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FACULTY OF ENGINEERING AND TECHNOLOGY

DEPARTMENT OF WATER RESOURCES ENGINEERING

FINAL YEAR PROJECT REPORT

COMPARATIVE ASSESSMENT OF HEC-HMS AND HEC-HMS_XGBOOST MODELS TO SIMULATE STREAMFLOW UNDER CLIMATE CHANGE FOR FLOOD CONTROL STRUCTURE DESIGN.

CASE STUDY: RIVER SIPI CATCHMENT.

BY

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A final year project report submitted to the Department of Water Resources Engineering in partial fulfillment of the requirements for the award of a Bachelor of Science in Water Resources Engineering.

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ABSTRACT

Climate change has significantly intensified the frequency and magnitude of flood events in data-scarce tropical mountainous catchments such as the River Sipi catchment on the slopes, posing serious risks to infrastructure, agriculture, and livelihoods. Conventional physically-based models such as HEC-HMS exhibit critical limitations in capturing the nonlinear, complex dynamics of high-flow peak events under non-stationary climate conditions, compromising the reliability of flood control structure design in such areas. The study comparatively assessed the performance of the conventional HEC-HMS model and a hybrid HEC-HMS_XGBoost model in simulating streamflow under present and future climate scenarios for improved flood control structure design in the Sipi River catchment. The HEC-HMS and the hybrid models utilized historical hydrological data from 2010-2024 for calibration and validation. Future streamflow projections from 2025-2100 were generated by running both calibrated models with bias-corrected and downscaled CMIP6 climate data. Flood frequency analysis using the Gumbel extreme value distribution was applied to derive design discharges Q_{10}, Q_{25}, Q_{50}, and Q_{100}, which were subsequently used to size four flood control structures: culverts, spillways, bridge waterway openings, and detention basins. The hybrid model substantially outperformed HEC-HMS, achieving NSE values of 0.985 and 0.967 during calibration and validation, with KGE values of 0.934 and 0.893 respectively, compared to unsatisfactory HEC-HMS NSE values of 0.311 and 0.400. Future simulations revealed significantly divergent behavior under SSP5-8.5, HEC-HMS projected a Q_{100} of 30.32 m³/s, a 38.5% increase above its Q_{10} of 21.89 m³/s, while the hybrid model produced a more stable Q_{100} of 21.51 m³/s, only 20.7% above its Q_{10} of 17.82 m³/s. Notably, under SSP2-4.5 the hybrid model projected higher discharges than HEC-HMS, providing a physically corrected rather than uniformly lower estimates. Model divergence translated directly into significant structural sizing differences; culvert diameters differed by 14%, spillway crest lengths by 41%, bridge waterway spans by 36%, and detention basin volumes by 59% under SSP5-8.5 Q_{100}. The study concludes that the HEC-HMS_XGBoost hybrid model provides more reliable, physically plausible, and climate-resilient design discharges than standalone HEC-HMS, and recommends its adoption as the primary basis for flood control structure design in data-scarce tropical mountainous catchments. The standalone HEC-HMS projections under SSP5-8.5 are best reserved as upper-bound safety checks.

DECLARATION

I **CANWAT EMMANUEL** hereby solemnly declare to the best of my knowledge that this final year project report is entirely out of my efforts and original work. It was witten by me and has not been submitted to any other university or institution for the award of any degree or academic qualification by any individual.

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APPROVAL

This final year project report, submitted to the Department of Water Resources Engineering, has been carried out as partial fulfillment to the award of Bachelor of Science in Water Resources Engineering, being approved by **MR. MUYINGO EMMANUEL**, my project supervisor

Signature .... Date 12/06/2026

DEDICATION

I would like to dedicate this research project to my beloved parents, Mr. and Mrs. Labok, whose love, guidance, and unwavering support have been my greatest source of strength and inspiration throughout my academic journey.

I also dedicate this work to all my lecturers, classmates, and friends who have constantly encouraged me and contributed in one way or another to the successful completion of this research project.

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LIST OF ACRONYMS

CMIP6	Coupled Model Intercomparison Project Phase 6
CN	Curve Number
CORDEX	Coordinated Regional Downscaling Experiment
DEM	Digital Elevation Model
FAO	Food and Agriculture Organization
GCM	Global Climate Model
GEV	Generalized Extreme Value
GIS	Geographic Information System
HBV	Hydrologiska Byråns Vattenbalansavdelning (Hydrologic Bureau Water Balance Model)
HEC-HMS	Hydrologic Engineering Center - Hydrologic Modeling System
HEC-GeoHMS	Hydrologic Engineering Center - Geospatial Hydrologic Modeling System
IPCC	Intergovernmental Panel on Climate Change
KGE	Kling-Gupta Efficiency
LULC	Land Use Land Cover
ML	Machine Learning
MWE	Ministry of Water and Environment
NEMA	National Environment Management Authority
NFA	National Forestry Authority
NSE	Nash–Sutcliffe Efficiency
PBias	Percent Bias
QGIS	Quantum Geographic Information System
R^2	Coefficient of Determination

RCM	Regional Climate Model
RMSE	Root Mean Square Error
SDG	Sustainable Development Goal
SCS	Soil Conservation Service
SRTM	Shuttle Radar Topography Mission
SSP	Shared Socioeconomic Pathway
UNDRR	United Nations Office for Disaster Risk Reduction
UNMA	Uganda National Meteorological Authority
USACE	United States Army Corps of Engineers
USGS	United States Geological Survey
WEIS	Water and Environment Information System
XGBoost	Extreme Gradient Boosting

CHAPTER ONE: INTRODUCTION

1.1 Background

Accurate streamflow simulation under climate change scenarios is paramount for effective water resource management and the robust design of flood control structures globally(Bhusal et al., 2022). The challenge of simulating future streamflow is amplified by the uncertainty associated with climate change, which projects increases in rainfall variability and frequency of extreme events worldwide((IPCC, 2023). Recent global studies involving traditional HEC-HMS faces critical limitation due to its reliance on calibrated physical parameters and its occasional inability to precisely capture the complex, non-linear dynamics of high-flow events(Try & Qin, 2024). Climate change has intensified hydrological extremes, leading to an increase in both the frequency and magnitude of floods accounting for 40% of all natural disasters reported in various parts of the world (UNDRR, 2022). Floods have been reported to cause structural failure or overtopping, catastrophic damage, displacement, hindered agricultural practices and loss of lives and properties in downstream communities (Bai et al., 2019).

To overcome these challenges, conventional hydrological models such as the Hydrologic Engineering Center Hydrologic Modeling System (HEC-HMS) with machine learning algorithms, such as HEC-HMS_XGBoost, are increasingly being explored to enhance prediction accuracy and reliability(Yu & Zhang, 2023).

In Africa, the impacts of climate change on hydrological processes are particularly severe due to high exposure and low adaptive capacity. Many catchments across Sub-Saharan Africa have experienced intensified rainfall variability and extreme events, resulting in flash floods, soil erosion, and infrastructure damage (Ayalew et al., 2021). Flood modeling and forecasting remain limited by data scarcity, poor calibration, and lack of integration of modern computational tools (Adeniyi & Adeniyi, 2020).

Hybrid modeling frameworks that couple physical models like HEC-HMS with data-driven algorithms such as XGBoost can provide better simulation of runoff processes in data-limited basins (Omondi et al., 2023). Such advancements can support evidence-based planning and design of flood control infrastructure, crucial for sustainable development and climate resilience in African river basins.

East Africa has experienced increasing hydrological extremes in recent decades, including flash floods in Kenya, Uganda, and Ethiopia. Regional climate projections indicate a likely increase in rainfall intensity and variability under future climate change scenarios (IPCC, 2023). Hydrological modeling studies in the region have used tools like HEC-HMS, SWAT, and HBV for flood prediction; however, these models often struggle to represent non-stationary climate-driven processes accurately(Shekar & Vinay, 2021).

Recent studies in Kenya's Nzoia and Nyando catchments demonstrated that hybrid models incorporating machine learning algorithms outperformed traditional models in simulating streamflow under climate change scenarios(Olaka et al., 2019). Studies using HEC-HMS in Uganda, such as those on the Manafwa and Awoja catchments, have provided valuable insights into rainfall–runoff relationships and flood risks (Mugalu & Turyashemererwa, 2022). However, these studies often show performance limitations, especially under non-stationary climate conditions, because HEC-HMS alone may not adequately represent nonlinear hydrological responses(Zarei et al., 2025).

Integrating HEC-HMS outputs with machine learning models like XGBoost will improve predictive accuracy, support the design of more resilient flood control structures, and enhance disaster preparedness in the region.

The River Sipi catchment, located on the slopes of Mt. Elgon in eastern Uganda, is characterized by high rainfall variability, steep terrain, and rapid runoff response. The area has suffered recurrent flooding that affects farmlands, road networks, and settlements in Kapchorwa and downstream districts (NEMA, 2022). Despite this, limited hydrological studies have been conducted to evaluate streamflow patterns under projected climate scenarios.

Existing flood control structures and drainage systems are often designed based on outdated or incomplete hydrological data. Hence, the comparative assessment between HEC-HMS and the HEC-HMS_XGBoost hybrid model will provide vital insights into how future climate-induced changes in streamflow will influence the design and safety of such structures.

The findings of this study will provide a robust, data-informed foundation for flood control structure design in the Sipi River catchment (Luwa et al., 2021a)and address the gap in comparative model performance for hybrid models in data-scarce African mountainous catchments, offering decision-makers a scientifically superior tool for quantifying flood risk and ensuring the resilience and long-term sustainability of critical infrastructure in the face of an uncertain climate future (Sempewo et al., 2023).

1.2 Problem statement.

The accurate simulation of streamflow under climate change is critical for effective water resources management, secure and cost-effective design of flood control structures and sustainable development. The physically-based HEC-HMS model usually exhibits significant limitations in accurately capturing the non-linear, complex dynamics of high flow peaks in regions like the River Sipi catchment, Eastern Uganda, characterized by mountainous terrain with insufficient continuous hydro-meteorological data (Sempewo et al., 2023) and having a documented increasing trend in river flow and extreme wet events (Luwa et al., 2021a). The magnitude of future design floods derived from traditional HEC-HMS under climate change may threaten community safety, economic stability, and agricultural productivity, and expose existing infrastructures to devastating failure thus hindering the ability of water managers to select appropriate models for robust infrastructure design, flood mitigation, and climate adaptation strategies.

1.3 Purpose of the study

The purpose of this study was to comparatively evaluate the impacts of using the HEC-HMS model and the HEC-HMS_XGBoost hybrid model in simulating streamflow under climate change scenarios and to determine how these differences influence the design parameters of flood control structures in the Sipi River catchment.

1.4 Justification

Uganda is increasingly experiencing extreme hydrological events such as floods and prolonged droughts, mainly attributed to climate variability and land use changes(NEMA, 2022). In the Mt.

Elgon region, where the Sipi River catchment is located, frequent flooding has led to loss of life, destruction of infrastructure, and damage to agricultural land (Feyereisl G., 2020). The design and operation of flood control structures such as culverts, spillways, and detention basins rely heavily on accurate streamflow estimates under both current and future climatic conditions.

Conventional hydrological models like HEC-HMS are widely applied for streamflow simulation and flood forecasting. However, their performance is often constrained by parameter uncertainty, data scarcity, and inability to capture complex nonlinear processes under changing climate scenarios(Savino et al., 2023a). The integration of machine learning algorithms such as Extreme Gradient Boosting (XGBoost) with physical models has shown great promise in enhancing prediction accuracy(Yu & Zhang, 2023). Despite this, such hybrid modeling approaches remain underexplored in Uganda.

Therefore, this study provides a comparative assessment between traditional and hybrid hydrological modeling approaches under projected climate change scenarios. The results will inform the design and resilience of flood control structures, contribute to evidence-based water resources management

1.5 Objectives of the study.

General objective

To assess and compare the performance of the HEC-HMS and HEC-HMS_XGBoost models in simulating streamflow under climate change scenarios for improved flood control structure design in the Sipi River catchment.

Specific objectives

i. To develop and calibrate the HEC-HMS and HEC-HMS_XGBoost models using observed streamflow data from the Sipi River catchment.

ii. To simulate and analyze future streamflow under selected SSP climate change scenarios using both models.

iii. To compare the performance and implications of the two models on key flood control design parameters, such as design discharge and return periods.

1.6 Research Questions

How can the HEC-HMS and HEC-HMS_XGBoost hybrid models be developed and calibrated using observed hydrological data for the Sipi River catchment?

What are the projected streamflow variations in the Sipi River catchment under selected SSP climate change scenarios when simulated using HEC-HMS and HEC-HMS_XGBoost models?

How do the performance differences between the HEC-HMS and HEC-HMS_XGBoost models influence flood control structure design parameters under future climate conditions?

1.7 Significance of the study

This research addresses SDG11 by providing early warning information to communities for timely flood preparedness and evacuation, supporting the design of more effective flood control structures e.g., dikes, culverts, retention basins to protect farmlands and livelihoods, reducing loss of lives and property and directly enhancing community resilience and safety and by making settlements safer and more resilient to floods and contributes to Uganda Vision 2040's goal of ensuring disaster-resilient communities and sustainable human settlements. Government agencies responsible for water resources, environment, and disaster management like NEMA and MWE benefits from this study by having an access to more reliable hydrological data and models for planning, designing, and managing flood control projects. The research will also address SDG 13 (Climate Action) through enhanced climate resilience and adaptive capacity and contributes to Uganda Vision 2040's pillar on harnessing the environment and natural resources for sustainable development and building resilient infrastructure.

1.8 Scope of the Study.

1.8.1 Conceptual scope

The research focused on the comparative assessment of two hydrological modeling approaches the HEC-HMS model, a physically based hydrological model and the HEC-HMS_XGBoost hybrid model, a data driven machine learning enhanced approach to simulate streamflow responses of the Sipi River catchment under current and projected climate change scenarios

SSP2-4.5 and SSP5-8.5. The research evaluated the performance and accuracy of both models using statistical indicators such as the Nash Sutcliffe Efficiency (NSE), Root Mean Square Error (RMSE), and Coefficient of Determination (R^2) and analyzed how differences in simulated streamflow affect design discharges and return periods relevant for flood control structure design. The research was limited to only hydrological analysis and model comparison provides information that can guide flood control structure design and planning.

1.8.2 Geographical scope

The research was conducted in the Sipi River catchment, located approximately 918 km^2 within Sironko on the slopes of Mt. Elgon, Eastern Uganda. The catchment is characterized by steep terrain, high rainfall (~1800 mm/year), and recurrent flooding that affects the downstream communities of Kapchorwa and Bulambuli districts (Luwa et al., 2021b).

1.8.3 Time Scope

The research was conducted within a period of four months.

