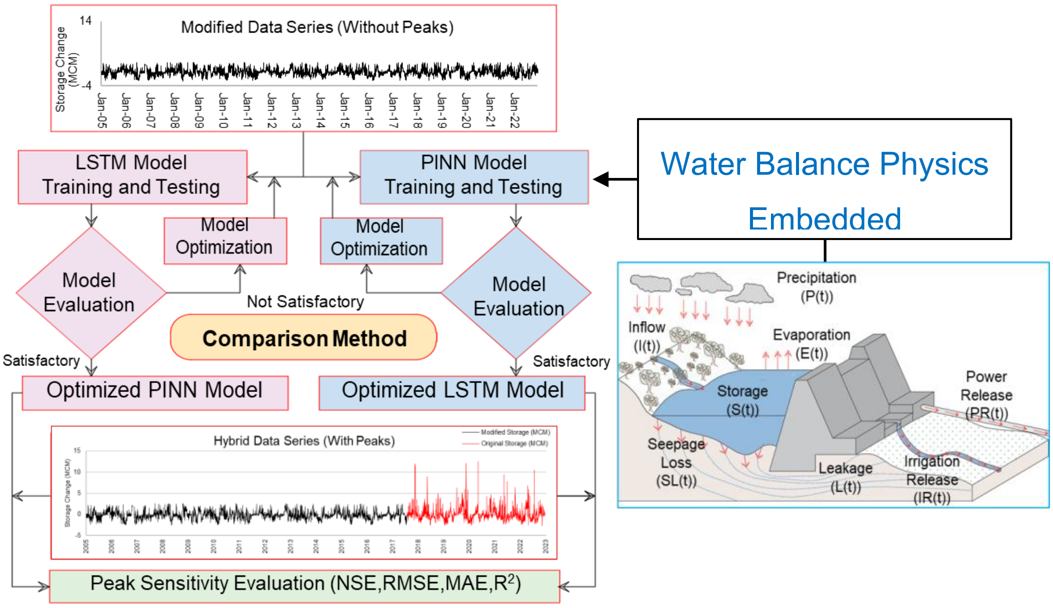


Figure 5-2: The methodology flowchart that followed for the comparison between LSTM and PINN models

After achieving stable convergence, model outputs were compared to observed daily storage changes. The PINN model demonstrated superior physical consistency, particularly in maintaining water balance under extreme inflow conditions, while the LSTM model exhibited higher temporal pattern accuracy for normal hydrological regimes. The comparative analysis revealed that although both architectures performed effectively, the PINN model provided better overall robustness and interpretability, particularly under stress scenarios involving rapid storage fluctuations. The selected best-performing model was then used as the core engine for the dynamic reservoir water balance simulation, generating the optimised water allocation dataset used in subsequent optimisation and climate impact assessments.

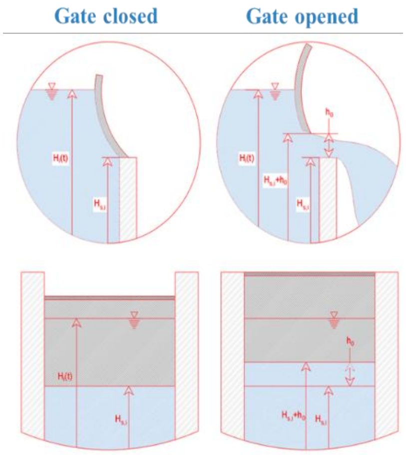
5.2. Development of Reservoir Water Allocation Model

The development of the reservoir water allocation model aimed to establish a dynamic and physically consistent framework for optimising the daily distribution of available water resources within the Samanalawewa Reservoir system. The model integrates hydrological, operational, and performance-based components to simulate real-world reservoir behaviour under varying climatic and inflow conditions. By coupling hydrological inflow simulations with rule-based operational logic, the model ensures that water is allocated efficiently among competing demands, primarily irrigation and hydropower, while maintaining essential operational thresholds such as minimum storage and environmental flow requirements. The allocation model was implemented in Python, enabling flexible simulation, parameter optimisation, and performance evaluation. Through a three-stage computational workflow, the model sequentially updates reservoir storage, determines release decisions based on operational priorities, and evaluates irrigation adequacy and power generation efficiency. This framework provides a practical decision-support tool for improving reservoir management strategies and enhancing resilience against hydrological variability and future climate change impacts.

5.2.1. Define Operation Schedule for the Reservoir

The operation schedule for the Samanalawewa Reservoir was defined through a structured, three-stage decision-support framework designed to represent realistic reservoir behaviour under varying hydrological and operational conditions. The primary objective of this operation schedule is to maintain a physically consistent water balance while optimising water allocation between irrigation and hydropower generation according to daily inflow variability. In Stage 1, the model simulates the hydrological mass balance of the reservoir by integrating inflow generation, storage variation, and hydraulic spillway behaviour. Simulated upstream inflows from the calibrated HEC-HMS model are added to the reservoir's initial storage, and adjustments are made for evaporation, seepage, and spillage losses (Equation (13)). Evaporation is estimated using the area–elevation–capacity (A–H–S) relationship and daily evaporation rates, while spillage is determined by the hydraulic characteristics of the radial spillway gates (Figure 5-3). The resulting net storage represents the useful storage available for reservoir operation at each daily timestep.

$$SP_{Calc,\,i}(t) = 0.0024\, n_i t_s C_d W_{s,i}\sqrt{2g}\left(\left(H_i(t) - H_{s,i}\right)^{\frac{3}{2}} - \left(H_i(t) - H_{s,i} - h_0\right)^{\frac{3}{2}}\right) \tag{13}$$



$W_{s,i}$ $-$ *Width of the spillway gate* (m)

g $-$ 9.81 $\mathrm{ms^{-2}}$

$H_i(t)$ $-$ *Reservoir water level at the begining of time step 't'* (m)

$H_{s,i}$ $-$ *Spill level of the* i^{th} *reservoir* (m)

h_0 $-$ *The height of the opening* (m)

q_0 $-$ *The discharge of water through one spillway gate* (m^3s^{-1})

n_i $-$ *The number of spill gates opened*

t_s $-$ *The duration of spill gate opened per day (hrs per day)*

q $-$ The discharge of water through spillway $(\mathrm{m^3s^{-1}})$

Q $-$ The discharge of water through spillway (MCM)

C_d $-$ *Coefficient of discharge* $(C_d \approx 0.63)$

Figure 5-3: The defined spillway operation and parameters related with it

In Stage 2, the operation schedule focuses on determining the water release for irrigation and hydropower based on predefined operational thresholds. A rule-based decision sequence was developed to ensure that minimum water requirements for irrigation and environmental flow are met before allocating water for power generation. The algorithm first checks if the available storage satisfies the minimum downstream requirement; if insufficient, reservoir releases are restricted to zero to preserve minimum storage levels. If sufficient water exists, the model sequentially evaluates whether the reservoir elevation exceeds the minimum operational and hydropower thresholds. Releases for irrigation are then prioritised, and hydropower generation is permitted only when the available storage exceeds the hydropower minimum level, ensuring that energy production does not compromise irrigation security.

Finally, Stage 3 evaluates the operational performance of the reservoir based on the discharge determined in Stage 2. The operational reliability of the reservoir is assessed by comparing simulated and observed discharges. This integrated, physics-consistent operational framework provides a robust representation of the Samanalawewa Reservoir's dynamic behaviour, ensuring sustainable and efficient water allocation that balances irrigation and hydropower demands under both normal and extreme hydrological conditions (Figure 5-4).

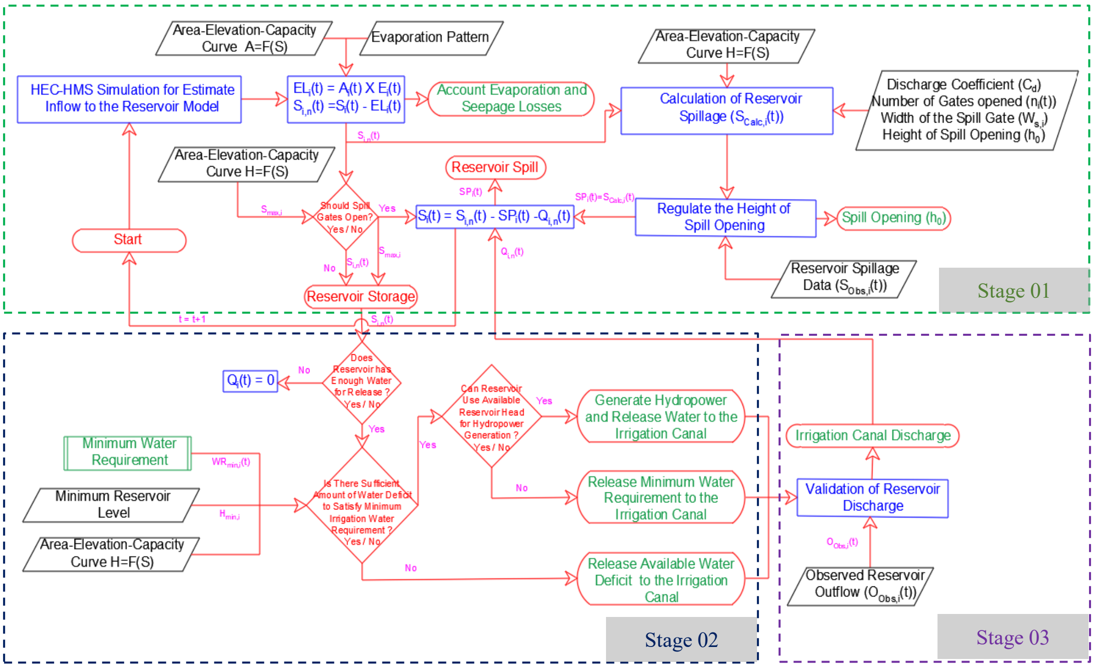


Figure 5-4: Developed dynamic water allocation model architecture

5.2.2. Development of Water Allocation Model Using Python

The reservoir water allocation model was developed in Python to simulate the daily water balance and operational decision-making of the Samanalawewa Reservoir. The primary objective of this model was to represent real-time reservoir behaviour through a dynamic and physically consistent computational framework that accounts for hydrological inflows, reservoir losses, and operational releases for irrigation and hydropower. The model was structured to read daily time series inputs, including inflow, precipitation, evaporation, hydropower demand, leakage discharge, irrigation release, and observed gross storage. These inputs were collected from the relevant authorities and pre-processed into a structured format compatible with the model's computational environment. The Area–Elevation–Capacity (A–H–S) relationship of the reservoir was integrated to support volume-based calculations, particularly for evaporation and spillway discharge estimation.

The model implementation was built around a custom Python function, which sequentially updates the reservoir storage on a daily basis. For each time step, inflow and precipitation are added to the current storage, and evaporation, seepage, and leakage losses are subtracted. Seepage losses were assumed to be 0.5% of the storage volume, while evaporation losses were calculated from the area–capacity relationship and daily evaporation rates. When the storage exceeded the reservoir's maximum capacity, spillage was automatically computed based on spillway discharge hydraulics and converted from cubic meters per second to million cubic meters per day using an appropriate conversion factor. The remaining net storage was then evaluated against the predefined operational thresholds, including dead storage, minimum irrigation requirement, and minimum hydropower storage, to determine the possible allocation of releases.

A rule-based decision sequence was implemented within the model to prioritise irrigation supply over hydropower generation during water-scarce conditions. If the available storage was below the minimum operational threshold, releases were restricted, whereas when sufficient water was available, both irrigation and hydropower demands were met according to their respective priorities.

5.2.3. Performance Evaluation of Water Allocation Model

The model output included daily estimates of net storage, spillage, irrigation and power releases, and changes in storage. The results were evaluated using statistical performance metrics, including the Nash–Sutcliffe Efficiency (NSE), Root Mean Squared Error (RMSE), Mean Squared Error (MSE), and the coefficient of determination (R^2), to ensure the accuracy and reliability of the simulation. Visualisation and performance evaluation were integrated into the Python workflow, with plots comparing the observed and simulated storage variations. A detailed log file recorded all daily computations, ensuring traceability and transparency of model behaviour. The final outputs were exported into Excel files for further analysis and validation. Overall, the developed Python-based reservoir water allocation model provided a computationally efficient and flexible tool capable of replicating the reservoir's operational dynamics and supporting subsequent optimisation and climate-resilience assessments.

5.3. Integration of Climate Change in Reservoir Water Management

This Section presents the integration of climate change into the reservoir water management framework to evaluate the performance and robustness of reservoir operations under future hydroclimatic conditions. The historically calibrated modelling framework is extended using downscaled climate projections to assess the impacts of projected changes in precipitation, inflows, evaporation, and water demands on reservoir storage and allocation decisions.

5.3.1. Development of Hydrological Model

Selection of Methods and Parameter Estimation

The Hydrologic Engineering Centre – Hydrologic Modelling System (HEC-HMS) was developed to simulate the rainfall–runoff process and to represent the hydrological behaviour of the basin under varying climatic conditions. It represents the physical components of a catchment through conceptual storage elements and mathematical relationships that describe precipitation losses, runoff transformation, baseflow generation, and flow routing. In this study, the HEC-HMS model was configured to assess both present and potential future reservoir inflows under climate change scenarios. To accurately represent the hydrological processes influencing evapotranspiration, interception, and water retention on the surface, the canopy and surface components were defined within the HEC-HMS framework. These components enable the model to account for water loss through vegetation cover and the temporary storage of precipitation on the land surface before infiltration and runoff occur. Various methods are available in HEC-HMS to represent these hydrological components; however, the most appropriate ones were selected to suit a continuous simulation. The selected methods are summarised in Table 5-1, which presents the primary model components and their corresponding methods adopted in this study

Table 5-1: The methods selected within the HEC-HMS model

Model Component	Method used
Canopy	Simple Canopy
Surface	Simple Surface
Loss	Soil Moisture Accounting (SMA)
Transform	SCS Unit Hydrograph
Baseflow	Linear Reservoir

To set up the model effectively, the Soil Moisture Accounting (SMA) algorithm was used for continuous simulation. This algorithm tracks the temporal variation of water storage in different layers of the soil profile, canopy, surface, soil, and groundwater zones. The configuration of these components was carefully adjusted to match the basin's physical and hydrological characteristics. A total of 24 parameters and five initial conditions were defined to describe canopy storage, soil storage, infiltration, percolation, and groundwater interactions. The lag time (t_p) required for the transform method in the SCS Unit Hydrograph was determined using the Soil Conservation Service (SCS) curve number method. The lag time was calculated according to Equation (14):

$$t_P = L^{0.8}\left((1000/CN - 10) + 1\right)^{0.7}/1900\,Y^{0.5} \tag{14}$$

where L is the longest flow path length (ft), Y is the average basin slope (%), and CN is the curve number. The remaining SMA parameters were initially assigned based on ranges suggested in previous studies and HEC-HMS technical guidelines.

The calibration and validation of the HEC-HMS model were carried out using three performance indicators to assess the accuracy and predictive capability of the model. The Mean Ratio of Absolute Error (MRAE) was selected as the primary objective function, as recommended by the World Meteorological Organisation (WMO) and adopted in various regional hydrological studies (Dissanayake, 2017; Perera & Wijesekera, 2011). The MRAE provides a robust measure of model bias and relative error, effectively evaluating deviations between observed and simulated flows. In addition to MRAE, two complementary objective functions were employed: the Nash–Sutcliffe Efficiency (NSE) (Nash & Sutcliffe, 1970) and the Percentage Error in Peak Flow (PEPF). The NSE evaluates the predictive accuracy of simulated streamflow time series, where values approaching 1 indicate excellent model performance. The PEPF, on the other hand, quantifies the deviation between observed and simulated peak discharges, providing insight into the model's capacity to capture extreme flow events. The recommended threshold values and performance categories for these objective functions are summarised in Table 5-2, which outlines the criteria for evaluating model efficiency.

Table 5-2: Recommended threshold values and performance categories for objective functions

Rating	**NSE**	**MRAE**	**PBIAS**
Very good	$0.75 < \text{NSE} \leq 1$	$0 < \text{MRAE} \leq 4$	$\text{PBIAS} \leq \pm 10$
Good	$0.65 < \text{NSE} \leq 75$	$4 < \text{MRAE} \leq 5$	$\pm 10 \leq \text{PBIAS} < \pm 15$
Satisfactory	$0.50 < \text{NSE} \leq 65$	$5 < \text{MRAE} \leq 7$	$\pm 15 \leq \text{PBIAS} < \pm 25$
Unsatisfactory	$\text{NSE} \leq 0.50$	$7 \leq \text{MRAE}$	$\pm 25 \leq \text{PBIAS}$

Model Optimisation

Following initial setup, sensitivity analysis was conducted to evaluate how individual parameters influence model performance and to identify the most sensitive variables for optimisation. In this analysis, one parameter was systematically varied between –50% and +50% of its base value in 10% increments, while holding other parameters constant. The results demonstrated that Soil Storage, Soil Percolation, and Maximum Infiltration Rate were the most influential parameters in determining the hydrological response of the basin. After identifying the sensitive parameters, a two-stage optimisation process was conducted. Initially, automatic calibration was performed using the built-in optimisation tools within HEC-HMS, employing the Univariate Gradient algorithm to minimise the selected objective functions. This was followed by manual calibration, where parameters were fine-tuned based on visual inspection of simulated and observed hydrographs to improve peak timing and baseflow representation. The final validation step ensured that the optimised parameters could reproduce flow behaviour under independent time periods not used during calibration. The validated parameter set demonstrated strong agreement between observed and simulated hydrographs, indicating reliable model performance. The optimised SMA and hydrological parameters obtained after calibration for the study sub-basin are summarised in Table 5-3.

Table 5-3: The parameter values used within the calibrated HEC-HMS model

Method	Parameters	Value
Soil Moisture Accounting Loss	Soil (%)	60
	Groundwater 1 (%)	29
	Groundwater 2 (%)	58
	Max Infiltration (mm/hr)	7.48
	Impervious (%)	3.4
	Soil Storage (mm)	77.56
	Tension Storage (mm)	47.54
	Soil Percolation (mm/hr)	7.35
	Groundwater 1 Storage (mm)	41.55
	Groundwater 1 Percolation (mm/hr)	4.32
	Groundwater 1 Coefficient (hr)	26.49
	Groundwater 2 Storage (mm)	270.08
	Groundwater 2 Percolation (mm/hr)	1.02
	Groundwater 2 Coefficient (hr)	223.64
SCS Unit Hydrograph	Lag time (min)	201
Simple Canopy	Initial Storage (%)	10
	Max Storage (mm)	9.8
Simple Surface	Initial Storage (%)	5.26
	Max Storage (mm)	9.8
Linear Reservoir	Groundwater 1 initial (m^3/s)	13
	Groundwater 2 initial (m^3/s)	0
	Groundwater 1 fraction	0.5
	Groundwater 2 fraction	0.5

5.3.2. Climate Data Downscaling and Future Climate Projections

Understanding the impacts of climate change on hydrological systems requires accurate projections of future climate conditions at the basin scale. Global Climate Models (GCMs), developed under the framework of the Coupled Model Intercomparison Project Phase 6 (CMIP6), provide valuable large-scale climate information. However, due to their coarse spatial resolution, typically between 100 and 300 km, GCM outputs are not directly applicable for regional hydrological studies.

Global Climate Models and Scenario Selection

The GCMs are physics-based numerical models that simulate interactions within the Earth's atmosphere, oceans, and land surfaces to predict responses to natural and anthropogenic climate forcing (Ashfaq et al., 2022). Within the CMIP6 framework, over fifty state-of-the-art GCMs contribute simulations under standardised radiative forcing and socioeconomic scenarios (Eyring et al., 2016). These models are used globally to assess potential variations in temperature, precipitation, and other climatic parameters over the twenty-first century.

To explore a comprehensive range of possible climate futures, the Shared Socioeconomic Pathways (SSPs) introduced in CMIP6 were utilised. For this study, two scenarios were selected:

- SSP2-4.5, representing an intermediate stabilisation pathway with moderate mitigation efforts
- SSP5-8.5, representing a high-emission, fossil-fuel-driven development pathway

These two scenarios were chosen because they provide a wide contrast between moderate and extreme climate outcomes, thus allowing an evaluation of potential hydrological impacts under varying emission trajectories. The CNRM-CM6-1 model from CMIP6 was selected for this research based on its demonstrated capability to simulate precipitation variability in tropical and monsoon-dominated regions (Jayaminda et al., 2023).

