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Modeling of Current and Future Low Flow Characteristics Under Climate Variability and Water Abstraction: Case of Likhubula River Catchment in Malawi

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Abstract

Water resources are essential in sustaining ecosystems, agriculture and the ever-growing water demands of human population. However, the delicate balance of water availability for these sectors is increasingly facing unprecedented present and future challenges due to climate change and anthropogenic pressures. This study was aimed at characterizing the current and future low flows under climate variability and water abstraction in the Likhubula River Catchment, key a sub-catchment of the major Shire River Basin in Malawi. The study employs a multi-faceted approach, where trend analysis is conducted using the Mann-Kendall test and the Sens Slope Estimator at α=0.05 significance level. The SWAT hydrological model was set up for simulating future streamflow conditions and forced with RCP and SSP scenarios. Flow duration curves (FDCs) and low flow frequency curves (LFFCs) were employed to compute low flow indices, including the Q90, Q95, 7Q2 and 7Q10. The SWAT model exhibited a satisfactory performance with an R^2, PBIAS, NSE and RMSE of 0.98, 3.6, 0.94 and 0.29 respectively during calibration and R^2, PBIAS, NSE and RMSE of 0.96, -2.4, 0.84 and 0.42 respectively, during calibration and validation. Examination of low flow indices indicated substantial increases in low flow frequencies after 2007 with anticipated further increases in low flow duration, magnitude and frequencies after 2027. The RCP4.5 and RCP8.5 indicate less severe low flows as compared to historical periods. The combinations of RCP and SSP scenarios has shown varying results, RCP4.5 & SSP2 indicating significant improvements, while others (e.g., RCP4.5 & SSP4, RCP8.5 & SSP4) showing potential for highly severe low flows; an indication that climate change and intensification of water abstraction activities have a significant impact on the magnitude, duration and frequency of low flows in the Likhubula catchment. Despite the non-significant increasing trend in rainfall being observed, both significant positive trend in temperature and significant declining trend in streamflow imply

radical environmental decision-making calls to deal with uncertain future using the 3-H approach. These findings provide crucial insights for sustainable water resource management as these low flow characteristics are critical for managing water quality and quantity.

Keywords: Climate Variability, Water Abstraction, Likhubula River, Low Flows, SWAT, Malawi.

1.0 Introduction

Freshwater resources are increasingly under pressure due to the combined effects of climate variability, climate change, and growing human demand. Rivers provide essential ecosystem services, supporting domestic water supply, agriculture, biodiversity conservation, and economic activities among others. However, increasing water withdrawals and changing climatic conditions are altering natural flow regimes, with low-flow conditions becoming a major concern for water security and river ecosystem sustainability (Opperman et al., 2019; Greve, 2023). River abstraction reduces discharge magnitude, alters flow timing, and affects critical ecological processes by reducing habitat availability, increasing water temperatures, and threatening aquatic biodiversity (Behboudian et al., 2021; Huang et al., 2021). These impacts are particularly significant in small catchments where river flows are highly sensitive to climatic fluctuations and human interventions.

Climate variability and change have profound implications for low-flow characteristics. Prolonged dry periods, reduced precipitation, increased evapotranspiration, and rising temperatures can decrease soil moisture, groundwater recharge, and baseflow contributions to rivers (Abbas, 2022; Olabiwonnu, 2022). In addition, anthropogenic activities such as irrigation expansion and domestic water abstraction can further intensify reductions in river discharge, particularly during dry seasons when natural flows are already limited. Recent studies have demonstrated that the combined influence of climate change and water abstraction can significantly modify streamflow regimes, highlighting the need to understand their interacting effects on future water availability (Dunne et al., 2022; Munoz et al., 2023).

Low-flow information are of particular interest in water resource development, operational management of water systems, water quality regulation, ecological protection, and drought management and decision-making under future streamflow uncertainty (WMO, 2008, Escalante-Sandoval, 2025). Low flow refers to the minimum sustained streamflow conditions of a river system over a specified period and is a critical component of water resources

planning, ecological protection, and drought management (Smakhtin, 2001). Reduced river flows are often associated with declining water availability, increased ecological stress, deterioration of water quality, and reduced reliability of water supply systems (Assefa, 2018). Consequently, numerous studies have investigated low-flow characteristics, trends, and future changes using statistical approaches, frequency analysis, and hydrological modelling.

Globally, low-flow studies have demonstrated significant spatial variability in the magnitude and direction of low-flow changes. Assefa (2018) analysed daily streamflow records from 15 stations in the Blue Nile Basin, Ethiopia, using different low-flow indices, including 3-day, 7-day, and 14-day sustained low flows. The study identified statistically significant declining trends at most stations, indicating increasing vulnerability to water scarcity. Similarly, Munoz et al. (2023) assessed low-flow variability in the lower Mississippi River using observed river gauge data and Community Earth System Model Large Ensemble simulations. The study showed that reservoir development between 1950 and 1980 reduced the frequency and duration of extreme low-flow events, while future projections indicated fewer but more intense low-flow events under a high-emission scenario.

Several studies have focused on improving low-flow estimation methods, particularly in ungauged catchments. Mandal (2009) developed a regional flow-duration curve (FDC) model for Irish rivers using catchment physiographic and climatic characteristics. The model successfully reproduced the lower portion of observed FDCs and provided a useful approach for estimating low-flow characteristics in ungauged basins. Similarly, Eris (2019) evaluated probability distribution functions for estimating low-flow frequency characteristics in Turkish river basins. The study demonstrated that suitable probability models, particularly three-parameter Log-Normal and Weibull distributions, can effectively represent low-flow duration-frequency relationships for different hydrological regions.

With increasing concerns about climate change impacts, hydrological models such as the Soil and Water Assessment Tool (SWAT) have become widely applied to assess historical and future low-flow responses. Ghermezcheshmeh et al. (2022) used SWAT in the Kan River Basin, Iran, to evaluate climate change impacts on streamflow and projected increased extreme low-flow events associated with rising temperatures (up to 4.2 °C) and declining precipitation by 2099. Shrestha et al. (2019) integrated SWAT with ten downscaled CMIP5 climate models under RCP 4.5 and RCP 8.5 scenarios in the Great Miami River Watershed, USA, and projected approximately 19% increases in 7-day low flows during the twenty-first century. In Namibia's

semi-arid Okavango–Omatako watershed, Negussie (2022) demonstrated that SWAT can reliably simulate both high and low flows, achieving strong calibration and validation performance (NSE = 0.82 and 0.80, respectively).

Other studies have reported contrasting future low-flow responses, highlighting the influence of regional climate characteristics and catchment conditions. Zuo et al. (2015), Mohammed et al. (2017), and Eisner et al. (2017) projected declining low flows and increasing hydrological drought risks in river basins in China, Bangladesh, and other global regions. Conversely, Xu et al. (2015) and Piniewski et al. (2017) projected increasing low flows in some Chinese and European catchments, demonstrating that climate change impacts on low-flow regimes are highly spatially variable. More recently, Daide et al. (2025) assessed low-flow trends in four Chilean river basins using hydrological alteration indices, baseflow indices, and precipitation indicators. The study reported declining low flows linked to reduced precipitation, altered snowpack dynamics, and climate change.

From the foregoing, it is evident that river basin specific studies are required to better understand low flows. Despite extensive global applications of low-flow assessment methods, studies integrating climate change projections, hydrological modelling, and water abstraction impacts remain limited in many African catchments. This gap is particularly evident in small mountainous catchments such as the Likhubula River Catchment in Malawi, where increasing irrigation demand and climate variability may significantly alter dry-season flow availability. Therefore, understanding current and future low-flow characteristics in such systems is essential for sustainable water resource management and climate adaptation.

The Likhubula River Catchment, a key tributary of the major Shire River in southern Malawi, represents an important example of a small river system experiencing increasing pressure from both climate variability and human water use (Nangoma, 2008). The river originates from the Mulanje Mountain ecosystem and supports domestic water supply, irrigation, and ecological functions for surrounding communities. Increasing agricultural activities, particularly irrigated farming, have resulted in growing water abstraction from the river, especially during the dry season when flows are naturally reduced (Namangale, 2021). These pressures, combined with projected changes in rainfall and temperature, may threaten the sustainability of the catchment's water resources and the ecological integrity of the river system.

Although numerous studies have examined climate impacts on river flows globally, limited attention has been given to the combined effects of climate variability and water abstraction on low-flow characteristics of small catchments in Malawi. Existing studies have largely focused on regional climate trends, lake-level fluctuations, or large river systems, leaving important knowledge gaps regarding localized hydrological responses. Understanding how low flows respond to future climate conditions and increasing abstraction is essential for sustainable water resource planning and ecosystem protection.

Therefore, this study aims to assess current and future low-flow characteristics of the Likhubula River Catchment under climate variability and changing water abstraction scenarios. The study integrates hydrological modelling, climate projections, and statistical analysis to quantify historical low-flow behaviour and evaluate potential future changes. Specifically, the study (1) examined the historical hydroclimatic trends of Likhubula River catchment, (2) analyzed the time series of Low flows hydrological variables of Likhubula River; and (3) simulated the current and future impacts of water abstraction and climate change on low flow characteristics of Likhubula River. The findings will provide scientific evidence to support sustainable water allocation, climate adaptation planning, and management of small river catchments in Malawi.

2 Study Area, Data and Methods

2.1 Description of Study Area

The Likhubula River is a sub-catchment of the Shire River Basin located in Mulanje District, approximately 65 km east of Blantyre City in southern Malawi (Figure 1). Originating from Mount Mulanje, the river is an important source of water for domestic supply, irrigation, and other socio-economic activities. Since 2007, the Southern Region Water Board has abstracted water from the river to supply Mulanje and Thyolo districts, while the Blantyre Water Board has undertaken gravity-fed water abstraction since 2019. The catchment also supports extensive commercial tea estate irrigation (Namangale, 2021), the Gibson Irrigation Scheme, and several rural water supply schemes established between 1975 and 2010, making it one of the most intensively utilized catchments in southern Malawi.

The hydrology of the catchment is strongly influenced by Mount Mulanje, whose orographic effects produce pronounced spatial variations in rainfall. The southeastern windward slopes receive substantially higher rainfall than the leeward slopes due to the combined effects of

topography and Chiperoni winds (Taulo et al., 2008). Mean annual rainfall at Mimosa Tea Research Station (650 m above sea level), located approximately 5 km from the mountain, is about 1,626 mm, with nearly 16% occurring during the dry season (May–October), contributing to sustained dry-season flows (Nangoma, 2008). The average maximum temperature remained relatively stable at approximately 28.5°C between 1963 and 1986. However, between 1987 and 2006, the average maximum temperature increased by approximately 1.5°C, reaching about 30.0°C. A similar warming trend was observed for minimum temperatures over the same period, indicating a consistent increase in both daytime and nighttime temperatures across the catchment (Nangoma, 2008).

According to the Malawi Population and Housing Census, Mulanje District has a population exceeding 684,107 people (National Statistical Office, 2018). Agriculture is the dominant livelihood, with many households practising small-scale irrigated farming to supplement household income and food security (Namangale, 2021; Nangoma & Nangoma, 2013). The catchment is characterized by fertile soils and reliable water resources that have supported extensive commercial tea production since the colonial period. Tea estates occupy approximately 30% of the arable land, while smallholder farming occurs on both the mountain foothills and the gently sloping eastern plains bordering Mozambique (Namangale, 2021; Nangoma & Nangoma, 2013). Population growth and limited cultivable land have also resulted in increasing encroachment into forested areas surrounding the catchment (Borgstein, 2017).

