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FACULTY OF ENGINEERING

DEPARTMENT OF WATER RESOURCES ENGINEERING

FINAL YEAR PROJECT REPORT

DEVELOPMENT OF A HYBRID MODEL FOR PREDICTION OF RIVER WATER QUALITY.

CASE STUDY OF MALABA RIVER CATCHMENT.

BY:

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Final Year project report submitted to the Department of Water Resources Engineering as a partial fulfillment of the requirements for the award of a Bachelor of Science in Water Resources Engineering of Busitema University.

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ABSTRACT.

Water quality degradation in transboundary catchments threatens public health and water supply, yet predictive tools combining physical hydrology with data-driven classification remain absent for data-scarce regions like Uganda's Malaba River catchment. This study developed, calibrated, and validated a hybrid SWAT-ANN model to predict river water quality classification from simulated hydrological and pollutant outputs. SWAT was set up using CHIRPS rainfall, NASA POWER climate data, land use, soil, and DEM, calibrated (2003–2014) and validated (2015–2025) against observed streamflow, achieving satisfactory performance (calibration NSE=0.79, R^2=0.85; validation NSE=0.69, R^2=0.76). An ANN with three hidden layers was trained on the Washington State WQI dataset (805 clean records) to classify water quality into five CCME classes, attaining 84.47% accuracy, with sediment and turbidity as dominant drivers. Applied to SWAT outputs, the hybrid model generated 276 monthly predictions (2003–2025), predicting Fair (48.6%) and Marginal (42.0%) as dominant classes, no Poor quality, and identifying hotspot subbasins (1,6,19,24). The Long-Wet season (March–May) showed 75.4% Marginal conditions, while July recorded the best quality. External validation achieved 100% agreement with primary field data (mean WQI 76.2, Fair) and seasonal benchmarks (4/4 seasons), with a paired t-test confirming no significant difference between observed and simulated streamflow (p=0.0506). The hybrid SWAT-ANN framework provides a physically grounded, data-driven water quality prediction tool supporting proactive management by MWE and NEMA.

Keywords: Hybrid model, SWAT, Artificial Neural Network, water quality prediction, Malaba River catchment, Water Quality Index.

DECLARATION.

I **LOLEM JOSEPH PELERINO** do hereby declare that to the best of my knowledge and belief, this report is my original work and has never been submitted to any other university, college, or Institution of higher learning for the purpose of meeting any academic requirement. It is therefore authentic and where any references or secondary information have been used, they have been given due acknowledgement.

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Signed.......................................

LOLEM JOSEPH PELERINO.

Date.......................................: 11/06/2026.

APPROVAL.

This is to certify that this project report is an authentic piece of work carried out by LOLEM JOSEPH PELERINO under my guidance and supervision. This report is submitted to the department of Water Resources Engineering, Busitema University, in partial fulfillment for the requirement of Award of a bachelor's degree in water resources engineering.

Supervisor's Name: Eng. BADAZA MOHAMMAD.

Signed.

(Project Supervisor)

Date....11/06/2026.............

DEDICATION.

I dedicate this work to my beloved parents, brothers, and sisters whose unwavering love, support, and encouragement have been the driving force towards my academic journey. Your guidance and sacrifices have shaped me into the person I am today.

ACKNOWLEDGEMENT.

I am grateful to my family members for their unwavering support and love. Your encouragement and sacrifices have been my driving force.

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LIST OF ABBREVIATIONS AND ACRONYMS.

ADE -	Advection–Dispersion Equation
ANN -	Artificial Neural Network
BOD -	Biochemical Oxygen Demand
BU -	Busitema University
CCME -	Canadian Council of Ministers of the Environment
CHIRPS -	Climate Hazards Group InfraRed Precipitation with Station data
CHLA -	Chlorophyll-a
DEM -	Digital Elevation Model
DO -	Dissolved Oxygen
EAC -	East African Community
GIS -	Geographic Information System
HRU -	Hydrologic Response Unit
IQR -	Interquartile Range
KGE -	Kling–Gupta Efficiency
ML -	Machine Learning
MUSLE -	Modified Universal Soil Loss Equation
MWE -	Ministry of Water and Environment (Uganda)
NASA POWER -	NASA Prediction of Worldwide Energy Resources
NEMA -	National Environment Management Authority (Uganda)
NSE -	Nash–Sutcliffe Efficiency
NTU -	Nephelometric Turbidity Unit
PBIAS -	Percent Bias
pH -	Potential of Hydrogen
R^2 -	Coefficient of Determination
RF -	Random Forest
SCS -	Soil Conservation Service
SDG -	Sustainable Development Goal
SRTM -	Shuttle Radar Topography Mission
SUFI-2 -	Sequential Uncertainty Fitting version 2
SWAT -	Soil and Water Assessment Tool

SWAT-CUP –	SWAT Calibration and Uncertainty Program
TN -	Total Nitrogen
TP -	Total Phosphorus
TSS -	Total Suspended Solids
UN WWD -	United Nations World Water Day
UNMA -	Uganda National Meteorological Authority
USDA -	United States Department of Agriculture
USGS -	United States Geological Survey
WQI -	Water Quality Index

CHAPTER ONE: INTRODUCTION.

1.1 Introduction.

This chapter introduces the foundation of the research study, providing an overview of the research background, problem statement, justification, objectives, significance, and scope. It outlines the global and local challenges of water quality degradation, emphasizing the situation in Uganda's Malaba River catchment. The chapter then defines the research problem and explains the motivation behind developing a hybrid model for improved river water quality prediction. It highlights the study's objectives and their relevance to sustainable water management. Additionally, it presents the significance of the research to policy, science, and community well-being. Finally, the chapter outlines the study's geographical, conceptual, and time scope, setting the stage for subsequent chapters.

1.2 Background of the study.

Water is an essential natural resource that sustains all forms of life, supports economic growth, and ensures public health and food security (UN WWD, 2023). However, water quality deterioration has become a major environmental concern globally, particularly in developing regions such as Sub-Saharan Africa. Rapid urbanization, agricultural intensification, and industrial development have increased the discharge of pollutants into freshwater systems, leading to severe ecological degradation and health risks (Kibret et al., 2022). In Uganda, rivers such as Malaba River, which traverses agricultural and urban landscapes in Eastern Uganda, are increasingly threatened by sedimentation, nutrient loading, and organic pollution (MWE, 2022).

Historically, water quality monitoring in Uganda has relied heavily on manual sampling and laboratory analysis, which, although accurate, are time-consuming, costly, and spatially limited (Joseph & Ekaal, 2023). Over the past two decades, statistical modeling approaches such as Multiple Linear Regression (MLR) and Water Quality Index (WQI) analysis have been used to describe relationships between physicochemical parameters like pH, turbidity, and dissolved oxygen (Tebyetekerwa et al., 2021). These models, however, assume linear relationships and are often insufficient for capturing the nonlinear and dynamic interactions that exist among hydro-meteorological and land-use variables influencing river water quality (Zhou et al., 2020).

The emergence of Machine Learning (ML) techniques has provided powerful tools for analyzing complex environmental data and improving predictive accuracy (Choubin et al., 2020). Models such as Random Forest (RF), Support Vector Machines (SVM), and Artificial Neural Networks (ANNs) have demonstrated strong capabilities in forecasting pollution indicators and assessing water quality under varying climatic and anthropogenic conditions (Wu et al., 2021). Despite these advances, ML models are often treated as "black box" systems that lack interpretability, making it difficult for water managers and policymakers to fully trust their predictions (Zhao et al., 2022).

To bridge this gap, researchers are increasingly advocating hybrid or integrated modeling frameworks that combine the transparency and simplicity of statistical models with the flexibility and learning ability of machine learning approaches (Chen et al., 2020). Such integration can enhance prediction accuracy while preserving the interpretability of relationships among variables, thereby supporting data-driven decision-making in water resources management.