Downscaling of Climate Data

Downscaling bridges the gap between coarse-resolution GCM outputs and the fine-scale data required for hydrological modelling. The statistical downscaling was selected for this study due to its computational efficiency and proven accuracy in hydrological applications. Specifically, the Long Ashton Research Station Weather Generator (LARS-WG) was employed to generate local-scale daily precipitation data. The observed daily precipitation data for a baseline period of 30 years (1992–2022) were used within the generator, and that weather data replicated the statistical characteristics, mean, variance, and frequency distribution of the observed climate records. Then LARS-WG was applied to downscale future precipitation projections from the CNRM-CM6-1 GCM under the two selected SSP scenarios (SSP2-4.5 and

SSP5-8.5). The model simulated future climate data for short term time horizon from 2021 to 2040.

The validation of the downscaled data was carried out by comparing the generated baseline climate statistics with historical observations using standard statistical indices such as mean absolute error (MAE) and correlation coefficient (R^2). The high correlation between observed and generated data indicated that the LARS-WG model accurately represented local climate variability, confirming its suitability for producing future projections.

5.3.3. Reservoir Water Allocation Projections under Climate Change

Following the development and validation of the historical reservoir water allocation model, the framework was extended to evaluate future reservoir operation under climate change conditions. This step aimed to quantify how projected climatic changes may influence reservoir inflows, storage dynamics, and water allocation between hydropower generation and agricultural irrigation, while preserving the same physically consistent and rule-based operational structure defined for the historical period.

Future water allocation simulations were conducted using climate-driven inputs derived under two Shared Socioeconomic Pathway (SSP) scenarios, namely SSP2-4.5 and SSP5-8.5. These scenarios represent moderate and high greenhouse gas emission trajectories, respectively, and provide a suitable range for assessing uncertainty in near-term climate impacts. The projection period selected for this analysis was 2021–2040, corresponding to the short-term planning horizon relevant for reservoir operation and infrastructure management.

Generation of Climate-Driven Model Inputs

The future inflow time series to the reservoir was generated by integrating downscaled precipitation projections into the calibrated HEC-HMS hydrological model. Daily precipitation projections were obtained using the LARS-WG statistical downscaling model driven by the CNRM-CM6-1 Global Climate Model under SSP2-4.5 and SSP5-8.5 scenarios. The downscaled precipitation data were then used as inputs to HEC-

HMS to simulate daily reservoir inflows, thereby ensuring physical consistency between climate projections and catchment hydrological response.

Future evaporation losses were projected using a data-driven LSTM model. This model captured the nonlinear relationship between air temperature, reservoir surface area, and observed evaporation losses. Historical temperature data were first projected for the 2021–2040 period using the same GCM–scenario combinations and downscaling approach, after which the trained LSTM model was applied to estimate future daily evaporation volumes. The model was trained using 70% of the historical data and validated using the remaining 30%, yielding satisfactory predictive performance prior to its application for future projections.

Projected precipitation over the reservoir surface was derived directly from the downscaled precipitation time series generated using LARS-WG, ensuring consistency with the inflow projections. Hydropower demand and total irrigation release were also projected using LSTM-based models that incorporated precipitation as a key explanatory variable. These models were trained on historical demand and release data, allowing future water demand patterns to evolve dynamically in response to projected climatic conditions.

Leakage losses were estimated using an empirical storage–leakage relationship derived from historical observations. Multiple functional forms were evaluated, including linear, exponential, logarithmic, power, and polynomial relationships. The polynomial formulation produced the highest correlation with observed leakage time series and was therefore selected to compute future leakage losses dynamically as a function of simulated reservoir storage at each time step by using Equation (15).

$$L(t) = 0.0543 \log_e S(t) - 0.0581 \tag{15}$$

5.3.4. Evaluation of Water Allocation Model under Climate Change

The evaluation of the reservoir water allocation model under climate change conditions was conducted to assess its robustness, operational feasibility, and adaptability when subjected to altered hydroclimatic regimes. Unlike the historical evaluation, which relied on observed storage data, the future evaluation focused on internal consistency, storage sustainability, and the system's ability to accommodate variations in hydropower and irrigation demands without violating physical and operational constraints.

The primary evaluation criterion was the behaviour of reservoir storage under each scenario relative to the baseline future projection. Storage time series obtained from the baseline simulations under SSP2-4.5 and SSP5-8.5 were treated as reference conditions representing climate-driven operation without deliberate changes to allocation priorities. All alternative scenarios were evaluated by comparing their storage trajectories against these reference series, allowing the identification of operational limits beyond which system reliability deteriorates.

Scenario-Based Allocation Analysis

For hydropower-focused scenarios, increases in power releases were evaluated in terms of their impact on minimum storage thresholds, frequency of storage depletion events, and long-term storage trends. Scenarios involving a 10% increase in hydropower release generally demonstrated limited impacts on storage sustainability, indicating potential operational flexibility under favourable inflow conditions. However, larger increases, particularly under the SSP5-8.5 scenario, resulted in more pronounced storage drawdown during dry periods, highlighting increased vulnerability under high-emission climate pathways. Conversely, reduced hydropower release scenarios improved storage stability but implied lost energy generation potential, emphasising the trade-off between energy reliability and water conservation.

Irrigation-based scenarios were evaluated using similar criteria, with particular attention given to the persistence of storage above dead storage levels and the avoidance of prolonged deficit conditions. Moderate increases in irrigation releases were feasible during periods of enhanced inflow but led to heightened storage stress during extended dry spells, especially under SSP5-8.5. Scenarios involving reduced irrigation demand improved storage resilience but raised concerns regarding agricultural water security, underscoring the interconnected nature of water–energy–food systems under climate change.

Across all scenarios, the water allocation model consistently respected predefined operational rules, including dead storage constraints, minimum hydropower operational levels, and prioritisation logic. The absence of physically implausible storage behaviour, such as negative storage or uncontrolled oscillations, demonstrated the numerical stability and physical soundness of the modelling framework under future climate conditions.

5.4. Chapter Summary

This chapter presents the development, implementation, and application of integrated machine learning and hydrological models for simulating reservoir water balance, optimising water allocation, and assessing climate change impacts on reservoir operations. This first describes the development of two machine learning architectures, PINNs and LSTM networks, for modelling daily reservoir storage dynamics. The PINN model explicitly incorporates reservoir water balance equations into the learning process, ensuring physical consistency even under extreme hydrological conditions. In contrast, the LSTM model captures nonlinear temporal dependencies in reservoir inflow–outflow processes using sequence-based learning. Both models were trained, optimised, and evaluated using multiple statistical performance metrics. Comparative evaluation demonstrated that the PINN model exhibited superior physical consistency, particularly under extreme flow conditions, while the LSTM model showed strong performance in capturing temporal variability during normal conditions.

Building on the machine learning framework, a dynamic reservoir water allocation model was developed to simulate real-time operational decision-making. The model integrates hydrological inflows, reservoir storage characteristics, operational rules, and performance objectives to optimise the allocation of water between irrigation and hydropower demands. A rule-based decision structure was implemented to prioritise irrigation and environmental flow requirements while maintaining minimum storage constraints before allocating water for hydropower generation. The operational framework was implemented in Python, enabling daily simulation of storage updates, releases, spillway behaviour, evaporation, seepage, and leakage losses.

The chapter further details the development and calibration of an HEC-HMS hydrological model to simulate rainfall–runoff processes within the study basin. Appropriate hydrological methods were selected for canopy interception, surface runoff, soil moisture accounting, baseflow, and channel routing. The model was calibrated and validated using multiple objective functions and sensitivity analysis to identify influential parameters and ensure robust representation of basin hydrology.

Climate change impacts were incorporated through the use of downscaled Global Climate Model projections under selected Shared Socioeconomic Pathways. Downscaled precipitation and temperature data were used to generate future inflow, evaporation, and leakage scenarios, which were subsequently applied to the reservoir allocation model to evaluate future operational performance.

CHAPTER 6

6. RESULTS

This chapter presents the performance of the machine learning models for reservoir water balance simulation, followed by the evaluation of the water allocation model, and concluding with the assessment of climate change impacts on future reservoir operation.

6.1. Integration of Machine Learning for Reservoir Water Balance

This section presents the results obtained from applying machine learning approaches to simulate the daily water balance of the reservoir. Two architectures, LSTM networks and PINNs, were evaluated using historical reservoir operation data under both normal and extreme hydrological conditions.

6.1.1. LSTM Model Training and Testing

The LSTM model was trained and tested to evaluate its capability in simulating daily reservoir water balance dynamics, with particular emphasis on its ability to reproduce changes in storage under varying hydrological conditions. Initially, the model was trained using a modified dataset, where extreme peak events were excluded to assess baseline learning performance under relatively stable flow conditions. As illustrated in Figure 6-1, The LSTM model demonstrates a strong agreement between simulated and observed storage changes during both training and testing phases. The predicted time series closely follows the observed variations, accurately capturing the temporal patterns and seasonal oscillations of storage change. This visual agreement is further supported by quantitative performance metrics, where the model achieved a Nash–Sutcliffe Efficiency (NSE) of 0.91 during training and 0.89 during testing, along with low RMSE (0.27 MCM for training and 0.32 MCM for testing) and MAE values. These results confirm the LSTM's effectiveness in learning temporal dependencies when extreme hydrological variability is absent.

However, the robustness of the LSTM model was notably challenged when evaluated using the hybrid dataset, which reintroduced peak flow events during the testing period. As shown in Figure 6-2, the model struggled to reproduce the magnitude and sharpness of extreme storage changes. While the timing of major events was generally captured, the predicted series exhibited excessive smoothing, leading to systematic underestimation of peak values and reduced variability. This limitation is reflected in the deterioration of performance statistics, with NSE and R^2 both declining to approximately 0.67 and RMSE increasing to 0.82 MCM during testing.

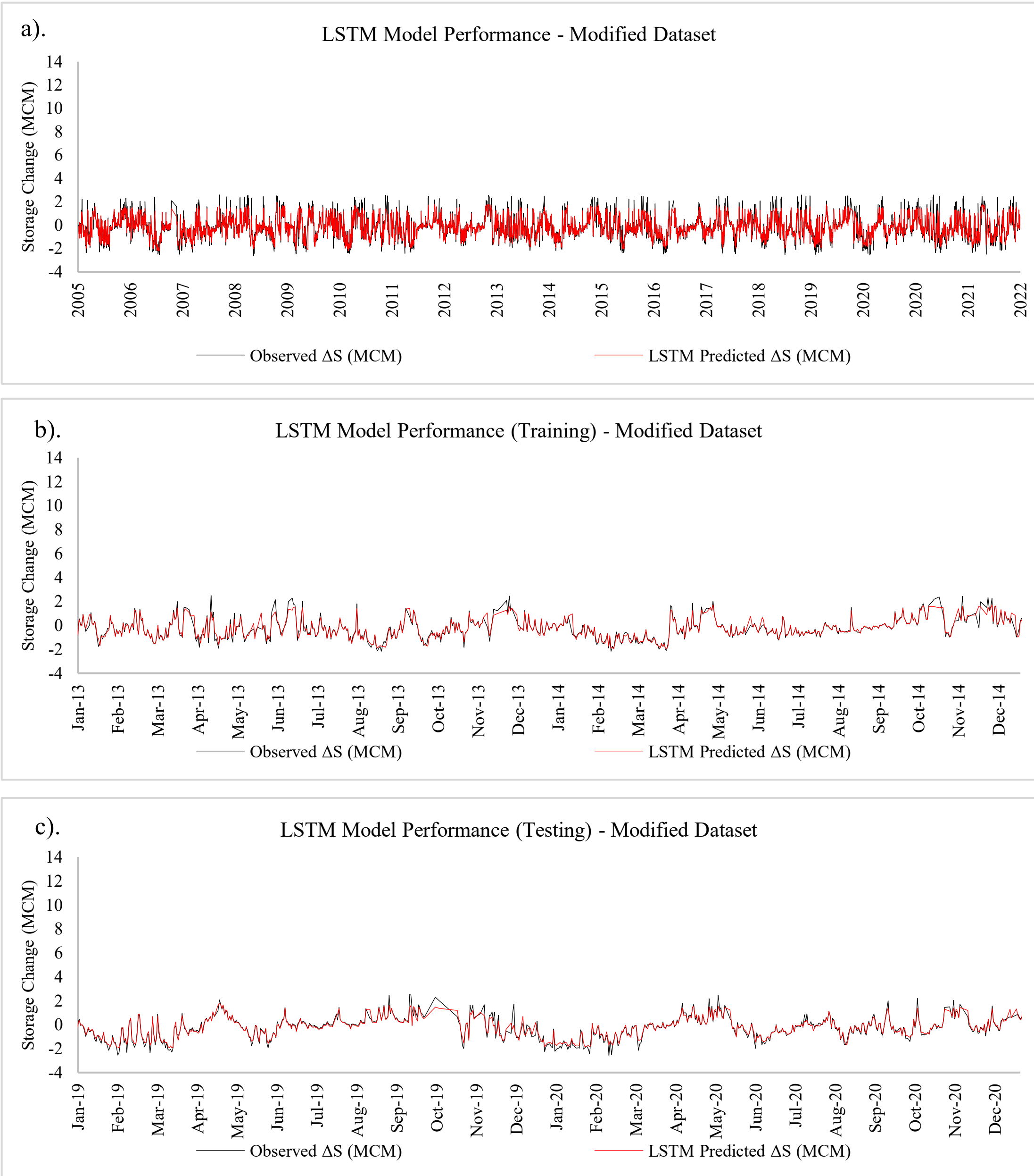


Figure 6-1: The time series plots for the matching between observed and simulated storage change from LSTM model for the modified dataset input: (a) time series plot for entire period considered (b) time series plot for two years from the training period (c) time series plot for two years from the testing period

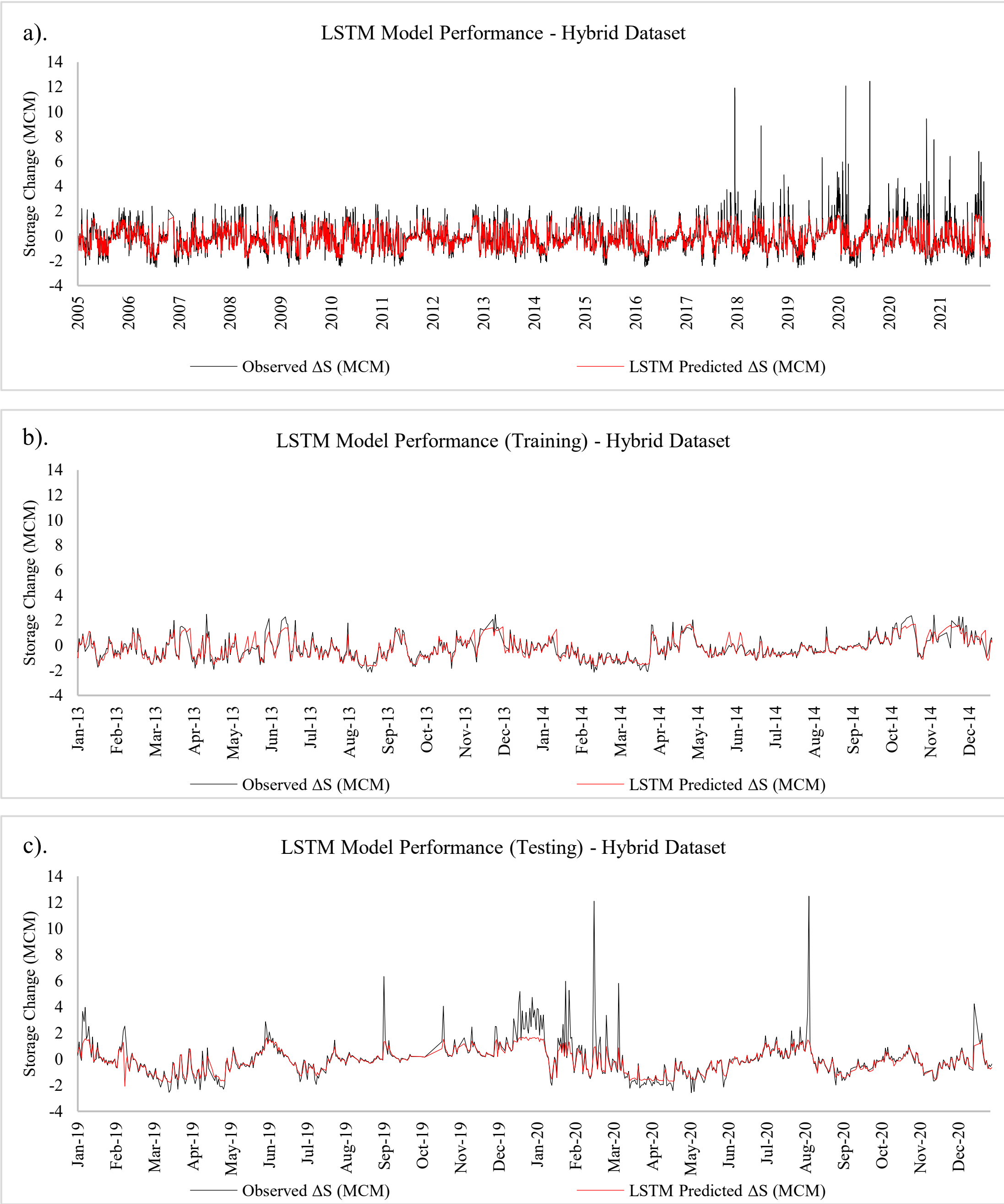


Figure 6-2: The time series plots for the matching between observed and simulated storage change from LSTM model for the hybrid dataset input: (a) time series plot for entire period considered (b) time series plot for two years from the training period (c) time series plot for two years from the testing period

6.1.2. PINN Model Training and Testing

The PINN model was developed to overcome the limitations of purely data-driven approaches by explicitly incorporating water balance principles into the learning framework. Similar to the LSTM evaluation, the PINN model was first trained and tested using a modified dataset that excluded extreme events to establish baseline performance. The results presented in Figure 6-3 show excellent agreement between predicted and observed storage changes throughout the training and testing periods.