The upper Likhubula catchment lies within the Mount Mulanje Forest Reserve, which covers approximately 65,000 ha and comprises montane grasslands, Afromontane forests, and the endemic Mulanje cedar (*Widdringtonia whytei*), Malawi's national tree (Beenhouwer, 2019). The reserve also includes eucalyptus and pine plantations established during the Mozambican refugee influx and contains one of the largest remaining tracts of mid-altitude rainforest in southern Africa. The reserve was gazetted in 1927 during the British Protectorate of Nyasaland, although commercial forest exploitation began in 1898 (Bayliss et al., 2007).

Studies have documented substantial degradation of the reserve over recent decades. Mulanje cedar cover declined from 1,462 ha in 1989 to 845.3 ha by 2004, primarily due to illegal logging and recurrent fires (Sakai, 1989; Bayliss et al., 2007). Similarly, Afromontane and mid-altitude forests declined from 9,292 ha in 1973 to 7,928 ha in 2002, highlighting widespread forest loss within the catchment (Bayliss et al., 2007). These land-use and land-cover changes have important implications for hydrological processes, including runoff generation, groundwater

recharge, and dry-season streamflow, particularly in a catchment experiencing increasing water abstraction.

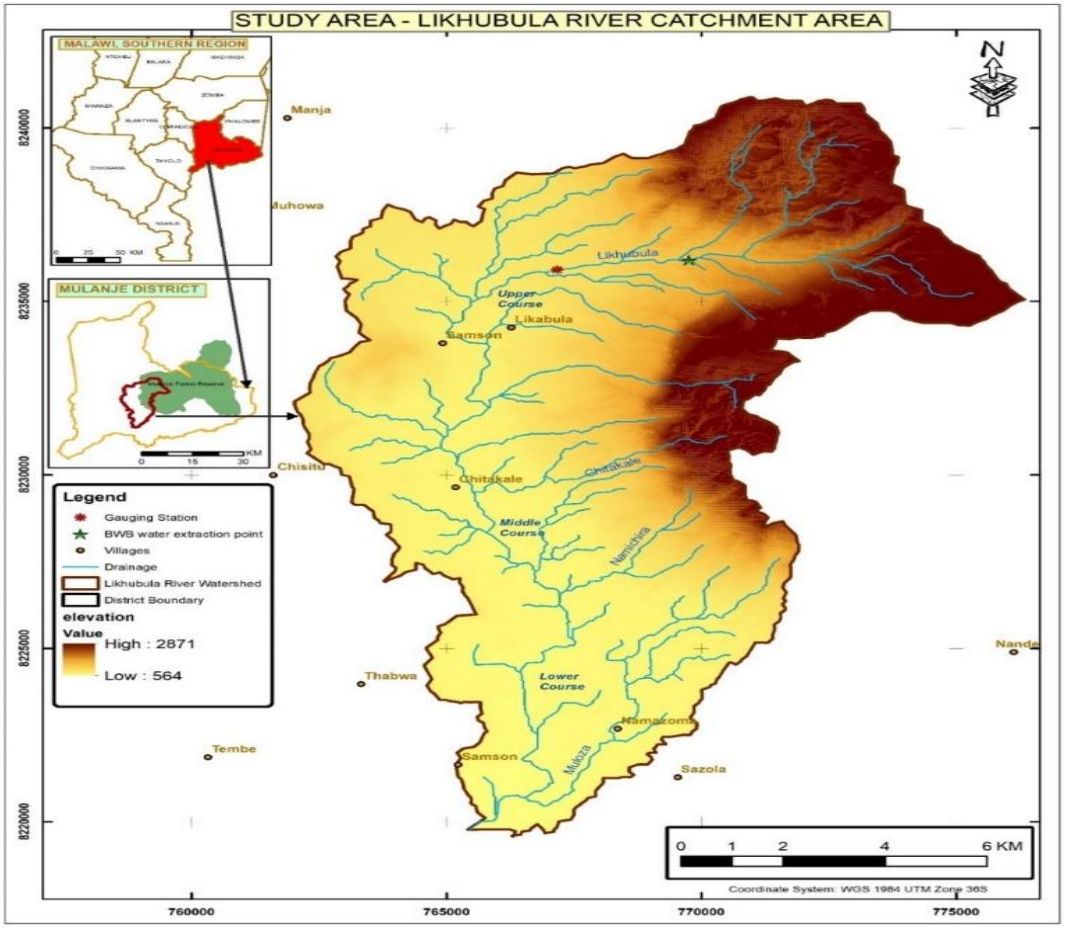


Figure 1: Map of the study area showing the (Likhubula River catchment area.

2.1 Data collection and Analysis Techniques

Daily climate (rainfall and maximum and minimum temperatures) and streamflow data for Mimosa meteorological station spanning from 1991 to 2022, was obtained from the Department of Climate Change and Meteorological Services (DCCMS) and the Department of Water Resources in the Ministry of Water and Sanitation, respectively. Table 1 shows the geographic and elevation data for Mimosa weather station and Likhubula hydrological station, respectively. The GEOGloWS hydrological model was used to fill gaps in the dataset. The observed streamflow data was used to bias-correct and reduce the differences between observed and modeled values as given in equation 1(Lozano et al., 2025; ECMWF, 2020). From the daily data, we derived monthly and annual series for trend analysis using the equation

$$Q_{corrected} = F^{-1}_{obs,m}\left(F_{(sim,m)(Q_{(sim)(d)})}\right), \quad (1)$$

where $Q_{corrected}$ = bias-corrected GEOGloWS streamflow; Qsim= GEOGloWS simulated streamflow in m; $F_{(sim,m)}$= cumulative distribution function of GEOGloWS simulated streamflow for month \(m\); and $F^{-1}_{obs,m}$= inverse cumulative distribution function of observed streamflow for month \(m\).

The significance and direction of trends in the data was determined using the non-parametric Mann-Kendall (MK) test (Mann, 1945, Kendall, 1975, Yue & Pilon, 2004) and the Sen's Slope Estimator (Sen, 2012) was used to quantity the magnitudes of trend slopes over time detecting any significant changes, and all statistical tests were evaluated at $\alpha = 5\%$ significance level. The MK trend statistic is recommended by the WMO in detection of trends in hydroclimate variables owing to its robustness and has been applied in a plethora of studies globally.

Table 1: Geographic and elevation data for hydroclimate stations in the study

Name	**Type**	**Latitude °S**	**Longitude °E**	**Elevation m.a.s.l.**
Mimosa	Meteorological	-16.03	35.51	646.39
Likhubula @ Likhubula Forest	Hydrological	-15.52	35.52	1025

2.2 SWAT Model Setup

2.2.1 Water Balance Concept in SWAT Model

The SWAT model, a physically based, semi-distributed and catchment scale model (Gassman et al. 2007; Babur et al. 2016) was used in modeling current and future flows in the basin. The SWAT distinguishes the hydrological modelling of a watershed into two main categories, the land phase and the routing phase. The land phase of the hydrologic cycle regulates the amount of water, sediment, nutrients, and pesticides that flow into the main channel of the sub-basin. The second stage of the hydrologic cycle is the flow of water or routing phase, silt, and other materials from the watershed's channel network to its outflow. The SWAT model simulates the hydrological cycle according to equation (Narzis, 2020)

$$SW_t = SW_0 + \sum_{i=1}^{t}\left(R_{day} - Q_{surf} - E_a - W_{seep} - Q_{gw}\right), \quad (2)$$

where SW_t is the final soil water content (mm H_2O), SW_0 is the initial soil water content on the day i (mm H_2O), t is the time (days), R_{day} is the amount of precipitation on day i (mm H_2O), Q_{surf} is the amount of surface runoff on day i (mm H_2O), w_{seep} is the amount of water entering the vadose zone from the soil profile on day i (mm H2O) and Q_{gw} is the amount of return flow on day i (mm H_2O) (Narzis, 2020). Amongst several suitable model candidates in the literature, the SWAT model was selected because of its extensive capacity to carry out simulations of the hydrological processes under anthropogenic and climate variability. The model can operate on different time scales, including the daily time step, which allows the user to identify daily fluctuations in with river discharge during low flow periods.

2.2.2 Watershed Configuration and Weather Data Input

The configuration of the SWAT model for the Likhubula River catchment requires the definition of watersheds using digital elevation models (DEM). An enhanced DEM-based approach for watershed delineation was utilized using ArcSWAT in the ArcMap environment. Prior to the model's execution, the DEM (Figure 8), land use (Figure 9) and soil (Figure 10), spatial datasets were configured to the UTM zone 36s projection, Following the loading of the study area's DEM grid into the SWAT model, the streams' locations were automatically delineated. This procedure was undertaken to determine the stream region, which helps in defining the stream's network hence the flow direction and flow accumulation grids were made during this delineation phase.

The model configuration involves the input of user-defined precipitation data in daily timescale over an extended period. Thus, the Mimosa meteorological stations' daily precipitation data spanning between 1991 and 2022, was employed in the research (Figure 4). The SWAT model calculates runoff volumes and peak flows using a master water balance technique (Arnold et al., 1998). The model setup also included the maximum and minimum air temperatures recorded at the Mimosa meteorological station from 1991 to 2022. To enable "buckets" in the SWAT model, e.g., reservoirs, aquifers, soil moisture, and wetlands to fill up and attain stable numbers, a two-year warm-up phase (1989–1990) was taken into consideration. Following model setup, the ArcGIS environment was used to run a daily time step SWAT model for the years 1991–2022, excluding the warm-up phase. In the output file type, the model was configured to produce the output in daily timestep since SWAT's default settings is in the monthly time step.

2.2.3 Model Calibration, Validation, Uncertainty, and Sensitivity Analysis

For model calibration, validation, sensitivity analysis, and uncertainty analysis, this study employed the Sequential Uncertainty Fitting Version 2 (SUFI-2) technique in the SWAT Calibration Uncertainties Program (SWAT_CUP). The outputs (for example, discharge) of the SWAT model served as inputs for the SWAT_CUP. To find the best model parameters, SWAT_CUP runs through multiple iterations. During each iteration, it generates and examines a range of possible simulation results, all of which fall within the 95 Percent Prediction Uncertainty (95PPU) range (Abbaspour et al., 2015). This range spans from the 2.5% to the 97.5% limits of the cumulative distribution, covering all likely estimated values. The goal of the 95PPU is to bracket as much of the observed data as it can inside the 95PPU envelope. Figure 2 shows a schematic relationship between SWAT and the five optimization programs used in SWAT-CUP.