Within the Ugandan context, the hybrid modeling approach presents a promising opportunity for improving predictive water quality assessments in rivers such as Malaba, where rainfall variability, land-use change, and anthropogenic activities interact in complex ways (MWE, 2022; Tebyetekerwa et al., 2021). This study therefore situates itself within this evolving field, seeking to contribute to national efforts toward sustainable water management in line with Uganda Vision 2040, the East African Community (EAC) Protocol on Environment and Natural Resources, and the United Nations Sustainable Development Goal 6 (Clean Water and Sanitation).

1.3 Problem statement.

River Malaba, a transboundary water resource shared between Uganda and Kenya, faces escalating water quality degradation driven by agricultural runoff, sediment loading, nutrient enrichment, and urban waste from Malaba town (Mwanake et al., 2025; Odongo and Ekaal, 2023). Field measurements at the Malaba Water Treatment Plant confirm elevated turbidity (56.0 NTU), above-normal phosphates (0.057 mg/L), and high color (260.6 mg/L), posing serious risks to communities dependent on the river (Odongo and Ekaal, 2023). Despite this documented deterioration, water quality assessment remains dependent on costly and spatially limited laboratory analysis that cannot provide continuous catchment-wide predictions. Physically-based models such as SWAT simulate pollutant dynamics effectively but cannot classify resulting conditions into actionable water quality categories, while standalone machine learning models classify water quality but lack the physical hydrological grounding to reflect catchment-specific processes (Maier et al., 2010; Arnold et al., 2012). No hybrid predictive framework currently exists for the Malaba catchment that integrates physically simulated pollutant dynamics with data-driven water quality classification. This study therefore develops a hybrid SWAT-ANN framework to predict water quality classification from simulated hydrological outputs, providing a continuous, low-cost tool to support anticipatory water quality management across the transboundary basin.

1.4 Justification.

The Malaba River, a critical transboundary water resource shared between Uganda and Kenya, is increasingly threatened by agricultural runoff, industrial discharges, and poor waste management practices. These pressures have led to sedimentation, nutrient enrichment, and organic pollution that compromise aquatic ecosystems, human health, and agricultural productivity (MWE, 2022; Mwanake et al., 2025). Existing water quality monitoring methods in Uganda are predominantly manual and reactive, relying on laboratory analyses and traditional statistical models that are inadequate for predicting complex hydrological and land-use interactions (Joseph & Ekaal, 2023). Developing a hybrid model that integrates the process-based Soil and Water Assessment Tool (SWAT) with machine learning techniques is therefore essential to improve predictive accuracy, enhance interpretability, and support data-driven decision-making in water quality management. (Zhou & Zhang, 2023).

Water pollution in the Malaba River will continue to worsen, resulting in declining biodiversity, unsafe water supplies, and human health risks within surrounding communities if this study is not undertaken. The inadequacy of a predictive management framework makes environmental agencies remain reactive, delaying interventions and worsening the socio-economic impacts of pollution (Ng et al., 2023). Conducting this study is therefore urgent to safeguard the Malaba River, promote sustainable water resource management, and support Uganda’s Vision 2040, the Third National Development Plan (NDP III), and Sustainable Development Goal 6 on Clean Water and Sanitation (UNEP, 2022).

1.5 Objectives of the study.

1.5.1 Main objective.

To develop a hybrid model for prediction of river water quality.

1.5.2 Specific objectives.

i. To develop a SWAT model to simulate streamflow and pollutant dynamics in the Malaba River catchment.
ii. To develop a machine learning model to predict water quality classification using SWAT simulated output.
iii. To evaluate and validate the performance of the predictive model.

1.5.3 Research questions.

i. How accurately does the SWAT model simulate streamflow and key pollutants in the Malaba River?
ii. What water quality classification does the hybrid SWAT-ANN model predict for the Malaba River catchment, and what seasonal patterns does it reveal?
iii. How does the performance of the hybrid model compare to the standalone physical and machine learning models in predicting river water quality?

1.6 Significance of the study.

This study is significant because it offers a proactive approach to addressing the escalating water quality degradation in the Malaba River, which is increasingly affected by agricultural runoff, industrial discharges, and urbanization (Ministry of Water and Environment, 2022; Mwanake et al., 2025). By integrating a physically based hydrological model (SWAT) with machine learning techniques, the research introduces a hybrid modeling framework capable of accurately predicting pollution dynamics under variable climatic and land-use conditions (Zhou & Zhang, 2023). This innovation will enable agencies such as the Ministry of Water and Environment (MWE) and the National Environment Management Authority (NEMA) to forecast water quality trends, design targeted control measures, and implement timely interventions (Ng et al., 2023). Scientifically, the study contributes to the advancement of environmental modeling by bridging process-based and data-driven approaches, while practically, it provides a decision-support tool for sustainable river basin management. The research also aligns with Uganda Vision 2040, the Third National Development Plan (NDP III), and Sustainable Development Goals 6 and 15, Clean water and

Sanitation, and healthy ecosystems for sustainable development (UN World Water Development Report, 2023).

1.7 Scope of the study.

1.7.1 Geographical Scope.

This study was carried out in the Malaba River catchment, located in Tororo District, Eastern Uganda, along the Uganda-Kenya border.

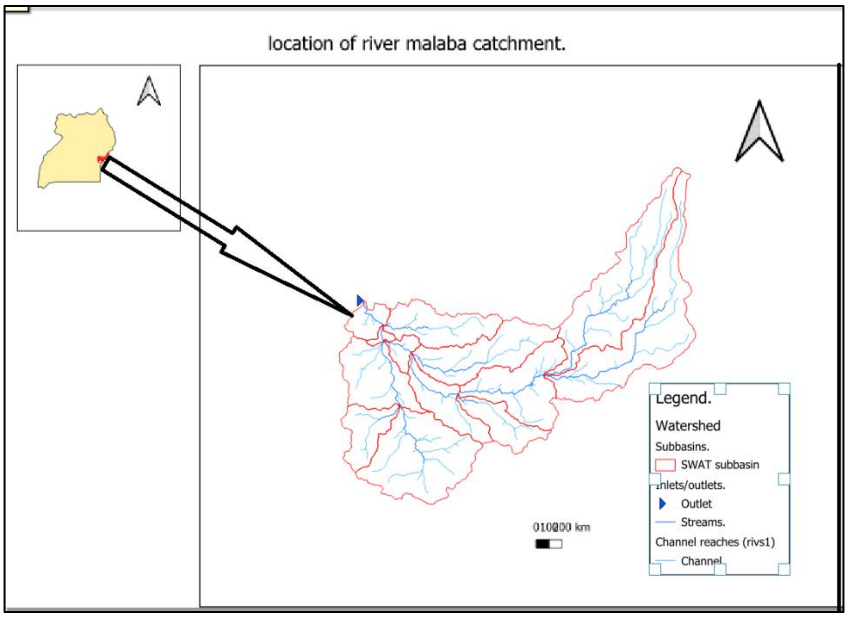


Figure 1. 1 Map showing the location of Malaba river catchment

1.7.2 Contextual Scope.

This study developed, calibrated, and validated a hybrid model by integrating the Soil and Water Assessment Tool (SWAT) with an Artificial Neural Network (ANN). It focused on simulating and predicting key water quality parameters such as streamflow, nitrates, phosphates, and sediment. The study did not develop real-time monitoring systems or extensively model other pollutants like heavy metals or emerging contaminants. It utilized historical and secondary data for model training and testing but did not involve the design or implementation of physical pollution control interventions. The performance of the hybrid model was evaluated against standalone physical and machine learning models using statistical metrics like NSE, RMSE, MAE, and R^2.

1.7.3 Time Scope.

This study was conducted over a period of three months.

