



FACULTY OF ENGINEERING AND TECHNOLOGY

DEPARTMENT OF WATER RESOURCES ENGINEERING

FINAL YEAR PROJECT

**COMPARATIVE ASSESSMENT OF HEC-HMS_ANN
AND HEC-HMS_XGBOOST MODEL PERFORMANCE
IN SIMULATING FUTURE STREAMFLOW IN
MOUNTAINOUS AND LOW-LYING CATCHMENTS**

BY

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Case studies of River Manafwa and Sezibwa catchments

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fulfillment of the requirement for the award of a Bachelor of Science in Water Resources
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ABSTRACT

Reliable streamflow prediction is critical for effective water resource management, particularly in data-scarce regions where traditional hydrological models like HEC-HMS often underperform due to structural uncertainties and limited data. This study addresses this challenge by developing and comparing hybrid models that integrate HEC-HMS with machine learning techniques Artificial Neural Networks (ANN) and Extreme Gradient Boosting (XGBoost) to enhance streamflow simulation accuracy in contrasting terrains. The Manafwa (mountainous) and Sezibwa (low-lying) catchments in Uganda served as case studies, utilizing historical hydrological data (2010–2018) for calibration and validation.

The HEC-HMS_ANN and HEC-HMS_XGBoost models were evaluated against standalone HEC-HMS, ANN, and XGBoost models using Nash-Sutcliffe Efficiency (NSE), Root Mean Square Error (RMSE), and coefficient of determination (R^2). Results demonstrated that hybrid models significantly outperformed individual approaches, with HEC-HMS_XGBoost achieving the highest accuracy (NSE: 0.9341 calibration, 0.9191 validation for Manafwa; NSE: 0.9513 calibration, 0.937 validation for Sezibwa). The XGBoost-based hybrid excelled in capturing both peak and low flows, while the ANN hybrid showed limitations in low-flow estimation. Topographical differences influenced performance, with the low-lying Sezibwa catchment exhibiting marginally better metrics than the mountainous Manafwa.

This research underscores the superiority of hybrid models, particularly HEC-HMS_XGBoost, in overcoming data scarcity and hydrological complexity. The findings provide actionable insights for policymakers and water managers to adopt context-specific models, enhancing flood preparedness and infrastructure resilience in diverse catchments. The study advances hydrological modeling in data-deficient regions, aligning with global sustainable water management goals.

DECLARATION

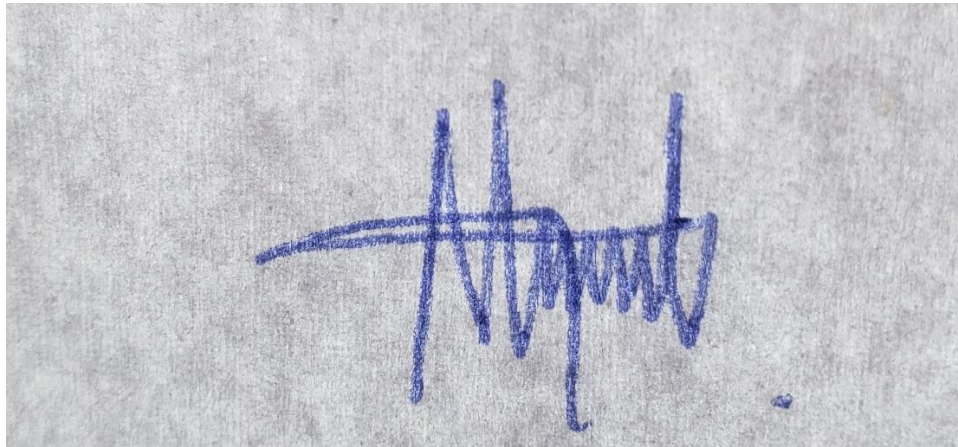
I Musamba Nicholas to the best of my knowledge declare that the work in this project is as a result of my efforts. Therefore, I declare that this report has been written by me and has not been utilized for academic award by an individual in any learning institution.

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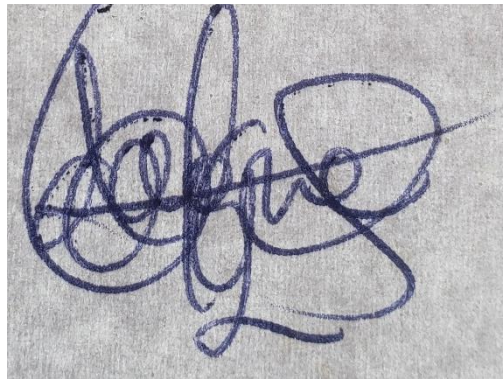
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APPROVAL

I present this project to the department of Water Resources Engineering for the award of Bachelor's in Water Resources Engineering with approval from my supervisor

Mr. Oketcho Yoronimo

Date: 28 /10/2025.....

A handwritten signature in blue ink, appearing to be 'Oketcho Yoronimo', written on a light-colored, textured surface.

Signature:

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My deep appreciation goes to my family members and family friends who supported me both financially and spiritually to see that this we reach this far. May the Almighty God bless the work of their hands.

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ABBREVIATIONS OR ACRONYMS

AI	artificial intelligence
ANN	artificial neural network
Xgboost	Extreme gradient boost
DEM	digital elevation model
FFNN	feed-forward neural network
FL	fuzzy logic
GRNN	generalized regression neural network
HEC-HMS	Hydrologic Engineering Centre Hydrological Modelling System
LS	linear scaling
LSTM	long short-term memory
MAE	mean absolute error
m a.s.l	meters above sea level
ML	machine learning
NSE	Nash–Sutcliffe efficiency index
RBFNN	radial basis function neural network
RMSE	root mean square error

SMA	soil moisture accounting
SVM	support vector machine
SWAT	soil and water assessment tool
WEAP	water evaluation and planning system

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