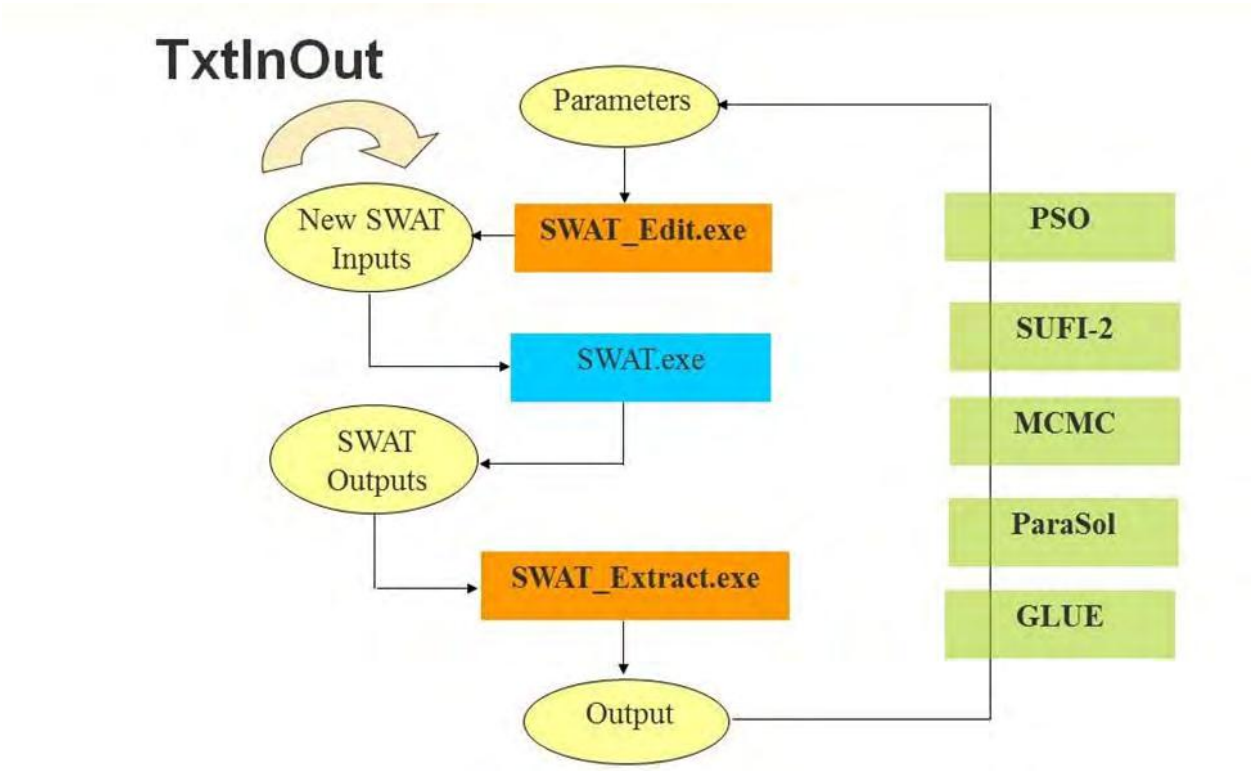


Figure 2: Connection between SWAT and five optimization programs.

Sensitivity of parameters was determined using the t-statistics and the p-value. The p-value quantifies the significance of the sensitivity, whereas the t-statistic is the coefficient of a parameter divided by its standard error. Higher absolute values of the t-statistic and smaller p-values indicate the most sensitive parameters. If the p-value for a model parameter in the sensitivity analysis is less than 0.05, the parameter is considered to be significant. The p-value

assesses the significance of the sensitivity, with a value near zero having more significance, whereas the t-stat measures sensitivity (a bigger absolute value indicates more sensitivity). SWAT-CUP uses a two-sided p-value by default. The most sensitive parameters in their order of sensitivity were: Average daily water removal from the reach for the month (WURCH), SCN runoff number for moisture condition (CN2), Soil hydraulic conductivity (SOL_K), Available water capacity of the soil layer (SOL_AWC), Threshold depth of water in the shallow aquifer (QWQMN), Deep aquifer percolation fraction (RCHRG_DP), Groundwater delay (day) (GW_DELAY), and Baseflow alpha factor (ALPHA_BF).

2.2.4 Model Performance Evaluation

Using the statistics recommended by Moriasi et al. (2007), the performance of the SWAT model was evaluated throughout both the calibration and validation phases. Based on the discharge time series, the used commonly used metrics for assessing model performance are the Nash coefficient (NC), PBIAS, and RSR, described by the equations

$$NSE = 1 - \left(\sum_{time}(d_{obs} - d_{sim})^2 \div \sum_{time}\left(d_{obs} - \overline{d_{obs}}\right)^2\right) \quad (3)$$

$$PBIAS = 1 - [\sum(Q_{Obs} - Q_{Sim}) \times 100 / \sum Q_{Obs}] \quad (4)$$

$$RSR = \frac{RMSE}{STDEV_{Obs}} = \left[\sum \sqrt{(Q_{Obs} - Q_{Sim})^2} / \sum \sqrt{(Q_{Obs} - Q_{obs})^2}\right] \quad (5)$$

where Q_{obs} is observed discharge and Q_{sim} is simulated discharge.

2.2.2 SWAT Modelling of Water Abstraction Scenarios

As part of the study, simulations were run with regular incremental adjustments to the parameters relating to water abstraction in SWAT model, with historical water withdrawals considered. The adjusted parameters include average daily water removal from the reach for the month (WURCH) and the Minimum and Maximum instream flow for irrigation diversion. A percentile range that represents an ad hoc and simplified representation of multiple, possible future water management scenarios across developing regions, including Malawi were considered (Brown et al., 2019). The narrative of these scenarios followed SSP scenarios, representing the broad range of middle-of-the-road (SSP2) and inequality (SSP4) scenarios (Wada et al., 2016; Greve, 2023).

2.3 Frequency Analysis of Low-Flows

Because observed streamflow records are often insufficient for reliable estimation of extreme low-flow events, theoretical probability distributions are used to extrapolate beyond the observed data (Kroll & Vogel, 2002, Eris, 2019, Tallaksen and Laaha, 2023). The study assessed low-flow characteristics using 3-, 7-, 30-, and 90-day minimum flow indices, including the 7-day low flows with 2- and 10-year recurrence intervals (7Q2 and 7Q10). Low flow series were derived using the Annual Minima Series (AMS) approach, where the Mean Annual 7-day Minimum Flow (MAM7), also referred to as dry weather flow, was calculated from the annual series of minimum 7-day average flows (Gustard et al., 1992). The use of 7-day averaged flows reduces the influence of short-term measurement errors and provides a robust indicator for characterizing sustained low-flow conditions (Smakhtin, 2001; Tallaksen et al., 2004). Additional flow-duration-based metrics, including Q90 and Q95 (flows exceeded 90% and 95% of the time, respectively), were used to describe flow reliability and drought-related conditions (Vogel & Fennessey, 1994). These low-flow indices were computed for pre- and post-water abstraction periods, as well as under future abstraction and climate change scenarios, to evaluate the sensitivity of the Likhubula River system to anthropogenic water withdrawals and climate variability.

To identify the most appropriate probability distribution for low-flow frequency analysis, the Normal, Log-Normal, Weibull, and Gumbel (Extreme Value Type I) distributions were fitted to the observed low-flow series. These distributions were selected because they are among the most applied probability models for hydrological frequency analysis, particularly for extreme events where the underlying probability distribution is unknown (Chow et al., 1988; Stedinger and Vogel, 1993). The Log-Normal distribution is widely used for positively skewed hydrological variables, while the Weibull and Extreme Value distributions are frequently applied for modelling minimum and extreme hydrological events, including low flows (Vogel & Kroll, 1992; Kroll & Vogel, 2002; Tallaksen et al., 2004). The Normal distribution was included as a reference distribution due to its simplicity and frequent use in hydrological statistics where data approximate normality (Stedinger and Vogel, 1993).

2.3.1 Candidate Distributions Goodness of Fit Tests

The goodness of fit was applied to ensure the reliability and accuracy of the chosen model among the candidate distributions (Eris, 2019). The study used the Kolmogorov-Smirnov, the Anderson Darling and the information criteria to determine the best-fit probability distribution.

Kolmogorov–Smirnov test was performed at significance level α ¼ 0.05 (Eris, 2019). The KS-test statistic measure is given as (Massa, 2016)

$$D\,n\ =\ max\,x\,|(x)-\ Fobs(x)|. \qquad (6)$$

The Anderson-Darling test was further applied due to its moderate power and data adaptability (Razali and Wah, 2011). The following formula was used to compute the test statistic (a^2) (Anderson, 2010)

$$a^2 = -\sum_{i=1}^{n}[(2i-1)\{\ln F_X\,(x_i)\} + \ln[1-\ F_X(\,x_{n+1-i)/n-n}), \qquad (7)$$

where f_x is the cumulative distribution function of the specified distribution and x_i is the ordered data.

Information criterion goodness-of-fit tests specifically the Akaike Information Criterion (AIC) and the Bayesian Information Criterion (BIC) were further employed to ascertain the best fitting probability distribution. The AIC and BIC formula given as (Syafrina, 2019)

$$\mathrm{AIC}\ =\ -2l\ +\ 2p, \qquad (8)$$

$$\mathrm{BIC}\ =\ -2l\ +\ p\log n, \qquad (9)$$

where l is the maximized log-likelihood for the model, p is the parameters of the model and n is the number of samples. In this context, the best model was decided based on which model has the smaller value among the Normal, log-normal, Weibull and Gumbel distributions.

2.3.2 Low Flow Frequency Analysis

Frequency analysis involved the use of probability distributions to establish the relationship between the intensity of an event for instance, low flows and the frequency of occurrence of the event (Eris, 2019). In the context of low-flow analysis in this study, the Average recurrence intervals (ARIs) were calculated from low flow-duration-frequency curves that are generated using the plotting position formula of the best fitting probability distribution, for example, the Weibull plotting position formula (Eris, 2019). Samat and Othman (2023) modelled the magnitude of low flow with return intervals of 2 and 10 years for durations of 7 days described by the low flow-duration-frequency curves. In this study, low flow frequency curves were plotted using the best fitting plotting position. The Average recurrence intervals (ARIs) were calculated using the Weibull plotting position formula (Samat & Othman, 2023)

$$T = \frac{N+1}{i}, \qquad (10)$$

where T is plotting position of annual low flow, in the year of ARI, N is the length of records in the years, and N is the rank of annual low flow in the series. Figure 3 summarizes the methodology used in this study.