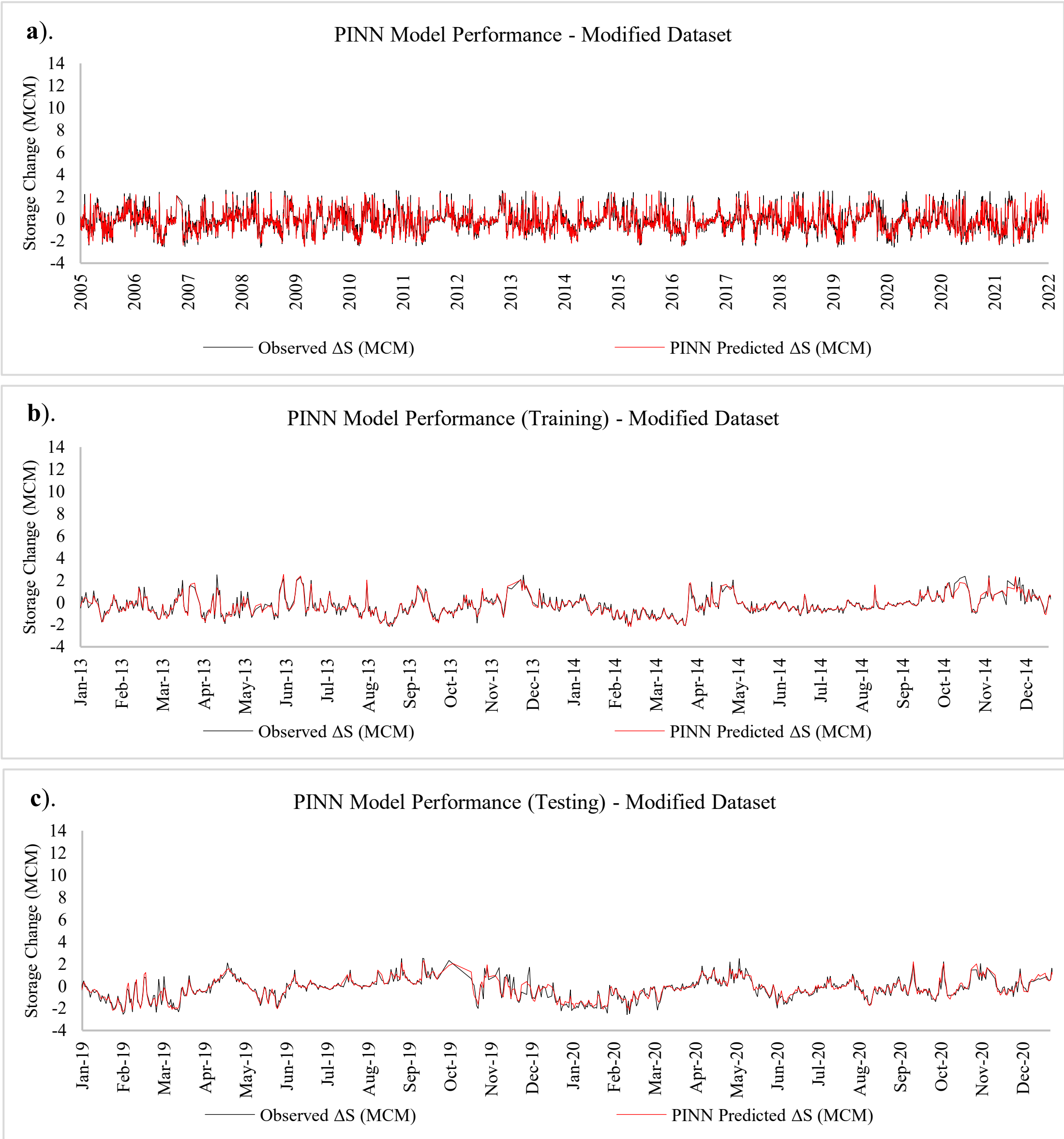


Figure 6-3: The time series plots for the matching between observed and simulated storage change from PINN model for the modified dataset input: (a) time series plot for entire period considered (b) time series plot for two years from the training period (c) time series plot for two years from the testing period

The PINN successfully captures both short-term variability and long-term trends with minimal deviation from observed values. This high predictive accuracy is confirmed by strong evaluation metrics, with NSE values of 0.92 during training and 0.87 during testing, along with low RMSE (0.25 MCM for training and 0.34 MCM for testing) and MAE values. As shown in Figure 6-4, PINN maintained a strong capability to track abrupt storage changes, accurately reproducing the timing, magnitude, and frequency of extreme events. Unlike the LSTM model, the PINN preserved sensitivity to sharp transitions in storage, reflecting the stabilising influence of embedded physical constraints.

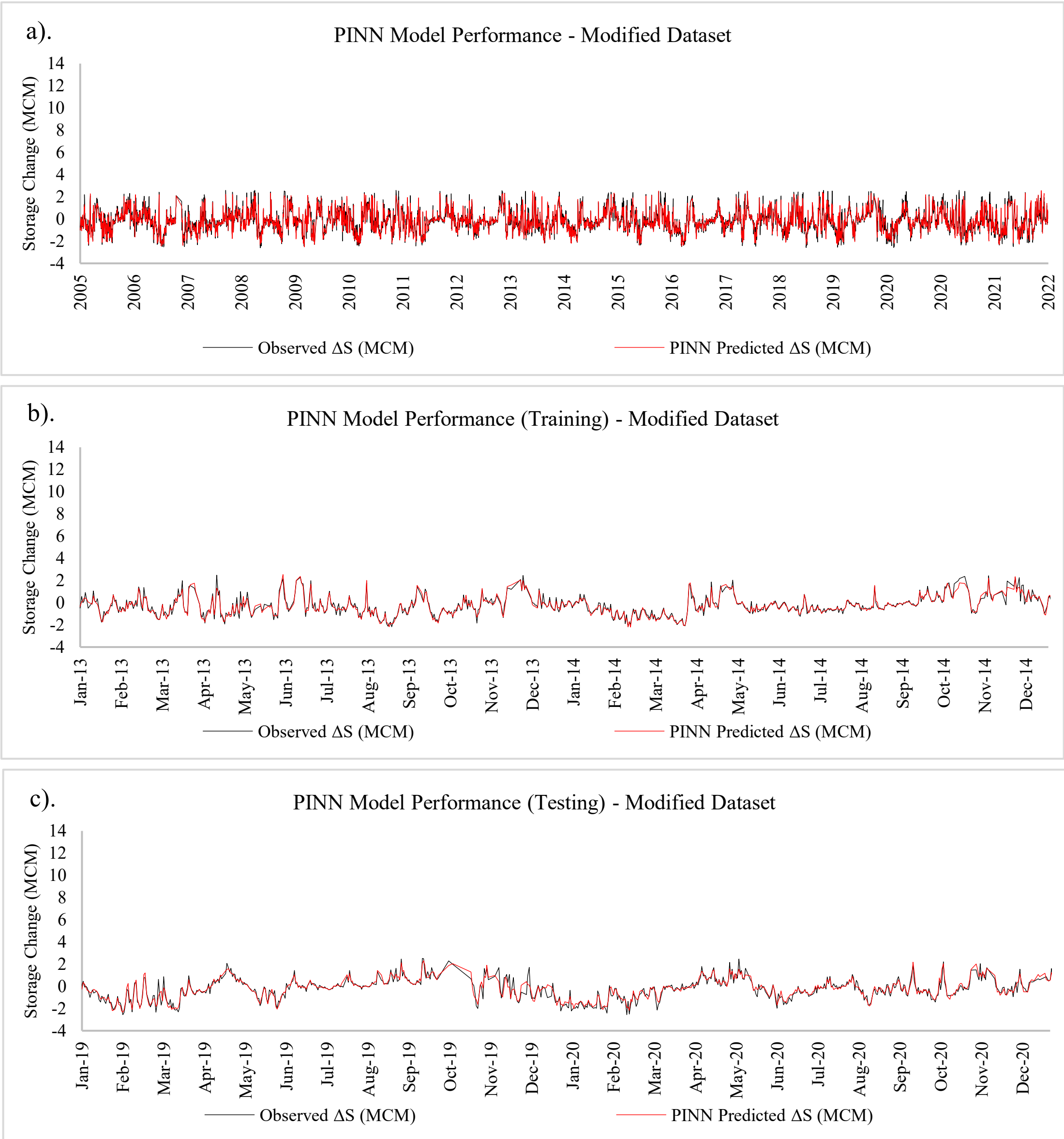


Figure 6-4: The time series plots for the matching between observed and simulated storage change from PINN model for the modified dataset input: (a) time series plot for entire period considered (b) time series plot for two years from the training period (c) time series plot for two years from the testing period

Although the inclusion of peak events introduced additional complexity, the PINN maintained acceptable predictive performance, achieving an NSE and R^2 of approximately 0.80 during testing, with moderate increases in RMSE (0.63 MCM) and MAE (0.42 MCM). These results indicate that the PINN model exhibits superior generalisation under hydrological extremes compared to the LSTM model (Figure 6-5).

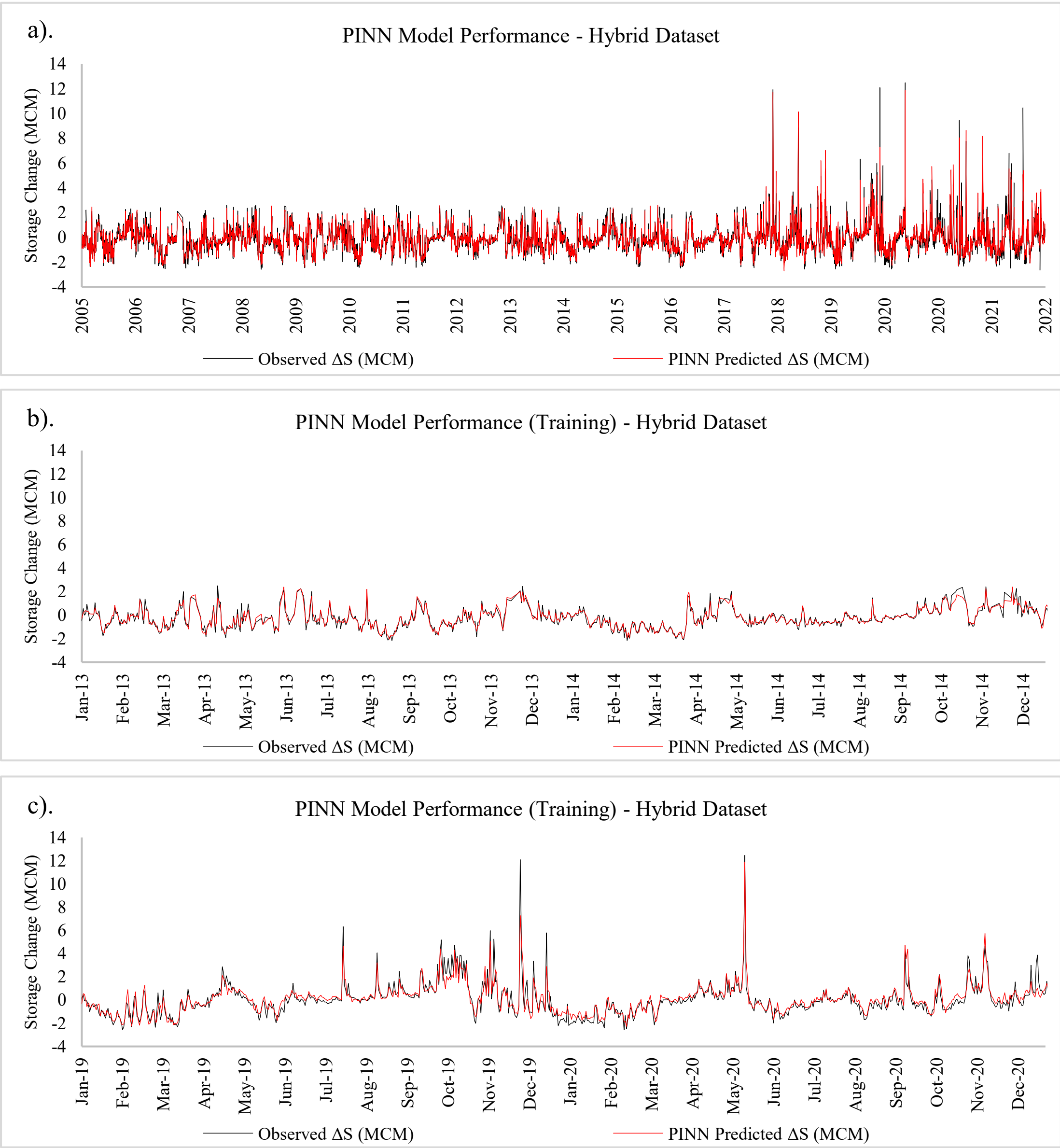


Figure 6-5: The time series plots for the matching between observed and simulated storage change from PINN model for the hybrid dataset input: (a) time series plot for entire period considered (b) time series plot for two years from the training period (c) time series plot for two years from the testing period

6.1.3. LSTM and PINN Model Performance Comparison

A comparative assessment of the LSTM and PINNs models was conducted to evaluate their capability in simulating reservoir water balance dynamics under both regular and extreme hydrological conditions. The comparison was based on training and testing results obtained using the modified dataset (with peak events removed) and the hybrid dataset (with peak events included), focusing on both statistical performance metrics and qualitative behaviour.

Under the modified dataset, both models demonstrated strong predictive skill, with high agreement between observed and simulated storage changes. The LSTM model achieved NSE and R^2 values exceeding 0.89 during training and testing, indicating its effectiveness in learning temporal dependencies and reproducing regular storage fluctuations. Similarly, the PINN model exhibited comparable and slightly superior performance, with NSE values of approximately 0.92 during training and 0.87 during testing, alongside lower RMSE and MAE values. This highlights that, under stable flow conditions, both data-driven and physics-informed approaches can accurately represent reservoir storage dynamics.

However, notable differences emerged when the models were evaluated using the hybrid dataset that included extreme storage change events. The LSTM model showed a marked decline in performance, characterised by an underestimation of peak magnitudes and a smoothing of sharp transitions in storage change. This degradation was reflected in reduced NSE and R^2 values (around 0.67 during testing) and increased RMSE, indicating limited robustness of the purely data-driven LSTM approach in capturing extremes outside its dominant training patterns.

In contrast, the PINN model maintained a substantially higher level of performance under hybrid conditions. Although some reduction in accuracy was observed relative to the modified dataset, the PINN successfully captured the timing, magnitude, and frequency of extreme events more effectively than the LSTM model. The testing NSE and R^2 values remained around 0.80, and the increases in RMSE and MAE were moderate and within acceptable limits. This improved robustness can be attributed to the explicit incorporation of physical constraints through the water balance formulation, which guided the learning process and prevented physically unrealistic predictions during periods of rapid storage change.

Table 6-1: The evaluation matrix values for training and testing of machine learning models

	Training				Testing			
	PINN		LSTM		PINN		LSTM	
	Modified Data	Hybrid Data	Modified Data	Hybrid Data	Modified Data	Hybrid Data	Modified Data	Hybrid Data
NSE	0.92	0.92	0.91	0.80	0.87	0.80	0.89	0.67
RMSE (MCM)	0.25	0.26	0.27	0.41	0.34	0.63	0.32	0.82
MAE (MCM)	0.18	0.19	0.15	0.22	0.25	0.42	0.19	0.35
R^2	0.92	0.92	0.91	0.80	0.87	0.80	0.89	0.67

6.1.4. Storage Change Residual Analysis for Both PINN and LSTM Models

Residual Distribution of Both Models

To evaluate the physical consistency of each model, residuals were computed as the difference between the predicted change in storage and the corresponding observed change in storage for the testing period. These residuals indicate how well each model preserves mass conservation and allows assessment of deviations from realistic physical behaviour. The box plots (Figure 6-6b**)** illustrate that PINN residuals are narrowly centred around zero (mean = −0.03 MCM, std = 0.62 MCM), while LSTM residuals are positively biased (mean = 0.35 MCM) and more dispersed (std = 1.09 MCM). LSTM residual extremes reach 12.36 MCM, over twice the maximum for PINN (5.62 MCM), indicating greater susceptibility to large errors. Histogram and Kernel Distribution Estimation (KDE) plots (Figure 6-6a) further reveal that PINN residuals are more symmetric (skew = 0.53) and less heavy-tailed (kurtosis = 8.70), whereas LSTM residuals are strongly right-skewed (skew = 3.71) with pronounced kurtosis (25.50), signifying frequent large overestimations (Table 6-2).

Temporal Dynamics of Storage Residuals

The residual time series (Figure 6-7) shows that PINN maintains smaller deviations from zero across the evaluation period, while LSTM residuals exhibit more frequent and higher-magnitude spikes, particularly during hydrological extremes. Rolling mean analysis (Figure 6-8) confirms that PINN maintains stable bias over time, whereas

LSTM displays seasonal bias fluctuations. Rolling standard deviation (Figure 6-9) indicates that LSTM residual variability periodically exceeds 2 MCM, while PINN remains more stable

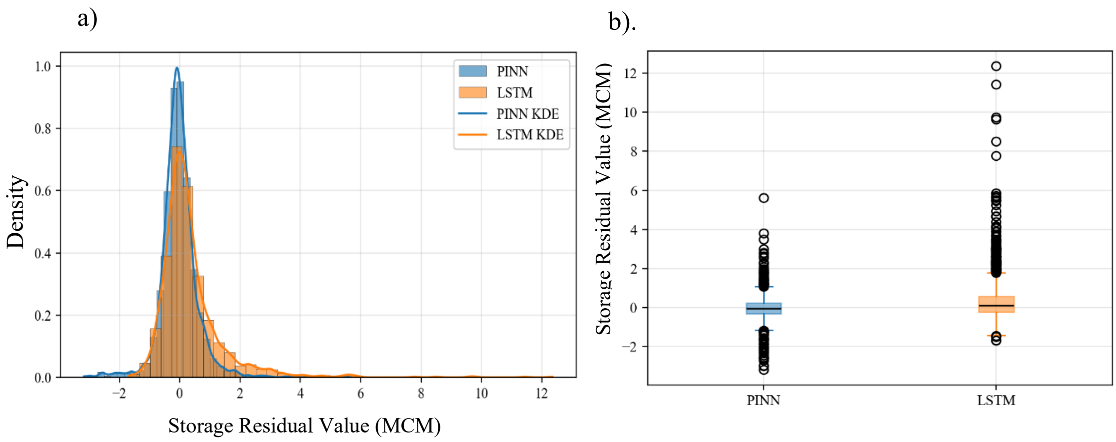


Figure 6-6: Comparison of storage residuals for both PINN and LSTM models (**a**) Histogram and KDE plots for storage residual change (**b**) Box plots for storage residual change

Table 6-2: Statistical parameter values for two storage residual time series

Metric	Mean (MCM)	Std. Dev (MCM)	Minimum (MCM)	25th Percentile (MCM)	Median (MCM)	75th Percentile (MCM)	Maximum (MCM)	Skewness	Kurtosis
PINN	−0.03	0.62	−3.17	−0.32	−0.06	0.24	5.62	0.53	8.71
LSTM	0.35	1.09	−1.68	−0.22	0.11	0.59	12.36	3.71	25.50

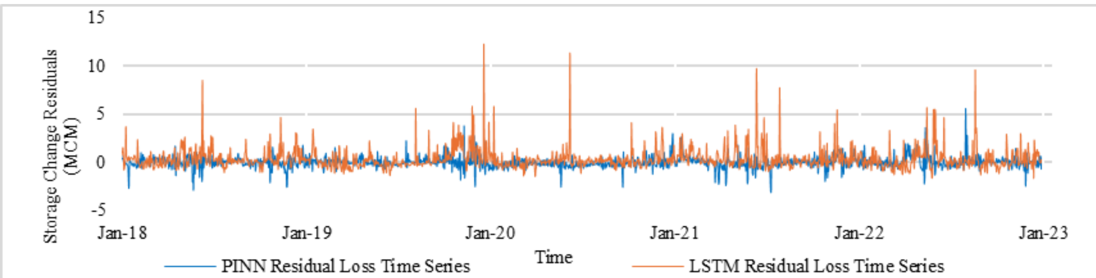


Figure 6-7: Storage residual time series plots for both PINN and LSTM models

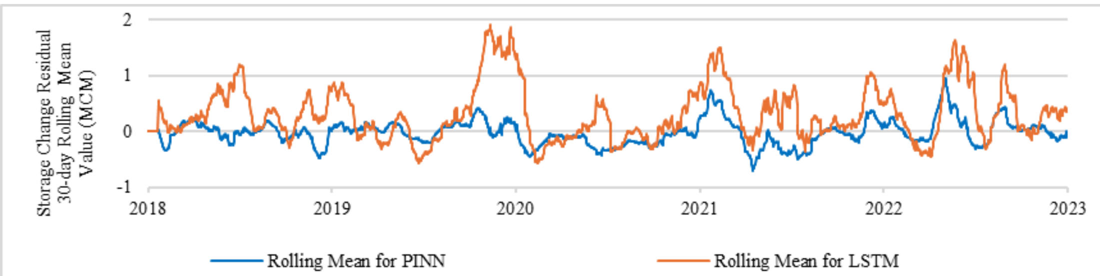


Figure 6-8: Rolling mean of storage change residual analysis for both LSTM and PINN models

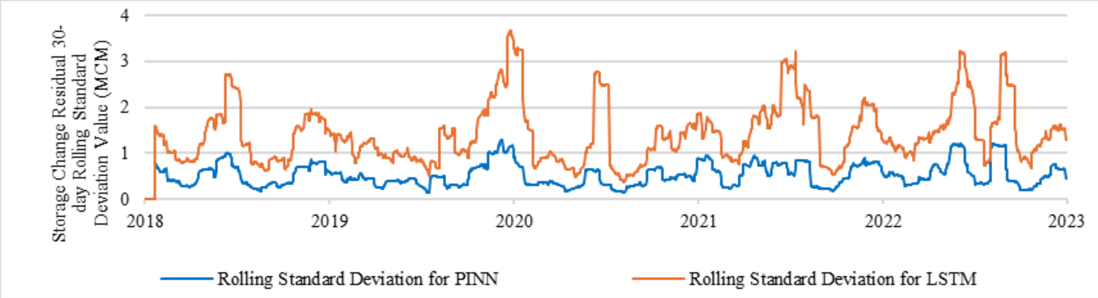


Figure 6-9: Rolling standard deviation of storage change residual analysis for both LSTM and PINN models

6.1.5. Evaluation of parameter variation with storage change for PINN and LSTM

A sensitivity analysis was conducted to investigate the response of the predicted storage change to variations in each input parameter included in the water balance equation. This analysis was crucial to assess the physical interpretability of both the PINN and the LSTM models and their capacity to reflect real hydrological behaviour under parametric perturbations. That was performed by systematically varying each right-hand side (RHS) parameters of the water balance equation from -50% to 50% of their original values, while keeping all other parameters constant. Eleven data sets were generated per parameter to simulate these changes, and the resulting average predicted change in storage was recorded for each model.