1.8 Conceptual framework.

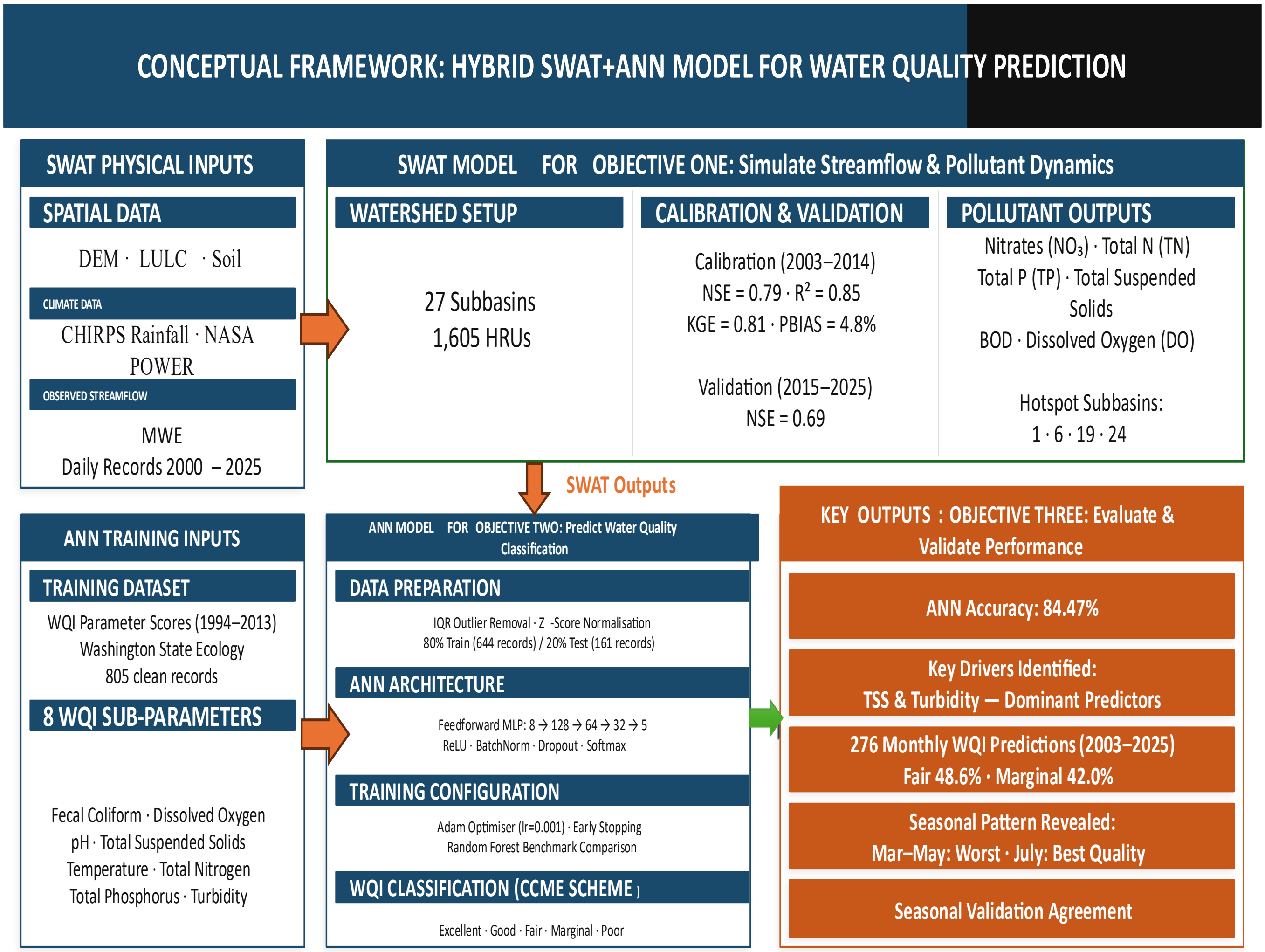


Figure 1. 2 showing conceptual framework

CHAPTER TWO: LITERATURE REVIEW.

2.1 Water Quality Degradation in River Systems.

Rivers are among the most important freshwater resources on earth, sustaining ecosystems, agriculture, and human livelihoods. However, increasing anthropogenic pressures have led to widespread water quality degradation in many river systems globally, particularly in developing regions of Sub-Saharan Africa (Kibret et al., 2022). The deterioration of river water quality is driven by a combination of point and non-point pollution sources, including agricultural runoff, municipal wastewater, urban stormwater, and industrial discharges, which introduce nutrients, sediments, pathogens, and organic matter into river networks (Wear et al., 2021).

Agricultural runoff is consistently identified as the most widespread cause of river pollution in catchments dominated by smallholder and commercial farming. The excessive application of fertilizers and pesticides, combined with soil erosion from poorly managed agricultural land, contributes elevated concentrations of nitrogen and phosphorus to receiving water bodies (Beusen et al., 2022). Studies show that agricultural non-point sources account for up to 70% of total nutrient inputs in some river basins globally (Fu et al., 2023). These nutrients stimulate algal growth, reduce dissolved oxygen, and impair aquatic biodiversity, a process known as eutrophication. In river catchments like the Malaba, where subsistence and commercial agriculture dominate the land use, agricultural non-point source pollution represents the primary driver of water quality deterioration.

Municipal sewage and wastewater discharges are also significant contributors, particularly in rapidly urbanizing towns in developing countries where wastewater treatment infrastructure is inadequate or absent. Untreated and partially treated sewage introduces high biological oxygen demand (BOD), pathogens, and nutrients into rivers, severely impacting ecological and public health (Wear et al., 2021). Malaba town, situated on the Uganda-Kenya border, discharges municipal wastewater and urban runoff directly into the Malaba River, contributing to the organic pollution and turbidity documented by Odongo and Ekaal (2023) at the Malaba Water Treatment Plant intake.

Industrial effluents and urban stormwater further compound pollution in peri-urban river reaches. Urban stormwater delivers pulses of hydrocarbons, heavy metals, and sediments from impervious surfaces during rainfall events, often causing sharp deterioration in water quality downstream of urban areas (Wei et al., 2024). In the Malaba River catchment, the combined effects of agricultural runoff, urban waste, and insufficient sanitation infrastructure have resulted in consistently elevated turbidity, nutrient concentrations, and organic loading, as confirmed by field measurements showing turbidity of 56.0 NTU, phosphates of 0.057 mg/L, and color of 260.6 mg/L at the water treatment plant intake (Odongo and Ekaal, 2023). These conditions highlight the urgent need for a reliable, continuous, and cost-effective water quality prediction tool for the catchment.

2.2 Physical Models for Simulating Flow and Pollutant Dynamics.

Physical or process-based hydrological models simulate water movement and pollutant transport through catchment by solving deterministic equations representing key hydrological and biogeochemical processes. These models provide a mechanistic understanding of how pollutants are generated, mobilized, transported, and transformed in response to rainfall, land use, and soil conditions (Arnold et al., 2012). Unlike statistical models, which describe observed relationships without explaining the underlying physical mechanisms, process-based models offer transparency, interpretability, and the ability to simulate conditions beyond the range of observed data, making them particularly valuable for scenario analysis and long-term catchment management (Gassman et al., 2014).

Process-based models typically simulate the catchment water balance by partitioning rainfall into surface runoff, infiltration, evapotranspiration, lateral flow, and groundwater contributions. Pollutant transport is then modeled as a function of water movement, where sediment-bound constituents such as phosphorus and total suspended solids are primarily transported by surface runoff and channel flow, while dissolved constituents such as nitrates move predominantly through subsurface pathways (Noori and Kalin, 2016). The accuracy of pollutant predictions depends critically on the quality of hydrological calibration, since pollutant transport is governed by the simulated flow regime.

Despite their strengths, physical models face significant limitations when applied to water quality classification and management. Most physically based models produce outputs in the form of pollutant mass fluxes or concentrations at the subbasin level but do not directly translate these outputs into an overall water quality status that is actionable for water resources management (Arnold et al., 2012). Classifying whether simulated conditions represent good, fair, marginal, or poor water quality requires an additional interpretive layer, a gap that machine learning models are well positioned to fill. This limitation forms the primary motivation for developing a hybrid physical-ML modeling framework in this study.