1.9 Conceptual Framework

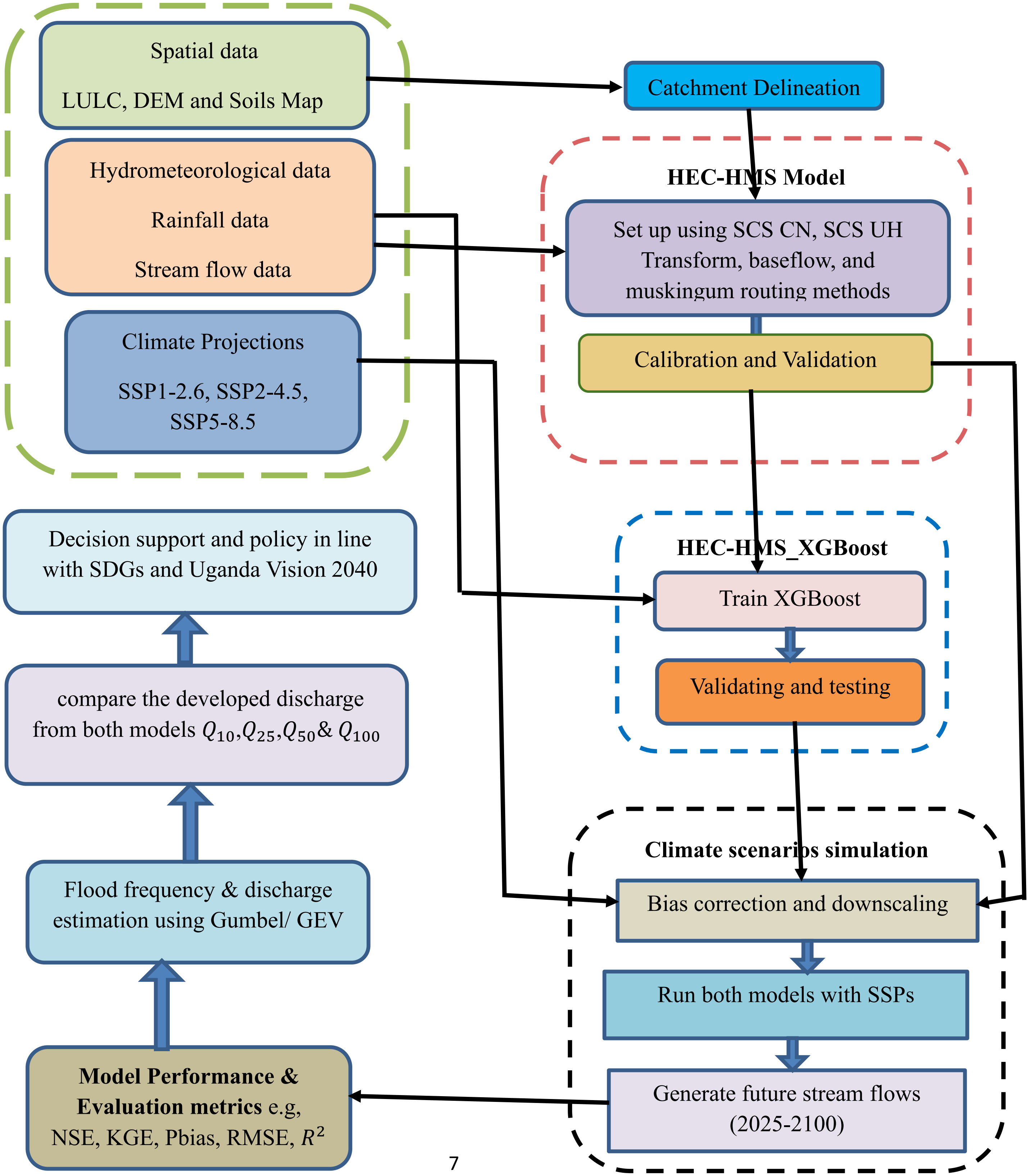


Figure 1: Showing the conceptual framework for all the phases of the research

CHAPTER TWO: LITERATURE REVIEW.

Introduction

Flood management and hydrological design depend fundamentally on accurate streamflow simulation under both current and future climatic conditions. Traditional physically based models such as the Hydrologic Engineering Center – Hydrologic Modeling System (HEC-HMS) have been widely adopted because they represent the rainfall–runoff transformation through process-based equations (USACE, 2021). However, their predictive accuracy is constrained by uncertainties in parameter estimation, simplifying assumptions about catchment processes, and limited data resolution (Ampas & Refanidis, 2025a).

Recently, hybrid modeling frameworks that combine physically based models with machine learning (ML) approaches have emerged to overcome these limitations. One promising approach integrates HEC-HMS with Extreme Gradient Boosting (XGBoost)—a powerful tree-based algorithm capable of learning nonlinear relationships and correcting residual errors from deterministic models (Szczepanek, 2022). Such HEC-HMS_XGBoost hybrid models have shown improved predictive accuracy in flow simulation, bias correction, and peak flow estimation (Ampas & Refanidis, 2025a).

Furthermore, the increasing influence of climate change on hydrological regimes under Shared Socioeconomic Pathways (SSPs) necessitates advanced modeling frameworks that can simulate future streamflow more reliably (Kartal, 2024a). These projections directly inform design discharge and return period estimates critical for the sizing and resilience of flood-control structures such as culverts, spillways, and retention dams.

2.1 Development and Calibration of HEC-HMS and HEC-HMS_XGBoost Hybrid Models

HEC-HMS development and calibration

HEC-HMS has been widely applied for rainfall runoff modeling across different catchments due to its modular structure and flexibility. (Herbei et al., 2024) demonstrated that accurate calibration using multi-objective optimization techniques (NSE, RMSE, KGE) improves its predictive performance. The model captures hydrological processes through components like infiltration SCS, Green-Ampt, baseflow (recession), and routing (Muskingum).

In East Africa,(Luwa et al., 2021) applied HEC-HMS to the Sipi sub-catchment and observed strong seasonal variation in flow due to orographic rainfall. Their calibration revealed sensitivity of the model to precipitation data quality and loss method selection.

However, limitations persist for example, parameter calibration is often non-unique (equifinality), leading to multiple parameters sets producing similar results (Beven, 2020), the model struggles with nonlinear interactions and anthropogenic influences not captured by its equations and also manual calibration is time-consuming and subjective.

Incorporating XGBoost to form a hybrid model

Machine learning, and particularly XGBoost, has been employed to enhance physical models through bias correction or residual modeling. (Szczepanek, 2022) demonstrated that XGBoost effectively learns nonlinear dependencies between meteorological inputs and discharge, outperforming linear regressions and neural networks in mountainous basins.

(Ampas & Refanidis, 2025) developed a hybrid model combining HEC-HMS with a weather-informed transformer-based ML model, achieving a greater than 20 % improvement in Nash–Sutcliffe efficiency (NSE) compared to stand-alone HEC-HMS. Similarly, (Riche et al., 2024) showed that gradient-boosting algorithms capture complex hydrological dynamics in flood-susceptibility mapping better than deterministic models.

The hybridization follows two strategies i.e residual learning where HEC-HMS outputs are used as inputs for XGBoost to model the residuals between observed and simulated flows and feature-enhanced learning in which XGBoost takes both HEC-HMS outputs and climatic predictors to refine streamflow estimation(Odey & Cho, 2025).

While hybrid models improve accuracy, challenges remain. Machine Learning requires large, high-quality datasets, often unavailable in small basins like Sipi River catchment. Overfitting and limited physical interpretability can reduce trust in extrapolations. Few studies quantify uncertainty propagation between physical and ML components.

2.2 Simulation and Analysis of Future Streamflow under Selected SSP Climate Scenarios

Climate-driven hydrological simulations

Future streamflow simulations rely on climate projections from CMIP6 Global Climate Models (GCMs) under SSP2–4.5 and SSP5–8.5 scenarios. These scenarios represent varying greenhouse-gas pathways influencing precipitation and temperature.

(Kartal, 2024a) used ML-based hydrological modeling to project future streamflow under CMIP6 scenarios, finding significant seasonal redistribution of runoff. (Jalowska et al., 2025) analyzed the impact of extreme rainfall changes on river discharge and flood extent using design rainfall approaches. Furthermore, studies emphasize that while ML-based models excel in pattern recognition, they can struggle to generalize under changing climate regimes if not retrained or adapted to projected conditions (Riche et al., 2024).

Despite the advancements in hybrid and climate-driven modeling, data scarcity and quality issues in developing regions hinder robust calibration and validation (Luwa et al., 2021). Bias and uncertainty in GCM projections, especially in mountainous regions, can distort future streamflow simulations (Abbas, 2023). Model transferability challenges in which ML components trained on present-day relationships may not generalize under future climate states (Riche et al., 2024). Limited uncertainty quantification where few studies explicitly propagate climate, model, and parameter uncertainties through to streamflow outcomes

2.3 Comparing Model Performance and Implications on Flood-Control Design Parameters

Comparative performance assessment

Comparative studies have shown that while physically based models (e.g., HEC-HMS, SWAT) provide robust physical interpretation, ML-based and hybrid approaches achieve higher predictive skill. (Szczepanek, 2022) and (Ampas & Refanidis, 2025) both reported improved peak flow predictions and lower RMSE values using hybrid models.

However, design discharges and return periods essential for engineering design—depend on accurate simulation of extremes. (Jalowska et al., 2025) emphasized that small differences in estimated peak flows can alter spillway sizing and freeboard requirements.

Metrics & evaluation

Comparisons typically use NSE, KGE, RMSE, bias, peak timing error, peak flow error but for engineering applications, the crucial comparison is how estimated design quantiles e.g., Q50, Q100 differ between modelling approaches and how those differences translate to elevation of freeboard, spillway sizing or culvert capacity. Several recent studies translate hydrological projection differences into design-level impacts e.g., changes in required spillway capacity

Comparative implications for design discharge and return periods

Accurate peak estimation is critical in deriving design discharges for hydraulic structures. (Jalowska et al., 2025) emphasized that mis-estimated design rainfall or runoff leads to under- or over-designed structures, affecting cost efficiency and safety. HEC-HMS allows synthetic extreme-event simulation through design storms, offering physically interpretable hydrographs suitable for frequency analysis. Yet, when forced by bias-corrected GCM data, its deterministic structure may fail to capture nonlinear catchment responses to extreme rainfall (Kartal, 2024b).

Hybrid models provide statistical flexibility by learning from historical residuals, thereby improving peak flow magnitude estimation. However, their dependence on the quality and range of training data poses reliability risks when extrapolating to unseen extreme or future climate conditions. Several authors caution that hybrid ML corrections may improve average flows but not necessarily extreme quantiles (Kartal, 2024b; Szczepanek, 2022).

In design practice, return periods are estimated by fitting probability distributions such as Gumbel or Log-Pearson III to simulated annual maximum series. Comparative analyses reveal that hybrid models generally produce narrower confidence intervals for Q_{10} to Q_{100} flows than purely physical models due to reduced residual variance (Ampas & Refanidis, 2025a).

Despite improvements, several limitations remain such as limited extreme-event representation in training data for ML components (Kartal, 2024a), transferability issues ML residual corrections may not hold under future non-stationary climates (Riche et al., 2024), sparse validation of hybrid models in tropical, data-poor catchments such as Mt. Elgon, where hydrological response is strongly nonlinear , insufficient integration of hydrological uncertainty into design decision-making most studies stop at statistical comparison rather than translating differences into structural sizing or risk metrics.

2.4 Research Gaps

While HEC-HMS has been successfully calibrated in regions such as Asia and Europe (Naresh & Naik, 2023), very few studies have applied the HEC-HMS_XGBoost hybrid framework in East African highland basins where steep topography and land-use variability strongly influence hydrological responses. Existing calibration practices often assume static parameter relationships, yet in tropical environments, rapid land-cover change, soil degradation, and rainfall variability make parameter transferability uncertain (Beven, 2020). Sparse meteorological and streamflow records in catchments like Sipi limit model calibration and validation accuracy, hindering the optimization of both physical and ML-based components (Luwa et al., 2021). There is no standardized method to integrate residual-correction algorithms like XGBoost directly into the HEC-HMS calibration process, resulting in fragmented workflows and inconsistent model coupling approaches (Ampas & Refanidis, 2025b).

Although CMIP6 provides improved resolution and scenario diversity, most studies still rely solely on HEC-HMS without ML enhancement to simulate streamflow under SSPs (Chin & Lai, 2025). Few studies explicitly quantify how uncertainties from GCM selection, downscaling, and bias correction propagate through hybrid models to affect streamflow projections (Savino et al., 2023b).

Existing studies seldom compare HEC-HMS and hybrid HEC-HMS_XGBoost outputs using identical SSP scenarios to quantify their relative influence on design discharge and return period estimation.(Ampas & Refanidis, 2025) Flood design methods in Uganda and similar regions still rely on stationary hydrological statistics, ignoring future variability in extreme rainfall and runoff under SSP5–8.5 (Luwa et al., 2021).

CHAPTER THREE: METHODOLOGY

Introduction

This chapter presents the methodology adopted to achieve the study objectives. It describes the study area, data sources and requirements, model development and calibration procedures, climate change scenario integration, hybrid model construction, evaluation criteria, and the comparative assessment framework for flood control design. The methodology ensures that the results are reproducible, scientifically rigorous, and suitable for the hydrological characteristics of the Sipi River Catchment in Eastern Uganda.

3.1 To Develop and Calibrate the HEC-HMS and HEC-HMS_XGBoost Hybrid Models Using Observed Streamflow Data.

3.1.1 Data acquisition and processing

Description of the Study Area

The Sipi River Catchment lies at latitude 1.382278˚N and longitude 34.314444˚E approximately 918 km² within Sironko on the northern slopes of Mt. Elgon in Eastern Uganda, covering parts of Kapchorwa, Bulambuli, and Sironko Districts. The catchment is characterized by steep slopes, high rainfall variability of 1,200 mm to 2,000 mm annually, and frequent flash floods, particularly during the March–May and August–November seasons (Luwa et al., 2021a).

The Sipi River drains into the larger Lake Kyoga Basin, forming an important tributary influencing downstream water levels and flood risks. The area’s dominant land uses include agriculture and forest cover on upper slopes, with settlements concentrated near valley bottoms, making flood risk reduction critical.

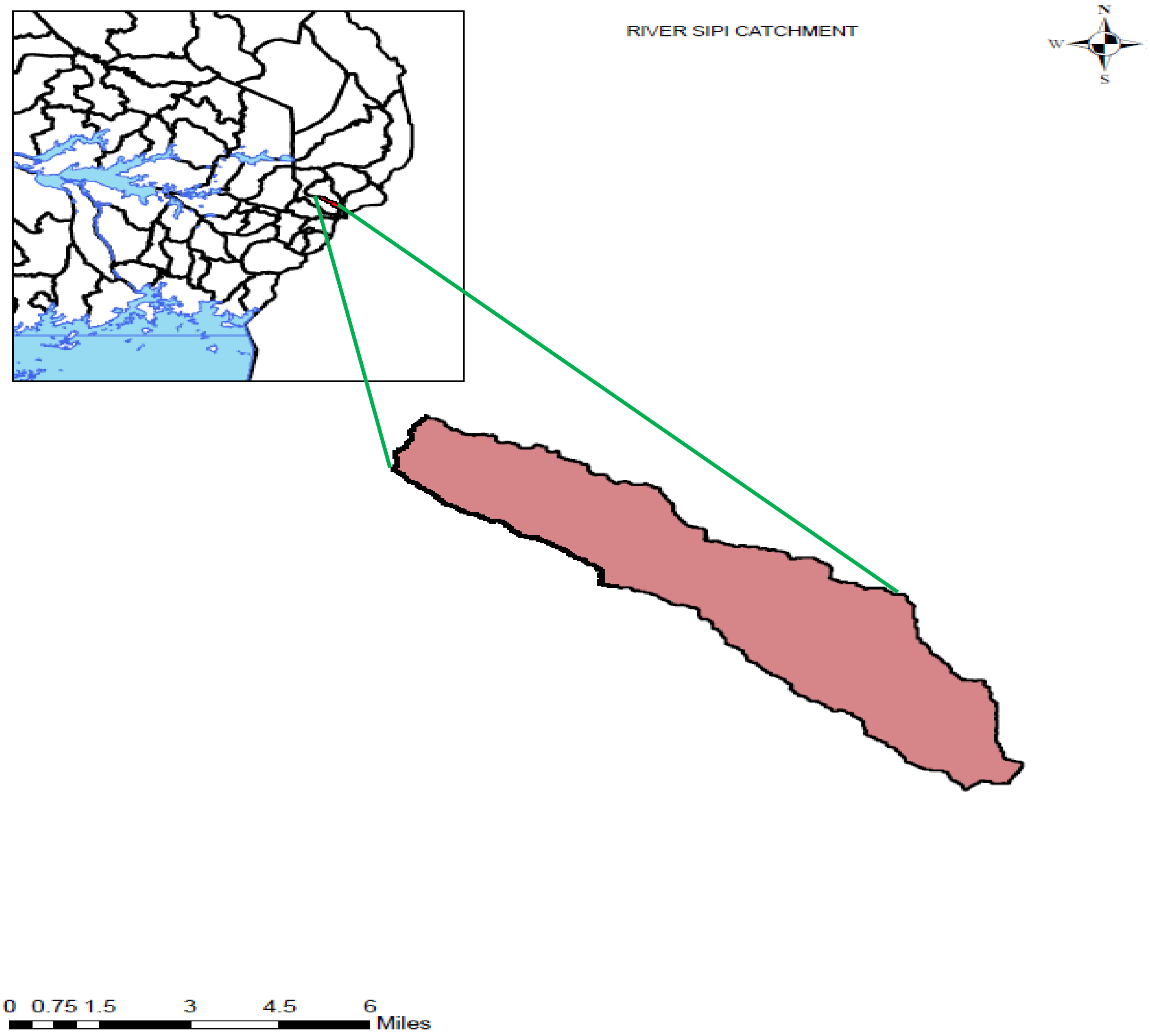


Figure 2: Showing the map of River Sipi catchment.