For the LSTM model, the average predicted storage change increased with increases in precipitation and inflow, indicating a positive relationship (Figure 6-10a & b). Conversely, an inverse relationship was observed with outflow parameters such as irrigation release, power release, and leakage, all of which led to a decrease in storage change with increasing magnitude (Figure 6-10c – f). However, the magnitude of sensitivity was relatively linear and consistent across the range, suggesting the LSTM's response was largely monotonic and lacking in nuanced physical feedback mechanisms. This is further evidenced by the nearly uniform gradients in the plots, particularly for power release and leakage, indicating that the LSTM model may have limited ability to learn nonlinear hydrological interactions between parameters and storage response.

In contrast, the storage changes in the PINN model response to precipitation and inflow displayed a non-linear increasing trend (Figure 6-11a & b), which more accurately represents the diminishing returns often observed in hydrologic systems. For instance, in the case of precipitation, after a certain threshold, additional increments led to a plateauing of storage gain, highlighting PINN's ability to internalise physical saturation behaviour. Similarly, the sensitivity to seepage loss followed a distinct pattern (Figure 6-11e) due to the functional dependency of seepage on storage, modelled as seepage loss = 0.001 × gross storage.

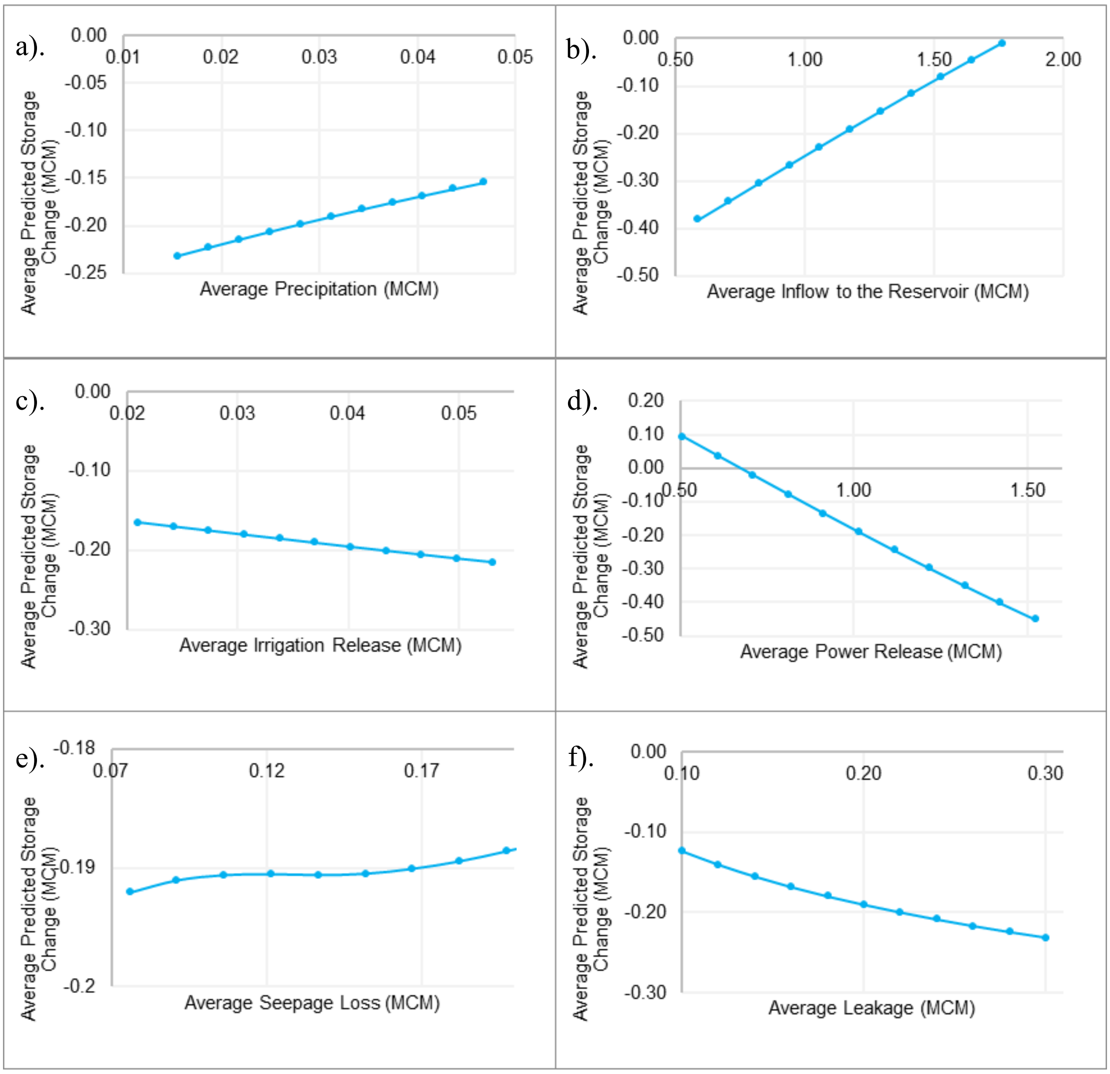


Figure 6-10: The variation of storage changes with the parameters involved in the water balance equation for the LSTM model: (a) average predicted storage variation with the average precipitation variation (b) average predicted storage variation with the average inflow variation (c) average predicted storage variation with the average irrigation release variation (d) average predicted storage variation with the average power release variation (e) average predicted storage variation with the average seepage loss variation (f) average predicted storage variation with the average leakage variation

This caused a positive feedback loop wherein increased storage values inherently elevated seepage loss, subsequently reinforcing higher storage predictions, a behaviour accurately captured only by the PINN model. Furthermore, the response curves for power release and leakage under the PINN model revealed a more elastic reaction to changes (Figure 6-11d – f), showcasing the model's capacity to encode hydrodynamic constraints. For example, the negative slope observed in the power release and leakage plots was sharper at lower values and gradually flattened, mirroring operational practices in reservoir systems where high releases typically coincide with flood management strategies, and the impact on storage is more dramatic at low release rates.

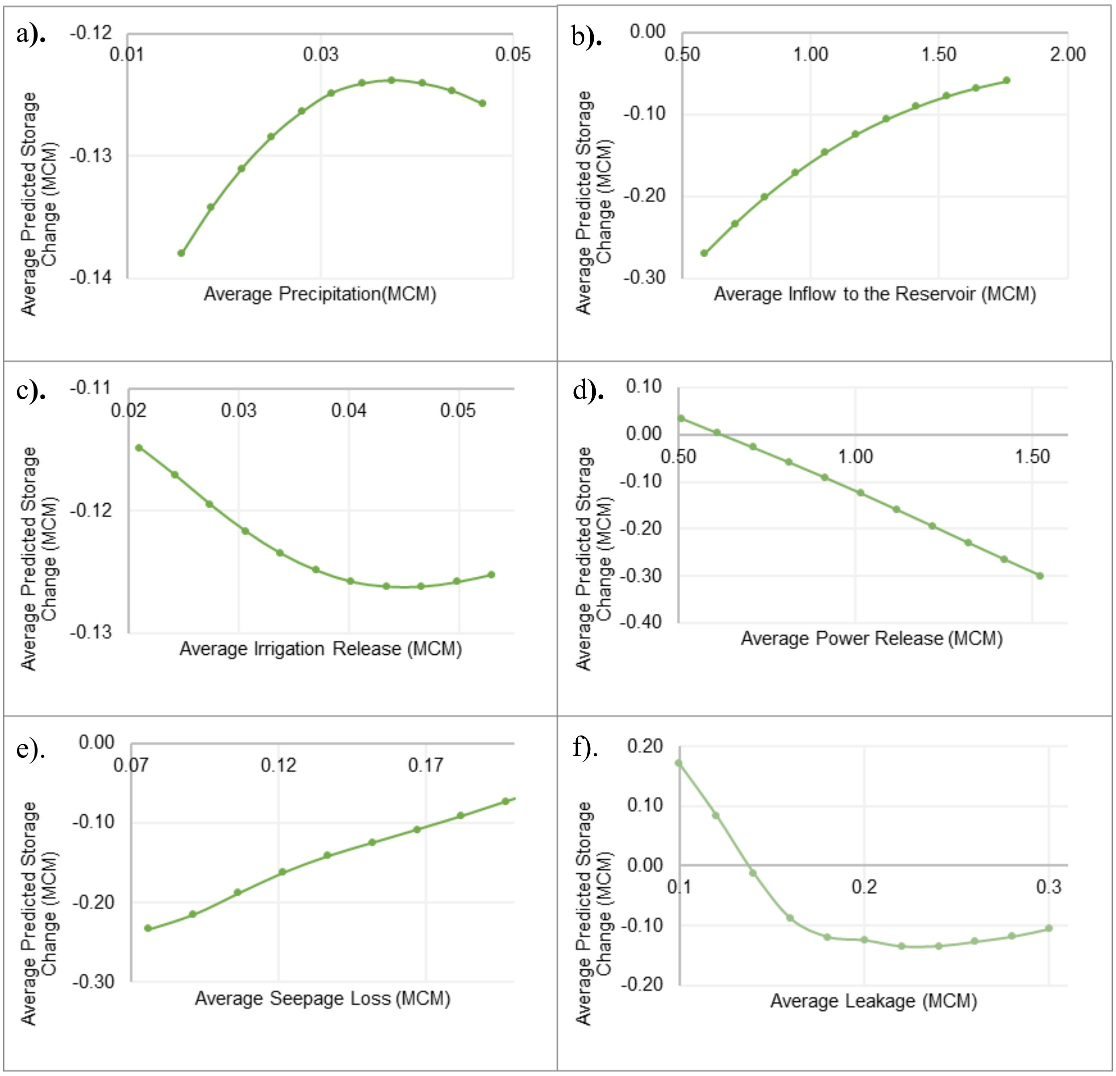


Figure 6-11: The variation of storage changes with the parameters involved in the water balance equation for the PINN model: (a) average predicted storage variation with the average precipitation variation (b) average predicted storage variation with the average inflow variation (**c**) average predicted storage variation with the average irrigation release variation (d) average predicted storage variation with the average power release variation (e) average predicted storage variation with the average seepage loss variation (f) average predicted storage variation with the average leakage variation

The analysis indicated that reservoir inflow and power release were the most sensitive variables affecting storage change, as they produced the largest variation in model response. Leakage and seepage loss also showed notable influence, particularly under the PINN-based simulations, whereas precipitation and irrigation release exhibited relatively lower sensitivity.

6.2. Development of Reservoir Water Allocation Model

This section presents the results of implementing the rule-based reservoir water allocation model developed using Python. The model integrates daily inflow, storage, and demand conditions to simulate irrigation and hydropower releases while maintaining operational constraints.

6.2.1. Water Allocation Model Performance

The results indicate a clear and consistent improvement in storage utilisation under the optimised operation scheme. The storage trajectory generated by the optimisation model (blue curve) remains systematically lower than the observed storage under current operations (orange curve), while still satisfying all operational constraints, including minimum storage, irrigation demand, and hydropower requirements (Figure 6-12). This difference reflects a reduction in unnecessary storage accumulation and spill-prone conditions that are prevalent under the existing operational policy.

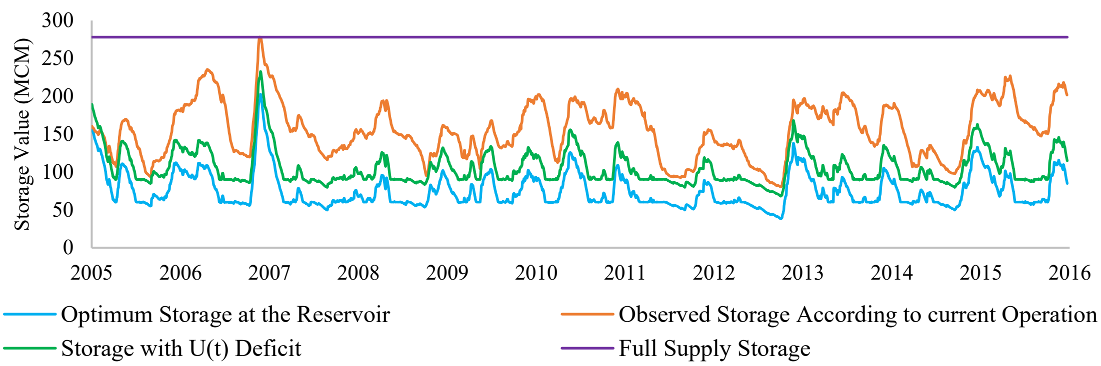


Figure 6-12: Reservoir water allocation model projected optimum water storage time series for the reservoir

The minimum difference between the observed storage and the optimised storage trajectories is approximately 30 MCM, indicating that this volume of water can be strategically reallocated. Such surplus storage has the potential to support either an expansion of irrigable agricultural areas or an increase in hydropower generation, thereby enhancing the overall productivity of the reservoir system.

The optimised final net storage curve (green line) further demonstrates that the reservoir maintains a stable operational regime after accounting for daily inflows, losses, and controlled releases. The close tracking of storage fluctuations to hydrological inputs suggests that the optimisation framework effectively balances inflow variability with demand-driven releases. Importantly, optimised operation reduces prolonged high-storage periods, which are associated with increased evaporation and spill losses, thus improving water-use efficiency.

The annual average deficit storage that can potentially be conserved through the proposed water balance–based operational strategy is illustrated in Figure 6-13. The results indicate noticeable interannual variability in the volume of deficit storage that could be saved during the study period from 2005 to 2015. The estimated annual average deficit storage ranges approximately from about 55 MCM to nearly 100 MCM, demonstrating that a substantial volume of water can be retained in the reservoir system through optimized operation.

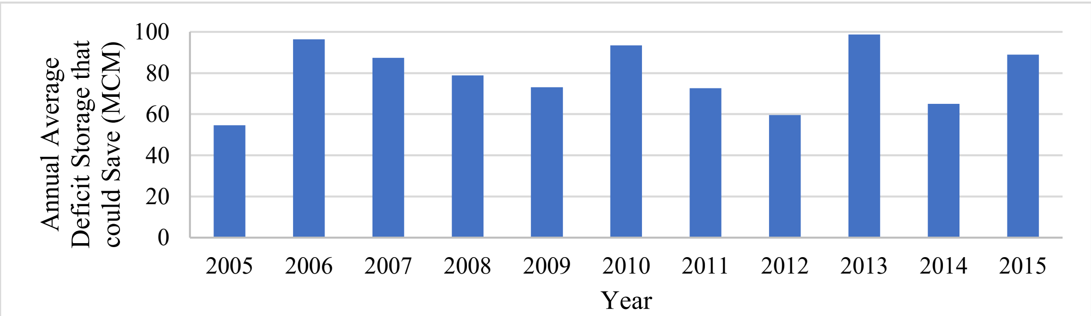


Figure 6-13: The variation of annual average storage that could save for the historical period

The lowest deficit storage savings are observed in 2005, with values close to 55 MCM, whereas the highest potential storage conservation occurs in 2013, approaching 100 MCM. Relatively high values are also observed in 2006, 2010, and 2015, indicating years with greater opportunities for operational improvements in reservoir water balance management. Overall, the results highlight that the proposed operational approach can consistently reduce storage deficits across different hydrological conditions, although the magnitude of improvement varies from year to year. This variability reflects the influence of interannual fluctuations in inflows, rainfall patterns, and reservoir release requirements. Nevertheless, the analysis clearly demonstrates that implementing the optimized water balance operation could enable the reservoir system to retain a significant amount of water annually, thereby improving system resilience and supporting more reliable water allocation for irrigation, hydropower generation, and other downstream demands.

6.3. Integration of Climate Change in Reservoir Water Management

This section presents the results of integrating climate change projections into the hydrological and reservoir operation modelling framework. Downscaled climate inputs were used to generate future inflow and demand projections, which were then incorporated into the water allocation model.

6.3.1. Development of Hydrological Model

Model Calibration

The rainfall–runoff hydrograph indicates that the model successfully captured the timing and magnitude of major flow peaks as well as low-flow conditions, demonstrating its capability to represent event-based and continuous hydrological processes (Figure 6-14). Flow duration curves (FDCs) further confirm the adequacy of calibration. The simulated flows closely follow the observed curves across a wide range of exceedance probabilities in both linear and logarithmic scales, indicating good representation of high, medium, and low flows (Figure 6-15 & Figure 6-16). Minor deviations at extreme low flows can be attributed to uncertainties in baseflow and soil moisture parameterisation.

Quantitative performance evaluation supports these visual assessments. The Nash–Sutcliffe Efficiency (NSE) value of 0.741 indicates good agreement between simulated and observed inflows, while the Mean Relative Absolute Error (MRAE) of 0.41 reflects acceptable overall error levels. The Percent Error in Peak Flow (PEPF) of 12.8% suggests that peak discharges were reproduced with reasonable accuracy during calibration (Table 6-3).

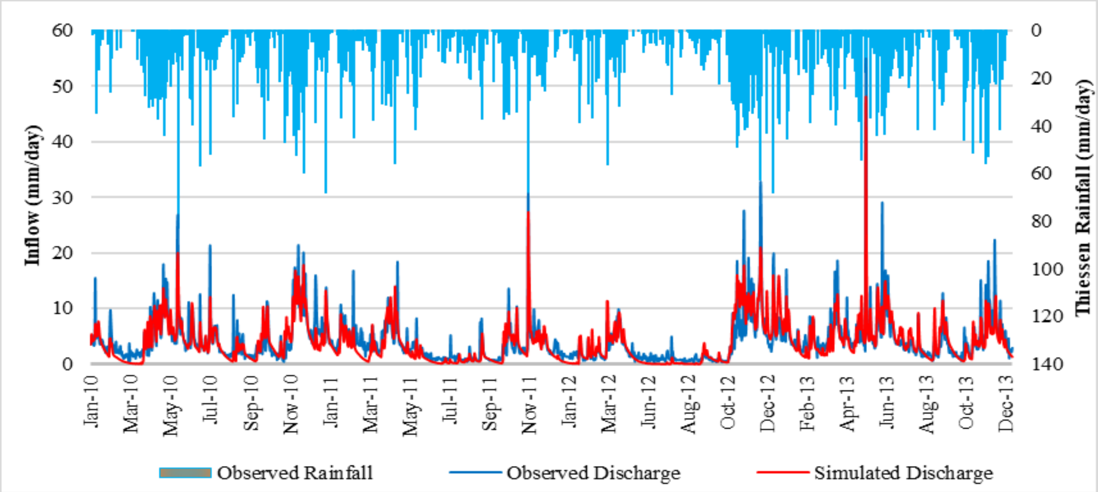
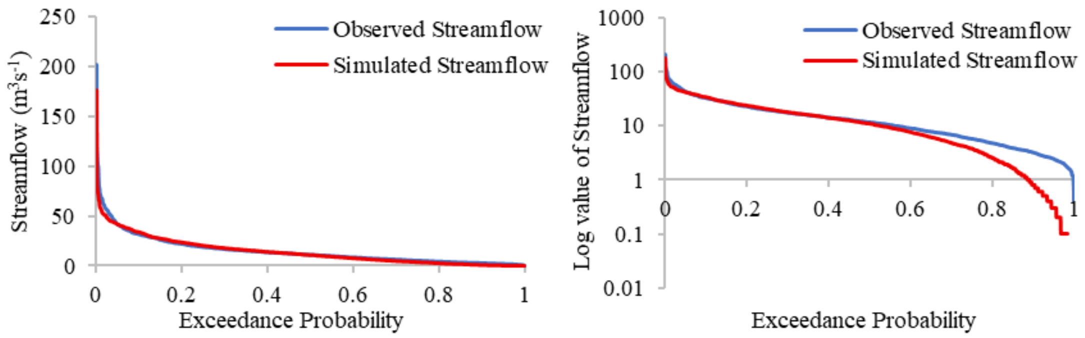


Figure 6-14: Rainfall - Runoff hydrograph for HEC-HMS model calibration



a). b).