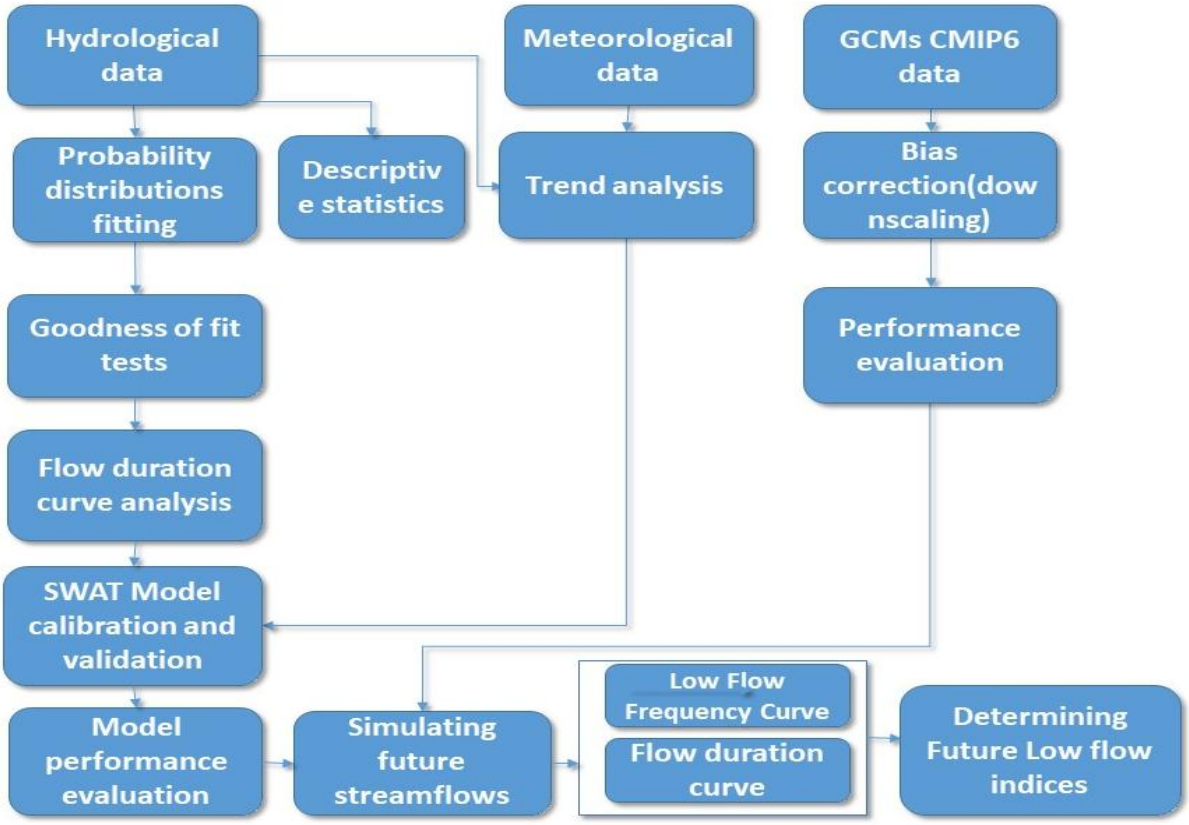


Figure 3: Flow chart for the summary of methodology used in this study

3 Results and Discussions

3.1 Hydroclimatic Trend Analysis

The Mann–Kendall (MK) test results indicate an overall statistically non-significant increasing trend in monthly and annual rainfall, whereas daily rainfall exhibited a statistically significant increasing trend at the 5% significance level during the study period (Table 2, Figures 4 to 6). These findings are consistent with Tadeyo (2020), who reported a non-significant positive rainfall trend at Mimosa Station, attributing the observed rainfall patterns to the orographic influence of the southern highlands, particularly the Mulanje Massif. Similar observations have

been reported by Ngongondo et al. (2011), who found no significant long-term changes in annual rainfall across much of southern Malawi, despite considerable spatial variability, and by Ngongondo et al. (2015), who demonstrated that rainfall variability in most parts of Malawi has been strongly influenced by long-term climatic fluctuations rather than persistent directional changes.

In contrast, maximum temperature showed a statistically significant increasing trend, while minimum temperature exhibited a positive but statistically non-significant trend. These findings agree with studies conducted in the Shire River Basin by Mtilatila et al. (2020) and Zuzani et al. (2019), which reported significant increases in temperature extremes. Similar warming trends have also been documented by Ngongondo et al. (2015) and Mtewa et al. (2025), highlighting increasing temperatures as a persistent feature of Malawi's climate. Rising temperatures have important implications for human health and well-being (Laisi, 2009). Exposure to extreme heat has been associated with increased heat-related mortality and morbidity, dehydration, cardiovascular and respiratory illnesses, reduced labour productivity, adverse pregnancy outcomes, and worsening mental health, particularly among vulnerable populations such as the elderly, children, pregnant women, and outdoor workers (IPCC, 2022; Kunda, 2024). Higher temperatures may also facilitate the transmission of some vector-borne diseases by altering the geographical distribution and life cycles of disease vectors.

The MK analysis further revealed an insignificant decreasing trend in streamflow (Table 2, Figure 7). Specifically, the results reveal a statistically significant negative trend in daily time scale, statistically insignificant positive trend in monthly scale and statistically insignificant negative trend in annual scale. These results are consistent with findings by Zuzani et al. (2019), who reported declining peak and low flows in the Shire River Basin. Continued reductions in streamflow could have profound implications for water security, ecosystem functioning, hydropower generation, irrigation, and domestic water supply. Lower streamflows reduce the dilution capacity of rivers, increasing the concentration of pollutants and pathogens, thereby elevating the risk of waterborne diseases such as cholera and diarrhoeal infections. Reduced water availability may also constrain agricultural production, contributing to food insecurity, malnutrition, and adverse maternal and child health outcomes, particularly in rural communities that depend heavily on rain-fed agriculture (MEPA, 2026). These findings underscore the need for integrated climate adaptation and sustainable water resource management strategies to enhance resilience to increasing hydroclimatic variability.

Table 2: Mann Kendall test results for Mimosa meteorological station

Temporal Scale	Statistic	Rainfall	TMIN	TMAX	Streamflow
Daily	MK Z-statistic	-17.39	-1.83	4.52	-14.30
	Sen's slope	-0.048	-0.003	0.008	-0.048
Monthly	MK Z-statistic	0.40	-5.45	-0.96	0.22
	Sen's slope	0.0004	-0.10	-0.003	4.1071e-05
Annual	MK Z-statistic	0.05	-3.52	0.13	-0.24
	Sen's slope	-0.003	-0.0004	0.00004	-0.0032

The study has revealed differences in trends of dissimilar temporal scales (daily, monthly and annual). This is because, in daily time series, the data captures fluctuations that occur at a short term. These include daily rainfall, extreme weather events or peak flows. Therefore, trend analysis results of the daily average data could highlight the periods when the flows were high or low that are not visible in the aggregated data set, for example, in data averaged over a month (Massei, 2020).

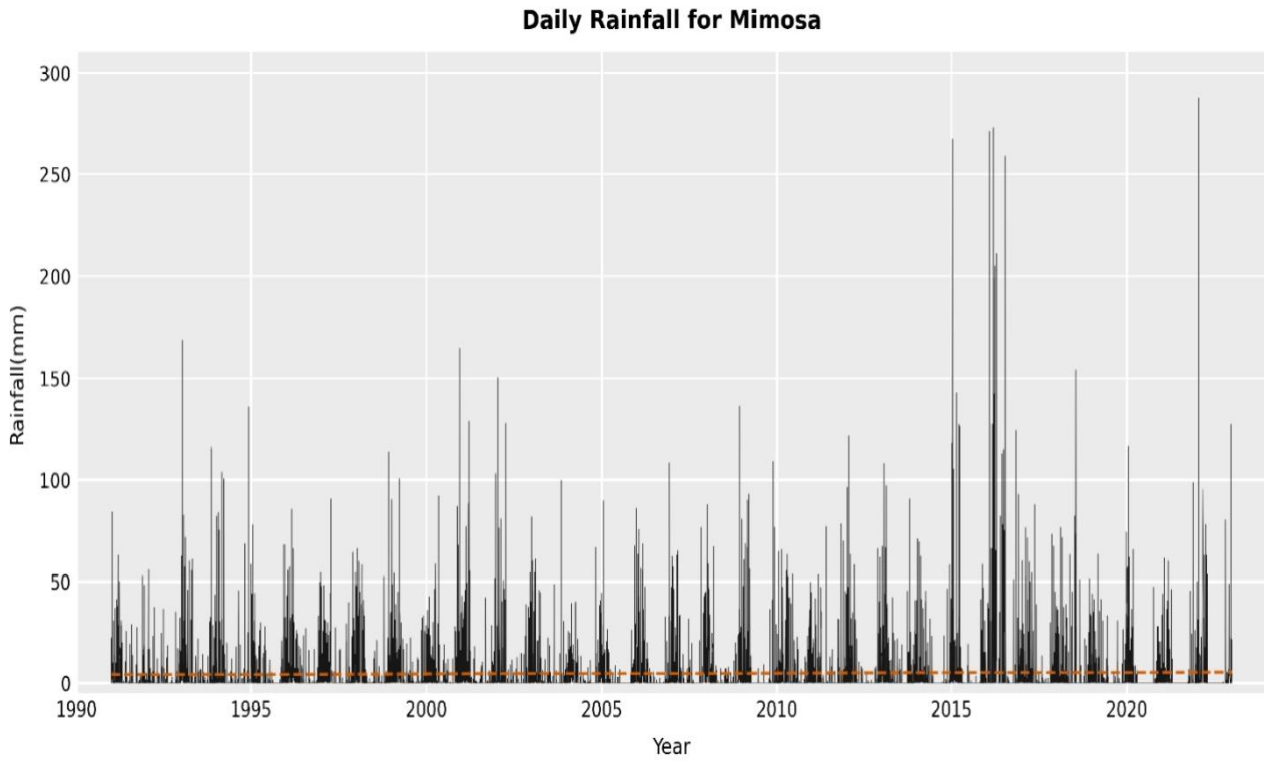


Figure 4: Trends in daily precipitation for Mimosa station (1991-2022)

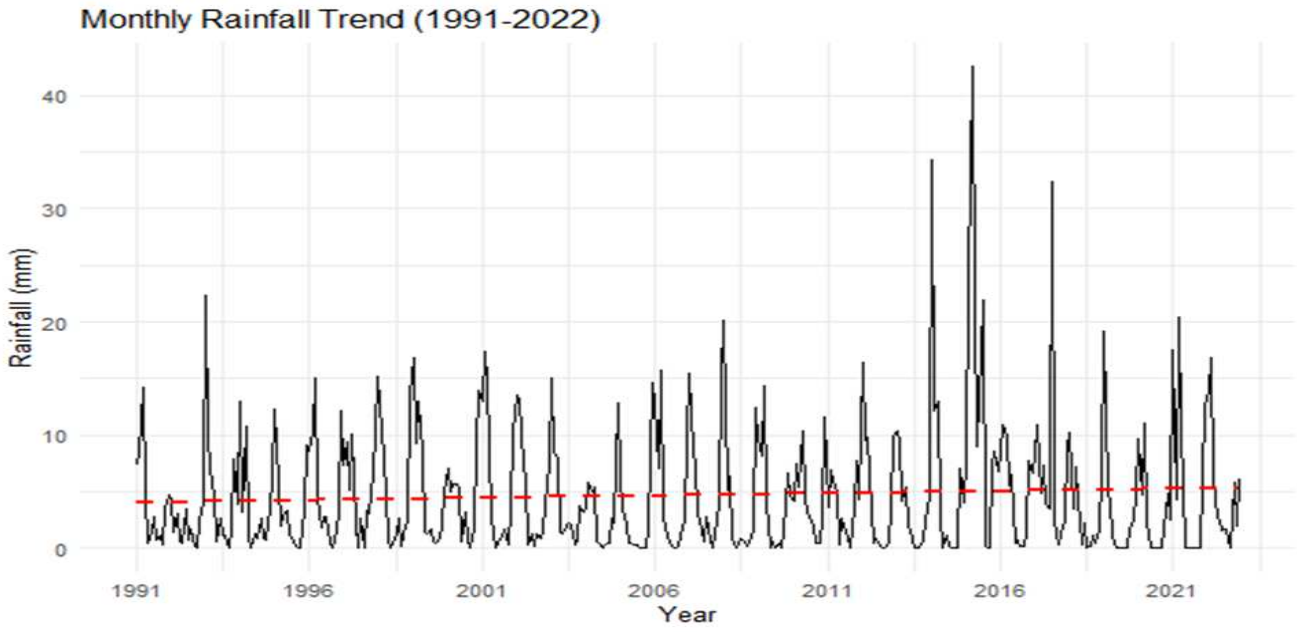


Figure 5: Trends in Monthly precipitation for Mimosa station (1991-2022)

