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Assessing the Impacts of Projected Climate Scenarios on Irrigation Reliability and Reservoir Sustainability in Sri Lanka's Dry Zone

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Abstract

Climate change poses major challenges for irrigation water management in Sri Lanka's dry zone. This study assesses the performance of the Nachchaduwa reservoir under historical and projected climate scenarios using multiple General Circulation Models (GCMs). Eight GCMs were ranked through compromise programming, with the top three models bias-corrected and downscaled to generate climate projections for Shared Socioeconomic Pathways (SSP) scenarios: SSP2-4.5 and SSP5-8.5 under near-future (2015–2050) and mid-future (2051–2075). The ensemble GCM data were input into HEC-HMS and HEC-ResSim to simulate inflows, reservoir water levels, and releases for these future scenarios. Additionally, the CROPWAT model was used to estimate current and future irrigation water requirements, supporting assessments of Reliability, Resilience, and Vulnerability (RRV) metrics and the Reservoir Sustainability Index (RSI). Trend analysis shows an increase in precipitation of 2.6%–14.2%, most notably under SSP5-8.5. Furthermore, maximum and minimum temperatures also trend upwards compared to the baseline, with minimum temperatures rising by 3.9% to 9.6% and maximum temperatures by 1.5% to 5.4%. HEC-HMS simulations suggest mean annual flow volumes will decrease slightly under SSP2-4.5 and rise markedly under SSP5-8.5. Mean annual irrigation demand is projected to increase by 40.5%-43.6% in the near and mid-term future across both SSP scenarios. Reliability stays around 60%, while resilience varies between 48% to 58%, indicating moderate recovery periods after deficits. Vulnerability remains below 30%, reflecting insufficient flows to meet irrigation demands, while the RSI ranges from 0.22 to 0.35. Combining RRV metrics with RSI indicates that the Nachchaduwa reservoir is moderately sustainable under future climate scenarios. Nonetheless, implementing adaptive strategies such as optimised operations and effective management is crucial to maintaining irrigation reliability.

Keywords: Nachchaduwa reservoir, climate change scenarios, irrigation demand, Reliability-Resiliency-Vulnerability metrics, Reservoir Sustainability Index, HEC-HMS, HEC-ResSim, CROPWAT

1. Introduction

Reservoirs serve multiple purposes, such as irrigation, domestic, industrial water supply, hydropower, flood control, fisheries and recreational activities (Heydari et al., 2016; Salwey et al., 2024). However, when it comes to a multipurpose reservoir, reliability should be measured to evaluate the satisfactory level that can meet the demand without failure (Chaves et al., 2023; Olukanni et al., 2018). The ideal volume of storage reservoirs must be recognised by the flow rate, which varies over time, to fulfil the requirements. When the natural flow of the river exceeds demand, it is referred to as the wettest time, while the dry season is defined as the opposite. (Salazar et al., 2024). The critical period is crucial, as it is the demand scarcity which determines the reservoir volume (Lai et al., 2022). The hydrological design aims to calculate the storage capacity to sustain yield within a certain failure probability and maintain the risk thresholds (Hou et al., 2024; Wang et al., 2021). Climate variability is one of the factors which can affect reservoir reliability for an extended period and is characterised by a series of low and high inflows to the hydrological persistence (Chaves et al., 2023; Espanmanesh et al., 2024). The Intergovernmental Panel on Climate Change (IPCC) has noted that global and regional climate change has a significant impact on greenhouse gases (GHG), which have altered the natural composition of the atmosphere (Atique & Mahmood, 2014). Melkamu et al. (2017) mentioned that increasing GHG changes the pattern of temperature and precipitation, thus influencing the hydrological process and availability of water resources for different purposes. Consequently, agricultural systems are affected by GHG (Lampole et al., 2017; Hatfield et al. 2020; IPCC, 2021). Therefore, studying the impact of climate change on rainfall-runoff is crucial to understanding the performance of reservoir operations.

The Centralised Coupled Model Intercomparison Project (CMIP) has developed various climate models to enhance understanding of past, present, and future climate changes and serves as a vital tool for projecting future climate patterns (Eyring et al., 2016; Riahi et al., 2017; Srivastava et al., 2020). Climate change significantly impacts temperature and precipitation, with extreme weather events heavily affecting socio-economic sectors (Cramer, 2014; Field & Barros, 2014; UN-Water, 2020). While numerous General Circulation Models (GCMs) are available, selecting the appropriate GCM for a specific region remains crucial (Lin & Tung, 2017). The choice often depends on various factors, including the model's objectives and projected scenarios. Several

studies have focused on model selection using statistical methods; for example, Khadka et al. (2022) evaluated 28 climate models from CMIP5 and 32 GCMs from CMIP, using 25 performance metrics to rank models across Southeast Asia. Baghel et al. (2022) ranked 18 CMIP6 models based on four performance statistics in the Songkhram River Basin in Thailand. Pradhan et al. (2021) assessed the performance of 12 CMIP5 GCMs in simulating precipitation and temperature, applying four performance indicators in the Koshi River Basin, Nepal. All these studies aimed to identify the most suitable GCMs for regional assessments.

Combining climate forecast data from GCMs with hydrological models is one of the most reliable methods for assessing changes in water resources (Shrestha et al., 2025; Wang et al., 2024). The complex hydrological systems within river basins are especially vulnerable to climate change effects because of their highly interconnected processes. Satellite-based raster data is widely utilised for long-term rainfall and temperature analysis due to its greater accuracy and higher spatial and temporal resolution (Wu et al., 2019). Raw GCMS cannot be directly used for climate change impact studies due to issues such as limited spatial resolution, simplified thermodynamic procedures, and physics. Therefore, precipitation and temperature data require bias correction prior to further impact assessments. Seneviratne et al., (2012) emphasised the importance of bias correction in the specific IPCC report. Several bias correction methods have been developed for downscaling GCM data (Chen et al., 2011a; Chen et al., 2011b; Johnson & Sharma, 2011; Mohan & Bhaskaran, 2019; Hemanandhini and Rajkumar, 2023; Shanmugam et al., 2023). Multiple approaches for bias correction exist; climate factors are adjusted using techniques such as power transpiration and linear scaling based on observed and model means. Distribution mapping or quantile mapping creates transfer functions to adjust simulated climate variables (Shanmugam et al., 2023). Various studies recommend performance metrics and skill scores to evaluate GCMs, including correlation coefficient (CC), normalised root-mean-square deviation (NRMSD), and root-mean-square error (RMSE) (Macadam et al., 2010; Sun et al., 2015). The individual performance of models and weighting schemes in multi-model ensembles can also be employed to assess GCMs (Fordham et al., 2011; Sreelatha & Anand Raj, 2019).

Food security and the vulnerability of impoverished rural farmers are expected to worsen due to climate change, especially in arid and semi-arid regions where they are more susceptible to heatwaves, irregular water supplies, floods, and droughts. Variations in river flows and

groundwater recharge are key sources of irrigation, and changes in evaporation and rainfall patterns further affect agriculture. The growing demands from various industries and agriculture are contributing to a global water shortage. According to FAO (2011), over 40% of rural populations worldwide live in river basins with limited water resources. River discharge mainly determines water availability for the agricultural, residential, and industrial sectors. Changes in hydrological processes can threaten both the quantity and quality of water, leading to floods and water shortages (Ficklin et al., 2018).

To ensure national food security in Sri Lanka, the Dry Zone produces about 2.1 million tonnes of paddy, making up 80% of the country's total output. Paddy cultivation is the main livelihood for small farming households in rural areas of the Dry Zone. Due to significant fluctuations in rainfall patterns and the unreliability of rainfed rice production, this zone relies heavily on irrigation (Final report, 2005). The irrigation schedule or practice depends on the water available or the irrigation frequency, which varies depending on crop type and rainfall characteristics. Considering the projected changes in all climatic factors, it is crucial to evaluate how climate change could affect crop water requirements. Numerous studies worldwide have examined the impacts of climate change on crop water needs (Awal et al., 2018; Chowdhury et al., 2016; Mohan & Ramsundram, 2014).

The Indian Ocean monsoon system has influenced the rainfall patterns of Sri Lanka over many decades (Clift & Plumb, 2008; Naveendrakumar et al., 2018). Temperature and rainfall are influenced by El Niño and La Niña, which significantly affect the system (Chandimala & Zubair, 2007; Zubair et al., 2008). El Niño weakens Walker circulation, resulting in reduced rainfall from July to August and January to March, and increased rainfall during the northeastern monsoon from October to December (Zubair et al., 2003; Zubair & Ropelewski, 2006). Based on yearly rainfall, Sri Lanka's climate divides into three zones: wet, dry, and intermediate. These zones are characterised by the Southwest monsoon rains, altitude, soil types, land use patterns, and vegetation. The Wet zone receives over 2,500 mm of high rainfall without distinct dry periods, whereas the Dry zone gets less than 1,750 mm and has a clearly defined dry season. The Intermediate zone has average rainfall between 1,750 and 2,500 mm, with a shorter, less obvious dry season (National Guideline for Climate-Smart Agricultural Technologies and Practices, 2019). In Sri Lanka's Dry Zone, a water collection system was established by the ancient capital

Anuradhapura in the third century BCE. Tank cascade systems were initially part of this system, later enhanced and expanded. To improve local water supply, a supra-regional canal network was constructed in the fifth century CE (Abeywardana et al., 2019).

In Sri Lanka, the cascade-style man-made reservoirs known as tanks or wewas collect and store surface water in shallow valleys. Channels and spillways connect these reservoirs and enhance the downstream flow. Based on the surface area and the irrigated land, reservoirs are categorised as major, medium, minor, and micro tanks (Murray, 2004). For example, a water surface of over 200 hectares and a command area exceeding 600 hectares are regarded as major tanks, situated in the downstream part of the cascade (Murray et al., 2004; Bebermeier et al., 2017). Governmental bodies oversee major tanks, while smaller tanks in upstream zones are managed by local village communities (Bebermeier et al., 2017). Approximately 35% of irrigated paddy fields in Sri Lanka benefit significantly from the Village Tank Cascade System (VTCS) (FAO, 2011). VTCSs evolved from traditional farming practices to enable effective water management in Sri Lanka's dry zone, which receives less than 1750 mm of rain annually. They feature a distinctive hydrological network, comprising interconnected tanks built within catchments of the dry zone to store, transport, and utilise water from transient streams (Madduma Bandara, 1985). A village tank supplies water to a paddy field, which subsequently directs water downstream to irrigate its command area.