Figure 6-15: The flow-duration curves plotted for calibration period (a) flow duration curve in normal scale (b) flow duration curve in log scale

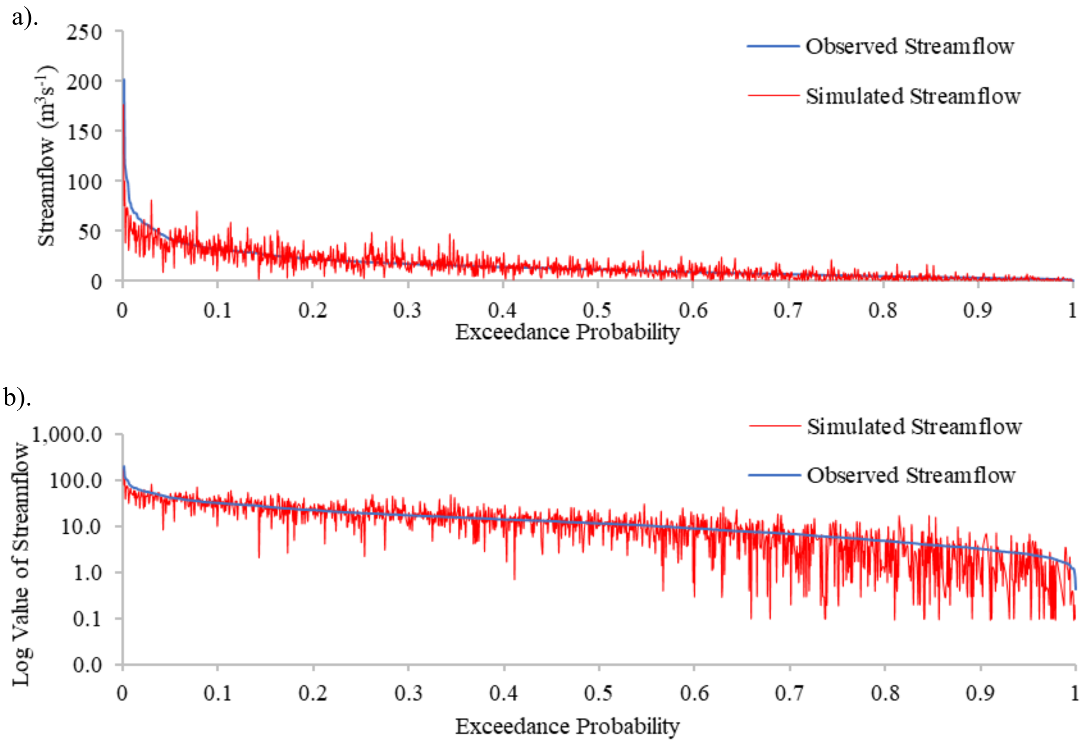


Figure 6-16: The flow-duration curves plotted for calibration period sorted by observed streamflow (**a**) flow duration curve in normal scale (**b**) flow duration curve in log scale

Model Validation

The rainfall–runoff hydrograph for the validation period shows strong agreement between observed and simulated inflows, with the model effectively reproducing seasonal flow patterns and major storm-driven peaks (Figure 6-17). Flow duration curves for the validation period also demonstrate close alignment between observed and simulated flows over most exceedance probabilities in both normal and log-transformed scales (Figure 6-18 & Figure 6-19).

Statistical evaluation confirms the robustness of the model during validation. An NSE value of 0.750 reflects slightly improved performance compared to calibration, while the MRAE of 0.54 remains within acceptable limits. The PEPF value of 21.2% indicates a moderate increase in peak flow error, which is expected when applying the model to an independent period (Table 6-3).

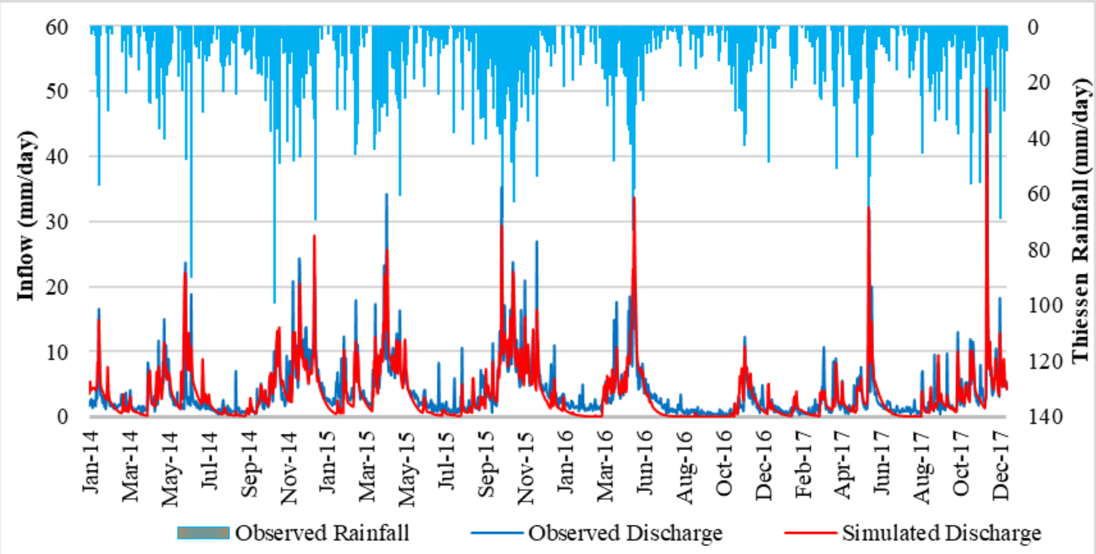
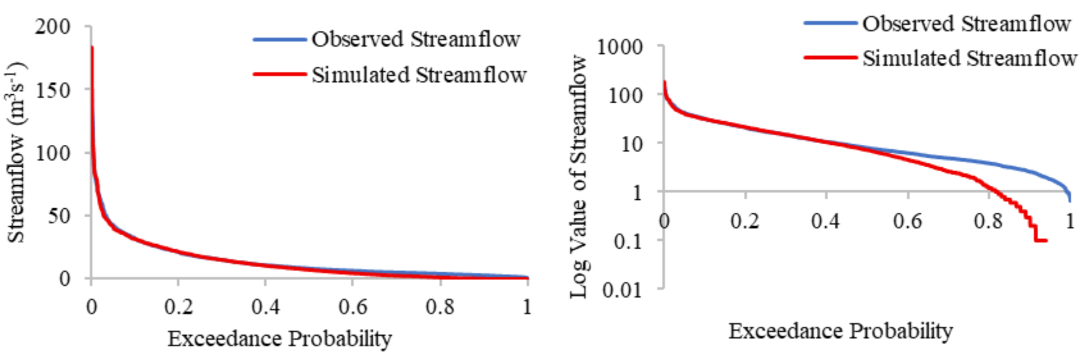


Figure 6-17: Rainfall - Runoff hydrograph for HEC-HMS model validation



a). b).

Figure 6-18: The flow-duration curves plotted for validation period (a) flow duration curve in normal scale (b) flow duration curve in log scale

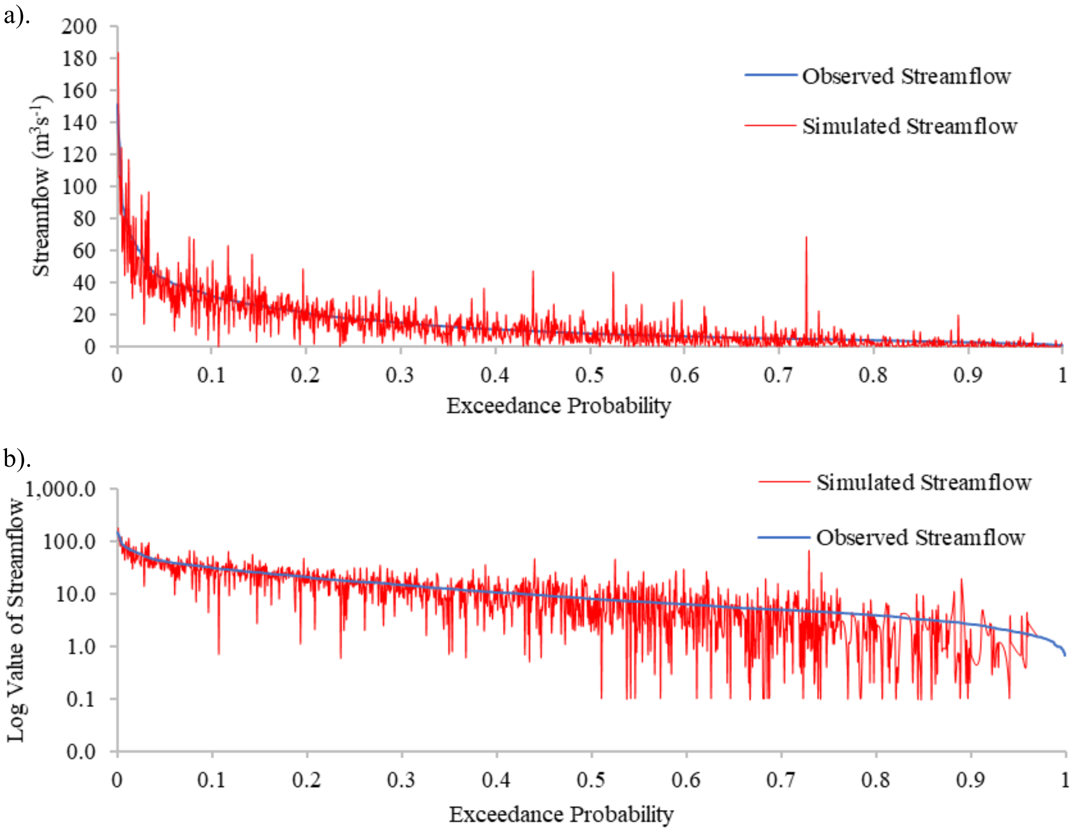


Figure 6-19: The flow-duration curves plotted for validation period sorted by observed streamflow (**a**) flow duration curve in normal scale (**b**) flow duration curve in log scale

Table 6-3: The evaluation matrix values for calibration and validation of the HEC-HMS model

Model Step	NSE	MRAE	PEPF(%)
Calibration	0.74	0.41	12.80
Validation	0.75	0.54	21.20

Overall, these results demonstrate that the HEC-HMS model structure and calibrated parameters are suitable for simulating historical conditions and can be confidently applied for future scenario and climate-driven impact analyses.

6.3.2. Water Allocation Projections

Generation of Climate-Driven Inputs

Future inflow projections derived from downscaled precipitation under SSP2-4.5 and SSP5-8.5 scenarios exhibited noticeable changes in magnitude. Projected evaporation, irrigation demand, and hydropower demand time series reflected nonlinear responses to changing climatic conditions, as captured through LSTM-based forecasting models.

Water Allocation Model Performance

Future water allocation projections were evaluated for the period 2021–2040 under climate-driven inflows and demands generated for SSP2-4.5 and SSP5-8.5 scenarios. The resulting reservoir storage dynamics are presented in Figure 6-20.

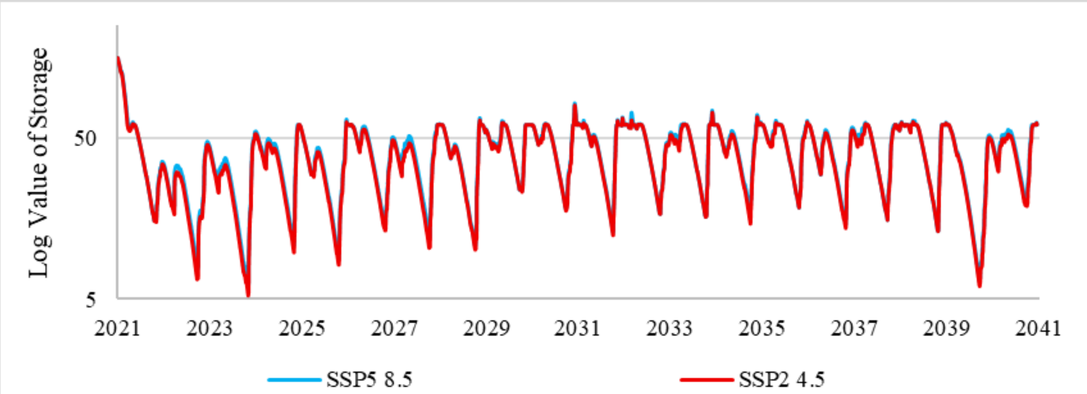


Figure 6-20: Future projected storage time series under SSP2 4.5 and SSP5 8.5 scenarios

Figure 6-21 and Figure 6-22 illustrate the projected time series of precipitation, reservoir inflow, hydropower release, and irrigation release under the SSP2-4.5 and SSP5-8.5 climate scenarios. Under SSP2-4.5, precipitation and inflow exhibit relatively smooth temporal variations, resulting in a more regulated reservoir response characterised by sustained inflows and moderate release patterns. Hydropower and irrigation releases under this scenario show gradual seasonal modulation with limited short-term fluctuations, indicating a comparatively stable water allocation regime. In contrast, projections under SSP5-8.5 reveal markedly increased temporal variability across all variables, with precipitation occurring in short-duration, high-intensity events that generate sharp inflow peaks followed by rapid recessions. This highly intermittent inflow regime leads to episodic hydropower releases concentrated around peak flow events, interspersed with extended periods of minimal release, while irrigation releases display pronounced fluctuations with noticeable reductions during prolonged low-inflow conditions. Overall, the SSP5-8.5 scenario is associated with a more volatile and event-driven allocation pattern compared to the relatively stable and predictable behaviour observed under SSP2-4.5.

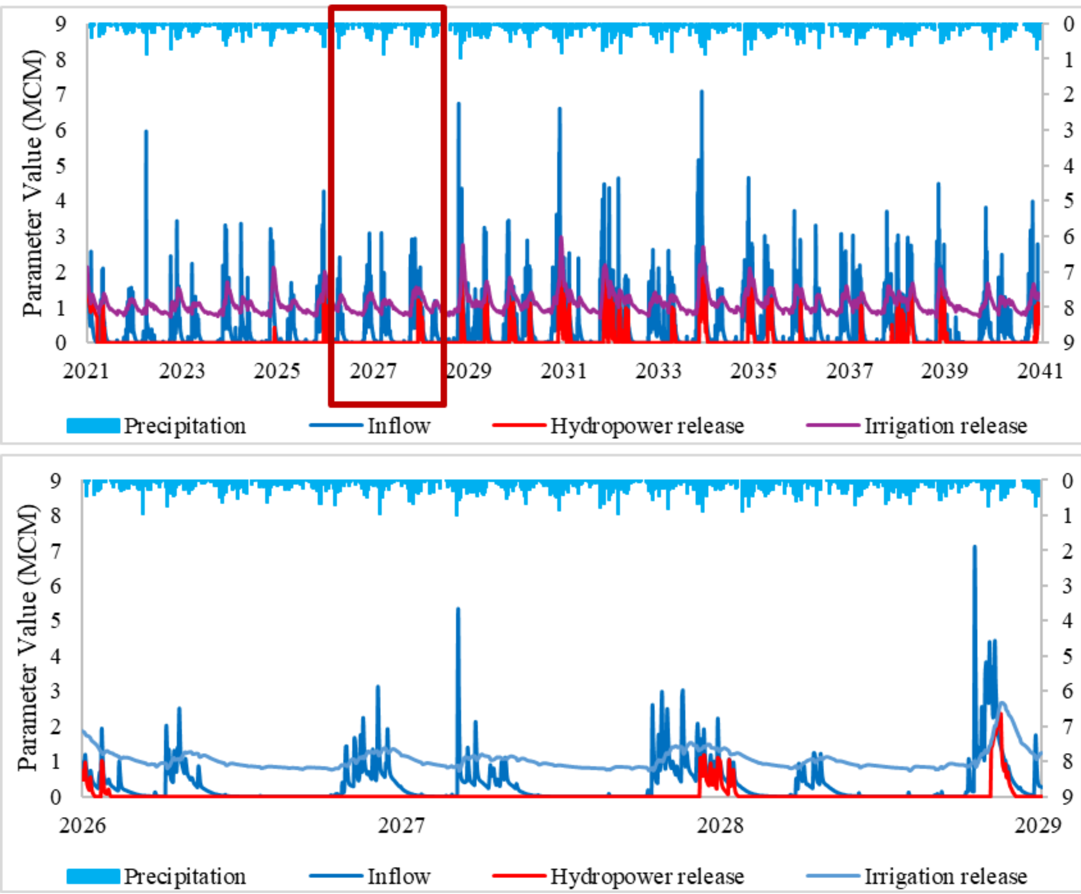


Figure 6-21: The projected water allocation for the reservoir under SSP2 4.5

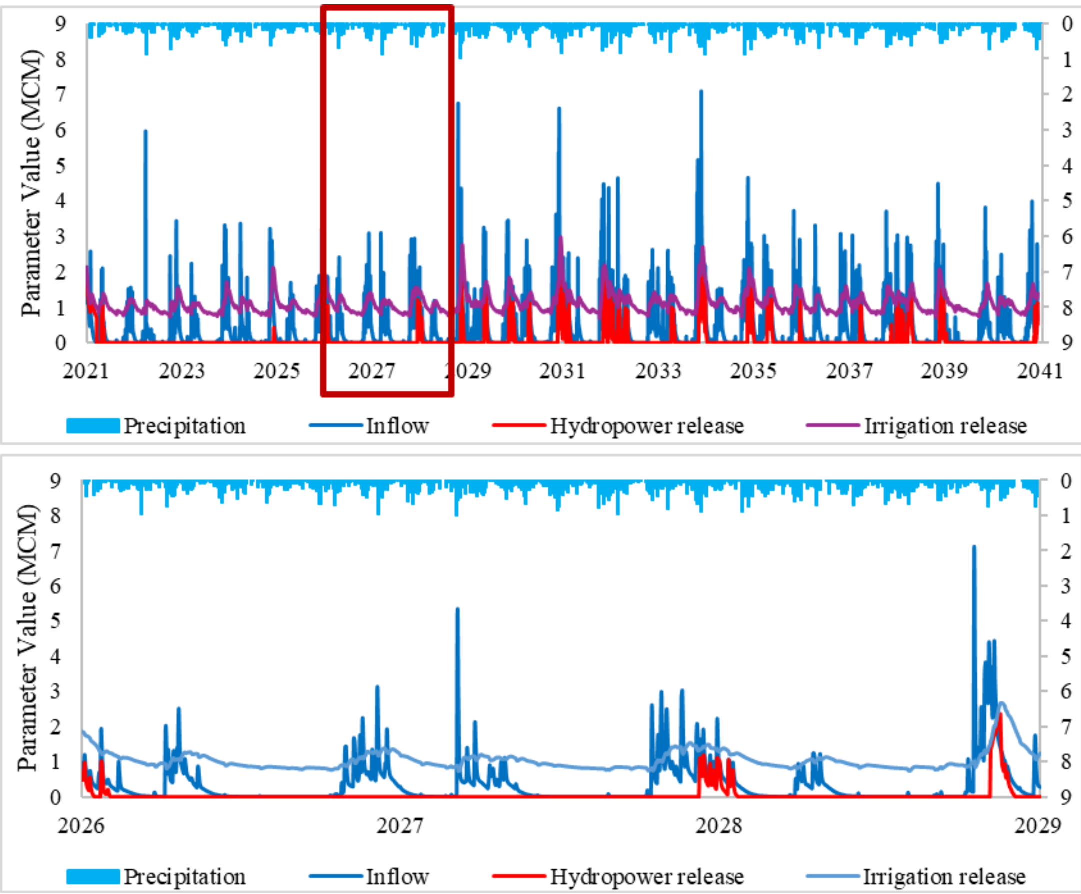


Figure 6-22: The projected water allocation for the reservoir under SSP5 8.5

During the historical period, precipitation and inflow exhibit recurring seasonal patterns with intermittent high-flow events, while hydropower and irrigation releases generally follow a regulated operational regime with relatively consistent magnitudes and temporal continuity (Figure 6-23). In comparison, future projections show a clear departure from historical behaviour, particularly under SSP5-8.5, where precipitation becomes more temporally concentrated, and inflow responses are dominated by sharper peaks and rapid recessions. While SSP2-4.5 projections retain some characteristics of the historical regime, including smoother inflow sequences and comparatively stable release patterns, both future scenarios exhibit increased short-term variability relative to the baseline. Hydropower releases in the projections become increasingly episodic, especially under SSP5-8.5, with longer periods of reduced or zero release compared to the historical record, whereas irrigation releases display greater fluctuations and reduced temporal stability during projected low-inflow conditions. Overall, the comparison indicates a transition from a historically regulated and seasonally structured water allocation system toward a more variable and event-driven operational regime in the future, with the magnitude of deviation increasing from SSP2-4.5 to SSP5-8.5.