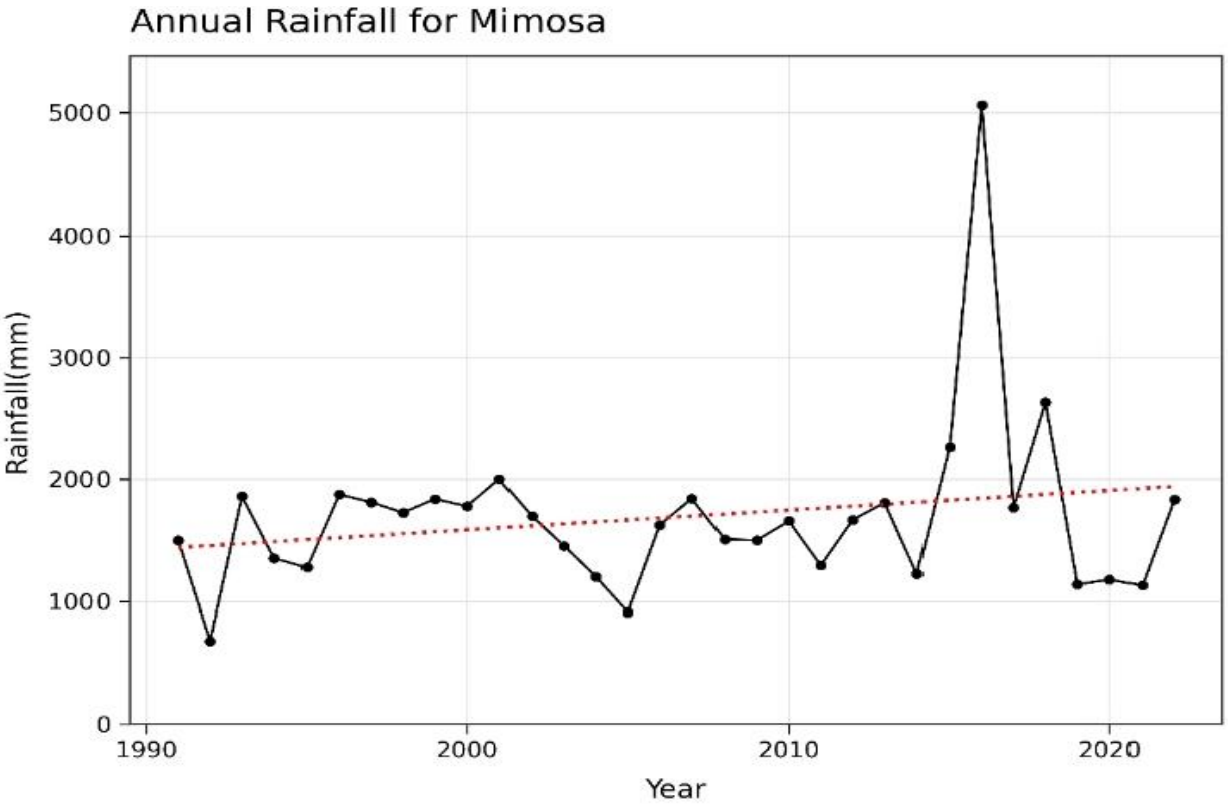


Figure 6: Graph showing trends in annual rainfall distribution for mimosa station (1991-2022)

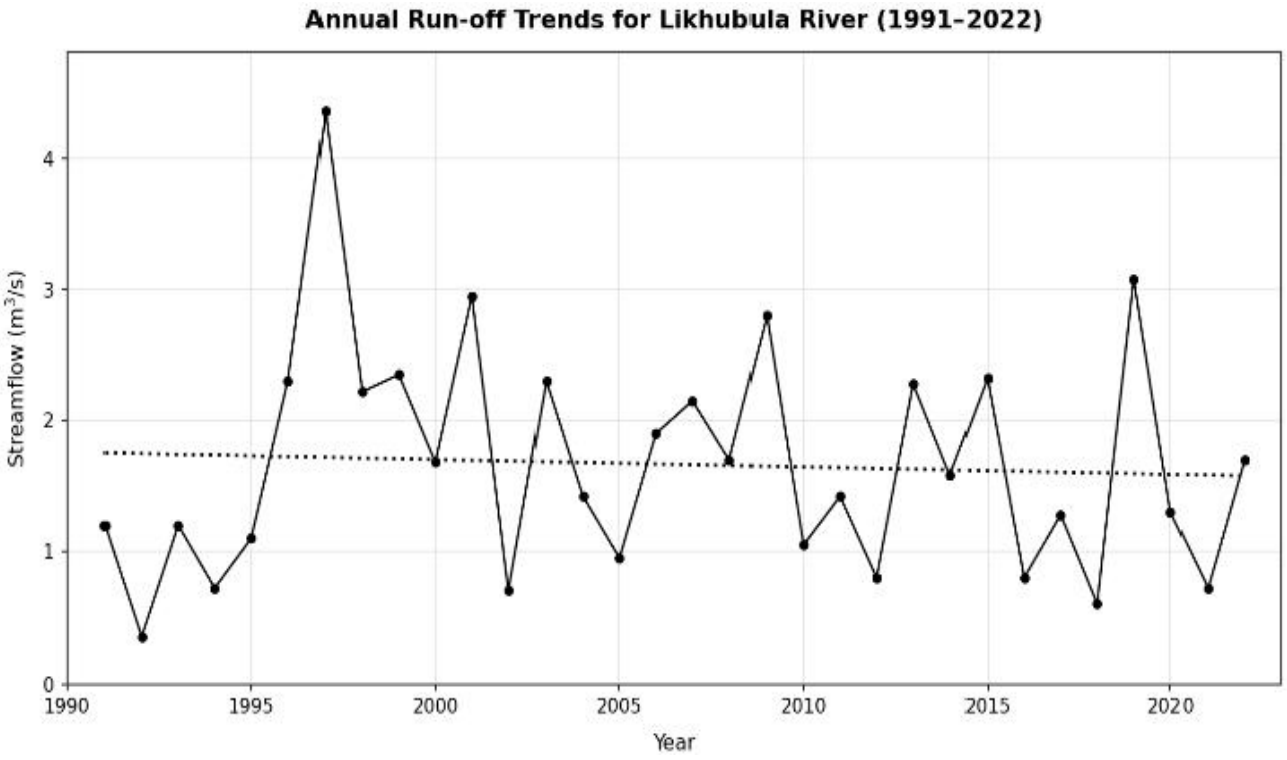


Figure 7: Annual run-off trends for Likhubula River (1991 – 2022)

3.2 Analysis of Low Flows Time Series

3.2.1 Goodness of Fit Tests of Distributions

The goodness-of-fit results (Table 3) indicate that the Weibull distribution provided the best representation of the observed streamflow data. The Normal, Log-normal and Gumbel distributions were rejected because they produced very low Kolmogorov–Smirnov (KS) and Anderson–Darling (AD) test p-values ($p < 0.001$), indicating poor agreement with the observed streamflow distribution. In contrast, the Weibull distribution produced the lowest KS statistic ($D = 0.0917$) with a non-significant KS test ($p = 0.054$), suggesting that the null hypothesis of a good fit could not be rejected at the 5% significance level. The Weibull distribution also recorded the lowest Akaike Information Criterion (AIC = 903.7) and Bayesian Information Criterion (BIC = 911.5), confirming it as the most parsimonious and statistically robust model among the candidate distributions.

Table 3. Distributions goodness of fit test results

Distribution	**Kolmogolov-Smirnov test**		**Anderson-Darling test**		**Information criteria**	
	D	P-value	Test statistic	P-Value	AIC	BIC
Normal	0.24	$2.2e\text{-}^{16}$	33.98	$4.92e^{-7}$	1545.3	1553.1
Log normal	0.41	$2.2*e^{-16}$	4.13	$2.5468e^{-7}$	936.9	944.8
Weibull	0.092	0.054	5.89	3.134	903.7	911.5
Gumbel	0.196	$1.058e^{-12}$	5.13	$3.96e^{-09}$	1069.5	1081.2

These findings are consistent with previous studies that have identified the Weibull distribution as one of the most suitable probability distributions for modelling low-flow characteristics. Assefa (2018) demonstrated that the Weibull distribution successfully characterised persistent low flows in the Blue Nile Basin, while Samat et al. (2023) recommended the Weibull distribution for low-flow frequency analysis because of its stability across different return periods. Similarly, Smakhtin (2001) recognised the Weibull distribution as one of the most reliable distributions for analysing low-flow frequency due to its flexibility in representing the skewed nature of streamflow records. However, other studies have reported different distributions depending on catchment characteristics. For example, Vivekanandan et al. (2021) found that the Log-normal distribution provided the best fit for low-flow estimation in the Cauvery River Basin, India, whereas Eris (2019) reported that the three-parameter Log-normal distribution performed best in most Turkish river basins. These contrasting findings indicate that no single probability distribution is universally applicable and that the choice of distribution depends largely on the hydroclimatic characteristics, catchment physiography, and streamflow regime of a particular basin.

3.2.2 Results of Model inputs preparation

Inputs of the SWAT hydrological model was prepared in ArcMap 10.3 and ArcSWAT 10.3 environments. The DEM, classified LULC map and soil map have been presented in Figures 8, 9 and 10 respectively. Table 4 provides the description of dominant Land Use Land Cover Classes, while Table 5 provides the map showing dominant soil classes for the Likhubula catchment.

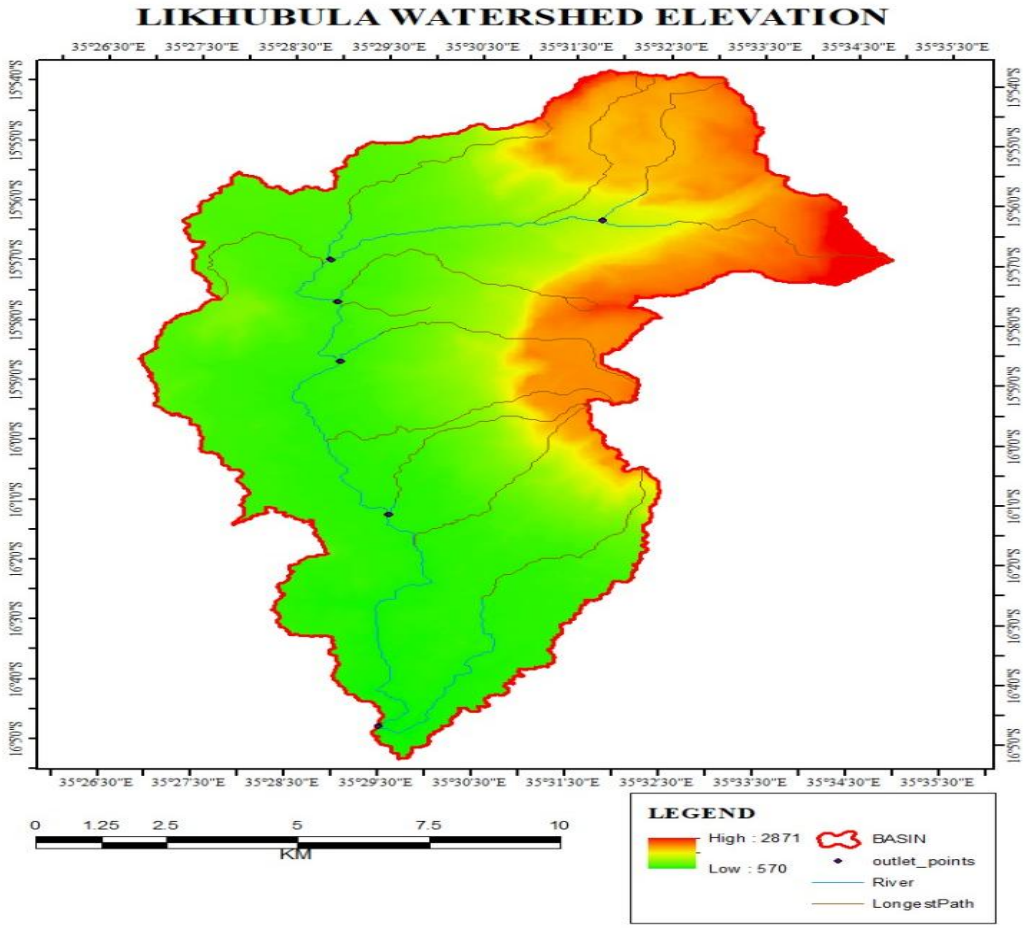


Figure 8: Digital Elevation Model for the Likhubula catchment.