Research Design

A comparative quantitative modeling design was employed. The approach integrated hydrological simulation using HEC-HMS with machine learning enhancement XGBoost under various Shared Socioeconomic Pathway (SSP) climate change scenarios. The research followed five key phases: data acquisition and preprocessing, model development and calibration, Climate scenario simulation, model evaluation and comparison, and design implications for flood control structures.

Data collection

Data Sources and Description

Table 1: Showing the data type, data sources for and their purposes

S/No	Data type	Data source	Purpose
1	Stream flow data (2010- 2024)	Ministry of Water and Environment (MWE) https://weis.mwe.go.ug/	Model calibration and validation
2	Rainfall, temperature data (2010- 2024)	Uganda National Meteorological Authority (UNMA) https://meteo.mwe.go.ug/	Climate input and hydrological modelling
3	Uganda DEM (30m× 30m resolution)	USGS Earth Explorer (SRTM) https://earthexplorer.usgs.gov/	Catchment delineation
4	LULC (2020 ESA Cover)	National Forestry Authority (NFA)	Estimation of curve numbers and surface parameters

		https://www.nfa.go.ug/	
5	Soil data	FAO/UNESCO soil map of the world https://www.fao.org/soils-portal/data-hub/soil-maps-and-databases/faounesco-soil-map-of-the-world/en/	To obtain parameters for infiltration and inform curve number.
6	Projected climate data (SSP2-4.5 and SSP5-8.5) (Near Future 2025-2055)	Coupled Model Intercomparison Project Phase 6 (CMIP6), downscaled by CORDEX-Africa https://cordex.org/data-access/cordex-cmip6-data/	Future climate scenario simulation

The development of the models required high-quality datasets representing the physical and hydro-meteorological characteristics of the Sipi River Catchment. The following datasets were collected.

Hydro-meteorological data
Daily rainfall, temperature (maximum and minimum), and streamflow for 15 years were obtained from the Uganda National Meteorological Authority (UNMA) and the Ministry of Water and Environment (MWE).

Spatial data
Digital Elevation Model (DEM) (30 m resolution, SRTM), land use land cover (LULC) maps from the National Forest Authority (NFA), and soil maps from FAO/UNESCO databases.

Data preprocessing included quality control, gap filling, spatial interpolation, and consistency checks. The DEM will be used for catchment delineation and stream network generation within the HEC-HMS environment, while soil and LULC data informed the curve number (CN) and infiltration parameters(Bajracharya et al., 2023).

3.1.2 Model Setup and Calibration (HEC-HMS)

The HEC-HMS model was set up within the delineated Sipi catchment using the following components.

Loss method (Soil Moisture Accounting Method)

The Soil Moisture Accounting (SMA) method was employed in this research because it is highly suitable for continuous long-term hydrological simulations, particularly where the objective is to represent watershed water balance processes over extended periods. The method is flexible and physically based, allowing simulation of infiltration, soil water storage, percolation, evapotranspiration losses, and groundwater recharge, thereby providing more realistic runoff estimates for long-term streamflow modelling in the River Sipi catchment. The SMA method requires parameters that describe the movement and storage of water within different watershed compartments, including canopy storage, surface depression storage, soil profile storage, tension zone storage, and groundwater reservoirs.

The general water balance principle governing the SMA method can be expressed as;

$P = Q + ET + \Delta S + G$ ………………………………………. Equation (1)

$P =$ precipitation input

$Q =$runoff generated

$ET =$ evapotranspiration loss

$\Delta S =$ change in soil moisture storage

$G =$ groundwater recharge or percolation

Transform method using SCS Unit Hydrograph

The Clark Unit Hydrograph method was used in this study to transform excess rainfall into direct runoff hydrographs. The Clark Unit Hydrograph method combines the effects of translation and attenuation of runoff as water moves through the catchment. It is particularly suitable for watershed-scale runoff modelling because it accounts for both travel time across the basin and storage effects within the drainage system.

The method required two parameters: the time of concentration, T_C and Storage Coefficient, R.

The time of concentration was estimated from the watershed's physical characteristics extracted from the Digital Elevation Model (DEM) and GIS analysis using;

$T_C = 2.2\left(\frac{L * L_C}{\sqrt{S}}\right)^{0.3}$………………………….. Equation (2)

Where;

$T_C =$ Time of concentration

$L =$ Longest flow path

$L_C =$ distance from the outlet to the centroid of the watershed.

$S =$ Watershed Slope.

The storage coefficient, which represents attenuation of the runoff hydrograph, was estimated using:

$R = \frac{13}{7} T_C$ …………………………………….. Equation (3)

Where;

$R =$ Storage coefficient

$T_C =$ Time of concentration

The Clark Unit Hydrograph method was selected because it provides a more realistic representation of runoff response in steep tropical mountainous catchments such as River Sipi catchment.

Baseflow method using Recession or Constant Monthly

The cell outflow hydrograph is then routed using a linear reservoir concept described using Equation (5).

$Q(t) = \Delta tR + 0.5\Delta tI(t) + [1 - \Delta tR + 0.5\Delta t]Q(t-1)$………… Equation (4)

where $Q(t)$ and $Q(t-1)$ are the outflows at current and previous time levels t and t-1, respectively; I(t) is the average inflow at time t; R is the storage coefficient used to represent discharge attenuation; and t is the time increment.

The base flow is computed using an exponential decrease function specified in Equation (6).

$Q = Q_O e - kt$ ………………………….Equation (5)

where Q_O is the averaged initial base flow before a storm and k is an exponential decay constant.

Routing method using Muskingum

The Muskingum routing method was implemented in this research because it is less complicated and requires fewer input data than other methods (Anaraki et al., 2023). The main objective of this method is to compute the runoff hydrography at the sub-basins outlet. It requires two input criteria: the attenuation flood wave (X) and the flood travel time (K) of the flood wave through routing reach(Van Kempen et al., 2021). Equation (7) was utilized to generate these values during the calibration process using observed hydrometeorological data.

$S = K[XI + (1-X)Q]$…………………………….Equation (6)

Calibration will be performed using historical streamflow data for a 70/30 split between calibration and validation periods. Optimization of parameters will be achieved using the HEC-HMS built-in Nash-Sutcliffe Efficiency (NSE) objective function, ensuring the model reproduces observed hydrographs accurately.

3.1.3 Development of the HEC-HMS_XGBoost Hybrid Model

The hybrid model integrates the physical structure of HEC-HMS with the predictive capability of Extreme Gradient Boosting (XGBoost). The process was as follows;

First run HEC-HMS to generate simulated discharge (Q_{HMS}).

Then compute the residuals.

$\varepsilon = Q_{obs} - Q_{HMS}$ ……………………… Equation (7)

Train XGBoost on input features e.g., rainfall, temperature, stream flow to model these residuals.

$\varepsilon = f_{XGB}\,(X)$ …………………………….. Equation (8)

Finally, I will generate the final hybrid prediction.

$Q_{Hybrid} = Q_{HMS} + f_{XGB}\,(X)$ ……………………… Equation (9)

The hybridization will aim to correct systematic biases and improve prediction accuracy. Both models will then be validated using independent datasets.

3.1.4 Model Performance Evaluation

Performance was evaluated using the following statistical indicators.

Nash-Sutcliffe Coefficient of Efficiency (NSE)

The Nash-Sutcliffe Coefficient of Efficiency (NSE) is a dimensionless type parameter. NSE ranges from -∞ to 1 and measures how well the simulated versus the observed data match as follows:

$NSE = 1 - [\frac{\sum_{i=1}^{n}(Q_{obs}-Q_{sim})^2}{\sum_{i=1}^{n}(Q_{obs}-Q_{mean})^2}]$ ………………………… Equation (10)

Where Q_{obs} and Q_{sim} are the observed and the simulated streamflow data, respectively. Q_{mean} is the mean value of observations from i = 1 to n.

Root Mean Square Error

The Root Mean Square Error (RMSE) is an error-index type parameter commonly used in hydrological modeling and it is a commonly used measure of the difference between the values predicted by the model and the values observed at the station (Haitham & Al-Mukhtar, 2022). The RMSE of a model prediction with respect to the estimated variable is defined as the square root of the mean squared error.

$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(Q_{obs} - Q_{sim})^2}$ …………….. Equation (11)

Coefficient of Determination (R^2)

The coefficient of Determination (R^2) is the square of the correlation (r) among observed and simulated values. R^2 ranges between 0 to 1. R^2 is presented, mathematically as;

$$R^2 = \left[\frac{\sum_{i=1}^{n}(Q_{obs}-Q_{obs\,ave})(Q_{sim}-Q_{sim\,ave})}{\sqrt{\sum_{i=1}^{n}(Q_{obs}-Q_{obs\,ave})^2\sum_{i=1}^{n}(Q_{sim}-Q_{sim\,ave})^2}}\right]^2 \text{ ……………………… Equation (12)}$$

Kling Gupta Efficiency (KGE)

$$KGE = 1-\sqrt{(r-1)^2+(\alpha-1)^2+(\beta-1)^2} \text{ ………………….. Equation (13)}$$

Percent Bias (PBias)

$$PBias = \frac{\sum_{i=1}^{n}(Q_{sim}-Q_{obs})}{\sum_{i=1}^{n}Q_{obs}} \times 100 \text{ ………………………………….. Equation (14)}$$

3.2 To Simulate and Analyze Future Streamflow under Selected SSP Climate Change Scenarios Using Both Models

3.2.1 Selection of Climate Models and Scenarios

Future climate projections were obtained from Coupled Model Intercomparison Project Phase 6 (CMIP6) Global Climate Models (GCMs) under three Shared Socioeconomic Pathways (SSPs); SSP1–2.6 (Low emissions), SSP2–4.5 (Intermediate) and SSP5–8.5 (High emissions) (Adib & Harun, 2022).

3.2.2 Downscaling and Bias Correction

Bias correction were applied to raw climate data using statistical techniques such as Quantile Mapping (QM) to align the GCM/RCM outputs with observed records. This ensures realistic rainfall and temperature projections for hydrological modeling (Neill et al., 2018).

3.2.3 Streamflow Simulation

Each scenario's rainfall and temperature projections was input into both the calibrated HEC-HMS and HEC-HMS_XGBoost models to simulate streamflow over future periods (e.g., 2025–2050, 2051–2080, and 2081–2100).

Outputs will include daily and monthly streamflow series, peak flow events, and long-term flow trends (Adib et al., 2022).

3.2.4 Uncertainty Analysis

Model uncertainty was assessed by comparing outputs from multiple GCMs and models. Ensemble mean and standard deviation will quantify the range of potential future flow conditions.

3.3 To Compare the Performance and Implications of the Two Models on Flood Control Design Parameters

3.3.1 Flood Frequency Analysis

Annual maximum streamflow values from each model (historical and future periods) was extracted to fit Extreme Value Distributions such as; Gumbel distribution and Generalized Extreme Value (GEV) distribution (Mishra et al., 2017).

3.3.2Design Discharge Estimation

Design discharges corresponding to standard return periods (10, 25, 50, and 100 years) were computed using;

$Q_T = \mu + k_T\sigma$ ………………………. Equation (15)

Where Q_T = design discharge for return period T, μ = mean of annual maxima, σ = standard deviation, and k_T = frequency factor.

3.3.3 Flood Control Structure Sizing Using Derived Design Discharges

The design discharges derived were applied to standard hydraulic engineering equations to size four representative flood control structures relevant to the Sipi River catchment: culverts, spillways, bridge waterway openings, and detention basins. For each structure type, the hybrid model's Q values were used as the primary design basis, while the standalone HEC-HMS SSP5-8.5 values were applied as the upper-bound safety check. All sizing computations assume concrete construction with Manning's roughness coefficient n = 0.013 and catchment slope derived from the 30 m SRTM DEM.

3.3.3.1 Culvert Sizing

The required culvert diameter was determined using Manning's equation for full-pipe circular flow:

$Q = \left({}^{1}/_{n}\right) \times A \times R^{23} \times S^{1/2}$ ……………………. Equation (16)

For a circular section: $A = {\pi D^2}/{4}$, $R = \frac{D}{2}$

Therefore, $D = (Qn/(0.3117 \times S^{1/2}))^{35}$ ……………. Equation (17)

Where D is the culvert internal diameter (m), Q is the design discharge (m^3/s), $n = 0.013$ for concrete, and $S = 0.015$ (1.5%) representing the average longitudinal slope of drainage channels in the Sipi catchment extracted from the DEM.

3.3.3.2 Spillway Crest Length Sizing

Spillways are critical flood-release structures for detention dams and retention basins along the Sipi River. The required spillway crest length was determined using the broad-crested weir spillway equation:

$Q = C \times L \times H^{32}$ …………………………. Equation (18)

Rearranging: $L = \frac{Q}{(C \times H^{32})}$ …………………. Equation (19)

Where L is the spillway crest length (m), $C = 1.80$ is the discharge coefficient for an ogee spillway, $H = 1.50$ m is the design head above the spillway crest (determined from the assumed reservoir freeboard and dam geometry), and Q is the design discharge (m^3/s).

3.3.3.3 Bridge Waterway Opening

Bridge structures crossing the Sipi River and its tributaries require adequate waterway openings to pass design floods without overtopping or causing unacceptable backwater. The minimum waterway area was computed from the continuity equation:

$A = {Q}/{V}$ …………… Equation (20)

Where A is the required waterway cross-sectional area (m^2), Q is the design discharge (m^3/s) taken at Q50 appropriate for road bridges per standard practice, and $V = 2.50$ m/s is the allowable mean flow velocity beneath the bridge (selected to limit scour in the weathered granite and volcanic soils of the Mt. Elgon foothills). The bridge span was then derived assuming a flow depth of 2.0 m, giving: Span = A / depth.

3.3.3.4 Detention Basin Storage Volume

Detention basins provide temporary flood storage to reduce peak discharges downstream. The required storage volume was estimated using the simplified storage-indication method based on the design inflow hydrograph and a fixed maximum allowable outflow through the outlet structure:

$S = \Delta t \times (Q_{peak} - Q_{out})$ …………… Equation (21)

Where S is the required storage volume (m^3), Δt is the duration of the flood peak above the allowable outflows, $Qpeak$ is the peak design discharge from Table 8, and $Qout = 5.0$ m^3/s is the design outlet discharge set to represent the pre-development bankfull capacity of the lower Sipi channel. The flood peak duration was estimated at $\Delta t = 1{,}800$ s (30 minutes) based on the time of concentration of 1,000 hours identified during HEC-HMS calibration and the steep flashy hydrograph response observed in the catchment. The required basin footprint was then estimated assuming an average depth of 3.0 m: Footprint area = S / depth.

Comparison and Implications

The derived design discharges from HEC-HMS and HEC-HMS_XGBoost were compared to assess; variability in estimated flood magnitudes, sensitivity of design parameters to climate scenarios and reliability of each model for structural flood design

Results will be used to inform flood control infrastructure planning, reservoir design, and climate adaptation strategies in the catchment by enabling the flood control structures to be selected and sized based on a more accurate projected future peak flow from one of the models and help reduce under estimation of flood magnitude, lowering the risk of structural failure.

CHAPTER FOUR: RESULTS AND DISCUSSIONS.