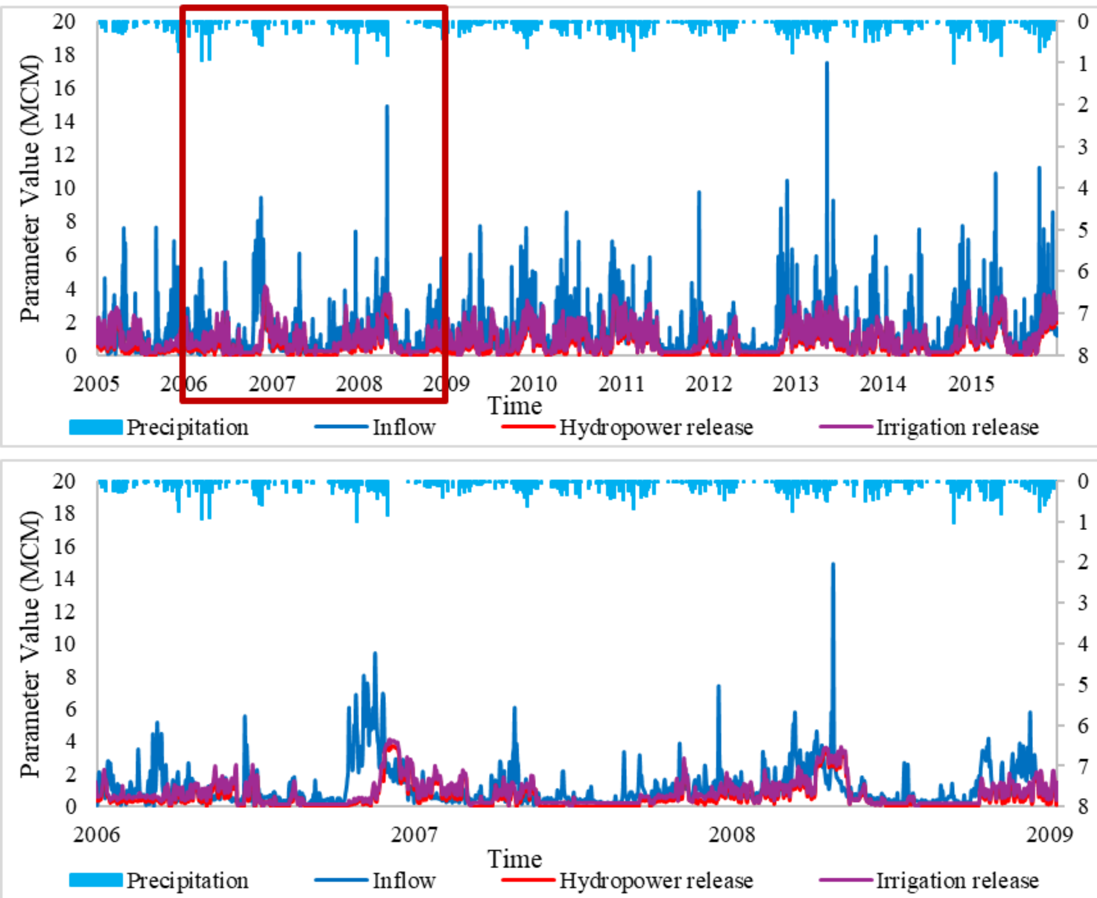


Figure 6-23: The historical water allocation according to water allocation model

6.4. Chapter Summary

This chapter presents the results from applying machine learning (ML) models, LSTM and PINN, to simulate reservoir water balance and evaluate the impact of climate change on water allocation. The models were tested using historical data, with a focus on both normal and extreme hydrological conditions.

The LSTM model demonstrated strong predictive performance, capturing general trends in reservoir storage but struggling to replicate extreme storage changes, as seen in underestimating peak values. In contrast, the PINN model, which integrates physical water balance principles, accurately reproduced both normal and extreme storage dynamics, showing superior generalisation and consistency during testing. The residual analysis showed that the PINN model had more stable residuals with lower variance, indicating better physical consistency.

The results from the reservoir water allocation model demonstrated the effectiveness of optimisation techniques. The optimised allocation schedule reduced unnecessary storage accumulation and spill losses, ensuring stable operation while satisfying irrigation and hydropower demands. The optimised model showed a better match with historical water demands and reservoir operation than the existing practices.

The hydrological model was successfully calibrated and validated, confirming the model's reliability for future analyses. The model's performance was supported by satisfactory flow duration curves and error metrics, ensuring that it can be confidently used for climate impact assessments.

Climate change projections under two scenarios, SSP2-4.5 (moderate) and SSP5-8.5 (high emissions), showed a clear divergence in future water dynamics. Under SSP5-8.5, there were significant increases in inflow variability, more frequent extreme events, and higher operational stress. In contrast, the SSP2-4.5 scenario led to less drastic changes, highlighting the importance of emission pathways in shaping future water management challenges.

CHAPTER 7

7. DISCUSSION

7.1. Performance of Machine Learning Models

A core requirement for reservoir water-balance simulation is physical feasibility: storage changes must remain consistent with conservation of mass as inflows, outflows, and losses evolve over time. This is not merely a theoretical preference; operational planning and constraint-based optimization typically assume that modeled storage and releases do not violate physically plausible bounds (e.g., negative storage, implausible jumps inconsistent with feasible fluxes).

In that context, results (Table 6-1) can be interpreted through the known structural differences between (i) long short-term memory (LSTM) networks and (ii) physics-informed neural networks (PINNs). LSTMs were designed to learn long temporal dependencies in sequential data via gated memory mechanisms (Hochreiter & Schmidhuber, 1997). Hydrologic studies have repeatedly shown that LSTMs can match or exceed established conceptual rainfall–runoff models when trained on sufficiently rich data, because they can learn non-linear input–state–output relationships from long records (Kratzert et al., 2019).

Consistent with the literature, the LSTM reproduced the *general trajectory* of storage and seasonal variability (Table 6-1), reflecting the LSTM's capacity to smooth noisy signals and encode persistence/lagged effects. This outcome is typical: LSTMs often deliver strong bulk-fit metrics (e.g., NSE) when trained and tested under regimes resembling the historical distribution that dominates the training set.

In the hydrologic ML literature, a common explanation is event scarcity and loss domination: rare peaks contribute fewer samples than "normal" conditions, so models trained with standard losses may prioritize reducing frequent moderate errors, producing a smoothing tendency and peak underrepresentation. (Martel et al., 2025), for example, explicitly highlight that peak events are rare and that scarcity can limit an LSTM’s ability to learn/predict extremes. Closely aligned, Xie et al. (2021) propose “physics-guided” LSTM training that injects or up-weights extreme-event information to improve flood peaks and reduce physically implausible outputs, reinforcing the idea that naive data-driven training alone may not robustly handle rare extremes.

PINNs incorporate governing equations, typically expressed as differential constraints, into the learning objective, acting as a regularizer that shrinks the space of admissible solutions toward physically consistent trajectories. In water-balance terms, this means the model is explicitly penalized when predicted storage changes do not match the mass-balance residual implied by inflow/outflow components. This “physics term” can reduce physically unrealistic oscillations and prevent the model from exploiting spurious correlations that would otherwise be statistically tolerated by purely data-driven training.

The presented comparative results (Table 6-1) are therefore consistent with the broader pattern seen in hydrologic physics-informed ML: models that embed conservation or process structure can maintain more credible behavior under stress conditions where extrapolation is required. For example, Bhasme et al. (2021) demonstrate that hybrid physics-informed ML can outperform purely conceptual or purely ML alternatives while also passing water-balance consistency checks, framing water-balance closure as an explicit validation dimension, not an afterthought. Similarly, Feng et al. (2023) report that physics-informed differentiable hydrologic models can approach or outperform LSTM skill in out-of-sample spatial/generalization settings while guaranteeing mass conservation and providing diagnostic physical variables, an argument that physical structure can improve robustness under extrapolation stress.

7.2. Impact of Climate Change on Reservoir Management

A central theme of this research is the impact of future climate variability on water resource management. The study incorporates climate change projections using downscaled climate data under two different scenarios, SSP2-4.5 (moderate) and SSP5-8.5 (high emissions). The results indicate significant changes in precipitation patterns, with SSP5-8.5 leading to more extreme hydrological variability and less predictable inflow patterns. These changes pose significant challenges to traditional reservoir management strategies, which are often based on fixed operating rules and historical hydrological data.

The SSP framework itself is documented as five socioeconomic narratives with different mitigation/adaptation challenges and emissions implications (Calvin et al., 2017). The "SSP2-4.5" and "SSP5-8.5" combine socioeconomic storyline families with radiative forcing levels, with CMIP6 providing internally consistent greenhouse-gas concentration pathways for these experiments (Meinshausen et al., 2020). From an operational reservoir perspective, the key point is not merely "climate change happens," but that hydroclimatic variability and extremes intensify in ways that undermine stationarity-based planning. The classic statement "stationarity is dead" in water management (Milly et al., 2008) provides a direct conceptual bridge to this study: reservoir operating rules tuned to the historical envelope can become systematically suboptimal or risky when inflow distributions shift.

The findings highlight that future climate change will exacerbate the challenges of balancing water demands for hydropower and agriculture. Under the SSP5-8.5 scenario, the increased frequency and intensity of extreme events, such as floods and droughts, make it difficult to rely on historical data for decision-making. This underscores the necessity for dynamic, real-time water allocation strategies that are adaptive to climate-induced changes in water availability. The dynamic optimisation model developed in this study addresses this need by integrating real-time data, predictive analytics, and climate projections into the water allocation process. This approach allows for more informed decision-making, minimising the risks associated with water shortages or excesses.

The study's projection of water allocation under future climate scenarios further emphasises the importance of flexible water management strategies. For instance, while hydropower generation may increase under certain climate conditions due to higher rainfall, irrigation needs may simultaneously increase, leading to competing demands on water resources. The ability of the model to dynamically allocate water between these two sectors is crucial for maintaining both agricultural productivity and energy production under uncertain climatic conditions.

7.3. Optimising Hydropower and Irrigation Balance

The study also addresses the challenge of optimising the balance between hydropower production and agricultural irrigation, two competing demands that often require different operational strategies. Hydropower generation benefits from large releases of water during high inflows, typically during the monsoon season, while irrigation requires a more consistent and predictable release pattern to support crop growth. The dynamic optimisation model developed in this study successfully navigates these competing demands by prioritising water allocation based on real-time data and projected needs.

This sits at the intersection of (a) predictive modeling and (b) decision/operations optimization. The reservoir-operations literature has long emphasized that multi-purpose systems require explicit trade-off analysis because objectives conflict (e.g., maximize energy, satisfy irrigation, maintain storage, avoid flood risk). Reviews such as Rani & Moreira (2010) describe simulation–optimization as a standard paradigm for reservoir operation, arguing that combining simulation with optimization often gives stronger decision-support performance than either alone, particularly under non-linear constraints and multi-objective settings.

One of the key findings is that the optimisation of water allocation can significantly enhance the operational efficiency of the reservoir. By adjusting the release schedules dynamically, the model reduces unnecessary water wastage due to spillages and ensures that water is available for both hydropower generation and irrigation. This dynamic allocation process maximises the utility of available water, contributing to greater energy reliability and irrigation stability. The ability to optimise both sectors simultaneously ensures that neither hydropower generation nor agricultural irrigation is disproportionately affected by the other, leading to improved overall water-use efficiency.

7.4. Operational Implications for Sri Lanka

The results of this study have significant operational implications for reservoir management in Sri Lanka, particularly within the Walawe River Basin where the Samanalawewa Reservoir supports both hydropower generation and agricultural irrigation. Previous studies have highlighted that water allocation conflicts between these sectors are a well-documented operational challenge in the basin. For instance, research by Molle et al. (2005) shows that hydropower releases from the Samanalawewa Reservoir can conflict with downstream irrigation requirements, emphasising the need for improved coordination and adaptive reservoir management strategies.

The findings support the need for such adaptive approaches by demonstrating that a dynamic water allocation framework, integrated with climate projections, can improve decision-making under uncertain future hydrological conditions. By incorporating projected inflow variability together with physically consistent water balance components, the model better represents the storage dynamics of the reservoir and the availability of water for competing uses.

In addition, operational conditions specific to the Samanalawewa system further highlight the importance of physically realistic reservoir modelling. For example, evaluations of the Samanalawewa Hydroelectric Power Project have documented persistent leakage and seepage from the reservoir structure, which can significantly affect storage levels and operational planning. Accurately representing such loss components in reservoir water balance calculations is therefore essential to avoid misallocation of water between hydropower generation and irrigation supply.

7.5. Contributions to Water Resource Management Literature

This study contributes to the growing body of research integrating machine learning techniques with traditional hydrological modelling for water resource management. Previous studies have demonstrated the effectiveness of data-driven models such as Long Short-Term Memory (LSTM) networks for hydrological prediction; however, these approaches often face limitations when representing rare extreme events or abrupt hydrological changes. The performance patterns observed in this study, particularly the reduced accuracy of the LSTM model during extreme conditions, are consistent with findings reported in recent research that highlight the challenges of handling peak events and out-of-distribution conditions in purely data-driven hydrological models (Martel et al., 2025; Xie et al., 2021).

A key contribution of this research is the application of physics-informed machine learning for reservoir water balance modelling and decision support. Physics-Informed Neural Networks (PINNs) incorporate governing physical constraints directly into the learning process, improving model consistency and reliability when compared with purely data-driven approaches. Recent studies have shown that integrating physical laws into machine learning frameworks can enhance model robustness, improve generalisation under changing climatic conditions, and increase interpretability in hydrological systems (Feng et al., 2023; Martel et al., 2025). The comparative results obtained in this study, particularly the improved performance and stability of the PINN-based framework, provide additional empirical evidence supporting this emerging research direction.

Furthermore, this research contributes to the literature by linking predictive modelling with reservoir operation and water allocation decision-making. Simulation–optimisation approaches have long been recognised as an effective framework for reservoir management (Rani & Moreira, 2010)(Rani & Moreira, 2010), while more recent studies highlight the importance of forecast-informed and adaptive operational strategies under hydrological uncertainty (Castelletti et al., 2023). By integrating hydrological predictions with a dynamic allocation model that balances hydropower generation and irrigation supply, this study demonstrates how machine learning predictions can be directly incorporated into reservoir operation frameworks. In doing so, the research provides a practical example of how predictive modelling, physical constraints, and operational decision-support tools can be combined to support climate-resilient water resource management.

CHAPTER 8

8. CONCLUSIONS

This study successfully developed and demonstrated a dynamic, machine learning–based framework for optimising water allocation between hydropower generation and agricultural irrigation in the Samanalawewa–Walawe reservoir system under present and future climate variability. By integrating a process-based hydrological model (HEC-HMS), physics-informed and data-driven machine learning models, and a rule-constrained dynamic water allocation algorithm, the research addressed the growing inadequacy of traditional rule-curve–based reservoir operations in a non-stationary hydroclimatic context.

The rainfall–runoff modelling using HEC-HMS reproduced the hydrological behaviour of the Samanalawewa sub-catchment with satisfactory accuracy. Calibration and validation results yielded Nash–Sutcliffe Efficiency values of approximately 0.74–0.75, accompanied by acceptable error statistics and realistic flow-duration characteristics. These results confirm that the model adequately captures monsoon-driven inflow variability and provides a reliable basis for simulating reservoir inflows under both historical and climate-conditioned scenarios. The robustness of the hydrological model is particularly important given its role as the primary inflow generator for downstream optimisation and climate impact analysis.

The comparative evaluation of machine learning models revealed that both the LSTM and PINN approaches performed strongly in simulating daily reservoir storage change under normal hydrological conditions, achieving high predictive skill with NSE values in the range of approximately 0.87–0.92. However, when hybrid datasets incorporating extreme hydrological events were considered, notable differences emerged. The LSTM model exhibited peak smoothing and a marked reduction in testing performance, with NSE values declining to approximately 0.67. In contrast, the PINN maintained higher robustness under extreme conditions, achieving a testing NSE of approximately 0.80, while also exhibiting lower residual variance and improved mass-balance consistency. Sensitivity analysis further indicated that the PINN preserved physically meaningful relationships between storage change and key water balance components, whereas the LSTM showed reduced interpretability and weaker physical coherence. These findings quantitatively demonstrate the advantage of embedding governing physical constraints within machine learning models, particularly for applications involving extremes and extrapolation beyond historical regimes.

The dynamic water allocation model, driven by the best-performing machine learning architecture and constrained by operational rules, produced an optimised storage trajectory that consistently remained below historically observed storage levels while satisfying minimum irrigation and hydropower requirements. This operational behaviour revealed a persistent surplus storage volume of approximately 30 MCM under historical conditions. From a quantitative perspective, this surplus represents a significant inefficiency in conventional reservoir operation, corresponding to unrealised potential for increased irrigation supply, enhanced hydropower generation through improved release timing, and reduced spill and evaporation losses. Qualitatively, the results indicate that existing rule-curve–based operations are overly conservative and insufficiently adaptive, particularly under increasing hydroclimatic variability.

The integration of future climate projections under SSP2-4.5 and SSP5-8.5 scenarios further highlighted the vulnerability of static reservoir operating policies. Projected changes in precipitation and temperature led to increased variability in inflows and evaporation losses, undermining the reliability of historical operating assumptions. Despite these challenges, the proposed dynamic optimisation framework maintained operational feasibility and stability under both scenarios, demonstrating its capacity to adapt release decisions to climate-conditioned inflows and demands. This confirms that climate-resilient reservoir management requires a transition from static, historically derived rule curves to adaptive, forecast-informed, and physically consistent decision-making frameworks.

Overall, the study provides strong quantitative and qualitative evidence that a physics-informed, dynamically optimised reservoir operation framework can significantly improve water-use efficiency, enhance hydropower reliability, and strengthen irrigation security under current and future climate variability. Beyond its application to the Samanalawewa–Walawe system, the framework offers a transferable methodological contribution for multipurpose reservoirs in monsoon-dominated and tropical regions facing similar challenges.

CHAPTER 9

9. RECOMMENDATIONS

Based on the outcomes of this study, it is recommended that reservoir operation practices in Sri Lanka move away from exclusive reliance on static rule curves and toward dynamic, forecast-based operational strategies. The identified surplus storage under current operations indicates substantial scope for improving system efficiency without compromising supply reliability or safety. Revising existing rule curves to incorporate inflow forecasts, climate signals, and real-time system states would allow reservoir operators to make earlier and more informed release decisions, thereby reducing downstream flood risk and minimising unnecessary storage-related losses.

The results also suggest that physics-informed machine learning models should be adopted as operational decision-support tools within reservoir management institutions. Compared to purely data-driven approaches, PINNs demonstrated superior robustness under extreme hydrological conditions and greater physical consistency, making them particularly suitable for real-time or near-real-time reservoir operation under climate uncertainty. Their integration into institutional workflows would enhance predictive reliability and support more transparent and defensible decision-making.

Effective implementation of such dynamic frameworks will require strengthened coordination among key agencies, including reservoir operators, the Department of Meteorology, and disaster management authorities. Timely access to accurate forecasts and operational data is essential for forecast-based reservoir operation, and improved data-sharing protocols would significantly enhance the effectiveness of adaptive water allocation strategies.

From a policy perspective, national water and energy planning frameworks should explicitly account for climate non-stationarity and operational uncertainty. The findings of this study support the need for climate-responsive reservoir operation policies that align with Sri Lanka's broader climate adaptation, disaster risk reduction, and water–energy–food nexus objectives.