The Malwathu Oya river basin experiences water shortages during the dry season, while its downstream areas flood during the rainy season. In 2011, 2014, and 2016, this basin faced severe flooding. The dry zone of Sri Lanka has made significant progress in rice cultivation, using efficient water management systems centred on reservoirs. Each year, there are considerable fluctuations in water resources available for irrigation. Water availability during the Yala season is often limited by factors such as eutrophication, heavy siltation, and aquatic weeds, all of which reduce reservoir capacity (Gunarathna & Kumari, 2014). Consequently, cropping intensity in the Yala season varies. Improving water management is vital to ensure farming during this period, as it accounts for 44% of the maximum resource utilisation area. An effective water management system is expected to be implemented, especially considering future population pressures (Final Report, 2005). Reservoirs are essential for rural livelihoods, but they often lack proper management and climate change adaptation strategies. Incorporating climate change impacts into

modelling techniques is necessary to optimise water availability. Recent research indicates that combining simulation and performance assessment is key to evaluating reservoir vulnerability to climate variability and droughts.

This study aims to assess the impacts of climate change scenarios on the climatic and hydrological conditions of the Malwathu Oya River Basin and to evaluate the performance of one of its major reservoirs, the Nachchaduwa Reservoir. The assessment is carried out using the Reliability-Resiliency-Vulnerability (RRV) framework and the Reservoir Sustainability Index (RSI). Future trends in temperature and precipitation for the period 2015–2075 were analysed using three Global Climate Models (GCMs) under two Shared Socioeconomic Pathways (SSP): SSP2-4.5 and SSP5-8.5. These projections were used to evaluate the impacts of climate change on streamflow and irrigation water requirements. The CROPWAT model was employed to estimate water irrigation demand, while runoff was simulated using the HEC-HMS hydrological model. Reservoir operations were modelled using the HEC-ResSim model based on the established rule curve. Finally, the performance of the Nachchaduwa Reservoir was assessed using the three key indices of the RRV framework to determine its capacity to meet irrigation water demands under future climate conditions. The novelty of this study lies in the integration of multiple GCMs and ensemble modelling techniques with hydrological and reservoir simulation tools. To the best of our knowledge, this is the first comprehensive study to apply such an integrated approach to evaluate reservoir performance and sustainability for irrigation supply in the Dry Zone of Sri Lanka.

2. Study area and data

Sri Lanka is an island country situated at the southern tip of the Indian Ocean, entirely within the tropical zone with latitudes of 5° 55' - 9° 50' N and longitudes of 79° 42' - 81° 53' E, covering an area of 65,609 km². The topography slopes from south-southwest to north-northeast. The southern part of Sri Lanka features high mountains rising above 1,500 m. The southwest and northeast monsoons significantly influence rainfall patterns across the country. According to the Department of Meteorology (1969), the southwest monsoon, often called the Yala season, begins in May and ends in September. The Maha season, or northeast monsoon, typically starts in November or thereabouts. Its timing varies throughout the year and is more unpredictable (Kitamura, 1990).

The Malwathu Oya river basin is the second-largest in the country, covering 3,284 km², and is extensively utilised for various purposes, including drinking water, fisheries, and irrigation for

around 200,000 local farmers in the North Central Province (Figure 1). This river basin plays a crucial role in the national economy by making a significant contribution to agricultural production. However, the river experiences seasonal and geographical fluctuations due to variations in climate across different times and areas. Anuradhapura District accounts for about two-thirds of the basin's upper catchment, while the lower catchment extends across Vavuniya and Mannar Districts. The upper watershed of Malwathu Oya is intercepted by five major reservoirs: Nachchaduwa, Mahakanadarawa, Nuwarawewa, Tissa Wewa, and Pavatkulam, along with several medium and minor tanks. The irrigation systems of Nachchaduwa, Nuwarawewa, and Tissa Wewa are supplemented with water diverted from the Mahaweli through the Kala Oya Yoda Ela, sourced from the Kala Oya basin.

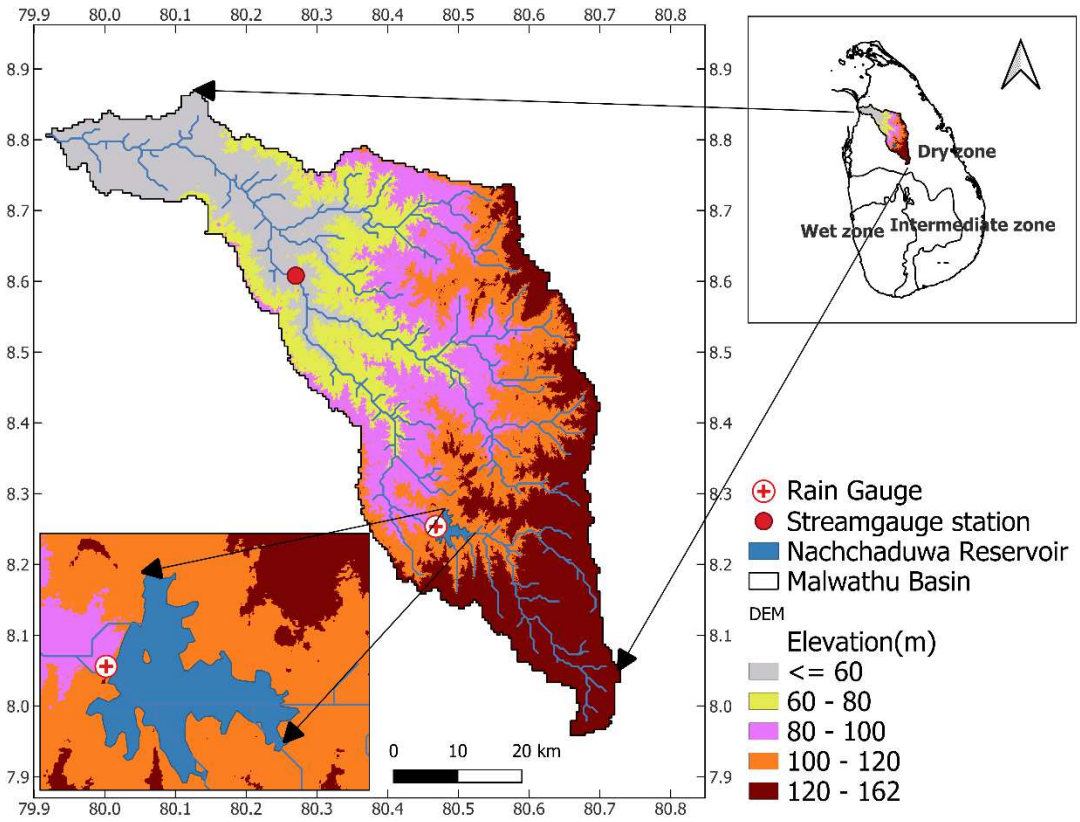


Figure 1. Study area map showing the Malwathu Oya River Basin and Nachchaduwa reservoir in Sri Lanka’s Dry Zone

Nachchaduwa Reservoir is situated in the uppermost part of the Malwathu Oya river basin and was constructed in 1906. It is owned by the Department of Irrigation. The reservoir's elevation is 96 m

above mean sea level in Sri Lanka's arid zone (Figure 1). It is designed to irrigate 5,960 acres, supporting 2,500 farming households, and functions to manage field channels and distributary canals. (https://icid-ciid.org/award/his_details/35). Paddy is the primary crop cultivated during the Maha season in Sri Lanka's arid zone. Various cash crops are grown during the Yala season alongside paddy, which occupies a smaller area due to limited irrigation water. Other field crops, such as Kurakkan, maize, sorghum, greengram, cowpea, soybeans, groundnuts, and chillies, are cultivated across both the Maha and Yala seasons in Sri Lanka. Key information about the Nachchaduwa Reservoir is summarised in Table 1.

Table 1 Characteristics of Nachchaduwa reservoir.

Reservoir Characteristics	**Value**	**Units**
Flood control water level	102.31	m (above MSL)
Normal high-water level	101.70	m (above MSL)
Minimum water level	94.06	m (above MSL)
Capacity at flood control water level	67.2	MCM
Capacity at normal high-water level	58	MCM
Capacity at minimum water level	2.1	MCM
Dam Characteristics		
Dam crest level	105.1	m (above MSL)
Dam length	1646	m
Service Spillway Characteristics		
Crest level	95.58	m (above MSL)
Maximum discharge capacity	312	m^3/s
Catchment Area	29000	Net (km^2)
Command Area	62670	Gross (km^2)

2.1 Data

2.1.1 Observed reference data

The Asian Precipitation — Highly-Resolved Observational Data Integration Toward Evaluation (APHRODITE) gridded data (0.25°× 0.25°) for Sri Lanka was utilised for rainfall, and gridded

minimum (Tmin) and maximum temperature (Tmax) data from Princeton University (1.0°× 1.0°) served as the observational data. The temperature dataset derives from Princeton University's global meteorological forcing (PGF) (Sheffield et al., 2006), which includes 1.0° resolution fields of near-surface meteorology for global land regions. The river basin inflow data, reservoir parameters, streamflow data, and crop data were obtained from the Department of Irrigation and the Department of Agriculture. Further details of this data are provided in Table 2.

Table 2. Data used in the study and sources

Data	**Time**	**Data resolution (spatial/temporal)**	**Source**
APHRODITE Precipitation data	1988 – 2015	0.25°× 0.25°/daily	Yatagai et al., (2012)
Princeton University Temperature data: Minimum and maximum temperatures (Tmin, Tmax)	1980 – 2015	1.0°× 1.0°/daily	http://hydrology.princeton.edu/data/pgf/
Reservoir data: Inflows, Release, Storage	2009 – 2021	point /daily	Department of Irrigation, Sri Lanka
Crop data: Crop area, crop type, crop calendar	2010 – 2021	-/season	Department of Agriculture, Sri Lanka

2.1.2 Climate models data

The IPCC has developed several climate datasets, with the latest being CMIP6. Eight precipitation and temperature datasets from GCMs within CMIP6, covering both historical (1985–2014) and future periods (2015–2075), were downloaded from the Earth System Grid Federation website (https://esgf-node.llnl.gov/search/cmip6/). These models were chosen based on previous studies

and literature reviews from Sri Lanka and the South Asian region. Specific details of this data are outlined in Table 3.