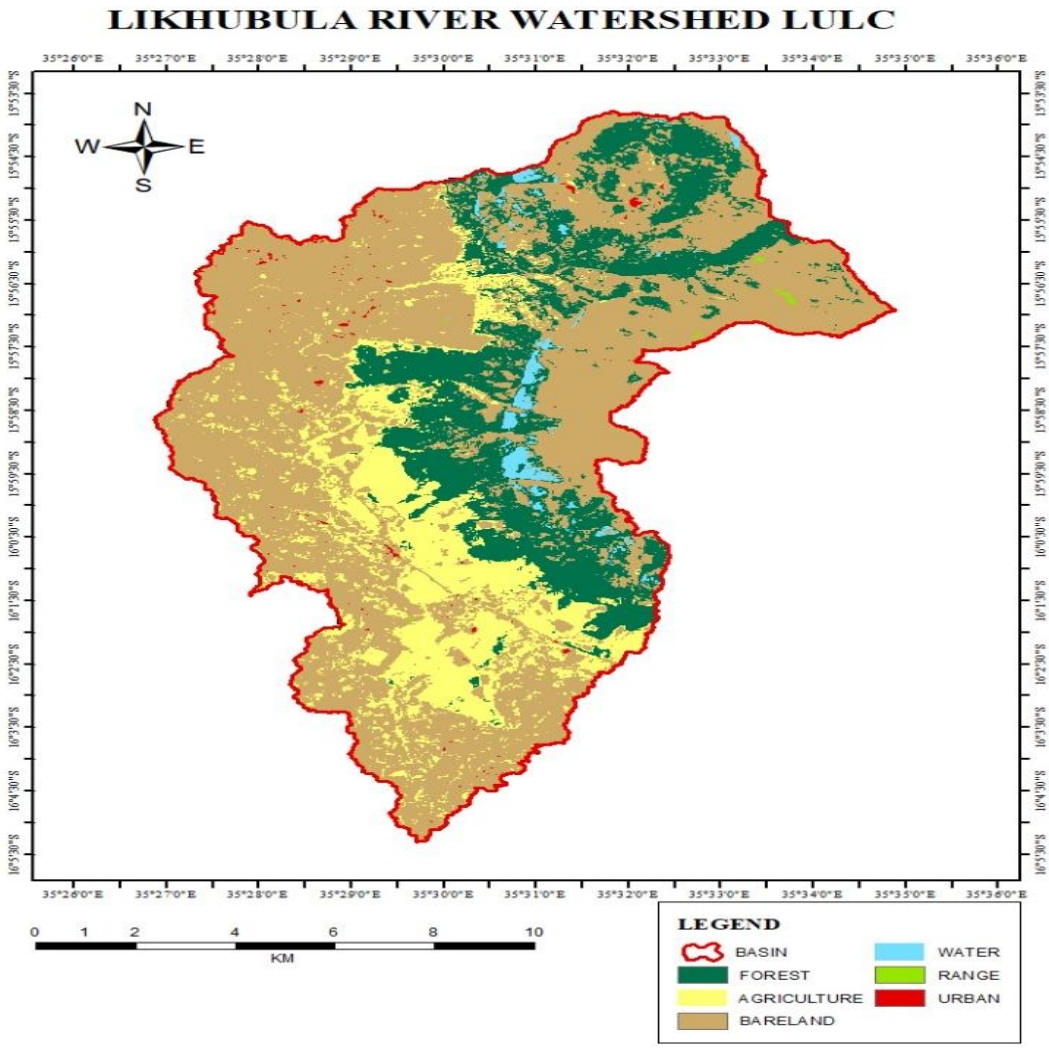


Figure 9: Land Cover Map for the Likhubula Catchment (2021).

Table 4: Description of Dominant Land Use Land Cover Classes

SWAT LULC CLASS	DESCRIPTION
Forest (FRST)	Mixed deciduous woodlands and different tree species.
Agricultural Land (AGRL)	Cultivated/ Grazing land/ exposed soil during the dry season
Bare Land (BARR)	Area of rock or soil with spare to no vegetation
Water (WATR)	Water bodies
Range Grass (RNGE)	Vegetation which includes medium to tall grassland and shrubs

Urban (URBN)	Built up areas such as residential, commercial, industrial, roads, schools and village settlement.

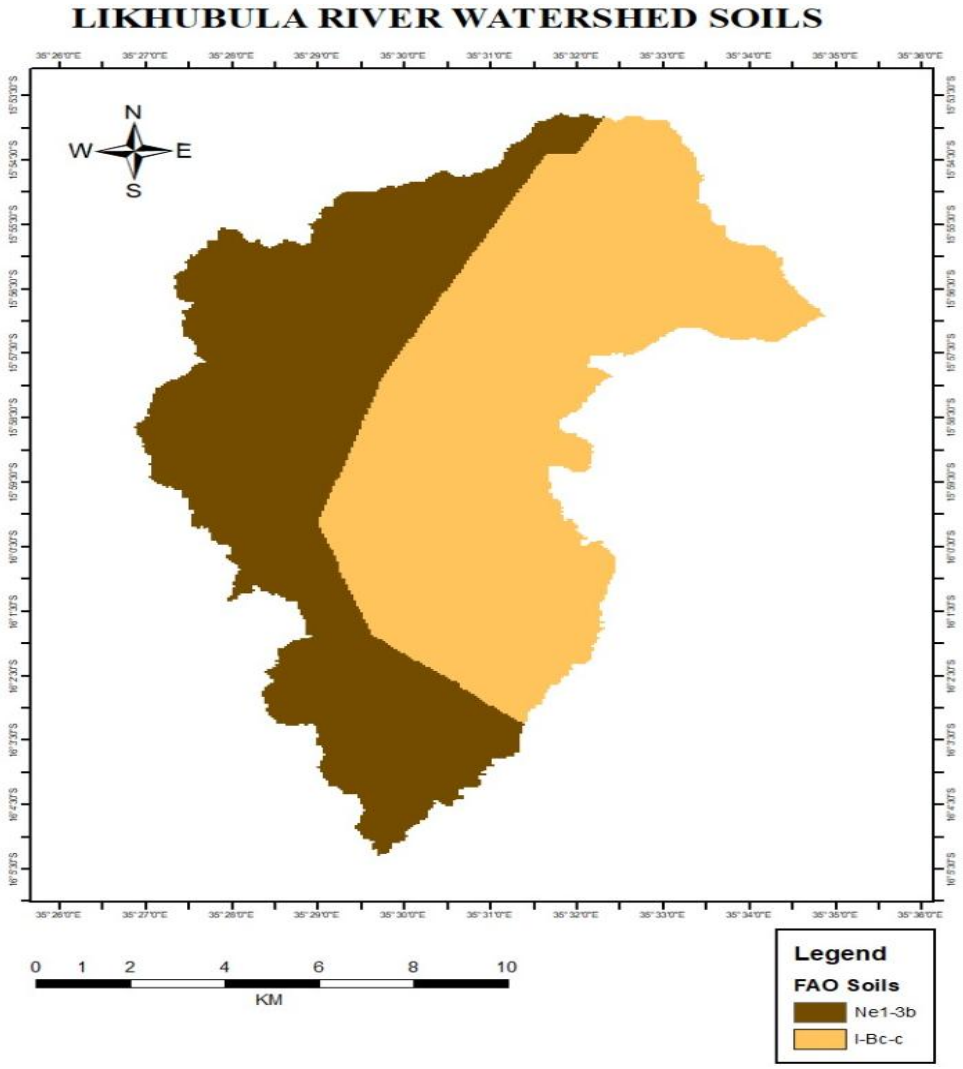


Figure 10: Map showing dominant soil classes for the Likhubula catchment.

Table 5: Description of Dominant Soil Classes for the Likhubula Catchment

SOIL TYPE	CODE	DESCRIPTION
Rhodic Ferral	Ne1-3b	Well drained, fine textured, low organic matter content, Reddish brown colour.
Humid Ferral	I-Bc-c	Well drained, very deep, High organic Matter content, low PH, Dark brownish colour.

3.2.3 Performance of the SWAT Model during Calibration and Validation

Model performance was evaluated using statistical metrics including the Nash-Sutcliffe Efficiency (NSE), Percent Bias (PBIAS), and Root Mean Square Error (RMSE), as outlined in Table 6 and shown in Figures 11 and 12.

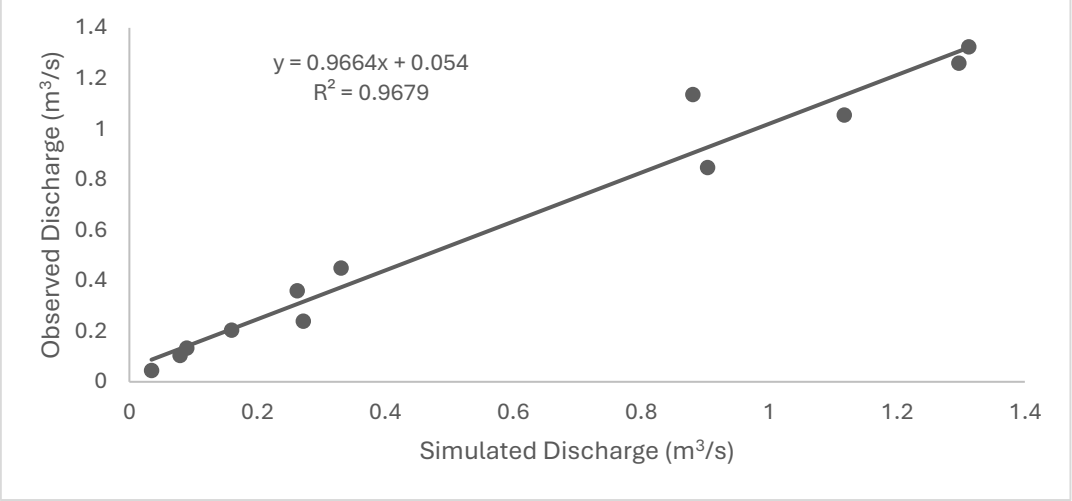


Figure 11: Scatter plot for mean monthly observed and simulated streamflow for the calibration (1993-2006)