Future research should extend the proposed framework to multi-reservoir and cascade systems, where upstream–downstream interactions and cumulative impacts introduce additional complexity. Incorporating explicit environmental flow requirements would allow a more holistic assessment of sustainability, while probabilistic optimisation using climate and inflow ensembles would improve risk-based decision-making. Finally, given the computational demands of physics-informed models, further work on training efficiency, model reduction, and transfer learning would enhance their scalability and operational feasibility.

BIBLIOGRAPHY

REFERENCES

Abera, F. F., Asfaw, D. H., Engida, A. N., & Melesse, A. M. (2018). Optimal Operation of Hydropower Reservoirs under Climate Change: The Case of Tekeze Reservoir, Eastern Nile. *Water 2018, Vol. 10, Page 273*, *10*(3), 273. https://doi.org/10.3390/W10030273

Adams, M., Stary, U., & Markart, G. (2010). *A comparison of hydrological models for forest management and climate change How can existing models capture and reproduce hydrological effects of forests?* 58. https://doi.org/10.13140/RG.2.1.3930.8329

Ahmad, M. J., Cho, G. ho, & Choi, K. S. (2022). Historical climate change impacts on the water balance and storage capacity of agricultural reservoirs in small ungauged watersheds. *Journal of Hydrology: Regional Studies*, *41*, 101114. https://doi.org/10.1016/J.EJRH.2022.101114

Alfieri, L., Perona, P., & Burlando, P. (2006). Optimal water allocation for an alpine hydropower system under changing scenarios. *Water Resources Management*, *20*(5), 761–778. https://doi.org/10.1007/S11269-005-9006-Y

Anderson, M. L., Chen, Z.-Q., Kavvas, M. L., & Feldman, A. (2002). Coupling HEC-HMS with Atmospheric Models for Prediction of Watershed Runoff. *Journal of Hydrologic Engineering*, *7*(4), 312–318. https://doi.org/10.1061/(ASCE)1084-0699(2002)7:4(312)

Ansar, A., Flyvbjerg, B., Budzier, A., & Lunn, D. (2014). Should we build more large dams? The actual costs of hydropower megaproject development. *Energy Policy*, *69*, 43–56. https://doi.org/10.1016/J.ENPOL.2013.10.069

Ashfaq, M., Rastogi, D., Abid, M. A., & Kao, S.-C. (2022). Evaluation of CMIP6 GCMs over the CONUS for downscaling studies. *Authorea Preprints*. https://doi.org/10.1002/ESSOAR.10510589.1

Ashofteh, P. S., Haddad, O. B., & A. Mariño, M. (2013). Climate Change Impact on Reservoir Performance Indexesin Agricultural Water Supply. *Journal of Irrigation and Drainage Engineering*, *139*(2), 85–97. https://doi.org/10.1061/(ASCE)IR.1943-4774.0000496

Ayalew, A. T., Lohani, T. K., & Meskr, Y. M. (2024). River Flow Analysis using HEC-HMS and Assessing the Impact of Climate Change on Hydropower Generation by MODSIM in the Koka Reservoir of Ethiopia. *Journal of Water Management Modeling*, *32*. https://doi.org/10.14796/JWMM.C530

Ba, J. L., Kiros, J. R., & Hinton, G. E. (2016). *Layer Normalization*. http://arxiv.org/abs/1607.06450

Bai, Y., Zhang, Z., & Zhao, W. (2019). Assessing the Impact of Climate Change on Flood Events Using HEC-HMS and CMIP5. *Water, Air, & Soil Pollution 2019 230:6*, *230*(6), 119-. https://doi.org/10.1007/S11270-019-4159-0

Bakker, K. (2012). Water security: Research challenges and opportunities. *Science*, *337*(6097), 914–915. https://doi.org/10.1126/SCIENCE.1226337;WEBSITE:WEBSITE:AAAS-SITE;JOURNAL:JOURNAL:SCIENCE;WGROUP:STRING:PUBLICATION

Bang, J. , S. N. U. S. R. of K., Lee, S. H. , T. A. and M. U. U., Choi, J. Y. , S. N. U. S. R. of K., & Lee, S. H. , S. N. U. S. R. of K. (2017). Evaluation of Reservoir Drought Response Capability Considering Precipitation of Non-irrigation Period using RCP Scenario. *Journal of The Korean Society of Agricultural Engineers*, *59*(1).

Basheer, M., Nechifor, V., Calzadilla, A., Gebrechorkos, S., Pritchard, D., Forsythe, N., Gonzalez, J. M., Sheffield, J., Fowler, H. J., & Harou, J. J. (2023). Cooperative adaptive management of the Nile River with climate and socio-economic uncertainties. *Nature Climate Change 2023 13:1*, *13*(1), 48–57. https://doi.org/10.1038/s41558-022-01556-6

Beça, P., Rodrigues, A. C., Nunes, J. P., Diogo, P., & Mujtaba, B. (2023). Optimizing Reservoir Water Management in a Changing Climate. *Water Resources*

Management, *37*(9), 3423–3437. https://doi.org/10.1007/S11269-023-03508-X/FIGURES/5

Ben Khélifa, W., & Mosbahi, M. (2021). Modeling of rainfall-runoff process using HEC-HMS model for an urban ungauged watershed in Tunisia. *Modeling Earth Systems and Environment 2021 8:2*, *8*(2), 1749–1758. https://doi.org/10.1007/S40808-021-01177-6

Bhasme, P., Vagadiya, J., & Bhatia, U. (2021). Enhancing predictive skills in physically-consistent way: Physics Informed Machine Learning for Hydrological Processes. *Journal of Hydrology*, *615*. https://doi.org/10.1016/j.jhydrol.2022.128618

Bhuvandas, N., Timbadiya, P. V, Patel, P. L., & Porey, P. D. (2014). *(PDF) Review of Downscaling Methods in Climate Change and Their Role in Hydrological Studies*. https://www.researchgate.net/publication/267448581_Review_of_Downscaling_Methods_in_Climate_Change_and_Their_Role_in_Hydrological_Studies

Bo, Y., Zhang, C., Fang, X., Sun, Y., Li, C., An, M., Peng, Y., & Lu, Y. (2025). Application of HP-LSTM Models for Groundwater Level Prediction in Karst Regions: A Case Study in Qingzhen City. *Water 2025, Vol. 17, Page 362*, *17*(3), 362. https://doi.org/10.3390/W17030362

Bozorg-Haddad, O., Dehghan, P., Zolghadr-Asli, B., Singh, V. P., Chu, X., & Loáiciga, H. A. (2022). System dynamics modeling of lake water management under climate change. *Scientific Reports*, *12*(1). https://doi.org/10.1038/S41598-022-09212-X

Calvin, K., Bond-Lamberty, B., Clarke, L., Edmonds, J., Eom, J., Hartin, C., Kim, S., Kyle, P., Link, R., Moss, R., McJeon, H., Patel, P., Smith, S., Waldhoff, S., & Wise, M. (2017). The Shared Socioeconomic Pathways and their energy, land use, and greenhouse gas emissions implications: An overview. *Global Environmental Change*, *42*, 153–168. https://doi.org/10.1016/j.gloenvcha.2016.06.010

Casadei, S., Di Francesco, S., Giannone, F., & Pierleoni, A. (2019). Small reservoirs for a sustainable water resources management. *Advances in Geosciences*, *49*, 165–174. https://doi.org/10.5194/ADGEO-49-165-2019

Castelletti, A., Ficchì, A., Cominola, A., Segovia, P., Giuliani, M., Wu, W., Lucia, S., Ocampo-Martinez, C., De Schutter, B., & Maestre, J. M. (2023). Model Predictive Control of water resources systems: A review and research agenda. *Annual Reviews in Control*, *55*, 442–465. https://doi.org/10.1016/j.arcontrol.2023.03.013

Chakkaravarthy, D. N. (2019). Water Scarcity- Challenging the Future. *International Journal of Agriculture Environment and Biotechnology*, *12*(3). https://doi.org/10.30954/0974-1712.08.2019.2

Chakraborty, S., & Biswas, S. (2021). Simulation of flow at an ungauged river site based on HEC-HMS model for a mountainous river basin. *Arabian Journal of Geosciences*, *14*(20). https://doi.org/10.1007/S12517-021-08385-5

Chamoglou, M., Vergos, I., Sidiropoulos, P., & Kagalou, I. (2018). Nutrient Concentrations in Seven Irrigation Reservoirs (Lake Karla Watershed Thessaly Greece). *Proceedings 2018, Vol. 2, Page 656*, *2*(11), 656. https://doi.org/10.3390/PROCEEDINGS2110656

Chea, S., & Oeurng, C. (2018). *(PDF) Flow simulation in an ungauged catchment of Tonle Sap Lake Basin in Cambodia: Application of the HEC-HMS model*. https://www.researchgate.net/publication/323120661_Flow_simulation_in_an_ungauged_catchment_of_Tonle_Sap_Lake_Basin_in_Cambodia_Application_of_the_HEC-HMS_model

Chicho, B. T., & Sallow, A. B. (2021). A Comprehensive Survey of Deep Learning Models Based on Keras Framework. *Journal of Soft Computing and Data Mining*, *2*(2), 49–62. https://doi.org/10.30880/JSCDM.2021.02.02.005

Choi, Y., Ahn, J., Ji, J., Lee, E., & Yi, J. (2020). Effects of Inter-Basin Water Transfer Project Operation for Emergency Water Supply. *Water Resources Management 2020 34:8*, *34*(8), 2535–2548. https://doi.org/10.1007/S11269-020-02574-9

Cuvelier, T., Archambeau, P., Dewals, B., & Louveaux, Q. (2018). Comparison Between Robust and Stochastic Optimisation for Long-term Reservoir Management Under Uncertainty. *Water Resources Management*, *32*(5), 1599–1614. https://doi.org/10.1007/S11269-017-1893-1/METRICS

Dabhade, P. D., & Regulwar, D. G. (2021). Sustainable Multi-Objective Multi-Reservoir Optimization Considering Environmental Flow. *Journal of Water Resource and Protection*, *13*(12), 945–956. https://doi.org/10.4236/JWARP.2021.1312051

Dai, B., Wang, J., Gu, X., Xu, C., Yu, X., Zhang, H., Yuan, C., & Nie, W. (2022). Development of Modified LSTM Model for Reservoir Capacity Prediction in Huanggang Reservoir, Fujian, China. *Geofluids*, *2022*. https://doi.org/10.1155/2022/2891029

Dau, Q. V., Kuntiyawichai, K., & Adeloye, A. J. (2020). Future Changes in Water Availability Due to Climate Change Projections for Huong Basin, Vietnam. *Environmental Processes 2020 8:1*, *8*(1), 77–98. https://doi.org/10.1007/S40710-020-00475-Y

De Lara, P. G., Lopes, J. D., da Luz, G. M., & Bonuma, N. (2014). (PDF) RESERVOIR OPERATION EMPLOYING HEC-RESSIM: CASE STUDY OF TUCURUÍ DAM, BRAZIL. *ICFM6*. https://www.researchgate.net/publication/263542045_RESERVOIR_OPERATION_EMPLOYING_HEC-RESSIM_CASE_STUDY_OF_TUCURUI_DAM_BRAZIL

De Silva, C. S., Weatherhead, E. K., Knox, J. W., & Rodriguez-Diaz, J. A. (2007). Predicting the impacts of climate change-A case study of paddy irrigation water requirements in Sri Lanka. *Agricultural Water Management*, *93*(1–2), 19–29. https://doi.org/10.1016/J.AGWAT.2007.06.003

Dissanayake, P. (2017). *Applicability of a two parameter water balance model to simulate daily rainfall runoff – case study of kalu and gin river basins in sri lanka*. http://dl.lib.mrt.ac.lk/handle/123/12889

Dobson, B., Wagener, T., & Pianosi, F. (2019). An argument-driven classification and comparison of reservoir operation optimization methods. *Advances in Water Resources*, *128*, 74–86. https://doi.org/10.1016/J.ADVWATRES.2019.04.012

Dogan, M. S., Lund, J. R., & Medellin-Azuara, J. (2021). Hybrid Linear and Nonlinear Programming Model for Hydropower Reservoir Optimization. *Journal of Water Resources Planning and Management*, *147*(3), 06021001. https://doi.org/10.1061/(ASCE)WR.1943-5452.0001353

Ebrahimian, H., Dialameh, B., Hosseini-Moghari, S. M., & Ebrahimian, A. (2020). Optimal conjunctive use of aqua-agriculture reservoir and irrigation canal for paddy fields (case study: Tajan irrigation network, Iran). *Paddy and Water Environment*, *18*(3), 499–514. https://doi.org/10.1007/S10333-020-00797-5

Ekanayake, P., Wickramasinghe, L., Jayasinghe, J. M. J. W., & Rathnayake, U. (2021). Regression-Based Prediction of Power Generation at Samanalawewa Hydropower Plant in Sri Lanka Using Machine Learning. *Mathematical Problems in Engineering*, *2021*. https://doi.org/10.1155/2021/4913824

El Jeitany, J., Pacetti, T., & Caporali, E. (2024). Evaluating climate change effects on hydrological functionality and water-related ecosystem services. *Ecohydrology*, *17*(4), e2557. https://doi.org/10.1002/ECO.2557;REQUESTEDJOURNAL:JOURNAL:19360592;WGROUP:STRING:PUBLICATION

Eriyagama, N., Smakhtin, V. U., Chandrapala, L., & Fernando, K. (2010). Impacts of climate change on water resources and agriculture in Sri Lanka: a review and preliminary vulnerability mapping. *IWMI Research Reports*. https://doi.org/10.22004/AG.ECON.94787

Eyring, V., Bony, S., Meehl, G. A., Senior, C. A., Stevens, B., Stouffer, R. J., & Taylor, K. E. (2016). Overview of the Coupled Model Intercomparison Project Phase 6 (CMIP6) experimental design and organization. *Geoscientific Model Development*, *9*(5), 1937–1958. https://doi.org/10.5194/GMD-9-1937-2016

Faber, B. A., & Harou, J. J. (2006). Multiobjective optimization with HEC Res-PRM - Application to the Upper Mississippi Reservoir System. *Operating Reservoirs* *in Changing Conditions - Proceedings of the Operations Management 2006 Conference*, *2006*, 215–224. https://doi.org/10.1061/40875(212)22

Farea, A., Yli-Harja, O., & Emmert-Streib, F. (2024). Understanding Physics-Informed Neural Networks: Techniques, Applications, Trends, and Challenges. *AI 2024, Vol. 5, Pages 1534-1557*, *5*(3), 1534–1557. https://doi.org/10.3390/AI5030074

Feng, D., Beck, H., Lawson, K., & Shen, C. (2023). The suitability of differentiable, physics-informed machine learning hydrologic models for ungauged regions and climate change impact assessment. *Hydrology and Earth System Sciences*, *27*(12), 2357–2373. https://doi.org/10.5194/hess-27-2357-2023

Fernando, S. (2014). *HYDRO POWER DEVELOPMENT IN SRI LANKA ITS ... - NARBO*. https://www.yumpu.com/en/document/view/24818061/hydro-power-development-in-sri-lanka-its-narbo

Garrote, L., Granados, A., Spiliotis, M., & Martin-Carrasco, F. (2023). Effectiveness of Adaptive Operating Rules for Reservoirs. *Water Resources Management*, *37*(6–7), 2527–2542. https://doi.org/10.1007/S11269-022-03386-9/FIGURES/7

Gleick, P. H., & Cooley, H. (2021). Freshwater Scarcity. *Annual Review of Environment and Resources*, *46*(Volume 46, 2021), 319–348. https://doi.org/10.1146/ANNUREV-ENVIRON-012220-101319/CITE/REFWORKS

Gu, W., Shao, D., Tan, X., Shu, C., & Wu, Z. (2017). Simulation and Optimization of Multi-Reservoir Operation in Inter-Basin Water Transfer System. *Water Resources Management*, *31*(11), 3401–3412. https://doi.org/10.1007/S11269-017-1675-9/METRICS

Gunathilake, M. B., Amaratunga, Y. V., Perera, A., Chathuranika, I. M., Gunathilake, A. S., & Rathnayake, U. (2020). Evaluation of Future Climate and Potential Impact on Streamflow in the Upper Nan River Basin of Northern Thailand. *Advances in Meteorology*, *2020*(1), 8881118. https://doi.org/10.1155/2020/8881118

Hasan, F., Medley, P., Drake, J., & Chen, G. (2024). Advancing Hydrology through Machine Learning: Insights, Challenges, and Future Directions Using the CAMELS, Caravan, GRDC, CHIRPS, PERSIANN, NLDAS, GLDAS, and GRACE Datasets. *Water 2024, Vol. 16, Page 1904*, *16*(13), 1904. https://doi.org/10.3390/W16131904

Hassan, Z., Shamsudin, S., & Harun, S. (2013). Application of SDSM and LARS-WG for simulating and downscaling of rainfall and temperature. *Theoretical and Applied Climatology 2013 116:1*, *116*(1), 243–257. https://doi.org/10.1007/S00704-013-0951-8

Hatamkhani, A., & Moridi, A. (2019). Multi-Objective Optimization of Hydropower and Agricultural Development at River Basin Scale. *Water Resources Management 2019 33:13*, *33*(13), 4431–4450. https://doi.org/10.1007/S11269-019-02365-X

He, S., Wang, D., Sang, X., & Niu, G. (2024). Water Resource Regulation and Evaluation Method Based on Optimization of Drought-Limited Water Level in Reservoir Group. *Sustainability 2024, Vol. 16, Page 7015*, *16*(16), 7015. https://doi.org/10.3390/SU16167015

He, X., Pan, M., Wei, Z., Wood, E. F., & Sheffield, J. (2020). A Global Drought and Flood Catalogue from 1950 to 2016. *Bulletin of the American Meteorological Society*, *101*(5), E508–E535. https://doi.org/10.1175/BAMS-D-18-0269.1

Heaton, J. (2018). Ian Goodfellow, Yoshua Bengio, and Aaron Courville: Deep learning. *Genetic Programming and Evolvable Machines*, *19*(1–2), 305–307. https://doi.org/10.1007/S10710-017-9314-Z

Herman, J. D., & Giuliani, M. (2018). Policy tree optimization for threshold-based water resources management over multiple timescales. *Environmental Modelling & Software*, *99*, 39–51. https://doi.org/10.1016/J.ENVSOFT.2017.09.016

Hochreiter, S., & Schmidhuber, J. (1997). Long Short-Term Memory. *Neural Computation*, *9*(8), 1735–1780. https://doi.org/10.1162/neco.1997.9.8.1735

International Water Management Institute (IWMI). (2013). *IWMI Annual report 2012*. https://doi.org/10.5337/2013.209

Jamali, A. A., Tabatabaee, R., & Randhir, T. O. (2021). Ecotourism and socioeconomic strategies for Khansar River watershed of Iran. *Environment, Development and Sustainability*, *23*(11), 17077–17093. https://doi.org/10.1007/S10668-021-01334-Y/METRICS

Jayaminda, C., Gunawardhana, L., & Rajapakse, L. (2023). Rating Performances of Global Climate Models in Capturing Monsoon Rainfall Patterns in Sri Lanka. *Moratuwa Engineering Research Conference, MERCon*, 264–269. https://doi.org/10.1109/MERCON60487.2023.10355390

Karamouz, M., & Houck, M. H. (1987). COMPARISON OF STOCHASTIC AND DETERMINISTIC DYNAMIC PROGRAMMING FOR RESERVOIR OPERATING RULE GENERATION. *JAWRA Journal of the American Water Resources Association*, *23*(1), 1–9. https://doi.org/10.1111/J.1752-1688.1987.TB00778.X

Karimi, A., & Ardakanian, R. (2010). Development of a Dynamic Long-Term Water Allocation Model for Agriculture and Industry Water Demands. *Water Resources Management: An International Journal, Published for the European Water Resources Association (EWRA)*, *24*(9), 1717–1746. https://doi.org/10.1007/S11269-009-9521-3

Karniadakis, G. E., Kevrekidis, I. G., Lu, L., Perdikaris, P., Wang, S., & Yang, L. (2021). Physics-informed machine learning. *Nature Reviews Physics 2021 3:6*, *3*(6), 422–440. https://doi.org/10.1038/s42254-021-00314-5

Kharin, V. V., Flato, G. M., Zhang, X., Gillett, N. P., Zwiers, F., & Anderson, K. J. (2018). Risks from Climate Extremes Change Differently from 1.5°C to 2.0°C Depending on Rarity. *Earth's Future*, *6*(5), 704–715. https://doi.org/10.1002/2018EF000813;WEBSITE:WEBSITE:AGUPUBS;ISSUE:ISSUE:DOI