Table 3. Eight CMIP6 GCM models evaluated in this study

GCM Model	**Spatial scale (Lat×Lon)**	**Institute**
Access_ESM_1_5	1.87°×1.25°	Commonwealth Scientific and Industrial Research Organisation, Australia
CanESM5	2.79°×2.81°	Canadian Centre for Climate Modelling and Analysis, Canada
CMCC_ESM2	1.0°×1.25°	Fondazione Centro Euro-Mediterraneo sui Cambiamenti Climatici (CMCC) in Lecce, Italy
EC_Earth3	0.35°× 0.35°	EC-Earth Consortium, Europe
CNRM_ESM2	1.40°×1.40°	Centre National de Recherches Meteorologiques (France)
GFDL_ESM4	1.25°×1.0°	NOAA/ Geophysical Fluid Dynamics Laboratory, USA
MIROC6	1.40°×1.40°	Atmosphere and Ocean Research Institute (The University of Tokyo), National Institute for Environmental Studies, and Japan Agency for Marine-Earth Science and Technology, Japan
MRI_ESM2_0	1.12°×1.12°	Meteorological Research Institute, Japan

3. Methodology

3.1. Ranking and selection of GCMs

Future climate conditions in the basin can be projected using GCMs data. Since many GCMs are available, selecting an appropriate model is essential for reliable climate impact assessments. The overall methodology framework, which connects the selection of GCMs, climate projection, streamflow and reservoir release predictions, calculation of crop water demand and irrigation water

needs, and the assessment of reservoir performance under current and future conditions, is shown in Figure 2.

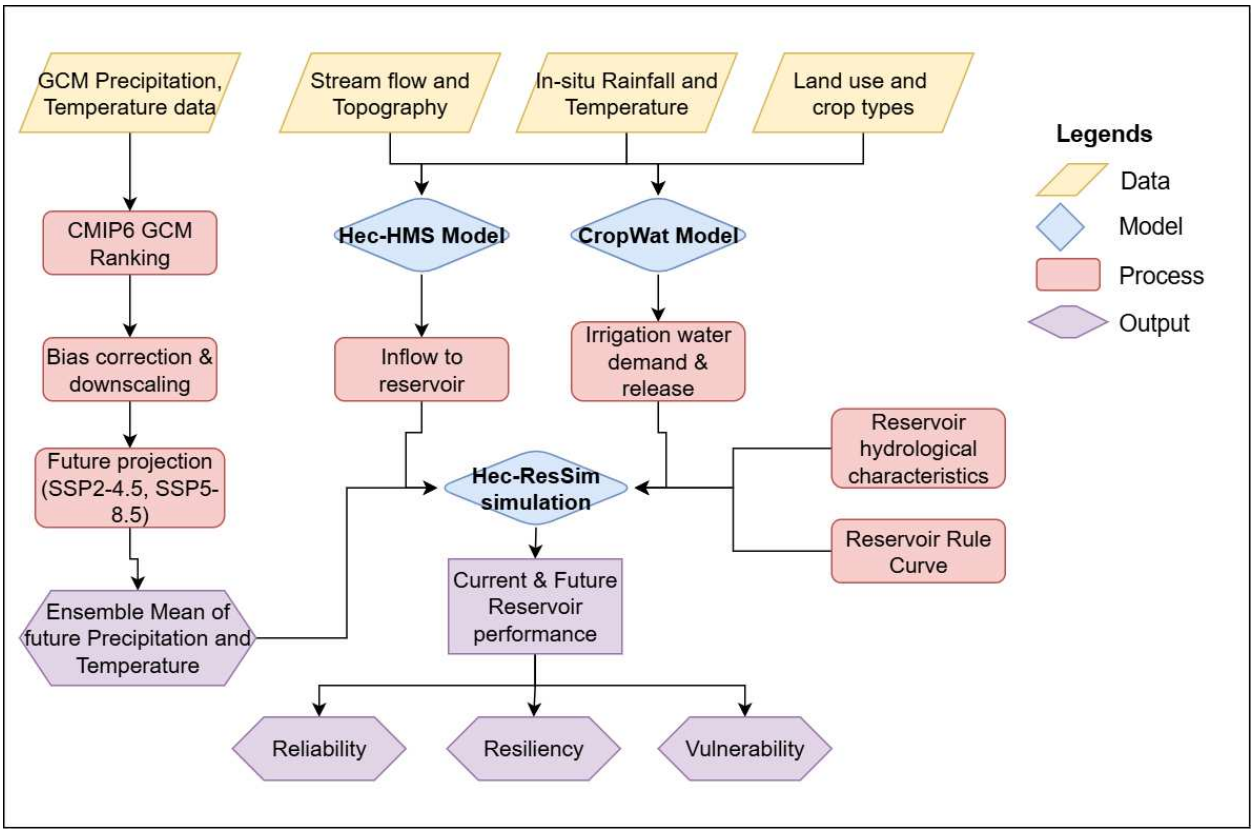


Figure 2. A framework for assessing the reservoir performance to irrigation water supply under climate change scenarios

This study evaluated the performance of eight CMIP6 GCMs in simulating precipitation, Tmin, and Tmax, comparing them with reference datasets: APHRODITE precipitation (0.25° × 0.25° resolution) and Princeton University's Tmin and Tmax datasets (Table 2). Model performance was evaluated using statistical measures that quantify how well GCM outputs match observed data. To select the most suitable GCMs, a Compromised Programming (CP) method was used, which combines multiple evaluation criteria—Normalised Root Mean Square Error (NRMSE), Normalised Mean Absolute Error (NMAE), and Relative Bias (RB). The formulas for NRMSE, NMAE, and RB are provided as follows,

$$NRMSE = \frac{\sqrt{\frac{1}{n}\sum_{i=1}^{n}(O_i - P_i)^2}}{\bar{O}} \times 100 \quad (1)$$

$$NMAE = \frac{\frac{1}{n}\sum_{i=1}^{n}|O_i - P_i|}{\bar{O}} \times 100 \quad (2)$$

$$RB = \frac{\sum_{i=1}^{n}(P_i - O_i)}{\sum_{i=1}^{n} O_i} \times 100 \quad (3)$$

O_i = observed values

P_i= predicted/simulated values

$\bar{O}$= mean of observed values

n= number of observations

CP ranks models based on their overall performance across variables (Precipitation, Tmin, Tmax) and statistical metrics (Ringuest & Ringuest, 1992). To ensure consistency, all metrics were normalised to a common scale (Anil et al., 2021). The distance between each GCM's performance and the ideal performance was then calculated using the Lp metric, expressed as:

$$Lp = \left(\sum_{j=1}^{n}\left|x_{ij} - x_j^*\right|^p\right)^{1/p} \quad (4)$$

Where Lp is the distance of the GCM model i to the ideal; the value of the jth performance metric for GCM model i; the ideal value of the jth metric; and p is the order of the norm (we used p=1 in this study, as we consider equal importance across all the metrics). equal importance across all the metrics).

The Lp metric is always positive, with lower values indicating better model performance; therefore, GCMs with the smallest Lp values are preferred (Perez-Verdin et al., 2018; Muhammad et al., 2019; Shiru & Chung, 2021). Based on this criterion, the best-performing climate models were selected for use in future climate projections, impact assessments, and adaptation planning. From these, the top-ranked GCMs were chosen to project future climate conditions across Sri Lanka and to simulate future streamflows in the Malwathu Oya River basin.

3.2. GCM bias correction

Biases in daily precipitation, Tmin, and Tmax from three top-ranked GCMS were corrected. This bias correction was applied to both historical data and two representative future scenarios (SSP2-4.5 and SSP5-8.5), which were then used to produce future projections. A quantile mapping (QM)

method was utilised to correct GCM precipitation data, while a linear scaling (LS) method was employed for GCM temperature datasets. The historical period covered 1988–2014, while the near-future and mid-future periods were considered as 2015–2049 and 2050–2075, respectively. A multi-model ensemble approach was used to combine outputs from the three GCMs, generating an ensemble mean for further analysis. The combined ensembled GCM projections, along with observed trends, were used for comparison of future climate scenarios.

3.3. Irrigation demand assessment

The FAO-developed CROPWAT model version 8.0 was used to estimate crop water and irrigation requirements. In addition, the CLIMWAT 2.0 climatic database was utilised alongside the CROPWAT model. This study employed Tmin, Tmax, and precipitation data from the Nachchaduwa station provided by the Meteorological Department, while RH, wind speed, and sunshine hours values were obtained from the CLIMWAT 2.0 model. Soil data was gathered from existing literature to estimate irrigation needs. Reference evapotranspiration (ET0) depends on temperature, wind speed, RH, and solar radiation. However, some studies assume temperature changes will be more significant than other parameters (Shahid 2011; Chowdhury et al. 2016; Mall et al. 2017; Bhatt et al. 2019). Therefore, in this study, Tmin, Tmax, and precipitation were used to estimate future (2015–2075) crop water and irrigation requirements, while other parameters were kept constant.

3.4. HEC-HMS hydrological model set up

The future inflow to the reservoir was simulated using a calibrated and validated Hydrologic Engineering Centre–Hydrological Modeling System (HEC-HMS). A systematic calibration and validation process was carried out for HEC-HMS to accurately replicate the hydrological response based on the historical datasets summarised in Table 2. HEC-HMS supports both distributed and lumped parameter methods for simulating streamflow in conceptualised river basins (Feldman, 2000; Ansari et al., 2023; Guduru et al., 2023; Izadi et al., 2024; Knebl et al., 2005). In this study, the model was configured to predict streamflow at a downstream gauging station and at the upstream reservoir inflow point. Observed precipitation and temperature data from rain gauge stations served as model inputs, and calibration was performed until the results closely matched observations. The Simple Canopy approach was employed to model vegetation–water interactions (Sok & Oeurng, 2016). For soil water balance, the Soil Moisture Accounting (SMA) method was

used, as it is suitable for continuous simulations under both wet and dry conditions (Feldman, 2000). Parameter values for SMA infiltration processes were assigned according to recommendations by Chow et al. (1988) and De Silva et al. (2014). Direct runoff was simulated using the Clark Unit Hydrograph method, chosen for its minimal input requirements. The two key parameters, the storage coefficient and the time of concentration, were estimated, with the latter calculated using the Kirpich formula (Kirpich, 1940). Daily streamflow data from 2009–2012 were utilised for calibration, while data from 2012–2015 were used for validation. Sensitivity analysis was conducted to identify the most influential parameters affecting runoff generation. Model performance was evaluated through visual comparison of simulated and observed hydrographs, with parameter adjustments made across multiple calibration trials. The overall accuracy of the model was assessed using statistical performance indicators.