This chapter presents the findings obtained from the calibration and validation of the HEC-HMS and HEC-HMS_XGBoost hybrid models, the projected future streamflow under selected climate change scenarios, and the engineering implications of the results on flood control structure design in the Sipi River catchment.

The models were evaluated using NSE, RSR, PBias, and R^2 To guide the interpretation of model performance, the table below summarizes rating categories for NSE, RSR and R^2.

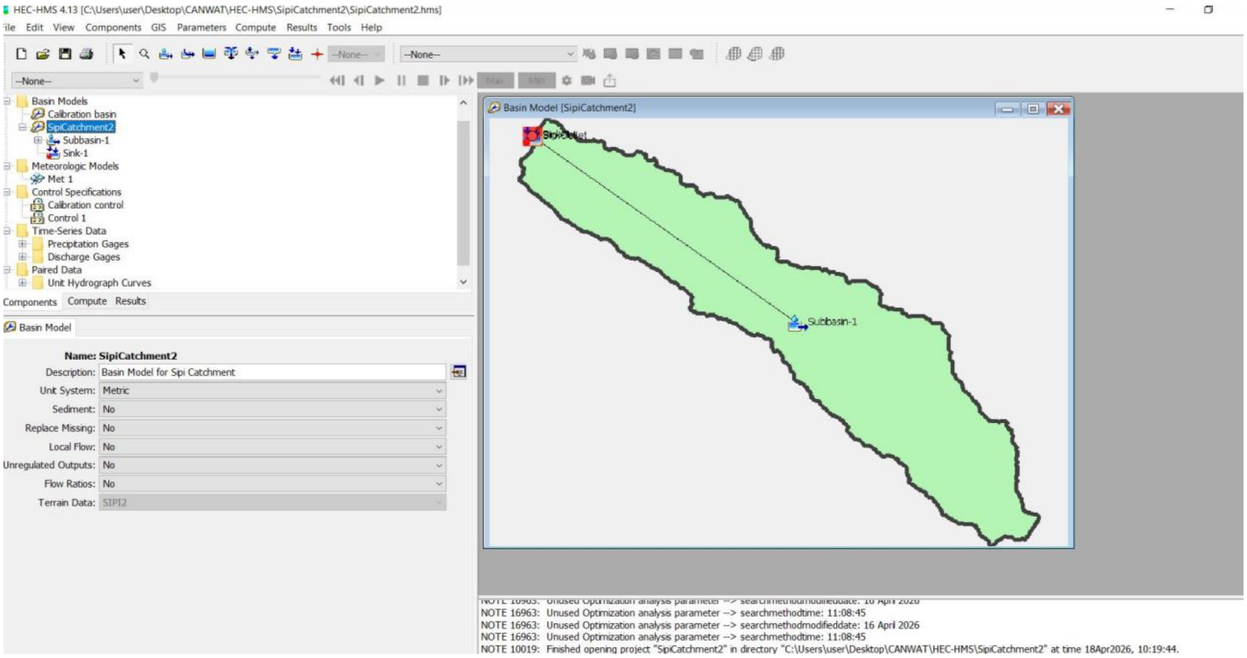
Table 2: Summary of metrics rating Categories

Performance Rating	$\boldsymbol{R^2}$	**NSE**	**RSR**	**PBias**
Very Good	$0.85 < R^2 \leq 1.00$	$0.80 < NSE \leq 1.00$	$0.00 < RSR \leq 0.50$	$PBias < \pm 5$
Good	$0.75 < R^2 \leq 0.85$	$0.70 < NSE \leq 0.80$	$0.50 < RSR \leq 0.60$	$\pm 5 < PBias \leq \pm 10$
Satisfactory	$0.60 < R^2 \leq 0.75$	$0.50 < NSE \leq 0.70$	$0.60 < RSR \leq 0.70$	$\pm 10 < PBias \leq \pm 15$
Unsatisfactory	$R^2 \leq 0.60$	$NSE \leq 0.50$	$RSR > 0.70$	$PBias \geq \pm 15$

4.1 To Develop and Calibrate the HEC-HMS and HEC-HMS_XGBoost Hybrid Models Using Observed Streamflow Data

4.1.1 Catchment Delineation and Parameterization

The Sipi River Catchment was accurately delineated into a sub-basin using the Sipi SRTM 30m DEM in the HEC-HMS 4.13 interface, with hydrological parameters such as curve numbers (CN), time of concentration, and basin lag time clearly defined.



Name: SipiCatchment2
Description: Basin Model for Sipi Catchment
Unit System: Metric
Sediment: No
Replace Missing: No
Local Flow: No
Unregulated Outputs: No
Flow Ratios: No
Terrain Data: SIPI2

```
NOTE 16963:  Unused Optimization analysis parameter --> searchmethodtime: 11:08:45
NOTE 16963:  Unused Optimization analysis parameter --> searchmethodmodifieddate: 16 April 2026
NOTE 16963:  Unused Optimization analysis parameter --> searchmethodtime: 11:08:45
NOTE 10019:  Finished opening project "SipiCatchment2" in directory "C:\Users\user\Desktop\CANWAT\HEC-HMS\SipiCatchment2" at time 18Apr2026, 10:19:44.
```

Figure 3: Delineated River Sipi Catchment.

4.1.2 Model Calibration and Validation Performance

The models were calibrated from 2010-2014 and validate from 2015-2020. The optimized parameters of the HEC-HMS models for the catchment are shown in the table below.

Table 3: Calibrated parameters.

Parameter	Optimized value
Loss Method: Soil Moisture Accounting	
Maximum infiltration (mm/hr.)	100
GW2 Storage(mm)	140
Soil percolation(mm/hr)	100
Soil storage(mm)	100
GW1 Storage	120
Tension storage	100

Simple Canopy method	
Initial storage percent (%)	50
Maximum storage (mm)	115
Transform Method: Clark Unit Hydrograph	
Concentration Time (Hr)	1000
Storage coefficient	1000
Baseflow method; Linear recession	
GW1- Fraction	0.7
GW1 Coefficient (hr)	860
GW2 Coefficient (hr)	200

The HEC-HMS model calibration run graph for Sipi River Catchment is from 2010-2014 is as shown below.

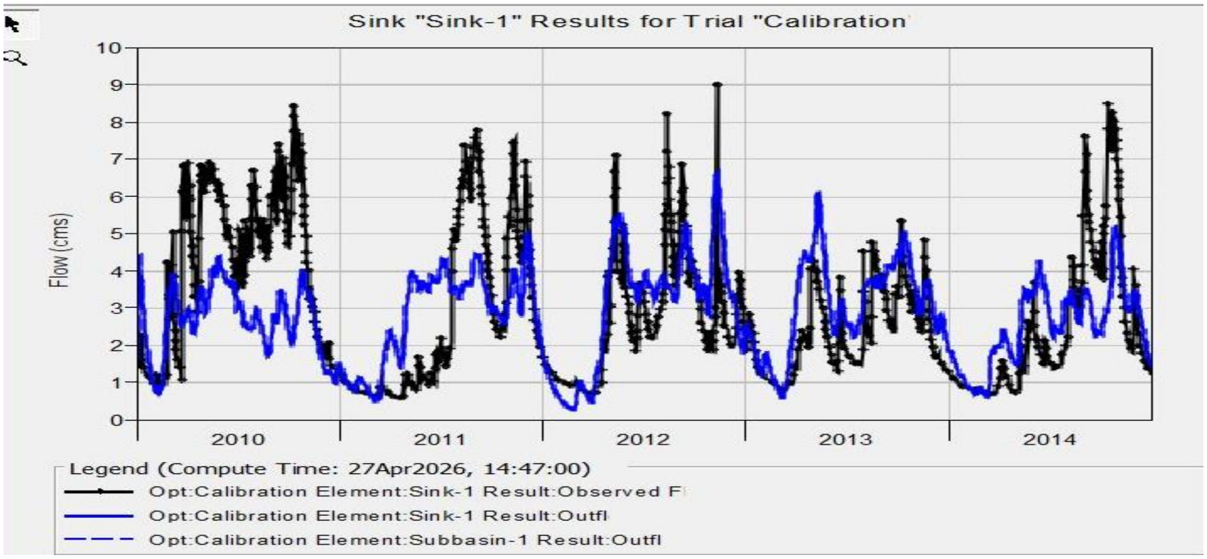


Figure 4: Sipi Catchment HEC-HMS Calibration run graph from 2010 to 2014.

The HEC-HMS model demonstrated moderate performance, capturing the seasonal trends, recession limbs, and timing of major peak events, including the peak on 10 November 2012.

However, the model underestimated peak discharges, with a simulated peak of 6.6 m^3/s compared to the observed 9.0 m^3/s, indicating reduced sensitivity to extreme runoff events. The model performed satisfactorily with PBIAS of -1.51% and moderate performance of NSE KGE of 0.311 and 0.313, respectively.

The HEC-HMS model validation run graph for Sipi River Catchment is from 2015-2018 is as shown below.

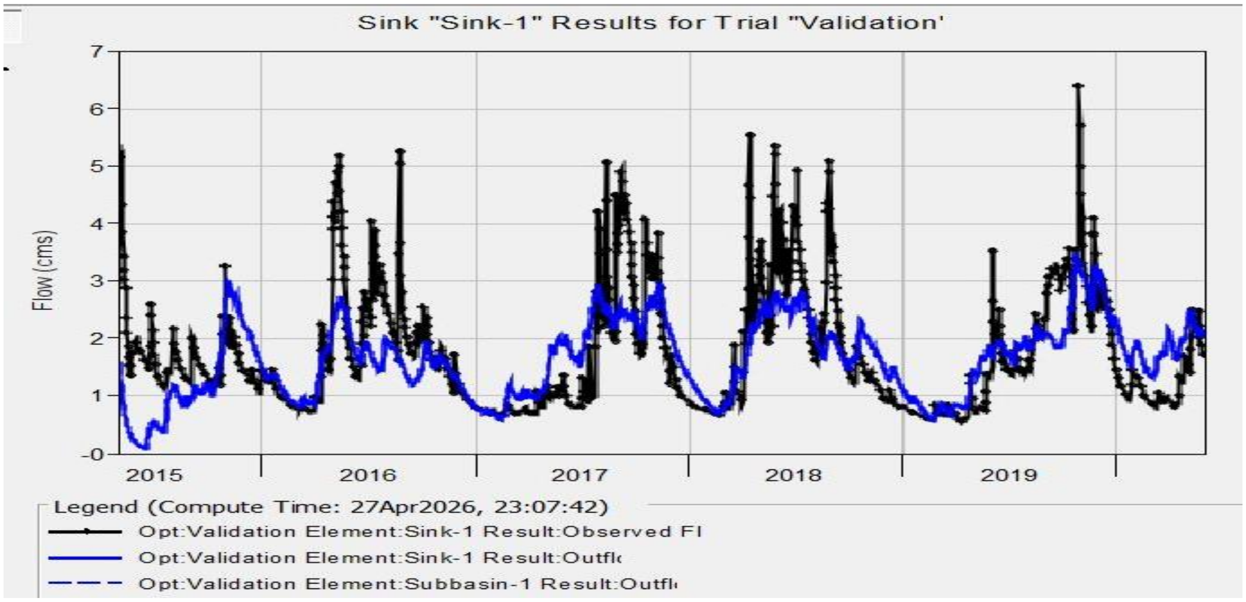


Figure 5: Sipi Catchment HEC-HMS Validation run graph from 2015 to 2020.

The HEC-HMS model performed moderately, following the observed seasonal pattern, timing of rising and recession limbs, and overall streamflow trends from 2015 to 2019. However, the model still underestimated several peak flow events, especially during high-flow periods, implying limited sensitivity to extreme runoff responses. The model performed satisfactorily with PBias of −4.77%, indicating a slight underestimation of total flow volume, and moderately with NSE of 0.400 and KGE of 0.430.

Performance Evaluation of the HEC-HMS model

The performance of the HEC-HMS model during the calibration and validation periods was evaluated using the NSE, PBias, Kling-Gupta Efficiency (KGE), and RMSE coefficients.

Table 4: Performance metrics for the HEC-HMS model.

Metrics	**RMSE**	**PBias**	**NSE**	**KGE**
Calibration	0.8	−1.51	0.311	0.313
Validation	0.78	−4.77	0.400	0.430

XGBoost modelling

XGBoost (Extreme Gradient Boosting) was implemented through setting up a python environment in Google Colab, using historical rainfall data and simulated streamflow as predictors.

Table 5: XGBoost alone optimized parameters.

Parameters	**value**
n_estimators	100
max_depth	4
learning_rate	0.1
sub_sample	0.8
colsample_bytree	0.8
random_state	42

Based on the optimized parameters above,

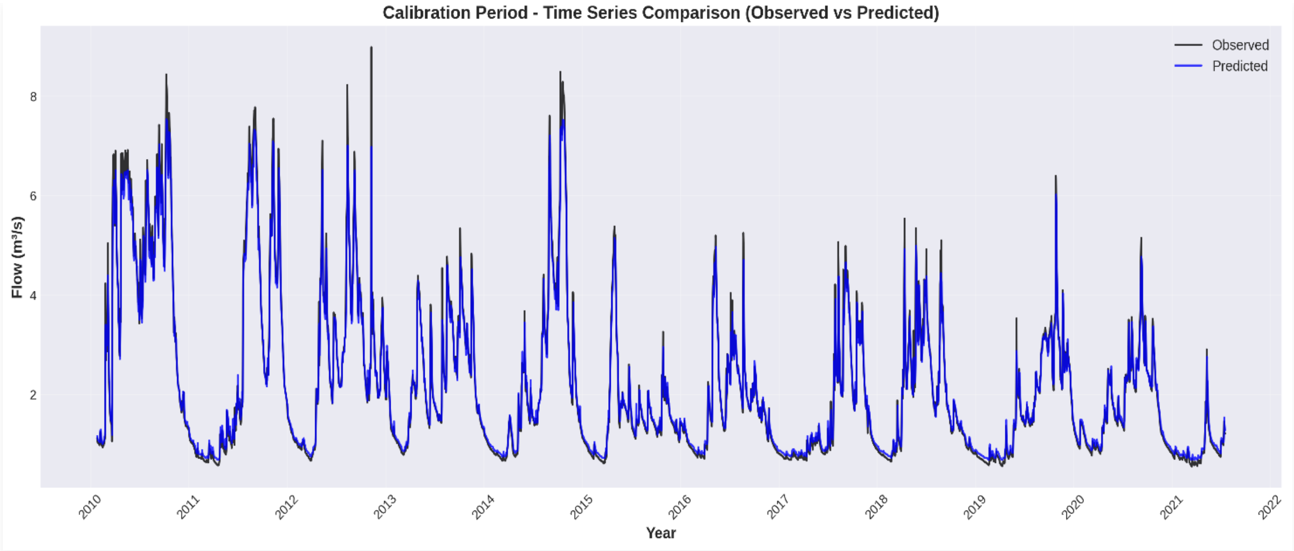


Figure 6: Sipi Catchment XGBoost Calibration graph from 2010 to 2022.

The Hybrid XGBoost model demonstrated significantly higher accuracy, successfully correcting the HEC-HMS model's residual errors and showing a strong correlation with observed peaks.