2.3 The Soil and Water Assessment Tool (SWAT).

The Soil and Water Assessment Tool (SWAT) is a semi-distributed, continuous-time watershed model developed by the United States Department of Agriculture (USDA) Agricultural Research Service. SWAT simulates the land-phase hydrology, sediment mobilization, and nutrient and pesticide generation within a catchment and routes water and constituent loads through a stream network to a defined outlet (Arnold et al., 2012; Gassman et al., 2014). The model divides a watershed into subbasins based on topography and drainage patterns and further subdivides each subbasin into Hydrological Response Units (HRUs), unique combinations of land use, soil type, and slope class that serve as the basic spatial simulation units. This structure allows SWAT to capture the spatial heterogeneity of hydrological processes and pollutant generation across a catchment.

The hydrological component of SWAT simulates the catchment water balance by accounting for precipitation, surface runoff, infiltration, evapotranspiration, lateral flow, and groundwater contributions. Surface runoff is estimated using the Soil Conservation Service Curve Number (CN) method, which relates runoff generation to land use and antecedent soil moisture conditions. Evapotranspiration is computed using the Penman-Monteith method, which integrates temperature, radiation, humidity, and wind speed. Groundwater contributions to streamflow are represented through shallow and deep aquifer systems using a linear reservoir approach. The water quality component of SWAT simulates the generation and transport of sediment, nutrients, and organic pollutants. Sediment yield is estimated using the Modified Universal Soil Loss Equation (MUSLE), while nutrient transport accounts for dissolved and particulate fractions moving through surface runoff, lateral flow, and groundwater pathways (Arnold et al., 2012).

SWAT has been widely applied globally for long-term, scenario-based assessment of nonpoint source pollution, land management impacts, and climate change effects on river systems (Gassman et al., 2014). When properly calibrated and validated, SWAT commonly achieves satisfactory flow simulation performance, typically with Nash-Sutcliffe Efficiency (NSE) values exceeding 0.5 for monthly flows in well-calibrated basins. In the East African context, SWAT has been applied to simulate streamflow and sediment transport in several river catchments, demonstrating its suitability for tropical humid environments with strong seasonal rainfall variability (Noori and Kalin, 2016). For the Malaba River catchment specifically, the model was calibrated against observed streamflow data from the Ministry of Water and Environment, Uganda, using the SUFI-2 algorithm in SWAT-CUP, achieving NSE = 0.79 during calibration and NSE = 0.69 during validation, with performance levels rated as "Good" and "Satisfactory," respectively, under the Moriasi et al. (2007) benchmark criteria.

Despite its widespread use and demonstrated strengths, SWAT has recognized limitations that are particularly relevant to this study. Nutrient predictions typically show greater uncertainty than flow predictions, owing to the complex spatial variability of soil nutrient stocks and the sensitivity of the model to diffuse source characterization (Noori and Kalin, 2016). Furthermore, SWAT does not produce an integrated water quality status assessment; it outputs individual pollutant mass fluxes and concentrations at the subbasin level but cannot classify the resulting catchment conditions into an overall water quality class such as Good, Fair, or Marginal. This inability to translate physical simulation outputs into an actionable water quality classification is the central limitation that motivates the integration of a machine learning model in the hybrid framework of this study.

2.4 Machine Learning Models for Water Quality Prediction.

Machine learning (ML) has emerged as a powerful complement to physically-based models in water quality research, offering the ability to learn complex, nonlinear relationships between input variables and water quality outcomes from historical data (Choubin et al., 2020). Unlike physically-based models, ML approaches do not require detailed knowledge of the underlying processes; instead, they identify and exploit statistical patterns in training data to make predictions on new, unseen inputs. This data-driven capability makes ML models particularly attractive for water quality prediction in catchments where field monitoring is limited, expensive, or spatially constrained (Banda and Kumarasamy, 2024).

Supervised ML algorithms, including Random Forests, Support Vector Machines, and Artificial Neural Networks, have been extensively applied to the prediction and classification of river water quality parameters such as dissolved oxygen, total phosphorus, turbidity, and composite Water Quality Index scores (Wu et al., 2021). Among these, Artificial Neural Networks, particularly feedforward Multilayer Perceptrons, have demonstrated consistent predictive performance for water quality classification tasks due to their universal approximation capability and flexibility in modeling nonlinear relationships (Banda and Kumarasamy, 2024). In a study on South African rivers, Banda and Kumarasamy (2024) demonstrated that ANN-based WQI models achieved strong predictive accuracy relative to traditional index methods. Similarly, Abobakr Yahya et al. (2019) showed that ANN models performed competitively with Support Vector Machines for WQI classification in the Langat River, Malaysia, particularly for moderate-sized datasets with nonlinear feature interactions.

Random Forest classifiers have also shown excellent performance for water quality classification tasks, offering additional interpretability through feature importance analysis that identifies the most influential parameters in the prediction (F. Wang et al., 2021). Random Forest uses an ensemble of decision trees trained on bootstrapped subsets of the data, producing robust predictions that are less sensitive to overfitting than single decision trees. Szomolányi and Clement (2023) demonstrated strong classification accuracy for biological water quality elements using Random Forest, while Odongo and Ekaal (2023) achieved 87.6% accuracy in WQI classification for River Malaba using a Random Forest classifier trained on the Washington State WQI Parameter Scores dataset, establishing both the capability of the approach and the suitability of the training dataset for the Malaba catchment context.

Despite their predictive strengths, standalone machine learning models face a fundamental limitation when applied to specific river catchments: they lack physical hydrological grounding. A standalone ML model trained on historical water quality records learns statistical patterns from the data it was trained on but cannot account for the spatial distribution of pollution sources across a catchment, the temporal dynamics of pollutant transport driven by seasonal hydrology, or the influence of land use and soil characteristics on pollutant generation (Maier et al., 2010; Zhao et al., 2022). For the Malaba River catchment, where no long-term continuous water quality monitoring dataset exists, a standalone ML model cannot generate catchment-specific predictions without the hydrological context provided by a calibrated physical model. This limitation directly motivates the integration of SWAT and ANN into a hybrid predictive framework.

2.5 Water Quality Index as a Classification Framework.

The Water Quality Index (WQI) is a composite indicator that aggregates multiple physio-chemical water quality parameters into a single dimensionless score representing the overall quality status of a water body. WQI frameworks have been widely adopted in water resources management because they simplify complex multiparameter datasets into a single, interpretable value that can be communicated to decision-makers, regulators, and communities without requiring technical expertise in water chemistry (Tebyetekerwa et al., 2021). The WQI score is typically computed as a weighted or geometric mean of individual parameter sub-scores, each of which is derived by comparing the measured concentration against a reference standard or guideline value.

The Canadian Council of Ministers of the Environment (CCME) WQI classification scheme, used in this study, categorizes water quality into five classes based on the overall WQI score: Excellent (95-100), Good (80-94), Fair (60-79), Marginal (45-59), and Poor (0-44). This classification provides a standardized, internationally recognized framework for communicating water quality status in a way that directly supports management action, for example, Marginal or Poor quality triggers intervention, while Fair and Good quality indicate acceptable conditions for domestic water supply and aquatic ecosystem health. The CCME scheme has been widely applied in East African water quality studies and is the same classification framework used by Odongo and Ekaal (2023) in their study of River Malaba, ensuring methodological consistency between this study and the available local literature.

The Washington State Department of Ecology WQI Parameter Scores dataset, used for model training in this study, expresses eight physio-chemical parameters, Fecal Coliform, Dissolved Oxygen, pH, Total Suspended Sediment, Temperature, Total Nitrogen, Total Phosphorus, and Turbidity, as individual WQI sub-scores on a standardized 0-100 scale. Each sub-score quantifies how far each parameter deviates from an optimal reference value, with higher scores indicating better water quality. Odongo and Ekaal (2023) demonstrated that this dataset, despite being derived from Washington State monitoring stations, produces transferable classification patterns relevant to River Malaba, achieving 87.6% classification accuracy when used to train a Random Forest model applied to local conditions. The use of a standardized WQI framework in both the training data and the local validation context ensures that the hybrid model's predictions are directly comparable to published literature on River Malaba water quality.