3.5. HEC-ReSim reservoir model setup for the Nachchaduwa reservoir

The Nachchaduwa reservoir model was used to simulate future reservoir operations from 2025 to 2075, employing the calibrated and validated HEC-ResSim reservoir simulation model. The process involved three main stages. The first stage established the watershed by defining its physical components, including stream networks, reservoirs, water demand diversions, and calculation points located at confluences, boundaries, or monitoring sites. Next, the reservoir network was configured as the core element of the model. This step incorporated reservoir characteristics, performance sets for different areas, and the allocation of downstream water demands. Irrigation needs were simulated through diversions, whereby water was extracted for irrigation and then returned to the river channel. Conversely, water allocated for domestic use was removed from the system and not returned. In the final stage, input data such as reservoir inflows, time steps, lookback periods, and other operational constraints for each scenario were integrated. Once the system was set up, the model was calibrated using data from 2005–2014 and validated with data from 2015–2021. After achieving satisfactory calibration and validation, the model was used to simulate future reservoir operations based on inflow forecasts generated by the hydrological model.

3.6 Model evaluation indices

This study used various performance indices to evaluate HEC-HMS and HEC-ResSim models. For HEC-HMS, indices included Nash–Sutcliffe Efficiency (NSE), Coefficient of Determination

(R^2), Root Mean Square Error (RMSE), and Percent Bias (PBIAS), which measure how accurately the model reproduces observed flows, the strength of correlation, and bias. HEC-ResSim was assessed using NSE, R, and Kling–Gupta Efficiency (KGE), providing a comprehensive evaluation of reservoir simulations by combining correlation, bias, and variability measures. Using these metrics ensures a balanced, reliable assessment of model performance, fostering confidence in scenario analysis and decision-making. The formulas for these performance indices are provided below,

$$\mathrm{NSE} = 1 - \frac{\sum_{i=1}^{n}(O_i - P_i)^2}{\sum_{i=1}^{n}(O_i - \bar{O}_i)^2} \quad (5)$$

$$\mathrm{PBIAS} = \frac{\sum_{i=1}^{n}(O_i - P_i)}{\sum_{i=1}^{n}(P_i)} \times 100 \quad (6)$$

$$r = \frac{n(\sum O_i P_i) - (\sum O_i)(\sum P_i)}{\sqrt{[n\sum O_i^2 - (\sum O_i)^2][n\sum P_i^2 - (\sum P_i)^2]}} \quad (7)$$

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(P_i - O_i)^2}{\sum_{i=1}^{n}(P_i - \bar{P})^2} \quad (8)$$

$$\mathrm{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(O_i - P_i)^2} \quad (9)$$

$$\mathrm{KGE} = 1 - \sqrt{(r-1)^2 + (\beta - 1)^2 + (\gamma - 1)^2} \quad (10)$$

$$\beta = \frac{\bar{P}}{\bar{O}} \quad (11)$$

$$\gamma = \frac{\sigma_p / \bar{P}}{\sigma_o / \bar{O}} \quad (12)$$

Where O_i is Observed data; $\bar{O}$ is the Mean of the observed data; P_i is predicted data; $\bar{P}$ is mean of predicted data; n is the number of observations; σ_p is the standard deviation of predicted data; σ_o is the standard deviation of observed data; n is the number of observations.

3.7. Reservoir performance analysis

The reservoir performance was evaluated with the RRV metric and the RSI index under future projected scenarios. The formulations for RRV and RSI are provided as follows,

$$Reliability = \frac{N_s}{N} \quad (13)$$

$$Resilience = \frac{N_r}{N_f} \quad (14)$$

$$Vulnerability = \frac{1}{N_f}\sum_{j=1}^{N_f} \mathrm{D}_j \quad (15)$$

$$RSI = Reliability \times Resilience \times (1 - Vulnerability\ ) \quad (16)$$

N_s is number of time steps when demand is fully satisfied (no failure); N is total number of time steps N_r is number of times the system recovers from a failure; N_f is total number of failure events; D_j is average deficit magnitude during the j^{th} failure period.

For the RRV and RSI analyses, reservoir performance was assessed by comparing the available water supply to the irrigation water demand at each time step (monthly, seasonal, or yearly). Reliability indicates the system's probability of meeting demand over time, with values near 1 (or 100%) showing high reliability. Resiliency reflects the system's ability to recover from failure, with higher values indicating faster recovery. Vulnerability measures the average severity of failures, with lower values representing less severe deficits. The Sustainability Index (SI) combines these metrics to evaluate system performance; higher SI values denote more sustainable, balanced reservoir operation (Hashimoto et al., 1982; Loucks, 1997; McMahon et al., 2006; Sandoval-Solis et al., 2011).

4. Results

4.1. CMIP6 GCM ranking, bias correction and future scenario projections

Based on statistical performance and the overall evaluation of CP, the total Lp summations were ranked to identify the most suitable models. According to these rankings, the three best-performing GCMs—EC-Earth3, MRI-ESM2.0, and CNRM-ESM2—were selected for further analysis of precipitation and temperature (Tmin and Tmax) in Sri Lanka. Table 4 presents the aggregated CP sum Lp values of the corresponding GCMs used in the ranking process.

Table 4. Compromised programming aggregated sum Lp values of the corresponding GCMs

GCM	Lp_Sum (Rainfall)	Lp_Sum (Tmin)	Lp_Sum (Tmax)	Total Sum	Rank

Access_ESM_1_5	86.8151	126.577	87.06	300.4521	5
CanESM5	92.0888	166.175	74.7268	332.9906	8
CMCC_ESM2	111.0982	127.0709	78.7807	316.9498	6
EC_Earth3	**87.3779**	**75.2503**	**81.4918**	**244.12**	**1**
CNRM_ESM2	**91.709**	**71.28**	**88.1575**	**251.1465**	**2**
GFDL_ESM4	99.6075	71.8944	92.5154	264.0173	4
MIROC6	90.04723	138.775	99.0054	327.8276	7
MRI_ESM2_0	**87.6884**	**89.4792**	**79.034**	**256.2016**	**3**
Note: Lp – compromised programming aggregated sum values					

4.2 Future projections of bias corrected GCMs

Figure 3 illustrates the temporal variability of precipitation and temperature over the Malwathu Oya River Basin, highlighting distinct shifts under SSP2-4.5 and SSP5-8.5 scenarios for the near-future (2025–2049) and mid-future (2050–2075) periods compared to the baseline (1988-2014). The baseline rainfall trend fluctuated significantly in the basin, while Tmin increased rapidly compared to Tmax, providing evidence of climate change. Relative to the baseline period, annual rainfall is expected to increase gradually, reaching 2-4% by the near-future. Subsequently, it is likely to increase more rapidly by 7% in the mid-future under the medium emission scenario SSP2-4.5. A higher emission scenario, SSP5-8.5, results in a doubling (14.22%) of annual rainfall changes compared to SSP2-4.5. These changes are expected to become more pronounced, with increased variability and more extreme weather events, leading to a higher risk of flooding. Furthermore, long-term shifts in precipitation patterns may occur, with some years experiencing sustained changes in average annual rainfall.

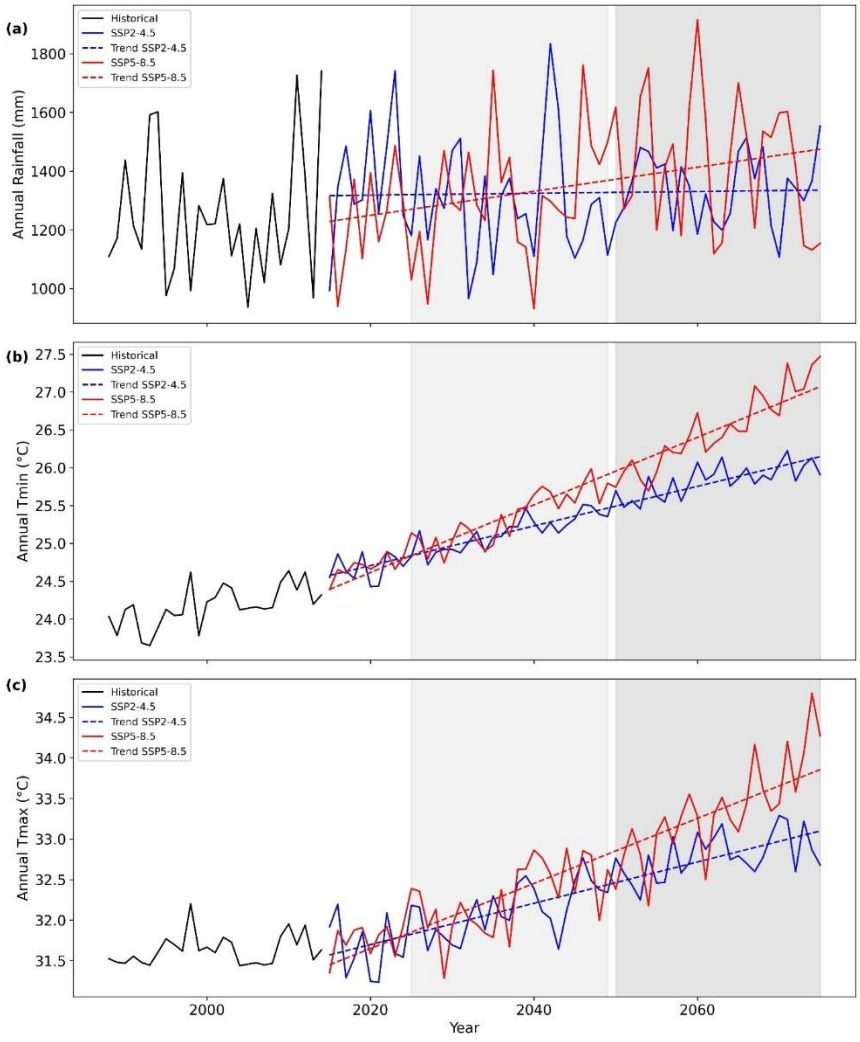


Figure 3. Baseline and future climate projections for the Malwathu Oya River Basin showing (a) Precipitation, (b) Minimum temperature, and (c) Maximum temperature under historical, SSP2-4.5, and SSP5-8.5 scenarios for near-future (2025–2049) and mid-future (2050–2075) in the Malwathu Oya River Basin.

The baseline period provides historical temperature data, acting as a reference for future trends. Projections for the near future indicate a gradual rise in average temperatures. This trend is expected to become more evident in the mid-term future, with notable increases in both Tmin and Tmax. The entire basin will remain substantially warmer, with an increase of 0.5-2.5°C in both Tmin and Tmax.