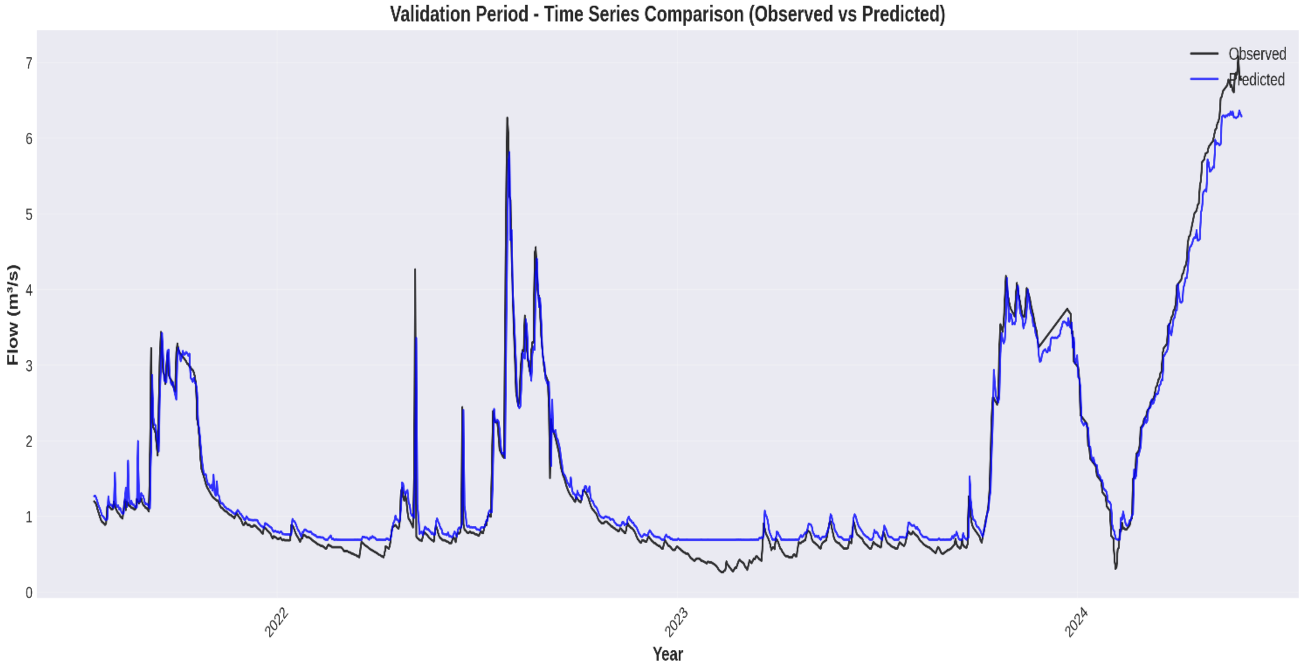


Figure 7:Sipi Catchment XGBoost Validation graph from 2022 to 2024.

The hybrid model effectively corrected the underestimation of peak and low flows observed in the original simulation, resulting in better agreement with the observed hydrograph during both high-flow and recession periods.

Performance metrics for XGBoost Modelling

Table 6: Performance metrics for XGBoost

Metrics	**RMSE**	**MAE**	$\boldsymbol{R^2}$	**NSE**	**RSR**	**PBias**	**KGE**
Calibration	0.1606	0.1039	0.9901	0.9901	0.0999	-0.1449	0.9372
Validation	0.2243	0.1475	0.9771	0.9771	0.1512	3.4869	0.9125

4.1.3Hybrid Model Performance

For the catchment, HEC-HMS_XGBoost model was developed using rainfall as the input variable and HEC-HMS simulated stream flow as the output variable.

The HEC-HMS_XGBoost model outperformed the standalone HEC-HMS model in both calibration and validation stages. By learning the non-linear residual errors from HEC-HMS outputs, the hybrid model minimized underestimations of peak discharges and improved low-flow prediction accuracy.

During the calibration run from 2010-2022,

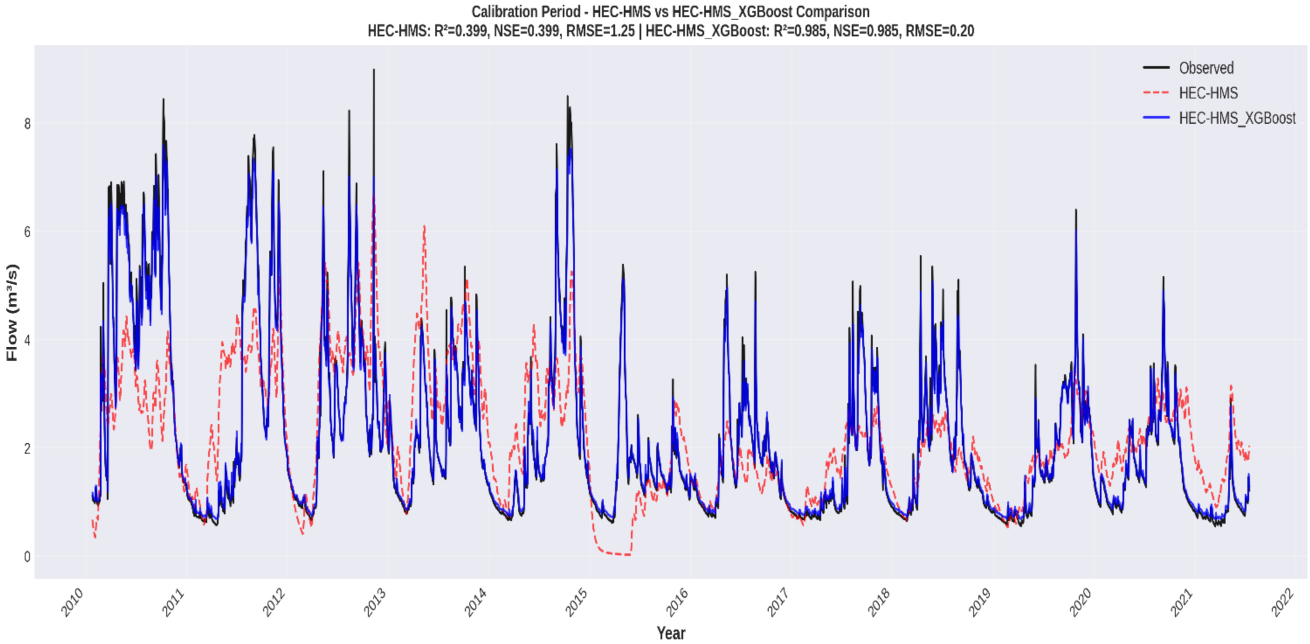


Figure 8: Sipi Catchment HEC-HMS_XGBoost Calibration graph from 2010 to 2022.

The HEC-HMS_XGBoost hybrid model closely follows the HEC-HMS simulated discharge pattern throughout the calibration period, with both hydrographs showing strong agreement in the timing and magnitude of runoff responses to rainfall events. The hybrid model effectively captures most of the peak flow events and low-flow recessions.

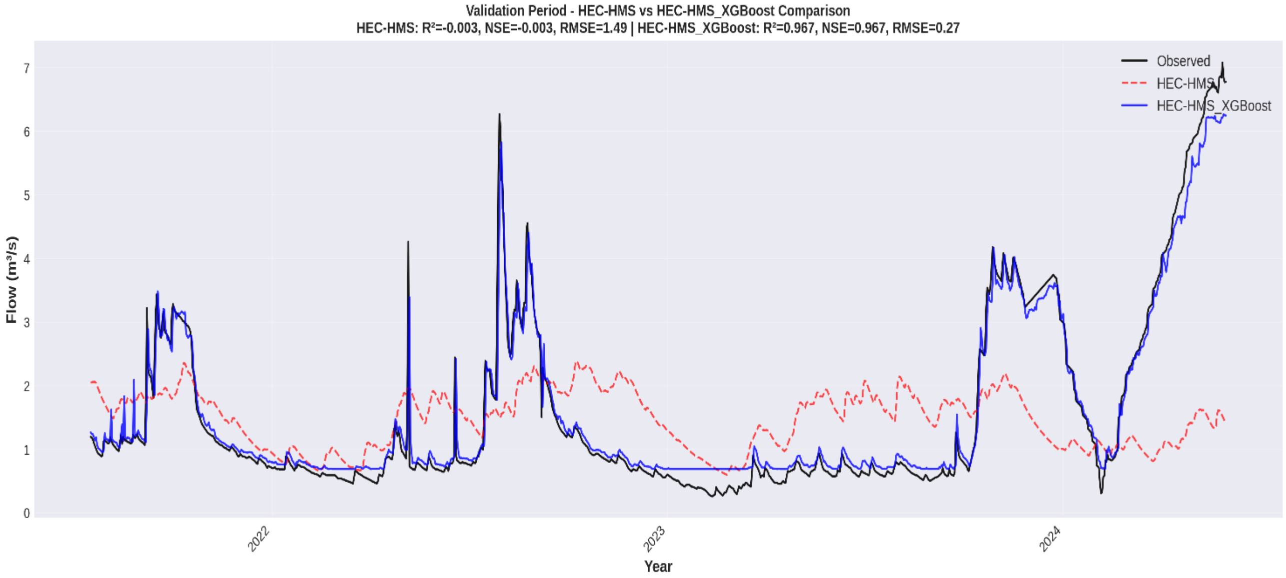


Figure 9: Sipi Catchment HEC-HMS_XGBoost Validation graph from 2022 to 2024.

The HEC-HMS_XGBoost model follows HEC-HMS simulated discharge pattern fairly well, especially in capturing the timing of peaks and low-flow periods. However, the XGBoost line appears smoother and sometimes underestimates the sharpest peaks, which means it captures the general trend better than the exact extremes.

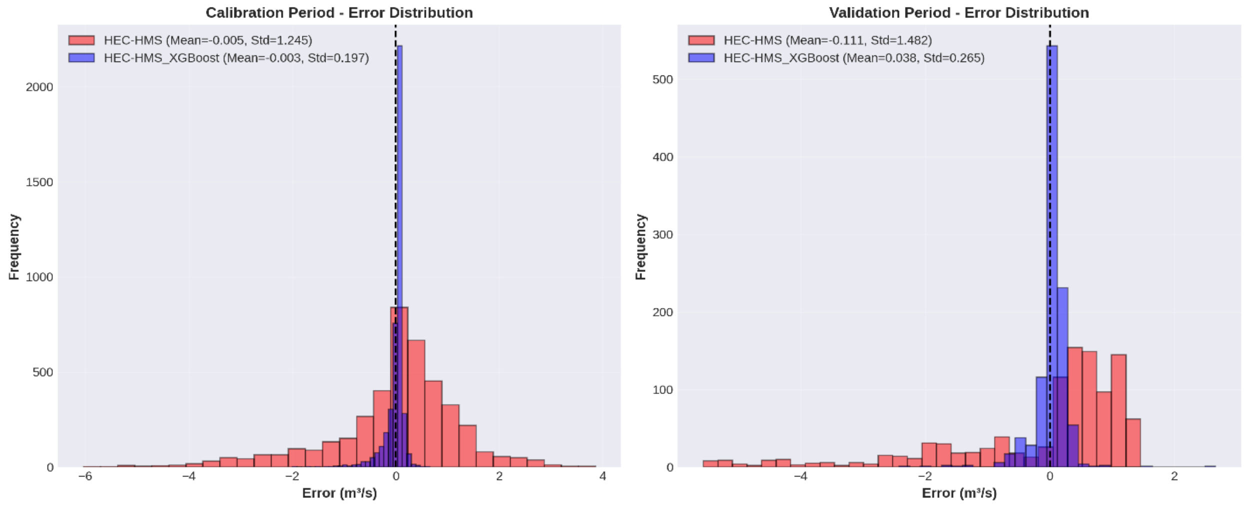
Table 7: Performance metrics for the HEC-HMS_XGBoost model

Metrics	**RMSE**	**MAE**	$\boldsymbol{R^2}$	**NSE**	**PBias**	**RSR**	**KGE**
Calibration	0.197	0.118	0.9850	0.9850	-0.14	0.123	0.9338
Validation	0.268	0.169	0.9674	0.9674	2.43	0.180	0.8934

4.1.4 Visual and Statistical Outputs

The graph below shows close agreement between observed and simulated hydrographs and the scatter plots next to it indicates strong correlation (R^2> 0.8) between observed and predicted flows.

This validates the suitability of combining conceptual and machine learning models for improved streamflow prediction in data-scarce tropical catchments such as Sipi River catchment.



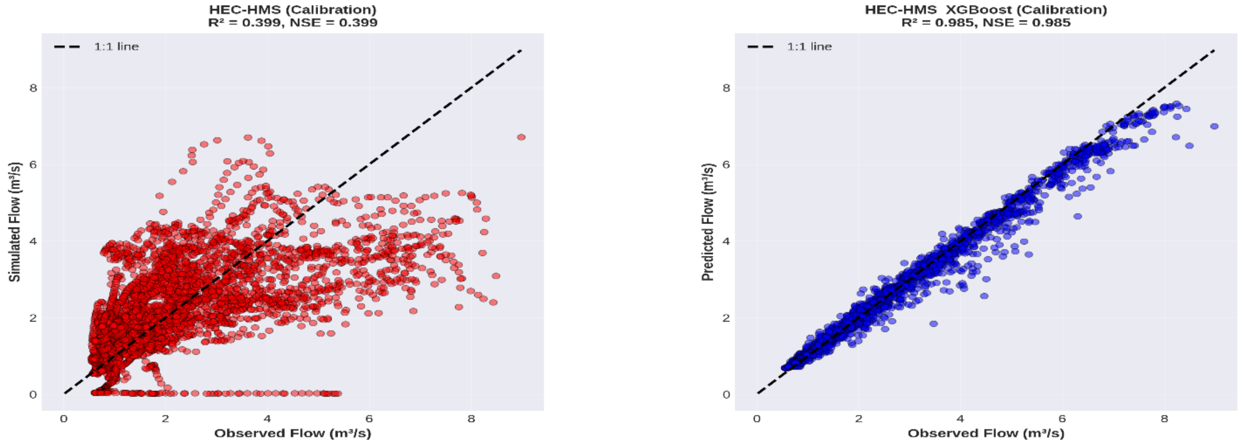


Figure 10: The scatter plots showing the comparison between observed and predicted flows by both models.

4.2 To Simulate and Analyze Future Streamflow under Selected SSP Climate Change Scenarios Using Both Models

This chapter focused on the use of climate projections to simulate future hydrological responses under different socioeconomic pathways (SSP1–2.6, SSP2–4.5, and SSP5–8.5). Raw climate projected data were obtained from CMIP6 GCM outputs under three SSP scenarios; SSP1–2.6, SSP2–4.5 and, SSP5–8.5.

The baseline period 2010-2025 was used for bias correction and model calibration, while the future period 2025-2100 was used for projection analysis.

4.2.1 Bias-Correction.

Bias correction was applied to raw GCM outputs to reduce systematic errors between simulated and observed climate variables to ensure realistic rainfall projections. The Quantile Mapping technique was used to adjust the projected rainfall distribution which improved agreement between observed and historical GCM data.

4.2.2 Projected Streamflow Patterns under each SSP Climate change scenarios.

In the SSP1-2.6 projected stream flow hydrograph, the HEC-HMS_XGBoost Hybrid model consistently shows higher peak flows, occasionally exceeding 15 m^3/s, compared to HEC-HMS, particularly in the wet seasons. Overall variability remains high, reflecting strong seasonal fluctuations.

In the SSP2-4.5 projected stream flow hydrograph, stream flow magnitudes are generally higher than under SSP126. The HEC-HMS_XGBoost Hybrid model again produces more pronounced peaks reaching 16 m^3/s, while HEC-HMS shows slightly lower but still elevated flows.

In the SSP5-8.5 projected stream flow hydrograph, both models project several sharp peaks above 15 m^3/s and frequent high-flow events, however the HEC-HMS_XGBoost Hybrid continues to simulate more extreme peaks than HEC-HMS, suggesting potentially greater flood risk under high-emission conditions.