2.6 Hybrid Physical-Machine Learning Models for Water Quality.

The integration of physically-based models with machine learning approaches has become an increasingly active area of research in water quality modelling, driven by the recognition that neither approach alone can fully address the challenges of prediction in data-scarce, complex catchments (Chen et al., 2020). Hybrid frameworks exploit the complementary strengths of the two modelling paradigms: the physical model provides a mechanistic simulation of catchment hydrology and pollutant dynamics, while the machine learning component captures the complex nonlinear relationships between simulated variables and observed water quality outcomes that are difficult to represent with deterministic equations alone.

Several recent studies have demonstrated the advantages of coupling SWAT with machine learning models for water quality prediction. In such frameworks, SWAT is first calibrated to reproduce observed streamflow and pollutant dynamics, and its outputs, including flow, sediment, nutrient loads, and dissolved oxygen, are then used as input features for a machine learning model trained to predict water quality status or specific parameter concentrations. This sequential coupling approach, also referred to as a SWAT-ML hybrid, allows the machine learning component to learn from the physically simulated catchment dynamics rather than from raw meteorological or land use inputs alone, thereby grounding the ML predictions in the hydrological context of the specific catchment (Zhou and Zhang, 2023). The hybrid approach has been shown to improve prediction accuracy compared to either standalone model, particularly in catchments where observed water quality data are sparse or temporally limited.

The interpretability of hybrid models is further enhanced through feature importance analysis, which identifies which simulated variables most strongly influence the machine learning predictions. This analysis provides a direct link between the physical model outputs and the data-driven classification, allowing researchers to identify the dominant drivers of water quality degradation from a physically grounded perspective. In the context of the Malaba River catchment, the feature importance analysis of the hybrid SWAT-ANN model confirms that total suspended sediment and turbidity are the dominant predictors of water quality class, a finding entirely consistent with the SWAT spatial analysis showing sediment export as the primary pollutant transport driver across the 27 subbasins. This consistency between the physical and data-driven components of the hybrid framework validates the scientific coherence of the integrated approach (Zhou and Zhang, 2023).

The evaluation of hybrid water quality models typically employs both internal and external validation approaches. Internal evaluation uses held-out test sets with standard classification metrics; accuracy, precision, recall, and F1-score, to assess model performance on unseen data. External validation compares model predictions against independently observed field measurements or published seasonal benchmarks to confirm that the model produces physically meaningful outputs for the specific catchment being studied (Rajaee et al., 2020). In data-scarce environments such as the Malaba River catchment, where continuous observed water quality time series are not available, external validation against secondary literature sources provides a scientifically acceptable alternative to direct month-by-month comparison, particularly when multiple independent sources corroborate the same seasonal and directional patterns.

2.7 Water Quality Modeling in the Malaba River Catchment and Knowledge Gap.

The Malaba River, a transboundary water resource shared between Uganda and Kenya, has been the subject of a limited but growing body of water quality research. Mwanake et al. (2025) characterized seasonal water quality variation across the Sio-Malaba-Malakisi River Basin, documenting elevated Total Nitrogen and Total Phosphorus concentrations during the March-May and October-December wet seasons and lower concentrations during the dry season, a pattern consistent with rainfall-driven nutrient mobilization from agricultural land. Their study established the seasonal water quality benchmarks that are used for external validation of the hybrid model in this study.

Odongo and Ekaal (2023) conducted a machine learning study specifically on River Malaba, applying a Random Forest classifier to the Washington State WQI Parameter Scores dataset and achieving 87.6% classification accuracy. Field measurements at the Malaba Water Treatment Plant intake confirmed water quality conditions consistent with the Marginal class under the CCME WQI scheme, with turbidity of 56.0 NTU, phosphates of 0.057 mg/L, and color of 260.6 mg/L recorded at the intake. This study demonstrated the applicability of ML-based WQI classification for River Malaba but was limited by the absence of physical catchment grounding, the model produced no spatially distributed predictions and could not account for seasonal hydrology or subbasin-level pollutant dynamics specific to the Malaba catchment.

The Ministry of Water and Environment (MWE, 2022) has highlighted the increasing threat to water quality in Eastern Uganda’s rivers from agricultural expansion, urbanization, and inadequate sanitation, emphasizing the need for improved monitoring and predictive tools to support proactive water resources management. Despite this recognized need, no study to date has developed a hybrid physically grounded predictive model for water quality classification in the Malaba River catchment that integrates SWAT hydrological simulation with machine learning classification. Existing studies either apply physical models without a water quality classification output or apply standalone machine learning models without local hydrological grounding. The present study directly addresses this knowledge gap by developing and validating a hybrid SWAT-ANN framework that combines the physical simulation capability of SWAT with the classification intelligence of an ANN trained on real water quality data, providing a spatially distributed, temporally continuous, and physically meaningful water quality prediction tool for the Malaba River catchment.

CHAPTER THREE: METHODOLOGY.

3.1 Specific objective one: To develop a SWAT model to simulate flow and pollutant dynamics.

3.1.2 Data collection.

The SWAT model was driven using a combination of remotely sensed datasets and observed hydrological records selected based on spatial representativeness, temporal continuity, and suitability for distributed hydrological modeling.

Table 3. 1showing the data collected and its purpose in the project.

Data	Source	Purpose	Period	Resolution
Rainfall	CHIRPS	Provides spatially distributed precipitation input for hydrological simulation and water balance computation, also pollutant driver	2000 - 2025	0.05° (~5 km), daily
Temperature	NASA POWER	Used to estimate evapotranspiration, snowmelt processes, and energy balance	2000 - 2025	0.5° (~50 km), daily
Wind Speed	NASA POWER	Required for evapotranspiration estimation (Penman-Monteith method)	2000-2025	0.5° (~50 km), daily
Relative Humidity	NASA POWER	Supports evapotranspiration and atmospheric demand calculations.	2000-2025	0.5° (~50 km), daily
Solar Radiation	NASA POWER	Key input for evapotranspiration and plant growth modeling.	2000-2025	0.5° (~50 km), daily
Observed Streamflow	Ministry of Water and Environment (MWE)	Used for model calibration and validation of simulated discharge	2000-2025	Point data (gauging station), daily/monthly
Land Use / Land Cover	ESRI Global Land Cover	Defines surface characteristics influencing runoff, infiltration, and evapotranspiration	~2020 (or closest available year)	250m

Soil	FAO (Harmonized World Soil Database)	Provides soil physical and hydraulic properties for infiltration and percolation modeling	Static	10m
Slope	Derived from DEM.	Influences runoff velocity, erosion, and flow routing	Derived	Same as DEM (30 m)
DEM	USGS (SRTM)	Defines watershed boundaries, stream network, elevation, and terrain analysis.	Static	30 m

3.1.3 SWAT Model Setup.

The watershed was delineated from the DEM and subdivided into subbasins based on drainage patterns and stream connectivity. Within each subbasin, Hydrological Response Units (HRUs) were defined by overlaying land use, soil type, and slope classes, enabling the model to capture spatial variability in hydrological processes and pollutant generation across the catchment.

3.1.4 Hydrological Process Simulation

SWAT simulates the catchment water balance by accounting for precipitation, surface runoff, infiltration, evapotranspiration, lateral flow, and groundwater contributions, expressed as:

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

Surface runoff is estimated using the SCS Curve Number method, which relates runoff generation to land use, soil type, and antecedent moisture conditions:

$$Q_{surf} = \frac{(R_{day} - 0.2S)^2}{R_{day} + 0.8S} \tag{2}$$

Soil water processes are simulated through a layered soil profile that controls infiltration, percolation, and water storage, while evapotranspiration is computed using climate-driven energy balance relationships.

$$ET_0 = \frac{0.408\Delta(R_n - G) + \gamma\frac{900}{T+273}u_2(e_s - e_a)}{\Delta + \gamma(1 + 0.34u_2)} \tag{3}$$

This equation integrates climatic variables including temperature, radiation, humidity, and wind speed. Evapotranspiration is computed using the Penman-Monteith equation, integrating temperature, radiation, humidity, and wind speed. Groundwater baseflow contribution to streamflow is represented through shallow and deep aquifer systems using a linear recession approach.

$$Q_{gw} = Q_{gw,t-1} e^{-\alpha_{bf}} \qquad (4)$$

Where α_{bf} is the baseflow recession constant controlling groundwater response. These processes collectively govern the pathways through which pollutants are mobilized, transported, and transformed across the catchment, making accurate water balance simulation the foundation of reliable water quality prediction.