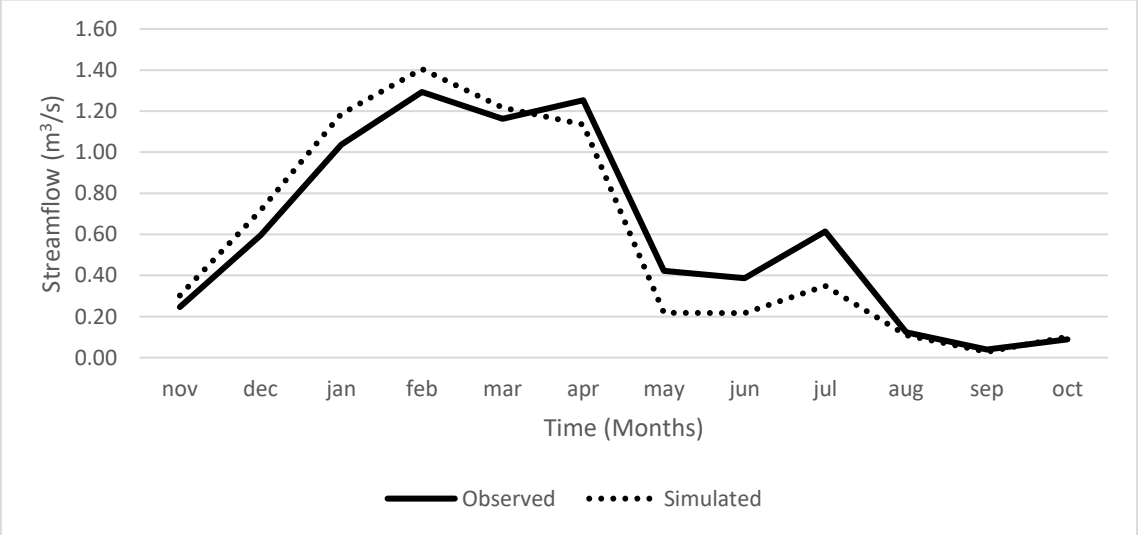


Figure 12: Linear plot for mean monthly observed and simulated streamflow for the validation period (2007-2022)

Table 6: Model performance evaluation metrics results

Model Performance metric	Value	
	Calibration period (1993-2006)	Validation period (2007-2022)
R^2	0.98	0.96
PBIAS	3.6	-2.4
NSE	0.94	0.87
R	0.29	0.42

According to recommendations by Moriasi et al. (2007), model performance is considered satisfactory if NSE >0.5, RSR ≤ 0.70, and PBIAS ± 25%. These recommended performance indicator values are typically for routine evaluations of water resources. Since this study aimed at predicting and analyzing future extreme flows which can be highly uncertain, higher acceptable levels of model performance indicators were adopted to reduce the uncertainty with the NSE>0.80, RSR ≤ 0.5 and PBIAS ± 10 % (Ngongondo et al, 2013). In line with this model performance evaluation criteria, the SWAT model demonstrated a satisfactory performance with an R^2, PBIAS, NSE and RMSE of 0.98, 3.6, 0.94 and 0.29 respectively during calibration and R^2, PBIAS, NSE and RMSE of 0.96, -2.4, 0.84 and 0.42 respectively during validation.

3.2.4 Monthly Streamflow Variability for Different Scenarios

For the baseline water abstraction scenarios, 1991-2006 boxplots (Figure 13 left) show higher variability in the month of February with highest mean discharge values peaking at 5.6 m^3/s compared to other months like September and October that have the Mean discharges of 0.2 m^3/s and 0.3 m^3/s respectively. During the 2007–2022 baseline period, streamflow exhibited higher variability during January, which recorded the highest mean discharge of approximately 2.5 m^3/s. Under both climate change and water abstraction scenarios, the period between 2007 and 2022 shows lower medians on majority of the months and less variability as compared to the period spanning between 1991-2006, hence indicating that climate change and intensified water extraction has resulted in reduced stream flows (Floriancic et al., 2021). These results are consistent with the findings of Chimtengo et al. (2014) who reported increased zero-flow occurrence and changes in flow characteristics due to water allocation practices and other anthropogenic influences in Rivirivi river, Malawi.

For projected scenarios, the RCP4.5 scenario (Figure 13), shows a wider range of mean discharge values for some months, indicating higher variability in stream flow. Under this scenario, January and February months have the highest mean discharge values, peaking around 2-2.5 m^3/s. On the other hand, September and October have the Mean discharges of 0.1 m^3/s and 0.2 m^3/s respectively. These findings suggest critical water scarcity for domestic water supply, irrigation in tea estates and public health during dry seasons (Laisi, 2009). The projected scenarios are signaling greater water challenges in the same dry seasons unless urgent sustainable abstraction measures are implemented (Floriancic et al., 2021).

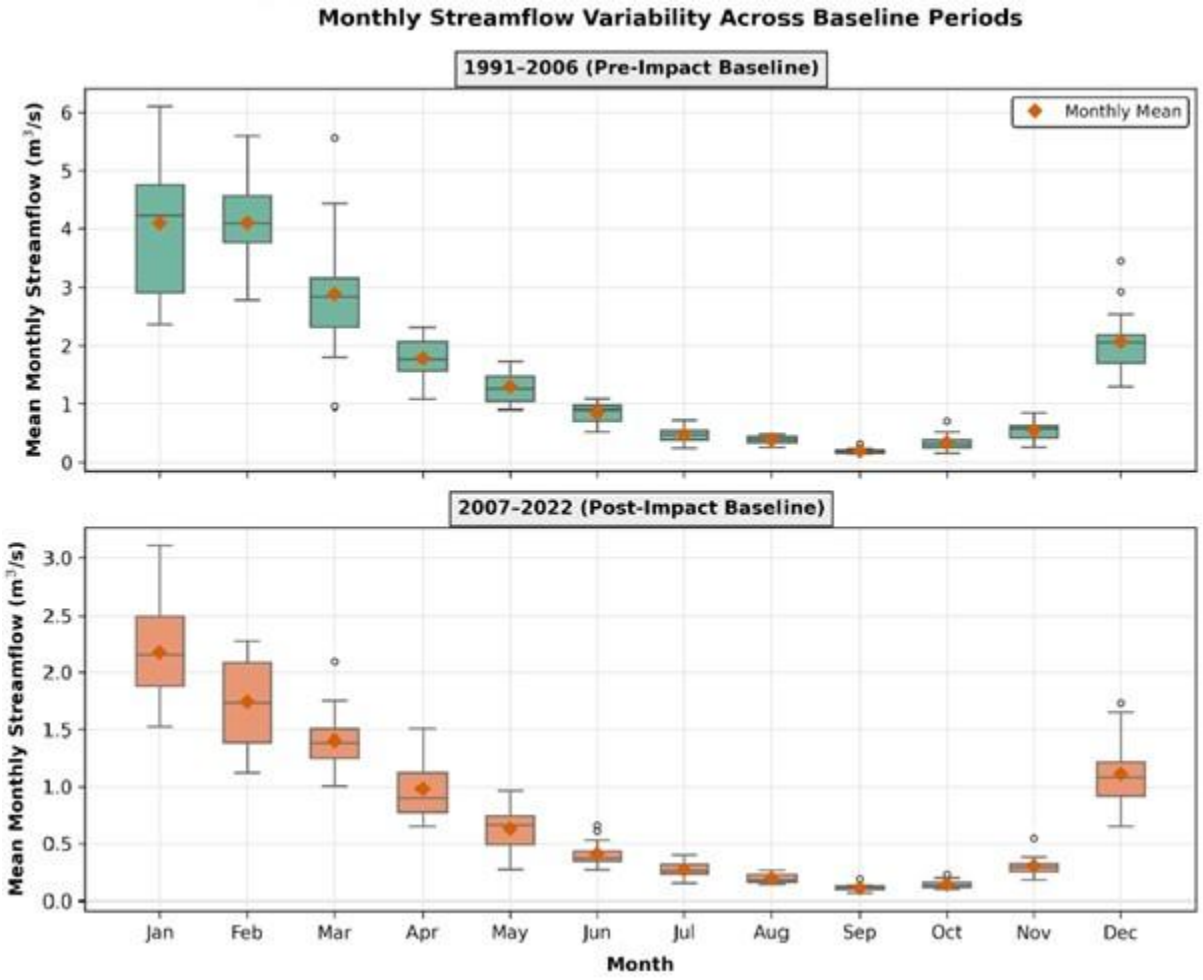


Figure 13: Box plot showing mean monthly stream flows for RCP4.5 and SSP2 scenarios

3.2.5 Low Flow Frequency Analysis

Figure 14 presents the Flow Duration Curves (FDCs) of 7-day minimum flows for the pre-impact and post-impact (2007–2022) periods, highlighting changes in the low-flow characteristics of the Likhubula River. The post-impact FDC shows a downward shift

compared with the pre-impact curve, indicating a reduction in flow availability across most exceedance probabilities following increased water abstraction activities. The difference between the two curves is more pronounced at higher exceedance probabilities, suggesting a greater reduction in dependable low flows during dry periods.

The Q90 and Q95 values derived further demonstrate the alteration of low-flow conditions, with lower exceedance flows observed during the post-impact period compared with the pre-impact period. This indicates that water abstraction has reduced the magnitude of sustained baseflows, potentially increasing pressure on dry-season water availability and ecosystem flow requirements.

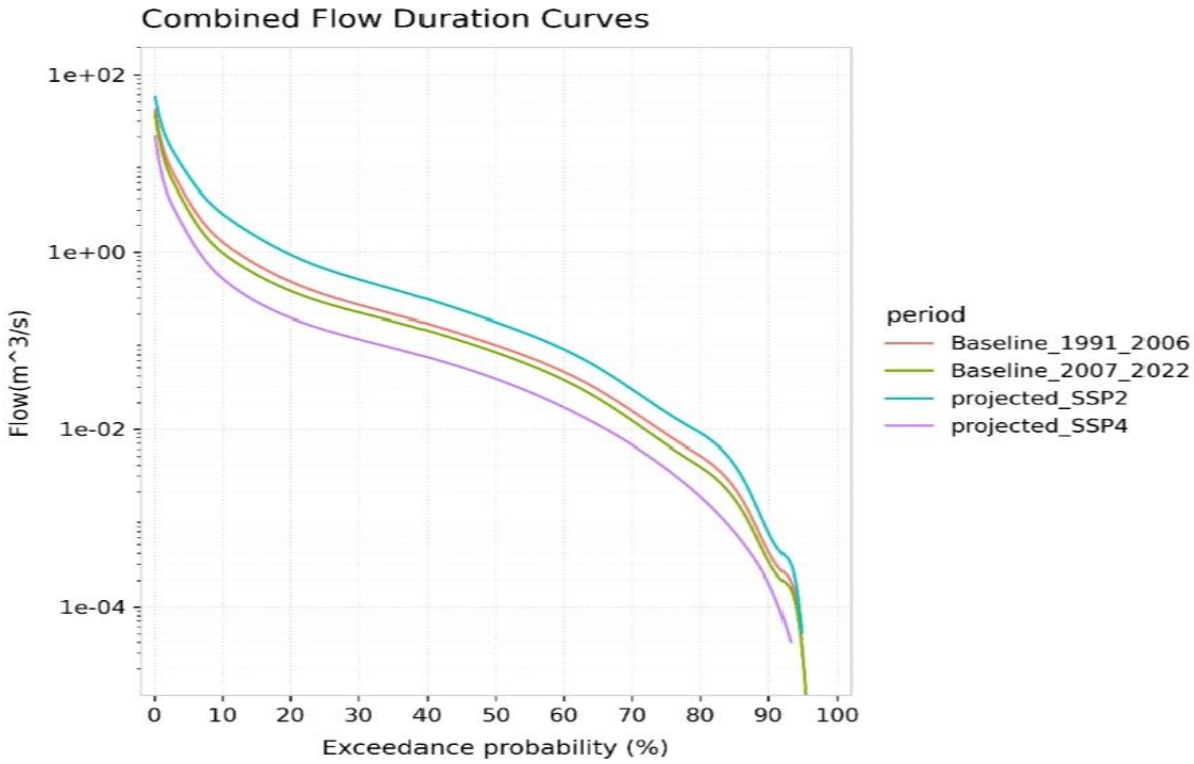


Figure 14: Flow duration curve for baseline and projected water extraction scenarios

The Flow Duration Curves (FDCs) provide valuable information on flow exceedance characteristics but cannot directly estimate low-flow magnitudes associated with specific return periods, such as the 7-day 2-year (7Q2) and 7-day 10-year (7Q10) low flows. Therefore, the annual series of 7-day minimum flows were fitted to probability distributions to develop Low Flow Frequency Curves (Figure 15). These curves were subsequently used to estimate the magnitude of extreme low-flow events corresponding to 2- and 10-year recurrence intervals (7Q2 and 7Q10), with results presented in Table 7.