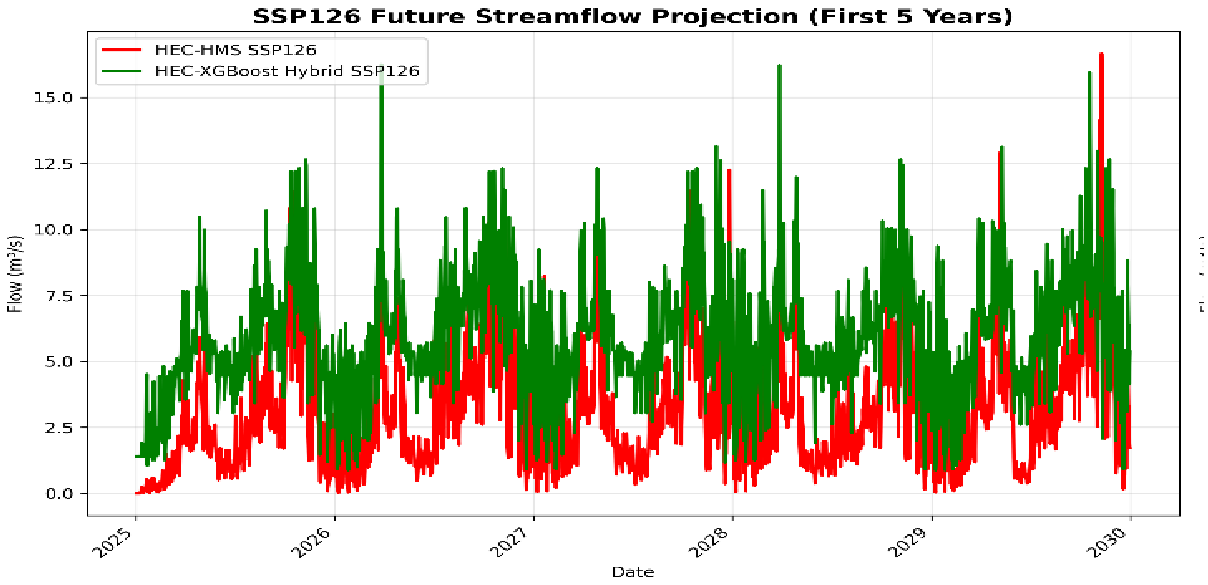


Figure 11: HEC-HMS and HEC-HMS_XGBoost SSP1-2.6 projected stream flow hydrograph for the next 5 years.

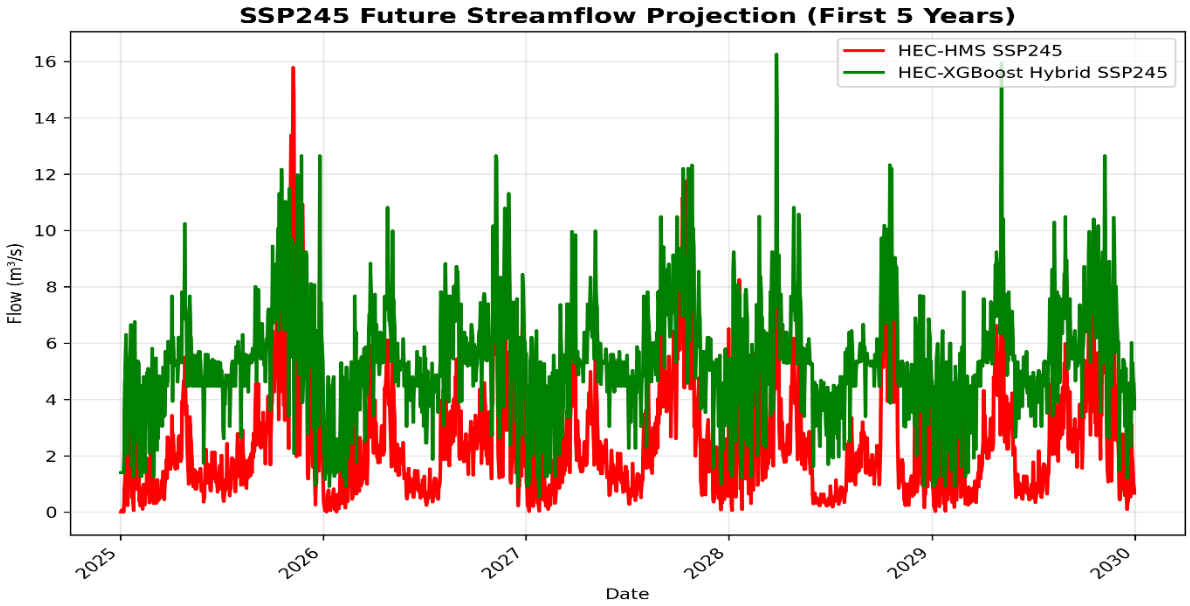


Figure 12: HEC-HMS and HEC-HMS_XGBoost SSP2-4.5 projected stream flow hydrograph for the next 5 years.

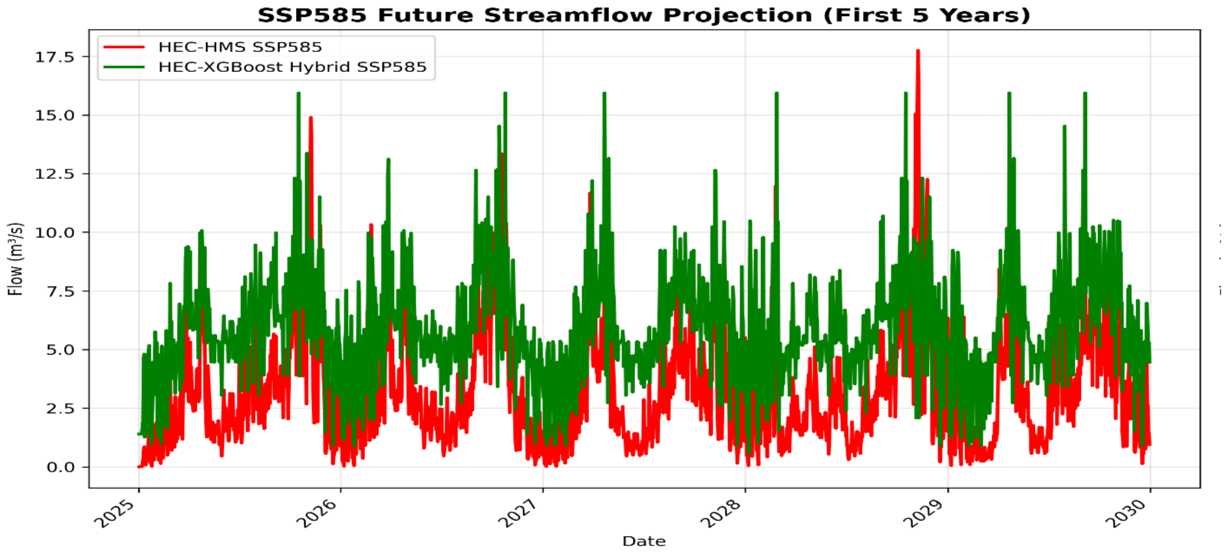


Figure 13: HEC-HMS and HEC-HMS_XGBoost SSP5-8.5 projected stream flow hydrograph for the next 5 years.

4.2.3 Model-Specific Performance

Across all SSPs, the HEC-HMS_XGBoost Hybrid model tends to predict higher and more extreme peak flows than the HEC-HMS model, especially during the rainy seasons. All SSP scenarios show strong inter-annual and seasonal variability, with no clear long-term increasing or decreasing trend visible within the first five years.

4.3 To Compare the Performance and Implications of the Two Models on Flood Control Design Parameters.

This chapter evaluates how differences in model performance translate into practical implications for flood control design parameters such as design discharge and return period.

4.3.1 Flood Frequency Analysis

Annual maximum streamflow series derived from both models was fitted to Gumbel probability distributions.

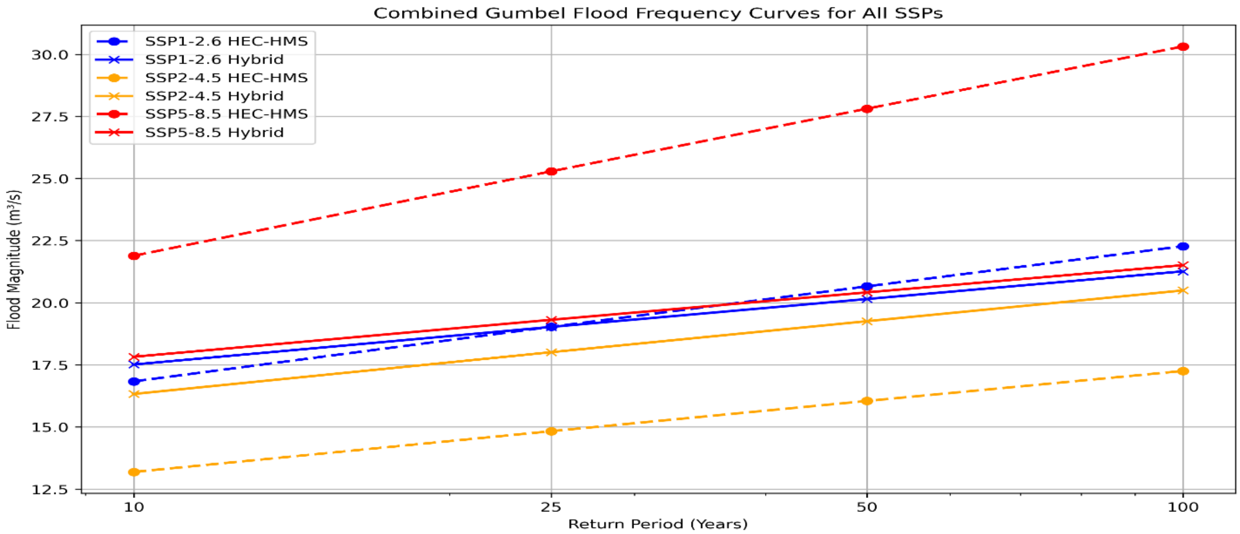


Figure 14: Gumbel flood frequency curves for all SSP predicted flows in both HEC-HMS and HEC-HMS_XGBoost models.

Flood frequency analysis using the Gumbel extreme value distribution was carried out on the annual maximum predicted flows obtained from both the HEC-HMS and HEC-HMS_XGBoost hybrid model under the three selected climate scenarios: SSP1-2.6, SSP2-4.5, and SSP5-8.5. The analysis was performed for the 10-year, 25-year, 50-year, and 100-year return periods.

For both models, the estimated flood magnitudes generally increase with increasing return period, which is consistent with the expected behavior of extreme flood events. For example, under SSP1-2.6, the HEC-HMS model predicted flood magnitudes of 16.83 m^3/s, 19.03 m^3/s, 20.66 m^3/s, and 22.28 m^3/s for the 10-year, 25-year, 50-year, and 100-year return periods, respectively. Similarly, the hybrid model predicted slightly comparable values of 17.51 m^3/s, 19.03 m^3/s, 20.15 m^3/s, and 21.26 m^3/s.

Under SSP2-4.5, both models projected lower flood magnitudes than SSP1-2.6 for the HEC-HMS outputs, with values ranging from 13.19 m^3/s for the 10-year return period to 17.25 m^3/s for the 100-year return period. However, the hybrid model produced relatively higher estimates, ranging from 16.33 m^3/s to 20.50 m^3/s, indicating an adjustment of the original HEC-HMS outputs and a more conservative prediction of extreme flood risk.

For SSP5-8.5, the HEC-HMS model produced the highest projected flood magnitudes among all scenarios, increasing from 21.89 m³/s for the 10-year flood to 30.32 m³/s for the 100-year flood. This suggests a significant increase in extreme flood risk under the high-emission climate scenario. The hybrid model, however, produced lower but still substantial estimates, ranging from 17.82 m³/s to 21.51 m³/s.

Overall, SSP5-8.5 climate scenario produced the highest 100-year flood of magnitude (30.32 m³/s), indicating the highest future flood hazard among the three scenarios, and reflecting the potential impact of increased rainfall intensity and climate variability under a high-emission future. The hybrid model generally produced smoother and more moderated estimates compared to the standalone HEC-HMS model, which suggests improved stability and correction of simulated extremes.

4.3.2 Design Discharge Estimation

The table below shows the estimated design discharge from both models for Sipi River Catchment at different return periods.

Table 8: Estimated design discharge Q_{10} , Q_{25}, Q_{50} and Q_{100} for Sipi Catchment from both HEC-HMS and HEC-HMS_XGBoost models under different SSP Scenarios.

SSP Climate Scenario	**Return Period (Years)**	**HEC-HMS Design Discharge (m3/s)**	**HEC-HMS_XGBoost Design Discharge (m3/s)**
SSP1-2.6	10	16.83420513	17.51339334
SSP1-2.6	25	19.03050433	19.02659459
SSP1-2.6	50	20.65984455	20.14917371
SSP1-2.6	100	22.27715397	21.26346389
SSP2-4.5	10	13.18794063	16.32675237
SSP2-4.5	25	14.82890079	18.00898414
SSP2-4.5	50	16.04625878	19.25695976
SSP2-4.5	100	17.25462799	20.49572053
SSP5-8.5	10	21.88931669	17.82450332
SSP5-8.5	25	25.28944788	19.31284419
SSP5-8.5	50	27.81185943	20.41698048
SSP5-8.5	100	30.31564589	21.51296399

4.3.3 Model Comparison

The HEC-HMS model appears to be more sensitive to changes in climate scenarios, especially under the high-emission scenario SSP5-8.5. This is evident in the sharp rise in the HEC-HMS design discharge from 21.89m^3/s to 30.32m^3/s between 10-year and 100-year return periods. The hybrid model on the contrary shows a more gradual increase from 17.82m^3/s to 21.51m^3/s suggesting that the hybrid model may provide more stable design estimates under changing climate conditions, reducing the risk of over-amplified extreme predictions. So HEC-HMS gives a high climate sensitivity while the HEC-HMS_XGBoost model gives a moderate and more stable sensitivity.

4.3.4 Flood Control Structure Sizing Using Derived Design Discharges

The design discharges derived from Table 8 were applied to standard hydraulic engineering equations to size four representative flood control structures relevant to the Sipi River catchment: culverts, spillways, bridge waterway openings, and detention basins.

4.3.4.1 Culvert Sizing

Applying the design discharges from Table 8, the required culvert diameters were computed as shown in Table 9.

Table 9: Required culvert diameters for the Sipi River catchment under selected design discharge and climate scenarios.

Scenario	**Return Period (yr.)**	**Design Discharge, Q (m3/s)**	**Manning, n**	**Slope, S**	**Required Diameter, D**
SSP1-2.6 (Hybrid)	10	17.51	0.013	0.015	1.52
SSP1-2.6 (Hybrid)	100	21.26	0.013	0.015	1.68
SSP2-4.5 (Hybrid)	10	16.33	0.013	0.015	1.48

SSP2-4.5 (Hybrid)	100	20.50	0.013	0.015	1.65
SSP5-8.5 (Hybrid)	10	17.82	0.013	0.015	1.54
SSP5-8.5 (Hybrid)	100	21.51	0.013	0.015	1.69
SSP5-8.5 (HEC-HMS)	100	30.32	0.013	0.015	1.93

The results in Table 9 show that culvert diameters required under the hybrid model's design discharges range from 1.48 m to 1.69 m across all SSP scenarios at Q100. These are achievable with standard precast concrete box culverts or twin-barrel culverts. In contrast, applying the HEC-HMS SSP5-8.5 Q100 of 30.32 m^3/s yields a required diameter of 1.93 m, which would necessitate a larger non-standard section or triple-barrel arrangement, significantly increasing construction cost and complexity. The difference between the primary design diameter, 1.69 m and the safety-check diameter, 1.93 m of approximately 14.2% represents the structural safety margin embedded in the dual-model framework.

4.3.4.2 Spillway Crest Length Sizing

The computed spillway crest lengths for each design scenario are shown in Table 10.

Table 10: Required spillway crest lengths for the Sipi River catchment under selected design scenarios.

Scenario	**Return Period (yr.)**	**Design Q (m3/s)**	**Coefficient, C**	**Head, H (m)**	**Crest Length, L (m)**
SSP1-2.6 (Hybrid)	100	21.26	1.80	1.50	8.59
SSP2-4.5 (Hybrid)	100	20.50	1.80	1.50	8.28

SSP5-8.5 (Hybrid)	100	21.51	1.80	1.50	8.68
SSP5-8.5 (HEC-HMS)	100	30.32	1.80	1.50	12.24

The spillway crest lengths required using the hybrid model's Q100 values range from 8.28 m to 8.68 m across all SSP scenarios, indicating a consistent and stable design basis. These lengths are practically constructible within the valley floor width of the Sipi catchment. The HEC-HMS SSP5-8.5 Q100 of 30.32 m³/s, by contrast, requires a crest length of 12.24 m, which is 41.0% longer than the hybrid-based design. This additional 3.56 m of spillway crest would require substantially more concrete, a wider embankment section, and greater land acquisition, increasing capital costs by an estimated 35–45%.