Table 5 shows the percentage changes in annual rainfall, Tmin, and Tmax relative to the baseline. The analysis under the SSP2-4.5 and SSP5-8.5 scenarios reveals significant trends. Rainfall is projected to increase by about 2 to 5% in the near-future and by 7 to 14% in the mid-future for SSP2-4.5, whereas SSP5-8.5 indicates a 22% decrease in the near-future and a 15% decrease in the mid-future. Tmax shows minor variation compared to Tmin, with a 4-5% increase in the near-future and a 7-10% increase in the mid-future across both scenarios. Tmax rises by 1 to 2% in the near-future and 3 to 6% in the mid-future for both SSP scenarios.

Table 5. Projected percentage changes in the climate variables for the Malwathu Oya River Basin for SSP2-4.5 and SSP5-8.5 scenarios under near-future (2025–2049) and mid-future (2050–2075) relative to the baseline (1988–2015).

Climate Variables (% change)	**Baseline (1988-2014)**	**SSP2-4.5**		**SSP5-8.5**	
		Near-Future (2024-2049)	Mid-Future (2050-2075)	Near-Future (2024-2049	Mid-Future (2050-2075)
Rainfall (mm)	1254.5 -	1287.9 +2.6	1342.1 +6.9	1309.1 +4.3	1433.0 +14.2
Temperature Minimum (°C)	24.2 -	25.1 +3.9	25.8 +6.8	25.3 +4.7	26.5 +9.6
Temperature Maximum (°C)	31.6 -	32.1 +1.5	32.8 +3.6	32.3 +2.0	33.3 +5.4

The comparison of average monthly rainfall, Tmax, and Tmin during the baseline (1988–2015) and future projections is shown in Figure 4. The analysis of average monthly rainfall and temperatures (Tmin and Tmax) reveals distinct seasonal patterns, with projected increases in temperature and variable rainfall trends under the SSP2-4.5 and SSP5-8.5 scenarios for both near- and mid-future periods. Examination of monthly averages indicates that April and May are

expected to experience the highest Tmax values, followed by June through September, while the lowest Tmax occurs in December and January. The average annual Tmin is projected to be highest in May and June compared to the baseline, with moderately elevated values from July to September; the minimum Tmin occurs from December to February. Rainfall is projected to peak from October to December, followed by January, with the lowest precipitation occurring in June and July.

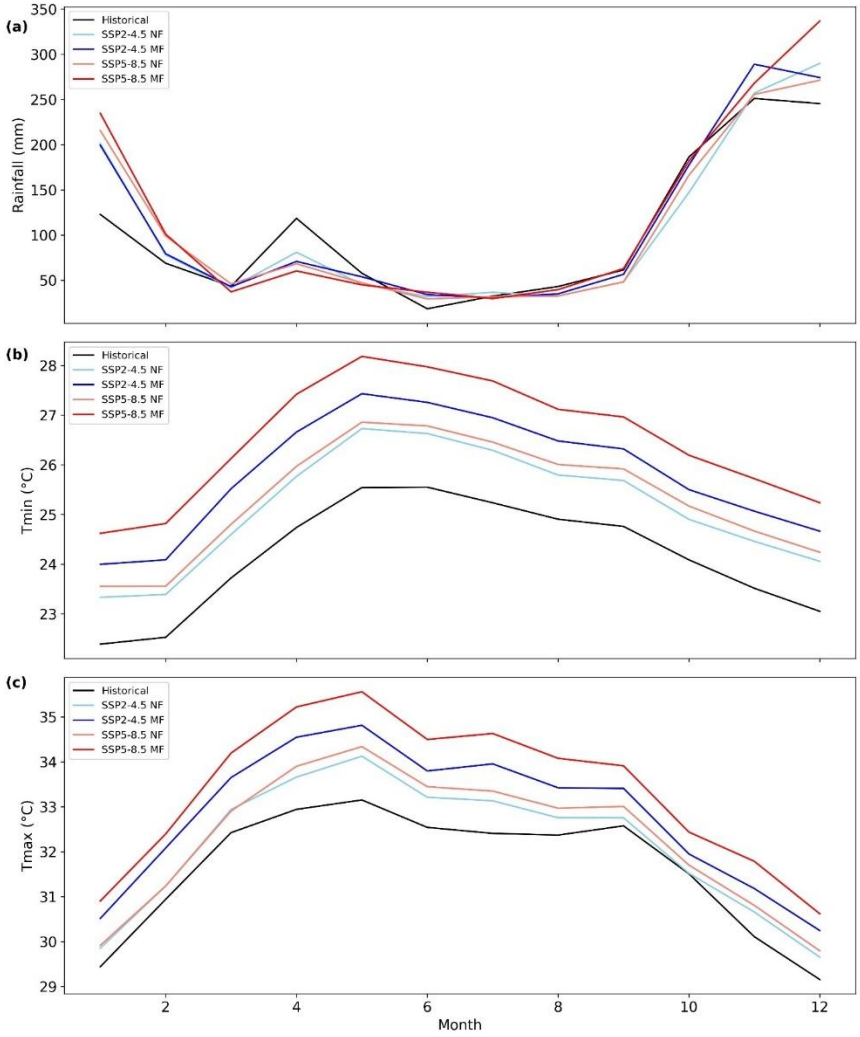


Figure 4. Average monthly (a) Rainfall, (b) Minimum Temperature, (c) Maximum Temperature during the baseline period (1988–2014) and future projections under SSP2-4.5 and SSP5-8.5 scenarios for the near-future (2025–2049) and mid-future (2050–2075) in the Malwathu Oya River Basin.

Figure 5 presents the percentage changes in rainfall, Tmin, and Tmax relative to the baseline scenario under future climate projections. The results indicate a clear upward trend in both Tmin and Tmax across all future scenarios, reflecting the intensification of warming due to climate change. The projected increase in Tmin is generally higher under SSP5-8.5 than SSP2-4.5, with the most pronounced warming occurring in the mid-future period. Tmax follows a similar trend, with increases exceeding those of Tmin, particularly under the high-emission SSP5-8.5 scenario.

In contrast, rainfall projections exhibit substantial temporal and scenario-dependent variability. Certain months, notably November to February and June, are projected to receive increased precipitation, while April to May and July to October show moderate to significant declines, suggesting a potential shift in the seasonal distribution of rainfall. Under SSP5-8.5, rainfall becomes more variable, with higher interannual fluctuations compared to SSP2-4.5. These projections imply that future climate conditions in the Malwathu Oya River Basin are likely to involve elevated temperatures and altered rainfall patterns, which may have important implications for water availability and hydrological processes in the region.

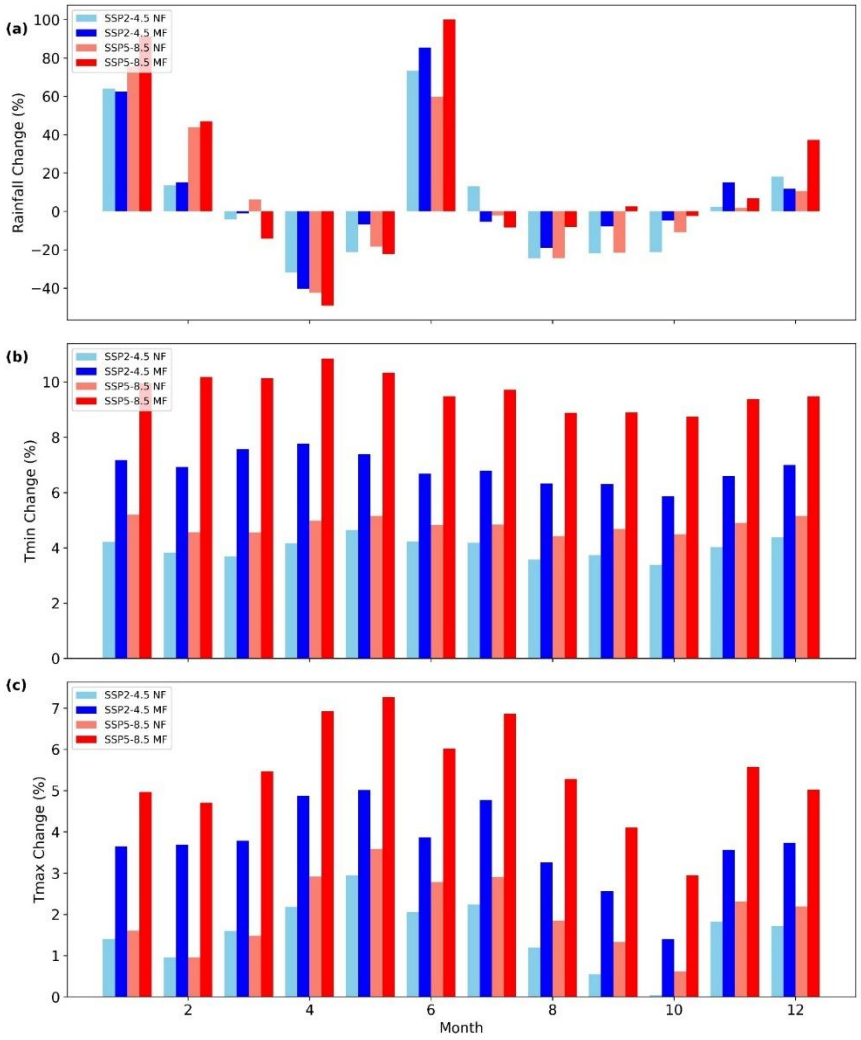


Figure 5. Percentage change in (a) Rainfall, (b) Minimum Temperature, and (c) Maximum Temperature during near-future (2025–2049), and mid-future (2050–2074) periods under SSP2-4.5 and SSP5-8.5 scenarios from the baseline scenario in the Malwathu Oya River Basin.

4.3 Hydrological simulations

4.3.1 HEC-HMS model calibration and validation for the baseline period

Figure 6 illustrates HEC-HMS model simulated and observed flow data at the Kappachchiya streamflow gauging station during both calibration and validation periods. The model's performance was evaluated using NSE, RMSE, and PBIAS metrics. The simulated hydrographs effectively reproduced the overall flow patterns and seasonal variability of the observed

streamflow. Model performance metrics indicated NSE values of 0.63 for calibration and 0.52 for validation, and PBIAS of 14.5% and 18.25%, respectively. According to Moriasi et al. (2007), NSE values above 0.50 and PBIAS within ±25% represent satisfactory performance for streamflow simulations. These results confirm that the HEC-HMS model reliably captures streamflow dynamics in the Malwathu Oya River Basin, demonstrating its suitability for scenario-based hydrological analyses in data-scarce, monsoon-influenced regions.