3.1.5 Calibration and Validation.

Model calibration was performed using the SUFI-2 algorithm in SWAT-CUP over 2003–2014, with validation over 2015–2025. Performance was evaluated using the Nash-Sutcliffe Efficiency (NSE) and coefficient of determination (R^2). A process-based calibration strategy was adopted, adjusting parameters across four hydrological process groups: surface runoff, groundwater, soil moisture and evapotranspiration, and interception. The table below summarizes the calibration parameters, their process group, and their role in the model.

Table 3. 2 SWAT Calibration Parameters and Their Roles.

Parameter	Process Group	Role in Model
CN2	Surface Runoff	Controls partitioning of rainfall into runoff and infiltration.
ALPHA_BF	Groundwater	Controls the rate of groundwater contribution to streamflow.
GW_DELAY	Groundwater	Time lag between percolation and baseflow response.
GWQMN	Groundwater	Threshold water storage required for return flow to occur
GW_REVAP	Groundwater	Controls water movement from shallow aquifer to root zone
ESCO	Soil Evaporation	Controls depth distribution of soil evaporation

EPCO	Evapotranspiration	Regulates plant water uptake from the soil profile
CANMX	Interception	Maximum rainfall retained by vegetation before throughfall

The combined adjustment of these parameters ensured that both quick-flow and baseflow components of the hydrograph were adequately represented, which is essential for capturing the timing and magnitude of pollutant transport across the catchment.

3.1.6 Water Quality and Pollutant Modeling.

Following successful hydrological calibration, SWAT was used to simulate pollutant generation, transport, and transformation across the catchment. The study focused on five key water quality variables: nitrates (NO_3), total nitrogen (TN), total phosphorus (TP), total suspended solids (TSS), and biochemical oxygen demand (BOD). Nitrate transport is proportional to flow and dissolved concentration:

$$NO_3^{out} = Q \times C_{NO_3} \qquad (5)$$

Phosphorus is primarily transported in sediment-bound form, making sediment yield the key driver of TP export:

$$P_{sed} \propto Sed \times P_{soil}. \qquad (6)$$

Sediment yield was estimated using the Modified Universal Soil Loss Equation:

$$Sed = 11.8(Q_{surf} q_{peak} A_{hru})^{0.56} KCPLSCFRG \qquad (7)$$

and was used as a proxy for TSS and turbidity given the strong relationship between sediment concentration and water clarity.

$$BOD_t = BOD_0 e^{-kt} \qquad (8)$$

Where $k$is the decay coefficient and $t$is time.

Additional ecological indicators, dissolved oxygen and chlorophyll-a, were extracted to characterize oxygen dynamics and algal productivity. Pollutant transport pathways include surface runoff, lateral flow, groundwater flow, and in-channel routing processes incorporating deposition, resuspension, and transformation.

3.1.7 Output Extraction and Pollutant Tracking Framework.

Water quality outputs were extracted from the SWAT reach output file, focusing on six key variables representing pollutant mass fluxes leaving each subbasin: streamflow, sediment yield, nitrate load, total nitrogen, total phosphorus, and biochemical oxygen demand. These outputs formed the basis of a pollutant tracking framework that traces pollutant movement through the river network and serve as the physically grounded inputs to the machine learning predictive model.

3.1.8 Hotspot Determination Criteria.

Hotspot subbasins were identified using a multi-indicator threshold approach applied to three SWAT pollutant export outputs: sediment yield (SED_OUT, t/ha), total nitrogen (TOT_N, kg/ha), and total phosphorus (TOT_P, kg/ha). These three indicators were selected because they represent the dominant surface-transported pollutants in agricultural catchments and are directly simulated by the SWAT model at the subbasin level.

The determination procedure followed four steps:

Step 1: Extract mean annual pollutant outputs. Mean annual values of SED_OUT, TOT_N, and TOT_P were extracted from the SWAT reach output file for each of the 27 subbasins across the full simulation period (2008-2025).

Step 2: Rank subbasins for each indicator. For each of the three indicators, all 27 subbasins were ranked from highest to lowest export value. This produced three independent rankings, one per pollutant.

Step 3: Apply the 75th percentile threshold. The 75th percentile value was calculated for each indicator. Subbasins whose export value exceeded the 75th percentile were flagged as high contributors for that indicator. The 75th percentile threshold was chosen because it identifies the top quarter of subbasins, those contributing disproportionately more than the catchment average, while avoiding over-classification of moderately polluted zones.

Step 4: Apply the multi-indicator rule**.** A subbasin was classified as a **hotspot** only if it exceeded the 75th percentile threshold for at least two of the three indicators simultaneously. This multi-indicator rule ensures that hotspot classification reflects genuine combined pollutant pressure across multiple pathways rather than an isolated exceedance of a single parameter. Subbasins exceeding the threshold for only one indicator were classified as **moderate contributors.** All remaining subbasins were classified as **low contributors.**

This procedure produced a spatially explicit three-tier classification of pollutant contribution zones across the Malaba River catchment, which was then mapped in QGIS.