4.3.4.3 Bridge Waterway Opening.

The computed bridge waterway requirements are shown in Table 11.

Table 11: Required bridge waterway opening dimensions for the Sipi River catchment under selected design scenarios.

Scenario	**Return Period (yr.)**	**Design Q (m^3/s)**	**Velocity, V (m/s)**	**Waterway Area (m^2)**	**Span (m) @ 2m depth**
SSP1-2.6 (Hybrid)	50	20.15	2.50	8.06	4.03
SSP2-4.5 (Hybrid)	50	19.26	2.50	7.70	3.85
SSP5-8.5 (Hybrid)	50	20.42	2.50	8.17	4.08
SSP5-8.5 (HEC-HMS)	50	27.81	2.50	11.12	5.56

The hybrid model's Q50 values across all SSP scenarios produce waterway areas of 7.70 m² to 8.17 m², corresponding to bridge spans of 3.85 m to 4.08 m at a flow depth of 2.0 m. These are achievable with single-span pre-stressed concrete or steel composite bridges of standard 4–5 m span, which are cost-effective and widely used in rural Uganda. In contrast, the HEC-HMS SSP5-8.5 Q50 of 27.81 m^3/s requires a waterway area of 11.12 m^2 and a span of 5.56 m, necessitating a wider bridge deck and deeper abutment foundations, increasing construction cost by an estimated 25–40%.

4.3.4.4 Detention Basin Storage Volume.

Table 12: Required detention basin storage volumes for the Sipi River catchment under selected design scenarios.

Scenario	**Return Period (yr.)**	**Peak Inflow (m^3/s)**	**Allowable Outflow (m^3/s)**	**Required Storage (m^3)**	**Basin Depth (m)**
SSP1-2.6 (Hybrid)	100	21.26	5.00	29600	3.0
SSP2-4.5 (Hybrid)	100	20.50	5.00	28200	3.0
SSP5-8.5 (Hybrid)	100	21.51	5.00	30000	3.0
SSP5-8.5 (HEC-HMS)	100	30.32	5.00	47800	3.0

The hybrid model's Q100 values under all SSP scenarios produce required storage volumes of approximately 28,200 m^3 to 30,000 m^3. At a basin depth of 3.0 m, this corresponds to a surface footprint of approximately 9,400 m^2 to 10,000 m^2 (roughly 1.0 hectare), which is feasible within the relatively flat valley terraces of the lower Sipi catchment. In contrast, the HEC-HMS SSP5-8.5 Q100 of 30.32 m^3/s yields a storage requirement of approximately 47,800 m^3, corresponding to a footprint of about 15,933 m^2 (approximately 1.6 hectares). This represents a 59.3% increase in required basin area, which would significantly affect land acquisition costs and the feasibility of siting the facility within the settled valley bottom.

4.3.5 Design Implications

Under SSP5-8.5, the significantly higher 100-year flood estimated by HEC-HMS suggests that future flood control structures such as bridges, culverts, spillways, and retention basins should be designed for greater flood conveyance capacity to accommodate increased extreme events under climate change.

For culverts on minor access roads where failure consequences are moderate, the hybrid model Q100 is recommended. For culverts on national roads or where downstream communities are at risk, the upper-bound HEC-HMS diameter of 1.93 m should be adopted.

The dual-model framework allows engineers to design the primary spillway based on the hybrid model’s physically plausible estimate while incorporating the HEC-HMS upper-bound value into the factor of safety analysis and risk-based design review, particularly for dams classified under Consequence Category II or III under Uganda’s dam safety guidelines.

The practical recommendation for bridge waterway design in the catchment is therefore to adopt the hybrid model’s Q50 as the primary design discharge and verify deck clearance and scour protection using the HEC-HMS upper-bound estimate for critical crossings on the main Sipi River channel.

The hybrid model’s detention basin estimate is recommended as the primary design volume, with the HEC-HMS estimate informing the maximum embankment height and freeboard allowance in the final structural design.

DISCUSSIONS.

The HEC-HMS model captured general seasonal trends and recession limbs but consistently underestimated peak discharges. It exhibited unsatisfactory performance metrics of NSE values of 0.311and 0.400 during calibration and validation, with KGE values of 0.313 and 0.430 respectively. Despite its satisfactory values of PBIAS of -1.51% to -4.77% indicating acceptable water balance, the low NSE and KGE demonstrate poor simulation of peak flow dynamics.

However, the standalone XGBoost model showed substantial improvement over HEC-HMS, achieving NSE values of 0.985 during calibration and 0.967 during validation, with corresponding KGE values of 0.934 and 0.893. This demonstrates that the machine learning algorithm alone can effectively learn rainfall-runoff relationships. However, purely data-driven models lack physical interpretability and may struggle under non-stationary climate conditions.

The HEC-HMS_XGBoost hybrid model which trains XGBoost to correct residual errors achieved equally outstanding performance of NSE 0.985 during calibration, and 0.967 during validation. The low RMSE values of 0.197 during calibration, 0.268 during validation, and RSR values of 0.123 and 0.180 confirm exceptional replication of observed flows, including peak magnitudes and timing.

Future simulations under three SSP scenarios revealed divergent behaviors between the two models. The standalone HEC-HMS model exhibited high sensitivity to climate input variability, projecting a wide range of discharges. Under SSP5-8.5 scenario, HEC-HMS projected a 100-year flood Q_{100} of 30.32 m³/s, a sharp 38% increase from its 10-year flood estimate of 21.89 m³/s. In contrast, the HEC-HMS_XGBoost hybrid model produced more moderate and stable projections across all scenarios. Under SSP5-8.5, the hybrid model's Q_{100} was 21.51 m³/s only 21% higher than its 10-year estimate of 17.82 m³/s. Notably, under SSP2-4.5, the hybrid model actually projected higher design discharges indicating that the hybrid model does not simply produce lower values but rather provides corrected, more physically plausible estimates.

Model divergence translated directly into major differences in infrastructure dimensions where culvert diameters differed by 14% (1.69 m vs 1.93 m), spillway crest lengths by 41% (8.68 m vs 12.24 m), bridge waterway spans by 36% (4.08 m vs 5.56 m), and detention basin volumes by 59% (30,000 m³ vs 47,800 m³) under SSP5-8.5 Q_{100}. These differences have direct consequences for structural type selection and capital cost. The hybrid model is recommended as the primary design basis with HEC-HMS SSP5-8.5 as the upper-bound safety check, provides flood control structures that are neither dangerously undersized nor wastefully over-engineered. A climate adaptation factor of 1.10 applied to the hybrid Q_{100} for structures with design life beyond 2040 bridges the gap between the two models in a risk-informed, cost-effective manner. By providing reliable, climate-resilient design discharges for culverts, spillways, bridges, and detention basins in the flood-vulnerable Sipi catchment, this study directly supports SDG 6,9,11,& 13, and contributes to Uganda Vision 2040's goal of resilient communities and sustainable water infrastructure.

Therefore, designing based solely on HEC-HMS outputs could lead to grossly over-engineered and unaffordable structures, while using an unreliable model could lead to unsafe under-design because the hybrid model would provide more reliable and stable estimates for climate-resilient hydraulic design. Therefore, this study recommends the HEC-HMS_XGBoost design discharge estimates as the primary basis for flood control structure design in the Sipi River catchment. The conventional HEC-HMS projections under SSP5-8.5, should be best reserved as an upper-bound safety check in a risk-based framework.

CHAPTER FIVE: CONCLUSIONS, RECOMMENDATIONS AND CHALLENGES FACED.

5.1 CONCLUSIONS

Based on the comparative assessment of the HEC-HMS and HEC-HMS_XGBoost models in simulating streamflow under climate change for flood control structure design in the Sipi River catchment, the following conclusions were drawn;

1. Superior Performance of Hybrid Model: While the HEC-HMS model showed moderate performance of NSE < 0.50, the hybrid model achieved an outstanding performance of NSE > 0.85 during both calibration and validation. This proves that integrating XGBoost hybrid with HEC-HMS to correct residual errors is a highly effective strategy for improving hydrological predictions in data-scarce, mountainous catchments.
2. Divergent Future Streamflow Projections: Future streamflow simulations under SSP1-2.6, SSP2-4.5, and SSP5-8.5 scenarios showed that the HEC-HMS model is highly sensitive to climate inputs, projecting extreme peak flows e.g Q_{100} under SSP5-8.5. In contrast, the HEC-HMS_XGBoost model produced more moderate and stable projections under the same SSP5-8.5, suggesting it may provide a more realistic and less volatile estimate of future flood risks.

3. Significant Impact on Design Parameters: The choice of model has a substantial impact on estimated design discharges for flood control structures. The difference in Q_{100} estimates under the high-emission scenario exceeds 40%, which would lead to vastly different infrastructure sizing, costs, and safety margins. Therefore, using a single model, especially a traditional one, is inadequate for climate-resilient design.
4. Hybrid Models for Climate-Resilient Design: This research concludes that the HEC-HMS_XGBoost hybrid model is a more reliable tool for informing flood control structure design in the Sipi River catchment. Its ability to capture non-linear dynamics and provide more stable extreme value estimates makes it preferable for planning under climate change uncertainty.
5. Contribution to SDGs and Uganda Vision Goals: The research successfully demonstrates an advanced modeling framework that directly supports SDGs 6, 9, 11, 13 and Uganda Vision 2040 by providing a scientific basis for building resilient and sustainable water infrastructure in a flood-vulnerable region.

5.2 RECOMMENDATIONS

Based on the findings and limitations of this study, the following recommendations were proposed to advance hydrological modelling and flood control structures designing in data-scarce regions like tropical mountainous catchments;

- Explore other deep learning algorithms such as LightGBM, CatBoost, Long Short-Term Memory (LSTM) networks, or Transformer-based models to determine whether even higher predictive accuracy can be achieved in a similar tropical mountainous catchment.
- Develop ensembles combining XGBoost, LightGBM, CatBoost, and Random Forest for residual correction to reduce model uncertainty and derive probabilistic design discharge confidence intervals.
- Integrate dynamic LULC change projections with climate change scenarios to assess their combined effect on future streamflow and flood risk.
- Conduct hydraulic modelling and flood inundation Mapping by coupling the hybrid model's outputs with hydraulic models such as HEC-RAS to simulate flood inundation extents, depths, and velocities providing more actionable spatial flood risk maps for planners and communities within the catchment.
- Test the HEC-HMS_XGBoost framework on the Manafwa, Suam, Nzoia, and Nyando catchments to establish transferability and support adoption as a regional standard for data-scarce highland basins.

5.3 CHALLENGES FACED DURING THE RESEARCH.

The research encountered several challenges during the comparative assessment of HEC-HMS and HEC-HMS_XGBoost models for streamflow simulation under climate change for flood control structure design in River Sipi catchment. These challenges include;

1. Data Scarcity and Quality: The most significant challenge was the limited availability of continuous, high-quality hydro-meteorological data. Streamflow and rainfall records for the Sipi catchment had numerous gaps and inconsistencies, requiring extensive preprocessing, gap-filling by linear interpolation and linear scaling.
2. Computational Intensity of Hybrid Modelling: Developing and optimizing the HEC-HMS_XGBoost hybrid model required iteratively running HEC-HMS, extracting outputs, and training XGBoost models in a Python environment, Google Colab. The procedures were computationally demanding and time-consuming.
3. Model Parameterization: For the HEC-HMS model, the calibration relied heavily on automated optimization, which can lead to multiple parameters sets giving similar results.

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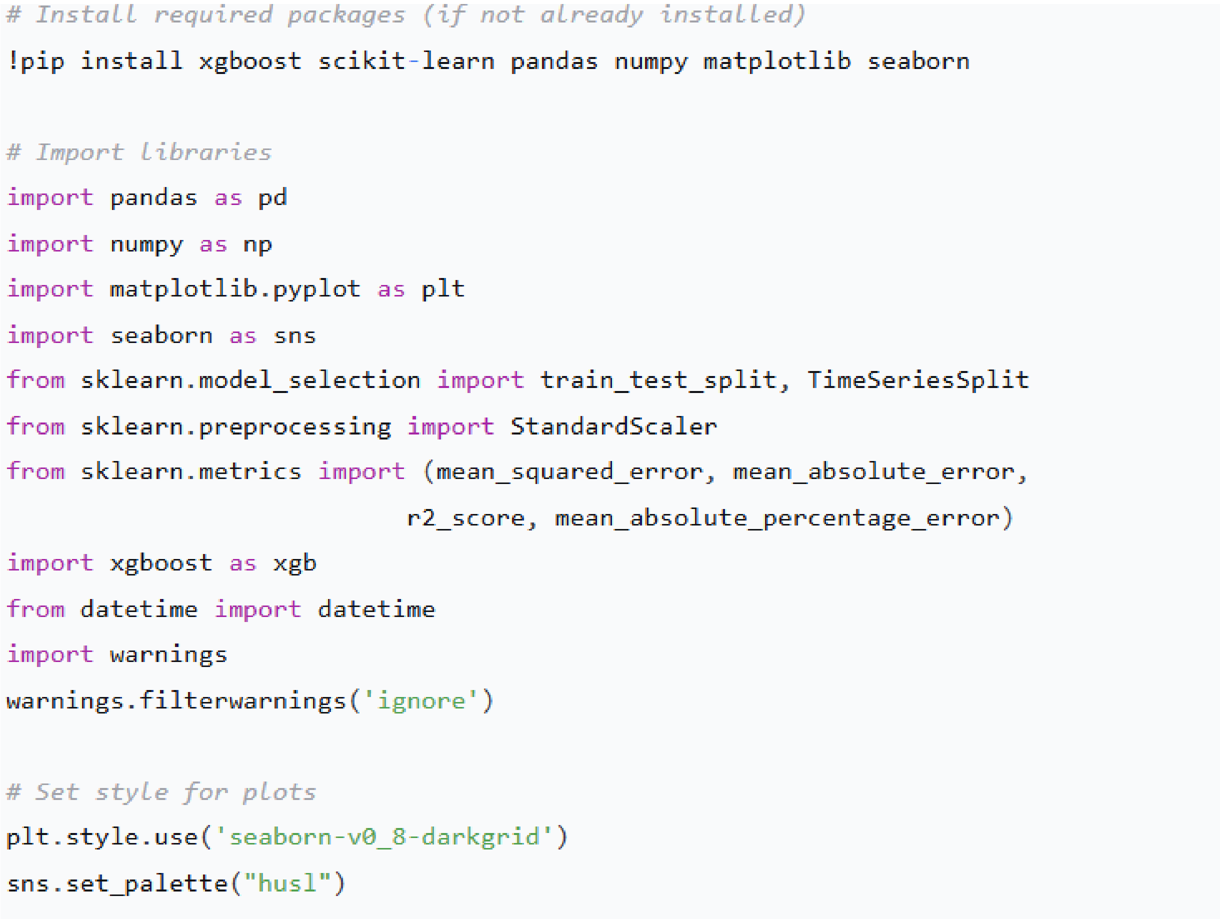
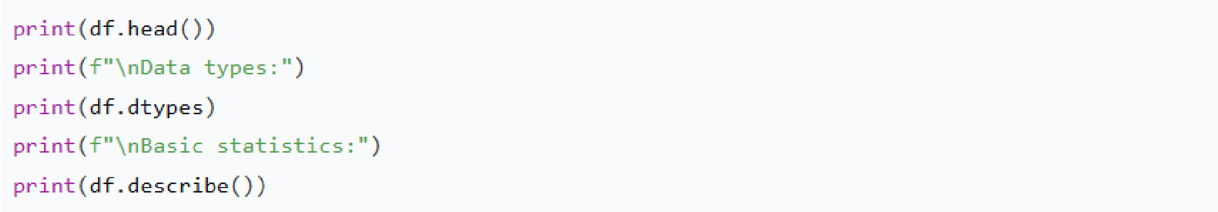
APPENDICES