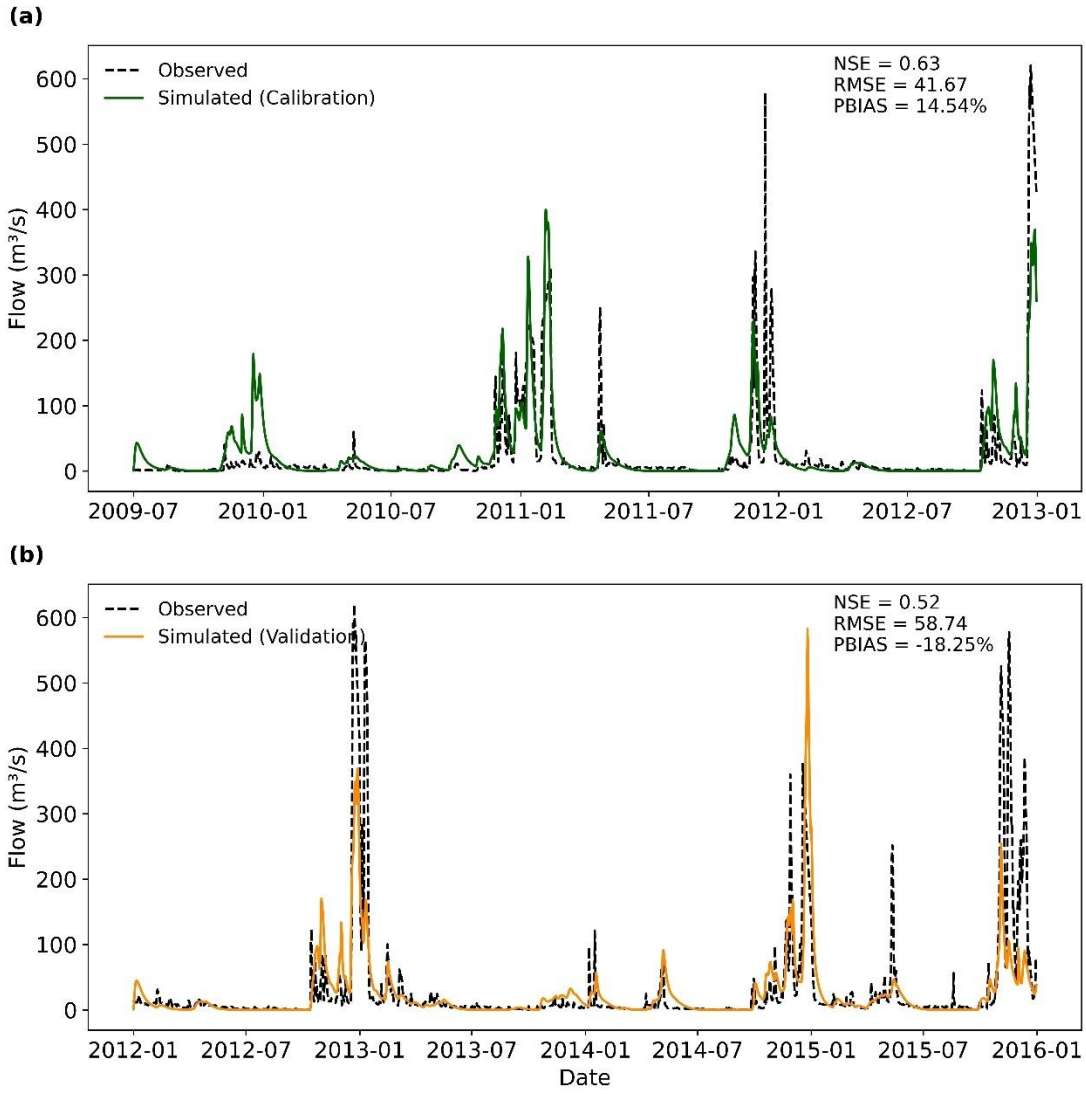


Figure 6**.** Calibration (July 2009–December 2012) and validation (January 2012–December 2015) of the HEC-HMS model for the Malwathu Oya River Basin.

4.3.2 HEC-HMS model simulation for future SSP scenarios

Figure 7 illustrates the annual average inflow to the Nachchaduwa Reservoir under both historical and future climate scenarios. The historical period exhibits higher interannual variability compared to the projected scenarios. Under the SSP2-4.5 scenario, the near-future period (2025–2049) shows a slight reduction in annual inflows relative to the historical baseline, while the mid-future period (2050–2075) displays minor declines in certain years, indicating moderate climate-induced variations. Overall, inflows under SSP2-4.5 are projected to decrease by approximately 1.83% in the near-future and 0.53% in the mid-future. In contrast, the SSP5-8.5 scenario indicates a notable increase in near-future inflows, followed by enhanced variability during the mid-future, with overall increases of 5.85% and 23.29%, respectively. These results suggest that future changes in temperature and precipitation patterns could significantly influence river discharge, potentially leading to greater hydrological variability and posing challenges for reservoir operation and water resource management under changing climate conditions.

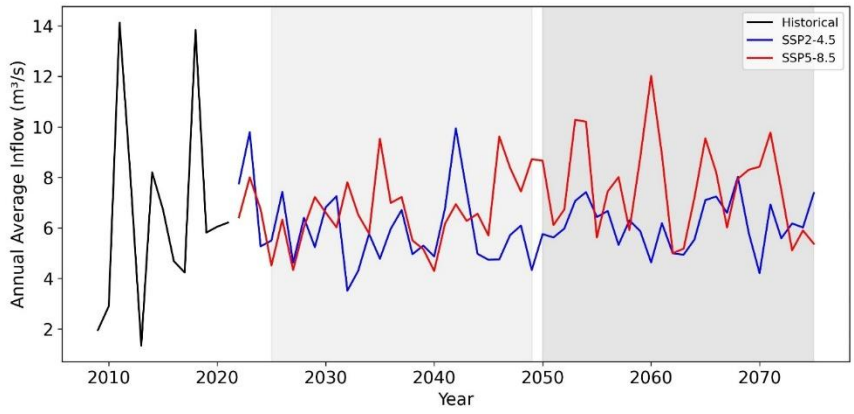


Figure 7**.** Annual average reservoir inflow in Nachchaduwa Reservoir under historical conditions and projected SSP2-4.5 and SSP5-8.5 scenarios for the near-future (2025–2049) and mid-future (2050–2075).

Figure 8 presents the average monthly streamflow of the reservoir throughout the year, from January to December. The observed fluctuations indicate that reservoir inflows closely follow the seasonal precipitation pattern, with peak flows occurring during the monsoon months. The overall pattern resembles the historical trend, characterized by high flow in January, a sharp decline between February and April, relatively low and stable flow from May to September, and a substantial increase beginning in October, peaking around November or December. Under the SSP5-8.5 scenario, greater monthly fluctuations are evident, with higher peak flows during wet

months and more pronounced reductions during dry months compared to SSP2-4.5, suggesting increased seasonal variability. The percentage change relative to historical conditions indicates that the largest positive deviations occur during peak inflow months (November to February), while the most significant reductions appear during the dry season (March to May and July to September). These findings imply that climate change may intensify intra-annual variability in reservoir inflows, potentially influencing water availability and necessitating adaptive management strategies for sustainable reservoir operation.

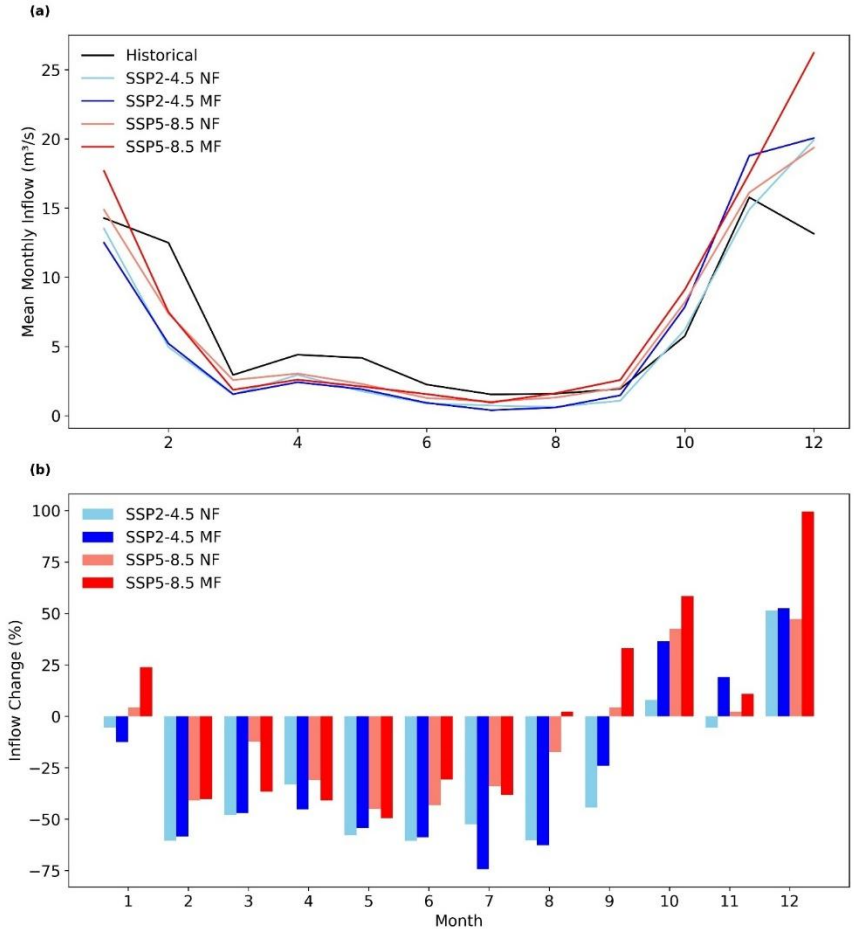


Figure 8. Reservoir inflows (a) Monthly fluctuations and (b) Percentage change in simulated inflows from baseline for SSP2-4.5 and SSP5-8.5 under near-future (2025–2049) and mid-future (2050–2075).