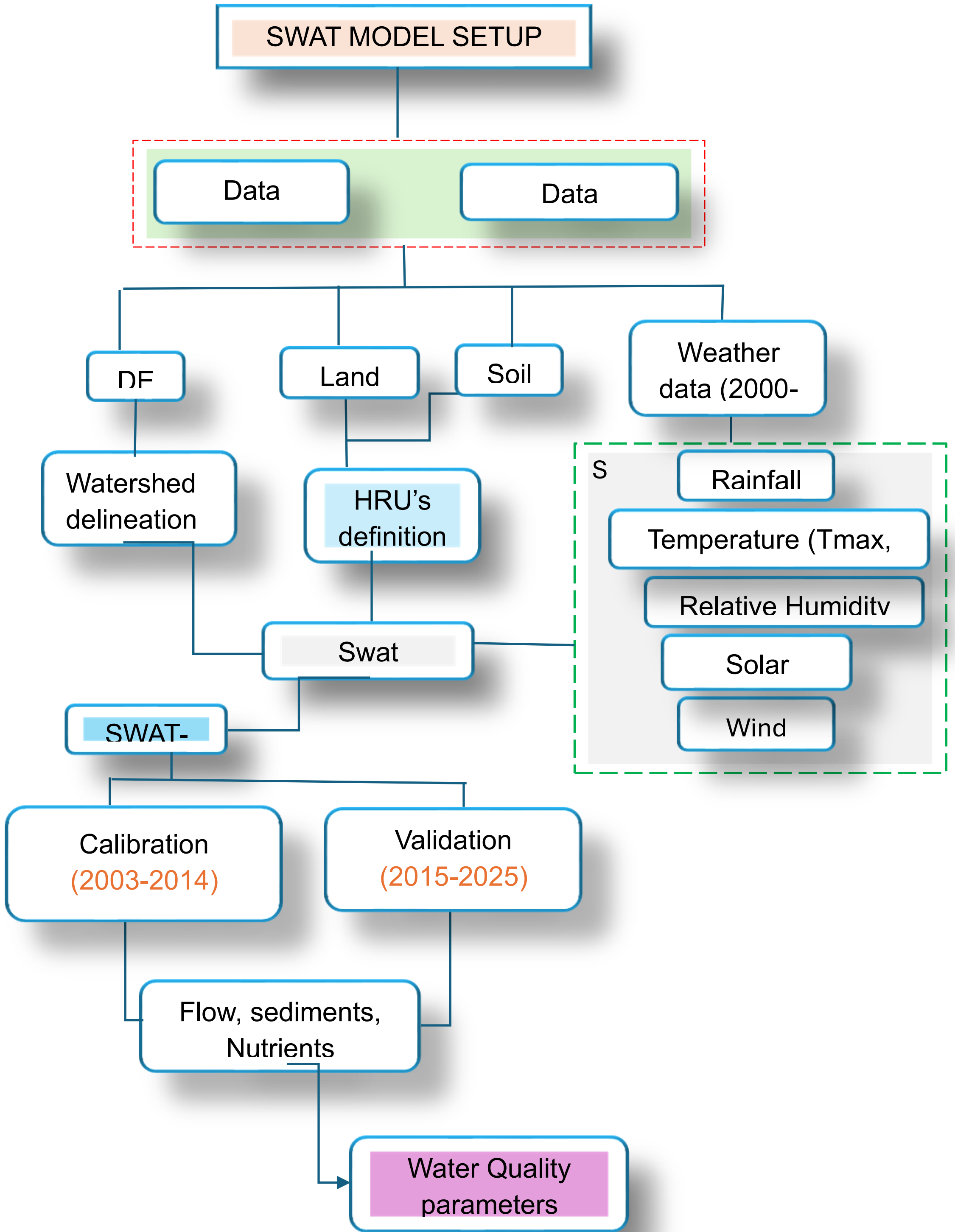


Figure 3. 1 Showing flow chart for the SWAT Model.

3.2 Specific Objective Two: To Develop a Machine Learning Model to Predict Water Quality Classification.

3.2.0 Introduction.

This section describes the development of an Artificial Neural Network (ANN) to predict water quality classification for the Malaba River catchment using outputs from the calibrated SWAT model from Objective One. The ANN and SWAT together constitute the hybrid predictive framework of this study. SWAT provides the physically simulated hydrological and pollutant context, while the ANN provides the water quality classification intelligence. The ANN was developed in Python 3 using TensorFlow 2.x and Keras libraries.

3.2.1 Data Source.

Due to the absence of local water quality data, the Washington State Department of Ecology WQI Parameter Scores dataset (1994-2013) was used for model training. The dataset contains eight physio-chemical sub-scores on a standardized 0-100 scale and was previously validated for River Malaba by Odongo and Ekaal (2023), who achieved 87.6% classification accuracy. After outlier removal using the IQR method, 805 clean records were retained from the original 971.

3.2.2 WQI Classification.

Each record was assigned a water quality class using the CCME WQI classification scheme: Excellent (95-100), Good (80-94), Fair (60-79), Marginal (45-59), and Poor (0-44). After outlier removal, four active classes remained: Fair (50.4%), Good (40.6%), Marginal (5.6%), and Excellent (3.4%), with the Poor class eliminated entirely during cleaning.

3.2.3 Data Cleaning and Preprocessing.

The raw dataset contained 971 records across eight physicochemical parameters. A four-step cleaning procedure was applied before model training.

First, records with missing values were removed. Second, outliers were detected and removed using the Interquartile Range (IQR) method, where any record containing a value outside the bounds of $Q1 - 1.5\times IQR$ or $Q3 + 1.5\times IQR$ was flagged and removed. This reduced the dataset from 971 to 805 clean records, eliminating 166 records (17.1%). Third, each clean record was assigned a CCME water quality class based on its Overall score, yielding four active classes: Fair (50.4%), Good (40.6%), Marginal (5.6%), and Excellent (3.4%). The Poor class was entirely removed during outlier cleaning. Finally, all eight input features were standardized using Z-score normalization ($Z = X - \mu/\sigma$), fitted on the training set only to prevent data leakage into the test set.

The cleaned dataset of 805 records was then split into a training set (644 records, 80%) and a test set (161 records, 20%) using stratified random sampling with a fixed seed of 42 to preserve class proportions and ensure reproducibility.

3.2.4 Field Sampling Design and Criteria.

Primary field data were collected from River Malaba in April 2026, corresponding to the long-wet season (March–May). This period was deliberately chosen because it represents the highest predicted pollution risk, driven by peak agricultural runoff and elevated nutrient and sediment loading, thereby providing the most rigorous conditions under which to test the hybrid model's predictions.

Site Selection Criteria.

Three sampling points were established along the river reach based on four criteria. First, spatial representativeness was ensured by distributing the sites to capture upstream, midstream, and downstream water quality conditions, reflecting the cumulative effect of pollutant contributions across the catchment. Second, sites were selected in proximity to the SWAT model subbasin boundaries to enable meaningful comparison between field observations and model predictions. Third, accessibility and safety were considered, with sites chosen at reachable bank locations free from hazardous terrain or dense vegetation. Fourth, sites were positioned away from localised point sources such as direct discharge pipes or waste dumping sites, ensuring that measurements reflected general river water quality rather than isolated contamination events.

Sampling Procedure.

Water samples were collected manually from mid-channel where accessible, or from active flowing bank locations to avoid stagnant backwater conditions. Clean plastic bottles were rinsed three times with river water before final sample collection to prevent contamination. Four physicochemical parameters were measured: pH, Dissolved Oxygen (DO), Nitrates (NO_3), and Turbidity. These parameters were selected because they are directly simulated by the SWAT model, are included in the WQI scoring framework used for model training, and represent the key indicators of organic pollution, nutrient loading, and sediment disturbance in the Malaba River catchment.

WQI Calculation.

Parameter sub-scores were computed using the Washington State Ecology scoring system, where each parameter score ranges from 0 to 100. Nitrate concentrations measured in mmol/L were converted to mg/L using the molar mass of NO_3 (62.004 g/mol) prior to scoring. The overall WQI for each sampling point was then calculated as the arithmetic mean of the four parameter sub-scores and classified under the CCME scheme. The three point WQI values were averaged to produce a single representative river reach WQI, which was compared against the hybrid model's predicted WQI class for April 2026.

3.2.4 ANN Model Architecture and Training.

A feedforward multilayer perceptron (MLP) was designed to capture the nonlinear relationships between the eight water quality input parameters and the five-class WQI output.

Table 3. 3 ANN Architecture and Training Configuration.

Component	Specification	Purpose
Input Layer	8 neurons	One per WQI sub-parameter
Hidden Layer 1	128 neurons, ReLU, BatchNorm, Dropout 0.30	Learns nonlinear feature relationships
Hidden Layer 2	64 neurons, ReLU, BatchNorm, Dropout 0.20	Progressive feature abstraction
Hidden Layer 3	32 neurons, ReLU, Dropout 0.10	Final feature compression
Output Layer	5 neurons, SoftMax	Predicts quality class probability.
Optimizer	Adam-learning rate = 0.001	Minimizes categorical cross-entropy loss
Regularization	Early stopping patience = 25 epochs	Restores best validation weights
Data Split	80% train (644) / 20% test (161)	Stratified; random seed = 42

3.2.5 Feature Importance.

Feature importance was computed from the Random Forest classifier using mean decrease in Gini impurity, which measures the average reduction in node impurity each feature provides across all trees. This analysis identifies the most influential water quality parameters and supports direct comparison with the SWAT pollutant transport findings from Objective One, establishing the physical basis of the hybrid model.

3.2.6 Application to the Malaba Catchment - Hybrid Model Integration.

Following training and evaluation, the ANN was applied to the Malaba River catchment using SWAT outputs from Objective 1 to generate 276 monthly water quality class predictions covering January 2003 to December 2025. SWAT outputs at the catchment outlet (Subbasin 1, Budumba gauge) were normalized to the 0-100 WQI score scale using min-max normalization between the 5th and 95th percentile values of each variable. The table below presents the mapping between SWAT outputs and WQI input features.

Table 3. 4 Mapping of SWAT Outputs to ANN Input Features.