Comparison of the baseline climatic conditions between 1991–2006 and 2007–2022 revealed a decline in extreme low-flow magnitudes during the latter period. The 7Q10 decreased from 0.96 m^3/s to 0.76 m^3/s, while the 7Q2 declined from 1.06 m^3/s to 0.83 m^3/s, indicating an increase in the severity of extreme low-flow conditions following the post-impact period. These reductions suggest that the river experienced lower minimum flow availability during the 2007–2022 period compared with the earlier baseline period. Muñoz et al., (2023) also observed that the severity and duration of low flow events of the Mississippi River intensified after the establishment of artificial reservoirs. Nevertheless, the latter projected a decrease in severity and duration of low-flow events through to the end of the 21st century under modelled climate scenarios.

In contrast, the flow exceedance indices showed an apparent improvement in sustained low-flow conditions. The Q90 increased from 0.02 m^3/s to 0.06 m^3/s, while Q95 increased from 0.01 m^3/s to 0.04 m^3/s, indicating higher flows were maintained for a greater proportion of time during the post-impact period. This difference between frequency-based extreme low flows (7Q2 and 7Q10) and exceedance-based indices (Q90 and Q95) highlights the complexity of low-flow responses, where changes in short-duration extreme events may not necessarily correspond to changes in overall flow persistence. In a similar study, Mwelwa (2024) indicated downward trends in streamflow under climate change and socioeconomic development in Luwombwa sub-catchment, Zambia.

Under water abstraction scenarios, the comparison between pre-impact (1991–2006) and post-impact (2007–2022) conditions showed a further reduction in extreme low-flow magnitudes. The 7Q10 decreased from 0.51 m^3/s to 0.47 m^3/s, while the 7Q2 declined from 0.56 m^3/s to 0.52 m^3/s, suggesting that abstraction contributed to increased pressure on minimum flow conditions. Similar effects of water abstraction on low-flow variability have been reported by Goshime et al. (2019), who found that abstraction accounted for approximately 23% of inflow reductions in Lake Ziway, Ethiopia.

However, the Q90 and Q95 values under abstraction scenarios increased from 0.08 m^3/s to 0.19 m^3/s and 0.04 m^3/s to 0.10 m^3/s, respectively. This indicates that while extreme minimum flows were reduced, the overall persistence of low flows within the catchment showed an apparent increase. The observed differences among low-flow indicators emphasize the importance of using multiple indices when assessing the impacts of climate variability and water abstraction on river flow regimes.

Analysis of the projected scenarios, the RCP4.5 and RCP8.5 indicate less severe low flows as compared to historical periods but RCP4.5 is slightly favorable than RCP8.5 with higher 7Q10 and 7Q2 values than the historical periods. For instance, RCP4.5 shows a 7Q10 of 1.11 and a 7Q2 of 1.22. SSP2 shows less severe low flows when compared to SSP4 which ascertains the influence of water extraction on low flow conditions in Likhubula catchment. The combinations of RCP and SSP scenarios have shown varying results as with combinations, for example, RCP4.5 & SSP2 indicates significant improvements, while others (e.g., RCP4.5 & SSP4, RCP8.5 & SSP4) showing potential for highly severe low flows. For example, according to Table 7, the RCP8.5 & SSP4 scenario shows a 7Q10 of 0.01, and 7Q2 of 0.02 indicating highly severe low flows. These findings are in line with Zhang (2022), who attributed an increase in low flows in Hanjiang River Basin to the decreasing duration of extreme precipitation and an increase of the dam height, which increased the storage capacity of extracted water. The projected low flows signal serious risks to human health and well-being of the current and future generations by heightening the hazard of waterborne diseases (e,g cholera), reduced agricultural production that leads to malnutrition and increased maternal and child health risks due to unsafe water sources (Gello, 2025). Furthermore, the current and projected low flows indicate that the environmental status of Likhubula river is at jeopardy of reduced ecosystem resilience, biodiversity loss, habitat degradation and impaired water quality due to the river's lower dilution capacity. (MEPA, 2026).

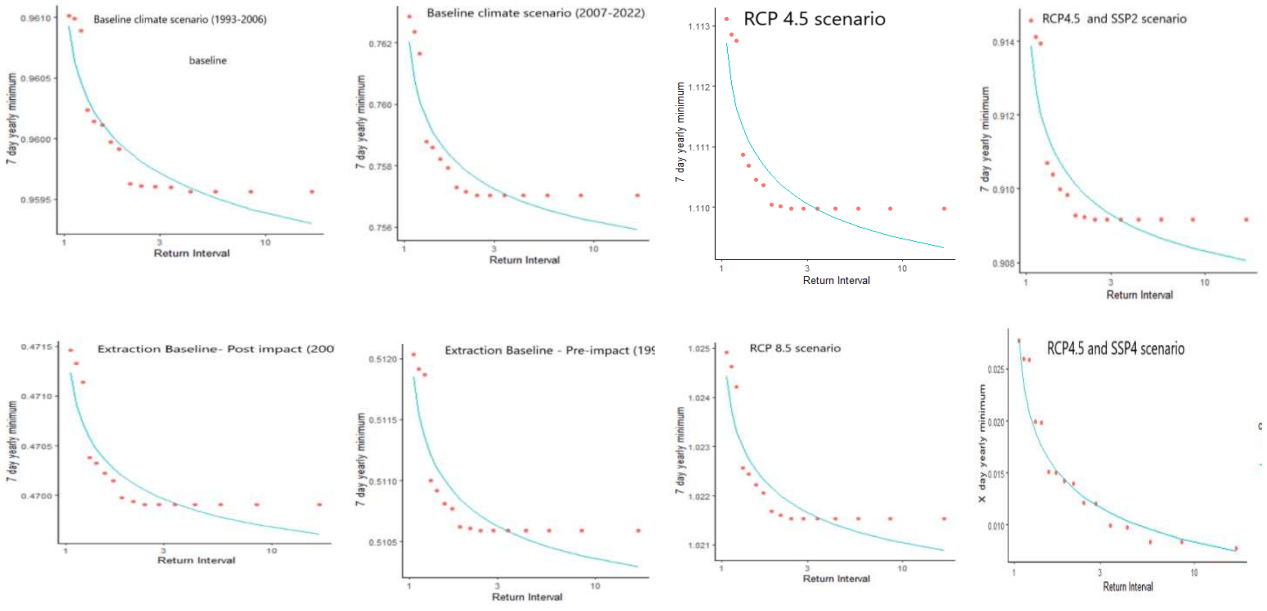


Figure 15: Low flow frequency curve for baseline and projected scenarios

Table 7: Low flow indices for different scenarios in observed and simulated periods

Index	1991-2006 (CM)	2007-2022 (CM)	1991-2006 (WS)	2007-2022 (WS)	RCP 4.5	RCP 8.5	SSP2	SSP4	RCP4.5 & SSP2	RCP4.5 & SSP4	RCP8.5 & SSP2	RCP8.5 & SSP4
7Q10	0.96	0.76	0.51	0.47	1.11	1.02	0.59	0.06	0.91	0.00	0.20	0.01
7Q2	1.06	0.83	0.56	0.52	1.22	1.12	0.65	0.73	1.00	0.01	0.22	0.02
Q90	0.02	0.06	0.08	0.19	0.03	0.04	0.03	0.06	0.16	0.03	0.03	0.01
Q95	0.01	0.04	0.04	0.10	0.01	0.01	0.02	0.03	0.10	0.02	0.01	0.01

According to the study, the low flow indices examined herein from observed data and modeled streamflow underscore considerable rises in low flow frequencies owing to increased water abstraction activities after 2007 and a further anticipated increase in low flows after 2027. Furthermore, analysis of low flow indices revealed an increase in the severity of low flow conditions from 2007 to 2022 as compared to the period between 1991 to 2006 particularly for climate scenarios. On the other end, the projected scenarios revealed that the RCP4.5 and RCP8.5 indicate less severe low flows as compared to historical periods with RCP4.5 being slightly favorable than RCP8.5. SSP2 exhibited less severe low flows when compared to SSP4, ascertaining the influence of water extraction on low flow conditions in Likhubula catchment. The combinations of RCP and SSP scenarios presented varying results, for example, RCP4.5 & SSP2 indicated significant improvements, while others (e.g., RCP4.5 & SSP4, RCP8.5 & SSP4) showing potential for highly severe low flows.

4 Conclusions

The present study demonstrates that climate change and intensification of water abstraction has a significant impact on both the magnitude, duration and frequency of low flows in the Likhubula catchment. These findings provide crucial insights for sustainable water resource management since predicting a river's low flow in terms of volume and frequency is essential for planning and building water resource projects, as low flow has a substantial influence on river sustainability conditions, water quality, and water availability. However, future research should consider conducting an inclusive assessment of hydrological change drivers by seeking to have a full understanding of the range of factors influencing hydrological change, including

other human activities such as land-use changes in addition to climate variability. For policy makers, efforts should be made to strengthen water abstraction regulation measures to ensure future sustainable use of water, especially during dry seasons.

5 Declarations

Ethics approval and consent to participate

The study did not involve human or animal subjects and therefore did not require formal ethics review.

Consent for publication

Not applicable.

Availability of data and materials

Data sets generated during the current study may be made available from the corresponding author on reasonable request.

Competing Interests

All authors declare that they have no competing interests.

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Authors' contributions

The study was conceptualized and designed by **Hopeson Nazombe, Cosmo Ngongondo**. Material preparation and data collection were performed by **Hopeson Nazombe, Cosmo Ngongondo** and **Elias Mwakilama**. The data analysis was performed by **Hopeson Nazombe** and **Elias Mwakilama**. The first draft of the manuscript was written by **Hopeson Nazombe** and all authors commented on previous versions of the manuscript. **All** authors read and approved the final manuscript.

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Declaration of generative AI and AI-assisted technologies in the writing process

During the final proofreading of this manuscript, the corresponding author used Grok and Scribbr, the two Free AI Paraphrasing Tools to paraphrase paragraphs and address redundancy issues. After using his tool/service, the author(s) reviewed and edited the content as needed and take(s) full responsibility for the content of the publication.

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