4.4. HEC-ResSim modelling of the Nachchaduwa reservoir

Figure 9 compares the observed and simulated reservoir performance, depicting both release and water level dynamics during the calibration period (July 2009–December 2014) and the validation period (January 2016–December 2021). Figure 9 illustrates the model's ability to replicate temporal variations in reservoir releases and water levels under real hydrological conditions. During both periods, the simulated releases closely follow the observed hydrograph, successfully representing peak flows and seasonal fluctuations. Similarly, the simulated water levels exhibit patterns that generally align with observed levels, with a slightly better agreement than that observed for release patterns. The deviations between simulated and observed water levels are likely attributed to unplanned or emergency reservoir operations at Nachchaduwa, which deviated from standard operating procedures. Overall, the results indicate that the reservoir model performs reasonably well in reproducing both releases and storage dynamics. Yassin et al. (2019) also noted that challenges in reservoir modeling can often lead to discrepancies in simulation results, emphasizing that water level dynamics typically have a greater influence on overall model performance than reservoir release.

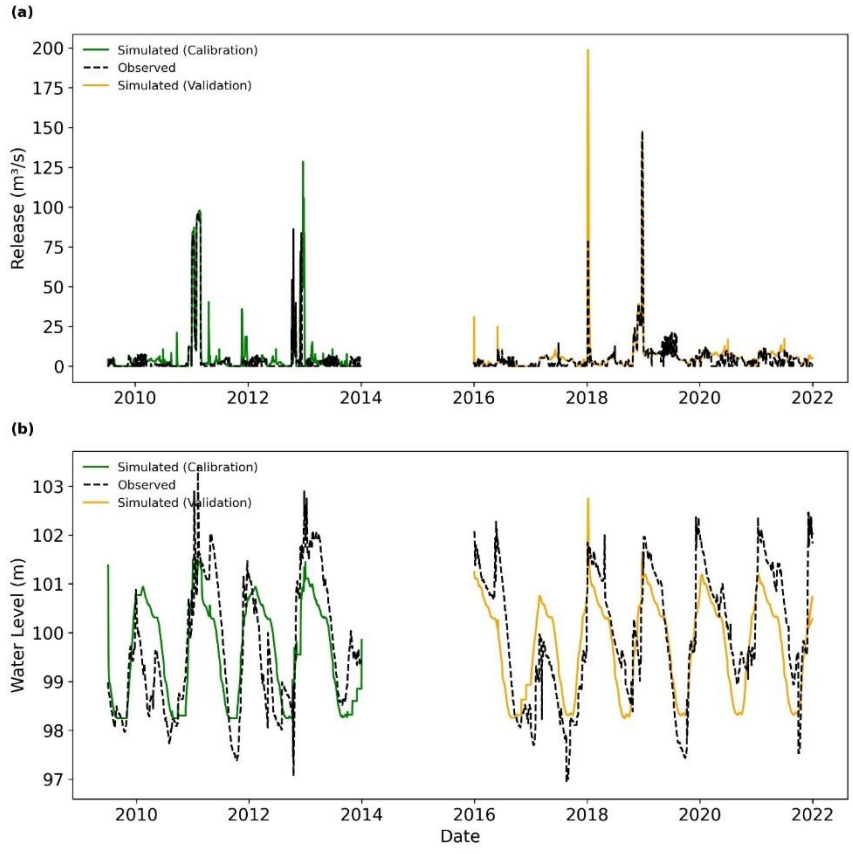


Figure 9. Observed and simulated reservoir performance during calibration (2009 – 2014) and validation periods (2016 – 2021) for (a) Reservoir release, and (b) Reservoir water level parameters.

HEC-ResSim reservoir performance was evaluated using performance indices, including the NSE, R, and KGE, with the results tabulated in Table 6. The reservoir model demonstrated satisfactory performance during both calibration and validation periods, according to Moriasi et al. (2007). For reservoir releases, the NSE values were 0.63 during calibration and 0.77 during validation, indicating that the model can explain over 60% of the variance in observed flows (Figure 9). The KGE values of 0.61 and 0.66 for calibration and validation, respectively, suggest satisfactory performance. This implies that the model reasonably captures the overall trends and variability of observed releases, although some deviations in the magnitude or timing of peaks are present. According to Moriasi et al. (2007), KGE values in the range of 0.6–0.7 are considered satisfactory, showing that the model is suitable for evaluating general reservoir behaviour. Meanwhile, the correlation coefficients of 0.85 and 0.93 for calibration and validation confirm a strong relationship. For reservoir water levels, NSE values are acceptable at 0.64 (calibration) and 0.62 (validation), with KGE values of 0.84 and 0.74, respectively, and R values of 0.84 and 0.81. This indicates that the model parameters are reasonable and the results are reliable.

Table 6 HEC-ResSim reservoir model performance during calibration and validation.

Index	**Calibration**		**Validation**	
	Release	Water level	Release	Water level
Nash Sutcliffe Efficiency	0.63	0.64	0.77	0.62
Kling-Gupta Efficiency	0.61	0.84	0.66	0.74
Coefficient of correlation	0.85	0.84	0.93	0.81

4.5 Baseline and future trends of average seasonal irrigation water requirement using the CROPWAT Model

Bias-corrected climate projections from CMIP6 GCMs, combined with the CROPWAT model, were used to estimate average seasonal crop water and irrigation water requirements for the

baseline period (2000–2022) and two future scenarios: SSP2-4.5 and SSP5-8.5. The resulting monthly irrigation water requirement volumes, expressed in Million Cubic Metres (MCM), are summarized in Table 7 for each scenario, including baseline, SSP2-4.5 near-future, SSP2-4.5 mid-future, SSP5-8.5 near-future, and SSP5-8.5 mid-future. The analysis shows that irrigation demand varies across months and scenarios, with the highest requirements from April to October, peaking in June and July due to low rainfall. Conversely, the lowest demands are in November and December, coinciding with the start of the monsoon. Although the SSP scenarios generally follow similar seasonal patterns to the baseline, slight variations in monthly IWR reflect the impacts of projected climate changes under different socio-economic pathways.

Table 7 Irrigation water requirement for different Scenarios

	Irrigation water requirement volume in MCM/month				
Months	Baseline (1988 – 2014)	SSP2-4.5 near-future (2024 – 2049)	SSP2-4.5 mid-future (2050 – 2075)	SSP5-8.5 near-future (2024 – 2049)	SSP5-8.5 mid-future (2050 – 2075)
Jan	1.80	0.76	0.91	0.61	0.61
Feb	1.22	1.64	1.65	1.37	1.37
Mar	2.36	3.34	3.35	3.04	3.65
Apr	6.64	10.15	10.45	10.60	10.89
May	7.08	10.80	10.65	10.64	11.25
Jun	7.73	9.86	10.01	10.15	10.15
Jul	7.42	10.04	10.65	10.50	10.95
Aug	6.07	8.82	8.97	8.97	8.97
Sep	1.63	2.35	2.36	2.35	2.35
Oct	6.412	10.49	9.58	9.88	9.43
Nov	0	0	0	0	0
Dec	0.11	0	0	0	0
Note: MCM – Million Cubic Meter					

Figure 10 illustrates the seasonal variations in ET_o under historical and future climate scenarios, highlighting potential shifts in evaporative demand driven by climate change. The monthly ET_o exhibits a clear seasonal pattern, with higher values during the dry months and lower values during the wet season. Future projections indicate an overall increase in ET_o compared to the historical baseline, with the most pronounced rises occurring in the mid-future period under both SSP scenarios. Near-future projections for SSP2-4.5 and SSP5-8.5 show moderate increases, suggesting intensified evaporative demand across the basin. The historical average ET_o is 4.9 mm/day, rising to 4.98–5.08 mm/day under SSP2-4.5 and 5.0–5.16 mm/day under SSP5-8.5. Across all scenarios, ET_o values range from 3.50 mm/day to 6.5 mm/day, with the highest evapotranspiration occurring in June (6.08–6.30 mm/day) and the lowest in December (3.62–3.74 mm/day). Higher ET_o under SSP5-8.5 is attributed to projected increases in both minimum and maximum temperatures. These results indicate that climate warming may elevate crop water demand and influence reservoir management, particularly during peak dry periods, underscoring the need for adaptive water resource planning.

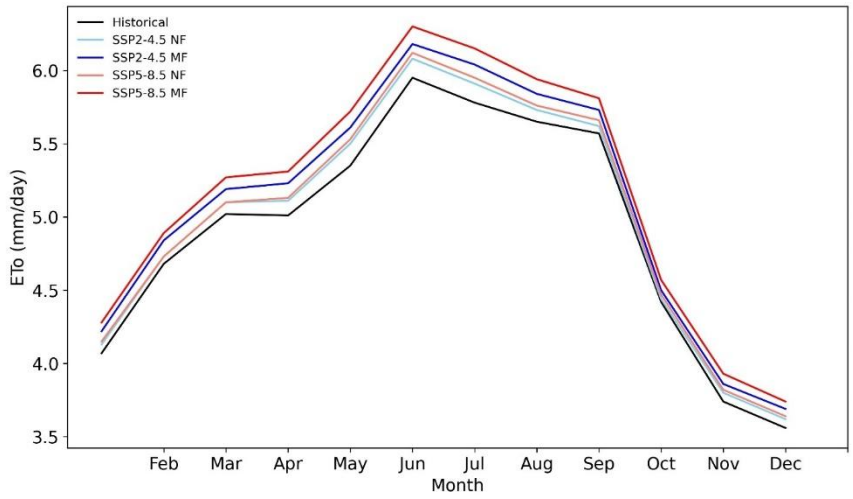


Figure 10. Monthly variation of ET_o under historical (1988–2015) conditions and projected future climate scenarios: SSP2-4.5, SSP5-8.5 under near-future (2025–2049) and mid future (2050–2075).

4.6 Estimation of reservoir performance indices

The RRV framework was employed to assess reservoir performance, with the computed reliability, resilience, and vulnerability indices under different scenarios presented in Figure 11. During the

historical period, the reservoir reliability is 0.69. Under the SSP2-4.5 scenario, reliability slightly decreases to 0.68 in the near-future and remains at 0.63 in the mid-future. For the SSP5-8.5 scenario, reliability declines further to 0.61 in the near-future and 0.60 in the mid-future, indicating a marginal reduction in the reservoir's ability to meet water demand under more extreme climate conditions. Resilience, reflecting the reservoir's capacity to recover from failures, is estimated at 0.53 under SSP2-4.5, increasing slightly to 0.59 in the near-future, then decreasing to 0.51 under SSP5-8.5 in the mid-future. Vulnerability, representing the severity of water shortages when they occur, is lowest during the baseline (0.13) and rises to 0.13, 0.20, 0.23, and 0.28 for SSP2-4.5 near-future, SSP2-4.5 mid-future, SSP5-8.5 near-future, and SSP5-8.5 mid-future, respectively.