Kim, S.-J., Kim, P.-S., & Lim, C.-Y. (2004). Behaviour Analysis of Irrigation Reservoir Using Open Water Management Program. *Journal of The Korean*

Society of Agricultural Engineers, *46*(1), 3–13. https://doi.org/10.5389/KSAE.2004.46.1.003

Kratzert, F., Herrnegger, M., Klotz, D., Hochreiter, S., & Klambauer, G. (2019). NeuralHydrology – Interpreting LSTMs in Hydrology. *Lecture Notes in Computer Science (Including Subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)*, *11700 LNCS*, 347–362. https://doi.org/10.1007/978-3-030-28954-6_19

Laksiri, K., Gunathilake, J., & Iwao, Y. (2005). *A Case Study of the Samanalawewa Reservoir on the Walawe River in an Area of Karst in Sri Lanka*. 253–262. https://doi.org/10.1061/40796(177)27

Lange, H., & Sippel, S. (2020). *Machine Learning Applications in Hydrology*. 233–257. https://doi.org/10.1007/978-3-030-26086-6_10

Latif, S. D. (2021). Developing a boosted decision tree regression prediction model as a sustainable tool for compressive strength of environmentally friendly concrete. *Environmental Science and Pollution Research*, *28*(46), 65935–65944. https://doi.org/10.1007/S11356-021-15662-Z

Le, X. H., Ho, H. V., Lee, G., & Jung, S. (2019). Application of Long Short-Term Memory (LSTM) neural network for flood forecasting. *Water (Switzerland)*, *11*(7). https://doi.org/10.3390/W11071387

Lebon, N., Dagès, C., Burger-Leenhardt, D., & Molénat, J. (2022). A new agro-hydrological catchment model to assess the cumulative impact of small reservoirs. *Environmental Modelling & Software*, *153*, 105409. https://doi.org/10.1016/J.ENVSOFT.2022.105409

Lee, E., Ji, J., Lee, S., Yoon, J., Yi, S., & Yi, J. (2023). Development of an Optimal Water Allocation Model for Reservoir System Operation. *Water (Switzerland)*, *15*(20), 3555. https://doi.org/10.3390/W15203555/S1

Lehner, B., Liermann, C. R., Revenga, C., Vörömsmarty, C., Fekete, B., Crouzet, P., Döll, P., Endejan, M., Frenken, K., Magome, J., Nilsson, C., Robertson, J. C., Rödel, R., Sindorf, N., & Wisser, D. (2011). High-resolution mapping of the world’s reservoirs and dams for sustainable river-flow management. *Frontiers in Ecology and the Environment*, *9*(9), 494–502. https://doi.org/10.1890/100125;JOURNAL:JOURNAL:15409309;PAGE:STRING:ARTICLE/CHAPTER

Leščešen, I., Tanhapour, M., Pekárová, P., Miklánek, P., & Bajtek, Z. (2025). Long Short-Term Memory (LSTM) Networks for Accurate River Flow Forecasting: A Case Study on the Morava River Basin (Serbia). *Water 2025, Vol. 17, Page 907*, *17*(6), 907. https://doi.org/10.3390/W17060907

Lin, N. M., & Rutten, M. (2016). Optimal Operation of a Network of Multi-purpose Reservoir: A Review. *Procedia Engineering*, *154*, 1376–1384. https://doi.org/10.1016/J.PROENG.2016.07.504

Luo, X., Yuan, S., Tang, H., Xu, D., Ran, Q., Cen, Y., & Liang, D. (2024). Enhanced physics-informed neural networks for efficient modelling of hydrodynamics in river networks. *Hydrological Processes*, *38*(4). https://doi.org/10.1002/HYP.15143

Maas, A. L. (2013). *Rectifier Nonlinearities Improve Neural Network Acoustic Models*.

Madhushankha, J. M. L., & Wijesekera, N. T. S. (2021). Application of HEC-HMS Model to Estimate Daily Streamflow in Badddegama Watershed of Gin Ganga Basin Sri Lanka. *Engineer: Journal of the Institution of Engineers, Sri Lanka*, *54*(1), 89. https://doi.org/10.4038/ENGINEER.V54I1.7438

Martel, J. L., Arsenault, R., Turcotte, R., Castañeda-Gonzalez, M., Brissette, F., Armstrong, W., Mailhot, E., Pelletier-Dumont, J., Lachance-Cloutier, S., Rondeau-Genesse, G., & Caron, L. P. (2025). Exploring the ability of LSTM-based hydrological models to simulate streamflow time series for flood frequency analysis. *Hydrology and Earth System Sciences*, *29*(19), 4951–4968. https://doi.org/10.5194/hess-29-4951-2025

Martinez-Alvarez, V., Maestre-Valero, J. F., Martin-Gorriz, B., & Gallego-Elvira, B. (2010). Experimental assessment of shade-cloth covers on agricultural reservoirs for irrigation in south-eastern Spain. *Spanish Journal of Agricultural Research*, *8*(SUPPL. 2). https://doi.org/10.5424/SJAR/201008S2-1355

Masson-Delmotte, V., Zhai, P., Pirani, A., Connors, S. L., Péan, C., Berger, S., Caud, N., Chen, Y., Goldfarb, L., Gomis, M. I., Huang, M., Leitzell, K., Lonnoy, E., Matthews, J. B. R., Maycock, T. K., Waterfield, T., Yelekçi, O., Yu, R., & Zhou, B. (2021). *Climate Change 2021: The Physical Science Basis. Contribution of Working Group I to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change*. https://www.ipcc.ch/report/sixth-assessment-report-working-group-i/

Meinshausen, M., Nicholls, Z. R. J., Lewis, J., Gidden, M. J., Vogel, E., Freund, M., Beyerle, U., Gessner, C., Nauels, A., Bauer, N., Canadell, J. G., Daniel, J. S., John, A., Krummel, P. B., Luderer, G., Meinshausen, N., Montzka, S. A., Rayner, P. J., Reimann, S., … Wang, R. H. J. (2020). The shared socio-economic pathway (SSP) greenhouse gas concentrations and their extensions to 2500. *Geoscientific Model Development*, *13*(8), 3571–3605. https://doi.org/10.5194/GMD-13-3571-2020

Milly, P. C. D., Betancourt, J., Falkenmark, M., Hirsch, R. M., Kundzewicz, Z. W., Lettenmaier, D. P., & Stouffer, R. J. (2008). Climate change. Stationarity is dead: whither water management? *Science (New York, N.Y.)*, *319*(5863), 573–574. https://doi.org/10.1126/science.1151915

Molden, D. (2020). Scarcity of water or scarcity of management? *International Journal of Water Resources Development*, *36*(2–3), 258–268. https://doi.org/10.1080/07900627.2019.1676204

Molle, F., Jayakody, P., Ariyaratne, B. R., & Somatilake, H. S. (2005). Balancing irrigation and hydropower: case study from southern Sri Lanka. In *Iwmi*. International Water Management Institute. https://hdl.handle.net/10568/39881

Morimoto, R. (2013). Incorporating socio-environmental considerations into project assessment models using multi-criteria analysis: A case study of Sri Lankan hydropower projects. *Energy Policy*, *59*, 643–653. https://doi.org/10.1016/J.ENPOL.2013.04.020

Muller, M., Biswas, A., Martin-Hurtado, R., & Tortajada, C. (2015). Built infrastructure is essential. *Science*, *349*(6248), 585–586. https://doi.org/10.1126/SCIENCE.AAC7606

Nascimento, P. H. M., Marcato, A. L. M., Cabral, V. A., Junior, I. C. S., Panoeiro, F. F., & Honório, L. M. (2021). Spillage Forecast Models in Hydroelectric Power Plants Using Information from Telemetry Stations and Hydraulic Control. *Energies 2021, Vol. 14, Page 184*, *14*(1), 184. https://doi.org/10.3390/EN14010184

Nash, J. E., & Sutcliffe, J. V. (1970). River flow forecasting through conceptual models part I - A discussion of principles. *Journal of Hydrology*, *10*(3), 282–290. https://doi.org/10.1016/0022-1694(70)90255-6

Ngo, L. Le, Madsen, H., & Rosbjerg, D. (2007). Simulation and optimisation modelling approach for operation of the Hoa Binh reservoir, Vietnam. *Journal of Hydrology*, *336*(3–4), 269–281. https://doi.org/10.1016/J.JHYDROL.2007.01.003

Nicklow, J., Reed, P., Savic, D., Dessalegne, T., Harrell, L., Chan-Hilton, A., Karamouz, M., Minsker, B., Ostfeld, A., Singh, A., & Zechman, E. (2010). State of the Art for Genetic Algorithms and Beyond in Water Resources Planning and Management. *Journal of Water Resources Planning and Management*, *136*(4), 412–432. https://doi.org/10.1061/(ASCE)WR.1943-5452.0000053

Nourani, V., Rouzegari, N., Molajou, A., & Hosseini Baghanam, A. (2020). An integrated simulation-optimization framework to optimize the reservoir operation adapted to climate change scenarios. *Journal of Hydrology*, *587*, 125018. https://doi.org/10.1016/J.JHYDROL.2020.125018

Ogilvie, A., Riaux, J., Massuel, S., Mulligan, M., Belaud, G., Le Goulven, P., & Calvez, R. (2019). Socio-hydrological drivers of agricultural water use in small reservoirs. *Agricultural Water Management*, *218*, 17–29. https://doi.org/10.1016/J.AGWAT.2019.03.001

Pathiraja, M. P. W., & Wijayapala, W. (2017). Optimization of the usage of Samanalawewa water resource for power generation. *1st International*

Conference - EECon 2016: 2016 Electrical Engineering Conference, 86–90. https://doi.org/10.1109/EECON.2016.7830940

Perera, K. R. J., & Wijesekera, N. T. S. (2011). Identification of the Spatial Variability of Runoff Coefficients of Three Wet Zone Watersheds of Sri Lanka. *Engineer: Journal of the Institution of Engineers, Sri Lanka*, *44*(3), 1. https://doi.org/10.4038/ENGINEER.V44I3.6960

Peretti, F., Menapace, A., Zanfei, A., & Righetti, M. (2025). Optimal irrigation scheduling for sustainable agriculture: Minimising energy costs in rotational management. *Agricultural Water Management*, *322*. https://doi.org/10.1016/J.AGWAT.2025.109986

Raissi, M., Perdikaris, P., & Karniadakis, G. E. (2019). Physics-informed neural networks: A deep learning framework for solving forward and inverse problems involving nonlinear partial differential equations. *Journal of Computational Physics*, *378*, 686–707. https://doi.org/10.1016/J.JCP.2018.10.045

Raman, H., & Chandramouli, V. (1996). Deriving a General Operating Policy for Reservoirs Using Neural Network. *Journal of Water Resources Planning and Management*, *122*(5), 342–347. https://doi.org/10.1061/(ASCE)0733-9496(1996)122:5(342)

Rani, D., & Moreira, M. M. (2010). Simulation-optimization modeling: A survey and potential application in reservoir systems operation. *Water Resources Management*, *24*(6), 1107–1138. https://doi.org/10.1007/s11269-009-9488-0

Rani, D., Mourato, S., & Moreira, M. (2020). A Generalized Dynamic Programming Modelling Approach for Integrated Reservoir Operation. *Water Resources Management 2020 34:4*, *34*(4), 1335–1351. https://doi.org/10.1007/S11269-020-02505-8

Renteria-Mena, J. B., & Giraldo, E. (2024). Predictive Modeling of Water Level in the San Juan River Using Hybrid Neural Networks Integrated with Kalman Smoothing Methods. *Information (Switzerland)*, *15*(12). https://doi.org/10.3390/INFO15120754

Saab, S. M., Othman, F. B., Tan, C. G., Allawi, M. F., & El-Shafie, A. (2022). Review on generating optimal operation for dam and reservoir water system: simulation models and optimization algorithms. *Applied Water Science 2022 12:4*, *12*(4), 73-. https://doi.org/10.1007/S13201-022-01593-8

Sabzipour, B., Arsenault, R., Troin, M., Martel, J. L., Brissette, F., Brunet, F., & Mai, J. (2023). Comparing a long short-term memory (LSTM) neural network with a physically-based hydrological model for streamflow forecasting over a Canadian catchment. *Journal of Hydrology*, *627*. https://doi.org/10.1016/J.JHYDROL.2023.130380

Saha, A., & Chandra Pal, S. (2024). Application of machine learning and emerging remote sensing techniques in hydrology: A state-of-the-art review and current research trends. *Journal of Hydrology*, *632*, 130907. https://doi.org/10.1016/J.JHYDROL.2024.130907

Salim, S., Ati, A. S., Ali, A., Yanti, D., Mandang, T., Purwanto, Y. J., Novitasari, F., & Maryati, S. (2024). Benefit distribution of the irrigation system: irrigation reservoir in Geyongan Village, Cirebon Regency, Indonesia. *IOP Conference Series: Earth and Environmental Science*, *1318*(1), 012006. https://doi.org/10.1088/1755-1315/1318/1/012006

Shelke, M., Londhe, S. N., Dixit, P. R., & Kolhe, P. (2023). Simulation of Reservoir Inflow Using HEC-HMS. *Lecture Notes in Civil Engineering*, *312 LNCE*, 227–237. https://doi.org/10.1007/978-981-19-9147-9_17

Shen, C., & Lawson, K. (2021). Applications of deep learning in hydrology. *Deep Learning for the Earth Sciences: A Comprehensive Approach to Remote Sensing, Climate Science and Geosciences*, 285–297. https://doi.org/10.1002/9781119646181.CH19;CTYPE:STRING:BOOK

Shevah, Y. (2019). Impact of Persistent Droughts on the Quality of the Middle East Water Resources. *Separation Science and Technology (New York)*, *11*, 51–84. https://doi.org/10.1016/B978-0-12-815730-5.00003-X

Smakhtin, V. U., & Weragala, N. (2005). *An assessment of hydrology and environmental flows in the Walawe River Basin, Sri Lanka*. International Water Management Institute. https://hdl.handle.net/10568/39198

Solgi, R., Loáiciga, H. A., & Kram, M. (2021). Long short-term memory neural network (LSTM-NN) for aquifer level time series forecasting using in-situ piezometric observations. *Journal of Hydrology*, *601*. https://doi.org/10.1016/J.JHYDROL.2021.126800

Sorachampa, P., Tippayawong, N., & Ngamsanroaj, K. (2020). Optimizing multiple reservoir system operation for maximum hydroelectric power generation. *Energy Reports*, *6*, 67–75. https://doi.org/10.1016/J.EGYR.2019.11.043

Srinivas, R., Singh, A. P., & Deshmukh, A. (2017). Development of a HEC-HMS-based watershed modeling system for identification, allocation, and optimization of reservoirs in a river basin. *Environmental Monitoring and Assessment 2017 190:1*, *190*(1), 31-. https://doi.org/10.1007/S10661-017-6418-0

Suo, M., Xia, F., & Fan, Y. (2022). A Fuzzy-Interval Dynamic Optimization Model for Regional Water Resources Allocation under Uncertainty. *Sustainability 2022, Vol. 14, Page 1096*, *14*(3), 1096. https://doi.org/10.3390/SU14031096

Tessey, J., Rita, M., & Ogunrinde, V. (2025). *Application of Machine Learning Algorithms in Distributed Hydrological Modeling for Evaluating Climate Change Impacts | Request PDF*. https://www.researchgate.net/publication/389636534_Application_of_Machine_Learning_Algorithms_in_Distributed_Hydrological_Modeling_for_Evaluating_Climate_Change_Impacts

Tian, J., Guo, S., Deng, L., Yin, J., Pan, Z., He, S., & Li, Q. (2021). Adaptive optimal allocation of water resources response to future water availability and water demand in the Han River basin, China. *Scientific Reports*, *11*(1). https://doi.org/10.1038/S41598-021-86961-1

Ward, M. N., Brown, C. M., Baroang, K. M., & Kaheil, Y. H. (2013). Reservoir performance and dynamic management under plausible assumptions of future climate over seasons to decades. *Climatic Change*, *118*(2), 307–320. https://doi.org/10.1007/S10584-012-0616-0

Warin, X. (2023). Reservoir optimization and machine learning methods. *EURO Journal on Computational Optimization*, *11*, 100068. https://doi.org/10.1016/J.EJCO.2023.100068

Weragala, D. K. N. (2010). Water Allocation Challenges in Rural River Basins: A Case Study from the Walawe River Basin, Sri Lanka. *All Graduate Theses and Dissertations, Spring 1920 to Summer 2023*. https://doi.org/https://doi.org/10.26076/e399-a114

Weragala, N., Kaluarachchi, J. J., & Smakhtin, V. (2007). *Water resources management under competing demands in the Walawe River Basin, Sri Lanka. Submitted to the Conference on International Water Resources: Challenges to the 21st century. Organized by the Universities Council on Water Resources*. https://digitalcommons.usu.edu/cee_facpub/1735

Wilby, R. L., Dawson, C. W., & Barrow, E. M. (2002). sdsm — a decision support tool for the assessment of regional climate change impacts. *Environmental Modelling & Software*, *17*(2), 145–157. https://doi.org/10.1016/S1364-8152(01)00060-3

Wu, C., Wang, Z., Yue, P., Lai, Z., & Wang, Y. (2024). Research on Optimal Operation of Cascade Reservoirs under Complex Water-Level Flow Output Constraints. *Water 2024, Vol. 16, Page 2963*, *16*(20), 2963. https://doi.org/10.3390/W16202963

Xie, K., Liu, P., Zhang, J., Han, D., Wang, G., & Shen, C. (2021). Physics-guided deep learning for rainfall-runoff modeling by considering extreme events and monotonic relationships. *Journal of Hydrology*, *603*. https://doi.org/10.1016/j.jhydrol.2021.127043

Xu, Q., Shi, Y., Bamber, J., Tuo, Y., Ludwig, R., & Zhu, X. X. (2023). *Physics-aware Machine Learning Revolutionizes Scientific Paradigm for Machine Learning and Process-based Hydrology*. https://arxiv.org/pdf/2310.05227

Yang, Z., Yang, K., Wang, Y., Su, L., & Hu, H. (2019). The improved multi-criteria decision-making model for multi-objective operation in a complex reservoir system. *Journal of Hydroinformatics*, *21*(5), 851–874. https://doi.org/10.2166/HYDRO.2019.150

Yi, S., Kondolf, G. M., Sandoval-Solis, S., & Dale, L. (2022). Application of Machine Learning-based Energy Use Forecasting for Inter-basin Water Transfer Project. *Water Resources Management 2022 36:14*, *36*(14), 5675–5694. https://doi.org/10.1007/S11269-022-03326-7

Zhang, Z., Qin, H., Yao, L., Liu, Y., Jiang, Z., Feng, Z., & Ouyang, S. (2020). Improved Multi-objective Moth-flame Optimization Algorithm based on R-domination for cascade reservoirs operation. *Journal of Hydrology*, *581*, 124431. https://doi.org/10.1016/J.JHYDROL.2019.124431

Zhao, C., Zhang, F., Lou, W., Wang, X., & Yang, J. (2024). A comprehensive review of advances in physics-informed neural networks and their applications in complex fluid dynamics. *Physics of Fluids*, *36*(10). https://doi.org/10.1063/5.0226562

Zhong, L., Lei, H., & Yang, J. (2024). Development of a Distributed Physics-Informed Deep Learning Hydrological Model for Data-Scarce Regions. *Water Resources Research*, *60*(6). https://doi.org/10.1029/2023WR036333

Ziaei, M., Shui, L. T., & Goodarzi, E. (2012). Optimization and simulation modelling for operation of the Zayandeh Rud Reservoir. *Water International*, *37*(3), 305–318. https://doi.org/10.1080/02508060.2012.688189;REQUESTEDJOURNAL:JOURNAL:RWIN20;WGROUP:STRING:PUBLICATION

Zomorodian, M., Lai, S. H., Homayounfar, M., Ibrahim, S., Fatemi, S. E., & El-Shafie, A. (2018). The state-of-the-art system dynamics application in integrated water resources modeling. *Journal of Environmental Management*, *227*, 294–304. https://doi.org/10.1016/J.JENVMAN.2018.08.097

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