XGBOOST Modelling

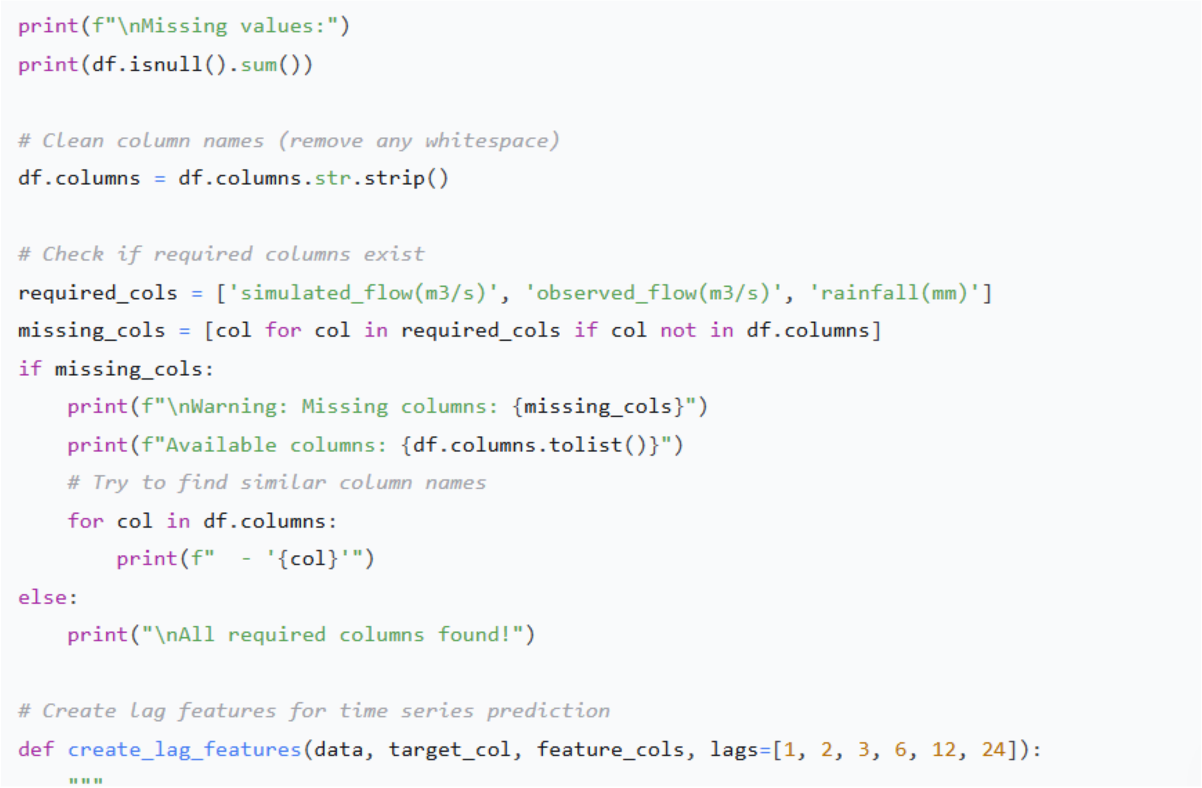


```
# Install required packages (if not already installed)
!pip install xgboost scikit-learn pandas numpy matplotlib seaborn

# Import libraries
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.model_selection import train_test_split, TimeSeriesSplit
from sklearn.preprocessing import StandardScaler
from sklearn.metrics import (mean_squared_error, mean_absolute_error,
                             r2_score, mean_absolute_percentage_error)
import xgboost as xgb
from datetime import datetime
import warnings
warnings.filterwarnings('ignore')

# Set style for plots
plt.style.use('seaborn-v0_8-darkgrid')
sns.set_palette("husl")
```

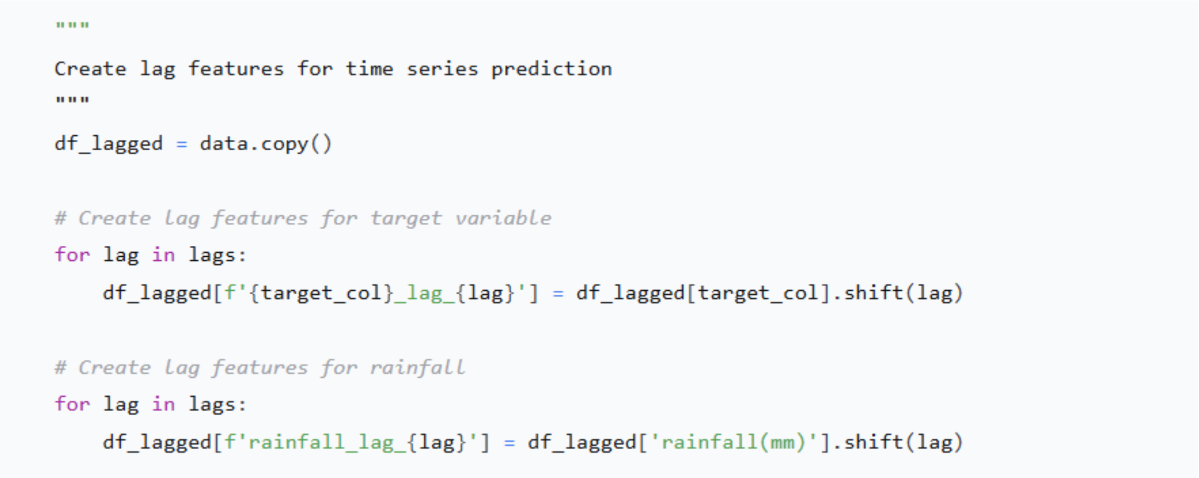
```
# Upload your file in Colab
from google.colab import files
print("Please upload your streamflow_data.csv file:")
uploaded = files.upload()

# Load the data
import io
df = pd.read_csv(io.BytesIO(uploaded['streamflow_data.csv']))

# Display basic information
print("\n" + "="*80)
print("DATA OVERVIEW")
print("="*80)
print(f"Dataset shape: {df.shape}")
print(f"\nColumn names: {df.columns.tolist()}")
print(f"\nFirst 5 rows:")
```



```
print(df.head())
print(f"\nData types:")
print(df.dtypes)
print(f"\nBasic statistics:")
print(df.describe())
```



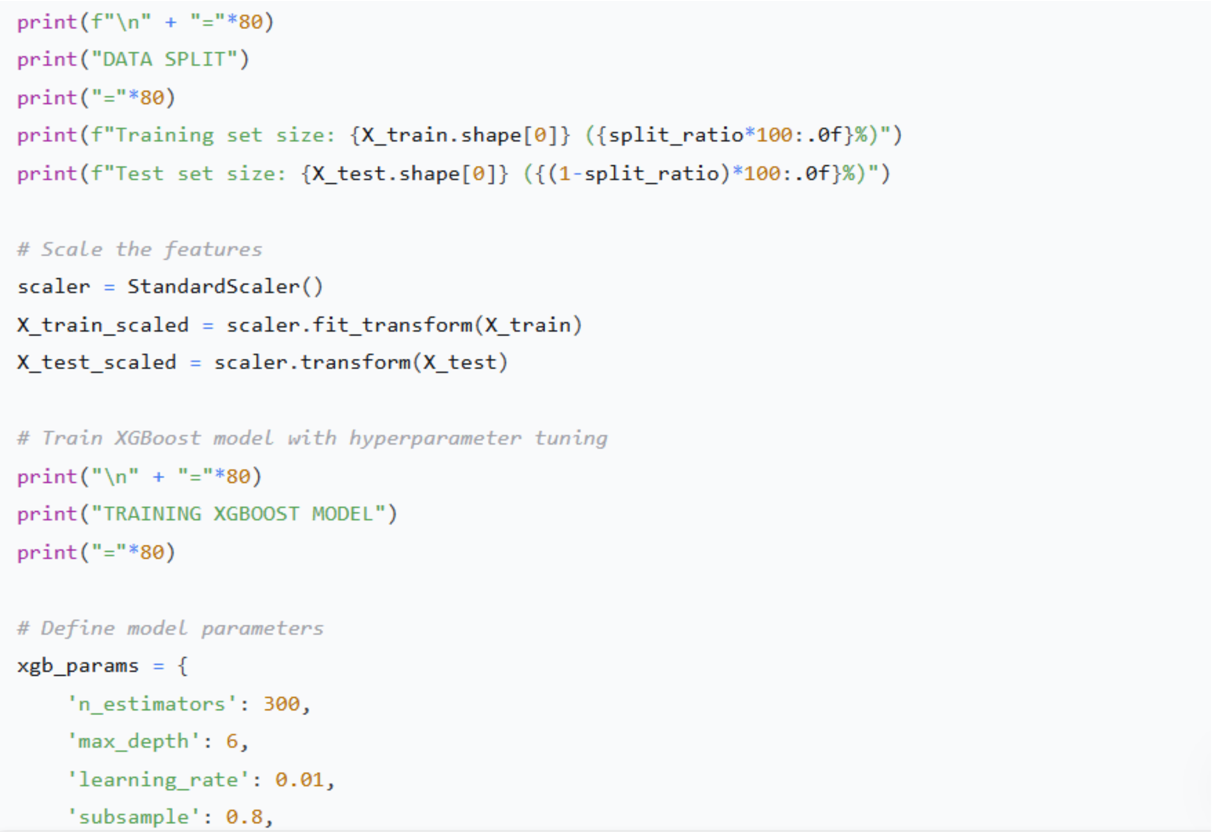
```
print(f"\nMissing values:")
print(df.isnull().sum())

# Clean column names (remove any whitespace)
df.columns = df.columns.str.strip()

# Check if required columns exist
required_cols = ['simulated_flow(m3/s)', 'observed_flow(m3/s)', 'rainfall(mm)']
missing_cols = [col for col in required_cols if col not in df.columns]
if missing_cols:
    print(f"\nWarning: Missing columns: {missing_cols}")
    print(f"Available columns: {df.columns.tolist()}")
    # Try to find similar column names
    for col in df.columns:
        print(f"  - '{col}'")
else:
    print("\nAll required columns found!")

# Create lag features for time series prediction
def create_lag_features(data, target_col, feature_cols, lags=[1, 2, 3, 6, 12, 24]):
    """
```



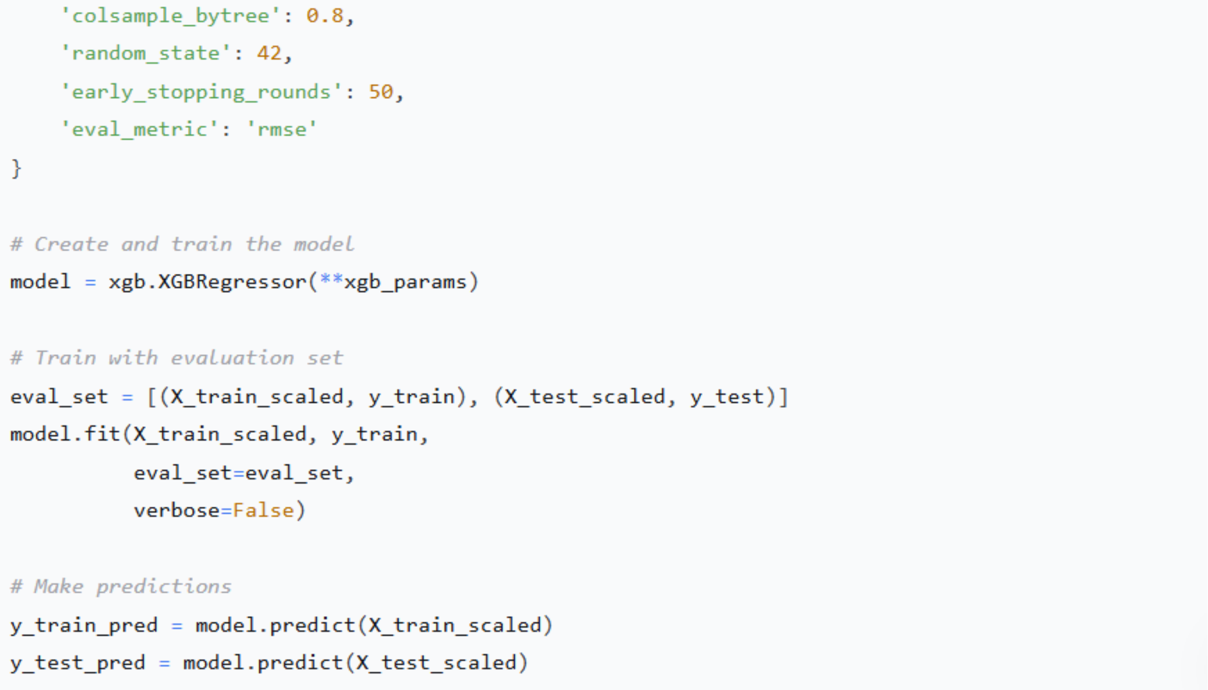
```
    """
    Create lag features for time series prediction
    """
    df_lagged = data.copy()

    # Create lag features for target variable
    for lag in lags:
        df_lagged[f'{target_col}_lag_{lag}'] = df_lagged[target_col].shift(lag)

    # Create lag features for rainfall
    for lag in lags:
        df_lagged[f'rainfall_lag_{lag}'] = df_lagged['rainfall(mm)'].shift(lag)
```

```
    # Drop rows with NaN values created by lags
    df_lagged = df_lagged.dropna()

    return df_lagged

# Prepare features and target
target = 'observed_flow(m3/s)'
features = ['simulated_flow(m3/s)', 'rainfall(mm)']

# Create lag features
print("\n" + "="*80)
print("CREATING LAG FEATURES")
print("="*80)
df_lagged = create_lag_features(df, target, features)
print(f"Original data shape: {df.shape}")
print(f"Data shape after adding lags: {df_lagged.shape}")

# Define feature columns (including lags)
feature_cols = [col for col in df_lagged.columns if col not in [target, 'simulated_flow(m3/s)', 'rainfall(mm)']]
feature_cols = features + feature_cols  # Add original features
print(f"\nFeature columns ({len(feature_cols)}):")
```

```
for col in feature_cols:
    print(f"  - {col}")

# Prepare X and y
X = df_lagged[feature_cols]
y = df_lagged[target]

# Train-test split (time series - use sequential split)
split_ratio = 0.8
split_idx = int(len(X) * split_ratio)

X_train = X[:split_idx]
X_test = X[split_idx:]
y_train = y[:split_idx]
y_test = y[split_idx:]
```



```
print(f"\n" + "="*80)
print("DATA SPLIT")
print("="*80)
print(f"Training set size: {X_train.shape[0]} ({split_ratio*100:.0f}%)")
print(f"Test set size: {X_test.shape[0]} ({(1-split_ratio)*100:.0f}%)")

# Scale the features
scaler = StandardScaler()
X_train_scaled = scaler.fit_transform(X_train)
X_test_scaled = scaler.transform(X_test)

# Train XGBoost model with hyperparameter tuning
print("\n" + "="*80)
print("TRAINING XGBOOST MODEL")
print("="*80)

# Define model parameters
xgb_params = {
    'n_estimators': 300,
    'max_depth': 6,
    'learning_rate': 0.01,
    'subsample': 0.8,
```



```
    'colsample_bytree': 0.8,
    'random_state': 42,
    'early_stopping_rounds': 50,
    'eval_metric': 'rmse'
}

# Create and train the model
model = xgb.XGBRegressor(**xgb_params)

# Train with evaluation set
eval_set = [(X_train_scaled, y_train), (X_test_scaled, y_test)]
model.fit(X_train_scaled, y_train,
          eval_set=eval_set,
          verbose=False)

# Make predictions
y_train_pred = model.predict(X_train_scaled)
y_test_pred = model.predict(X_test_scaled)
```