In addition to the RRV parameters, the RSI was computed for each scenario. Historical RSI is 0.32, increasing slightly to 0.35 under SSP2-4.5 in the near-future before declining to 0.24 in the mid-future. A similar trend is observed under SSP5-8.5, with near-future RSI slightly higher, indicating more severe potential water shortages under extreme climate conditions. These results demonstrate that reliability, resilience, and sustainability decline from SSP2-4.5 to SSP5-8.5, particularly under high-emission pathways, while vulnerability increases. Overall, the findings suggest that the reservoir may face unsustainable conditions under the SSP5-8.5 scenario compared to SSP2-4.5, emphasizing the need for adaptive water management strategies.

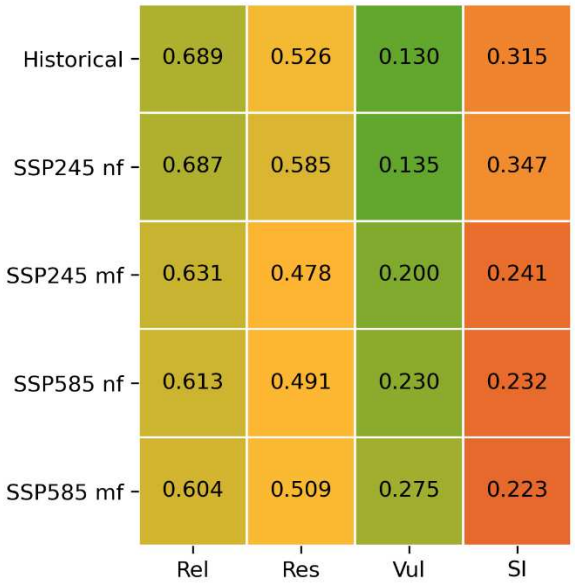


Figure 11. Reliability (Rel), Resiliency (Res), Vulnerability (Vul), and Reservoir Sustainability Index (SI) under historical and future conditions for SSP2-4.5 and SSP5-8.5 scenarios, for near-future (2025–2049) and mid-future (2050-2075).

5. Discussions

5.1. Importance of HEC-HMS model calibration and GCM Bias correction

Calibrating hydrological models in Sri Lanka is essential, especially given the anticipated impacts of climate change. Kahaduwa and Rajapakse (2021) highlighted that variations in precipitation, rising temperatures, and the increasing frequency of droughts and floods significantly affect water resources, underscoring the need for accurate calibration and bias correction in future inflow predictions. A 2020 study on village tanks reported substantial variability and low resilience, emphasizing the importance of carefully simulating storage using observed data (Perera et al., 2020). Therefore, applying bias correction to GCM outputs and rigorously calibrating streamflow models are critical steps for generating reliable inflow projections for the Nachchaduwa Reservoir, particularly when assessing future water resource reliability.

5.2. Historical performance and future challenges of Dry Zone reservoirs in Sri Lanka

Many small and medium-sized reservoirs in Sri Lanka have historically maintained reliable operation; however, recent studies reveal vulnerabilities even in well-managed systems. Research on village tanks indicates that while the reliability of water storage is moderate, resilience—the capacity to recover from dry periods or failures—is relatively low, highlighting susceptibility to climate variability and operational stresses (Perera et al., 2021). The Huruluwewa Irrigation System demonstrates that adaptive management strategies, including optimized release regimes, cropping patterns, and supplemental groundwater use, have been critical for sustaining water supply reliability during drought years across two cropping seasons (Amarasinghe et al., 2021). These findings suggest that although historical reliability metrics appear adequate, low resilience and heightened vulnerability reveal underlying fragilities, which are important for benchmarking Nachchaduwa Reservoir’s performance.

Projections for dry zone reservoirs in Sri Lanka indicate increasing risks to reliability under future climate change. A study of village tank cascades shows that suitable areas for paddy cultivation

could decline by up to ~96% due to changes in water availability, reflecting reduced reliability and greater irrigation deficits (Ratnayake et al., 2023). Kahaduwa and Rajapakse (2021) emphasize that altered hydrological and precipitation patterns further complicate reservoir management. Similarly, the Giritale Reservoir in the Polonnaruwa district demonstrates that shifts in rainfall and temperature can substantially modify inflow and reservoir behavior, threatening future reliability unless adaptation measures are implemented. Collectively, these studies indicate that Nachchaduwa Reservoir is likely to experience decreased reliability under future climate scenarios, particularly as seasonal variability, extreme weather events, and increased evapotranspiration reduce water availability.

5.3 Status of Nachchaduwa reservoir reliability in future climate scenarios

The assessment of the Nachchaduwa Reservoir under future climate scenarios underscores the challenges of maintaining irrigation water supply in Sri Lanka's dry zones. Projected changes in rainfall variability, combined with rising minimum and maximum temperatures (Tmin and Tmax), are expected to impact reservoir inflows, consistent with observations in tropical monsoon-driven catchments (Wijesekara et al., 2019; Gunawardhana & Kazama, 2011). Under the SSP2-4.5 and SSP5-8.5 scenarios, inflow projections indicate both seasonal shifts and overall fluctuations in annual water availability, resulting in lower reservoir reliability and increased irrigation deficits during dry periods compared to the historical baseline.

Historically, the reservoir has provided water with moderate seasonal variability; however, future climate projections suggest more erratic rainfall, shorter intense wet periods, and prolonged dry spells. Such variability complicates management by causing increased spills during heavy rainfall events and insufficient storage during dry periods, aligning with similar findings for reservoirs in South and Southeast Asia under comparable emission pathways (Kumar et al., 2020; Pokhrel et al., 2018). Simulations under future scenarios indicate declines in key performance indicators, including reliability, resilience, and vulnerability. Reduced inflows during dry seasons, coupled with increased evapotranspiration due to higher temperatures, exacerbate the mismatch between water supply and irrigation demand, particularly during the Yala season when irrigation requirements peak and natural inflows are minimal.

Resilience analysis shows that the reservoir's ability to recover from droughts diminishes in mid- and late-century projections, potentially leading to extended periods of stress that threaten crop

productivity. Vulnerability increases, especially under SSP5-8.5, as elevated evapotranspiration intensifies water scarcity. These findings highlight the need to reassess irrigation management strategies under future climate conditions. Adaptive measures—such as crop diversification, optimized water allocation rules, and the integration of supplementary groundwater resources—could help mitigate increasing deficits. Previous studies demonstrate that incorporating climate adaptation strategies into reservoir operations has been effective in other monsoon-fed systems (Shrestha et al., 2014; Ehsani et al., 2017).

5.4 Adaptation strategies for climate change scenarios in Nachcaduwa reservoir

Adaptation strategies, such as enhancing water use efficiency, promoting crop diversification, and integrating real-time reservoir operation models, could help mitigate some of the projected impacts. Strengthening catchment conservation and exploring supplementary water sources, including conjunctive use of groundwater, may further improve resilience to climate-induced variability. It is also important to acknowledge the limitations of the current study, as uncertainties in climate projections and hydrological modeling are inherent, particularly at the local scale. Future research should incorporate stakeholder-driven scenario planning to better capture a range of potential outcomes and guide adaptive management strategies.

Another key consideration is the potential for competing demands on the Nachchaduwa Reservoir, including irrigation, fisheries, and domestic water supply, especially during drought periods. The projected decline in sustainability indices under future scenarios indicates that existing operating rules may no longer ensure adequate water reliability. Transitioning to a multi-objective management approach that balances irrigation needs with ecological and livelihood requirements is therefore essential. Overall, the study demonstrates that climate change is likely to significantly reduce the reliability, resilience, and sustainability of the Nachchaduwa Reservoir for irrigation purposes. These results underscore the urgent need for proactive adaptation measures, combining both structural interventions and improved reservoir management, to safeguard agricultural productivity and rural livelihoods in the Anuradhapura region.

6. Conclusions

The capacity of Nachchaduwa Reservoir to meet irrigation needs is likely to be affected by future climate conditions unless proactive and integrated water management strategies are adopted. This

study highlights the urgency of integrating climate resilience into irrigation planning and reservoir operation frameworks in Sri Lanka. The key findings are summarized as follows:

- This study evaluated the Nachchaduwa reservoir's capacity to meet irrigation demands under both past and future climate scenarios, utilising RRV metrics and the RSI. Historically, the reservoir demonstrates moderate reliability and resilience, indicating satisfactory past performance.
- Future precipitation is expected to increase compared to the baseline, with intensified rainfall and more prolonged droughts. Both near and mid-term scenarios show rising percentages, especially in SSP5-8.5, which predicts a sharp increase in mid-term rainfall. Significant rises in Tmin and Tmax are observed, with mid-term minimum temperatures increasing notably.
- Climate change affects streamflow variability and crop water demand under different SSP scenarios. Both near- and mid-future scenarios predict increased crop water needs due to higher temperatures and altered rainfall patterns.
- Future climate scenarios under SSP2-4.5 and SSP5-8.5 indicate declining reservoir performance, with reduced reliability and resilience, increased vulnerability, lower RSI, and greater water stress in Nachchaduwa reservoir.

This research shows RRV metrics and RSI are valuable for assessing reservoir performance amid climate change. Results offer practical management insights, emphasising proactive adaptation strategies to sustain irrigation water supply as climate variability increases. Measures like optimised reservoir operation, water-saving irrigation, cropping adjustments, and tank cascade restoration are key to minimising the climate change impacts on the performance of Nachchaduwa reservoir.

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Data Availability

The bias-corrected GCM data and hydrological data generated from this study are given in the shared OneDrive cloud directory link as below

https://aitthai-my.sharepoint.com/:f:/g/personal/st122532_ait_ac_th/EqiGonutWGBDorVNUT7dmXUBzsQL0mzC7s_RM5_Sa1IFVg?e=7NAV7t

Script Availability

The developed R scripts for GCM bias correction and Python scripts for projections are given in the shared Onedrive cloud directory link as below,

https://aitthai-my.sharepoint.com/:f:/g/personal/st122532_ait_ac_th/Ehx0v58oF1xOrKS1nqzwCFMB9bYxcoWQtkgZBupTkj0lMw?e=ARM6pu

Conflict of Interest

There is no conflict of interest among the authors of this paper.

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