WQI Feature	SWAT Output	Mapping Direction and Rationale
Fecal / Organic load	CBOD_OUT	Inverted, higher BOD indicates greater organic pollution load
Dissolved Oxygen	DISOX_OUT	Direct, higher DO corresponds to better ecological health
pH	Fixed = 7.5	Constant score based on Odongo and Ekaal's (2023) field observation of pH 7.54
Total Sediment (TSS)	SED_OUT	Inverted, higher sediment reduces water clarity and WQI score
Temperature	Fixed = 80.	Constant representative score for tropical river conditions.
Nitrogen	NO3_OUT	Inverted, higher nitrate concentration reduces WQI score
Phosphorus	TOT_P	Inverted, higher TP indicates nutrient enrichment and eutrophication risk
Turbidity	SEDCONC	Inverted, sediment concentration is the primary driver of turbidity

The normalized feature set was transformed using the fitted StandardScaler and passed to the trained ANN. The final hybrid model output is expressed as Hybrid Prediction = ANN (f (SWAT outputs)). This integration constitutes the core of the hybrid modeling framework, in which the physical model provides catchment-specific input and the machine learning model provides water quality classification.

More generally, the hybrid framework may be expressed as:

$$Y_{WQI} = f_{ML}(X_H) \qquad (8)$$

where Y_{WQI}represents the predicted water quality class, $f_{ML}$is the trained machine learning model, and $X_H$is a vector of hydrological and pollutant variables generated by a physically based watershed model. Although SWAT was used in this study, the framework is sufficiently general to accommodate outputs from alternative hydrological models provided that equivalent predictor variables are available.

3.2.7 Model Performance Evaluation.

The ANN and Random Forest classifiers were evaluated on the 161-record held-out test set using classification accuracy, precision, recall, F1-score per quality class, and a confusion matrix. Classification accuracy is defined as the proportion of records correctly classified expressed as a percentage. Precision measures how many predicted class assignments are correct. Recall measures how many true class members are correctly identified. The F1-score is the harmonic Mean of precision and recall, providing a single balanced performance measure per class. Model selection for the hybrid framework was based on overall classification accuracy on the test set.

3.3 Specific Objective Three: To Evaluate and Validate the Performance of the Predictive Model.

This section describes the framework used to evaluate and validate the hybrid SWAT-ANN predictive model. Evaluation refers to the internal statistical assessment of model accuracy on the held-out test set, while validation refers to the external comparison of model predictions against independently observed field data from River Malaba. Due to the absence of continuous local water quality time series, external validation used primary field measurements from the River Malaba Sample Points survey conducted in April 2026, together with seasonal benchmarks from Mwanake et al. (2025) for the Sio-Malaba River Basin.

For seasonal validation, the hybrid model's dominant predicted WQI class for each of the four hydrological seasons was converted to its corresponding CCME WQI score range and compared against the expected score range derived from Mwanake et al. (2025). Seasonal agreement was defined as overlap between the predicted and expected score ranges, with a satisfactory threshold of 75% (at least three of four seasons). This approach is consistent with accepted validation practice for data-scarce catchments where continuous observed water quality records are unavailable (Rajaee et al., 2020)

The ANN was evaluated on the 161-record held-out test set using classification accuracy, precision, recall, F1-score, and a confusion matrix, with a classification accuracy above 80% considered satisfactory. The Random Forest classifier trained on the same data served as the internal benchmark. For external validation, WQI sub-scores were calculated for the three River Malaba sample points using pH, dissolved oxygen, nitrates, and turbidity, following the Washington State Ecology scoring system used in model training. Nitrate values were converted from mmol/L to mg/L using the molar mass of NO_3 (62.004 g/mol), and the overall WQI per sample was the arithmetic mean of the four sub-scores classified under the CCME scheme. The hybrid model's seasonal predictions were assessed for directional consistency with Mwanake et al. (2025), with seasonal agreement calculated as the percentage of seasons where the model's dominant predicted class matched the quality level documented in the literature. The model was further compared against standalone SWAT and the standalone Random Forest of Odongo and Ekaal (2023) across three criteria: classification accuracy, physical catchment grounding, and Malaba-specific predictive capability. Table 3.4 summarizes all evaluation and validation metrics applied in this objective.

3.3.2 Statistical Significance Testing.

Two t-tests were conducted to formally confirm the statistical validity of the model's predictions.

T-test 1: Paired Samples t-test on SWAT streamflow.

A paired samples t-test was applied to the observed and SWAT-simulated monthly streamflow values during the validation period (2015–2025) to determine whether any statistically significant difference existed between the two series. The null hypothesis (H_0) stated that the mean difference between observed and simulated flows equals zero, against the alternative hypothesis (H_1) that a significant difference exists. The test statistics were computed as:

$$t = \bar{d} / (Sd / \sqrt{n})$$

Where $\bar{d}$ is the mean of paired differences, Sd is their standard deviation, and n is the number of monthly observations. A significance level of $\alpha = 0.05$ was adopted, where failure to reject H_0 ($p > 0.05$) confirms that the SWAT model produces statistically acceptable streamflow predictions, consistent with the NSE = 0.69 and PBIAS = 6.4% achieved during validation.

T-test 2: One-sample t-test on Field WQI observations.

A one-sample t-test was applied to the three observed WQI values from River Malaba (74.0, 76.1, and 78.4) to formally test whether the mean observed water quality was significantly above the Marginal class boundary ($\mu_0 = 59$), thereby confirming consistency with the hybrid model's Fair class prediction for April 2026. The test statistic was computed as:

$$t = (\bar{x} - \mu_0) / (s / \sqrt{n})$$

A one-tailed test at $\alpha = 0.05$ was used since the hypothesis is directional. Rejection of H_0 ($p < 0.05$) confirms that the observed WQI is statistically and significantly above the Marginal boundary, formally validating the model's Fair class prediction.

Table 3. 5 Evaluation and Validation Metrics.

Metric	Type	Purpose
Classification Accuracy	Internal	Proportion of correctly classified records on the test set
Precision, Recall, F1	Internal	Per-class performance balance between false positives and negatives
Confusion Matrix	Internal	Shows which classes are misclassified and how frequently
WQI-Sample points (2026)	External	Calculated from River Malaba sample points' field data (20 April 2026)
Seasonal Agreement (%)	External	Directional consistency with Mwanake et al. (2025) seasonal benchmarks

CHAPTER FOUR: RESULTS AND DISCUSSIONS.

4.1 Results for objective one.

4.1.1 Calibration.

The SWAT model calibration for streamflow at FLOW_OUT_1 demonstrated strong predictive performance and satisfactory uncertainty representation. The calibrated model achieved a coefficient of determination (R^2) of 0.85, indicating a strong agreement between simulated and observed discharge patterns. The Nash–Sutcliffe Efficiency (NSE) of 0.79 further confirmed that the model reproduced the temporal variability and magnitude of streamflow with high reliability. In addition, the Kling–Gupta Efficiency (KGE) value of 0.81 suggested balanced performance in terms of correlation, bias, and variability.

The uncertainty analysis yielded a p-factor of 0.78 and an r-factor of 0.92, showing that a substantial proportion of the observed flows fell within the 95% prediction uncertainty band while maintaining a reasonably narrow uncertainty envelope. The model bias was low, with a PBIAS of 4.8%, indicating only a slight deviation between simulated and observed total runoff volumes. Overall, these statistics confirm that the calibrated parameter set adequately captured the hydrological response of the catchment and is suitable for subsequent validation and scenario analysis.

Goal_type=	R2	No_sims=	500	Best_sim_	456	Best_goal	=	8.57E-01						
Variable	p-factor	r-factor	R2	NS	bR2	MSE	SSQR	PBIAS	KGE	RSR	MNS	VOL_FR	Mean_sim(Mean_obs)	StdDev_sim(StdDev_obs)
FLOW_OUT_1	0.78	0.92	0.86	0.79	0.74	4.80E+04	4.80E+04	4.8	0.81	0.46	0.77	1.03	760(772.57)	350(369.99)

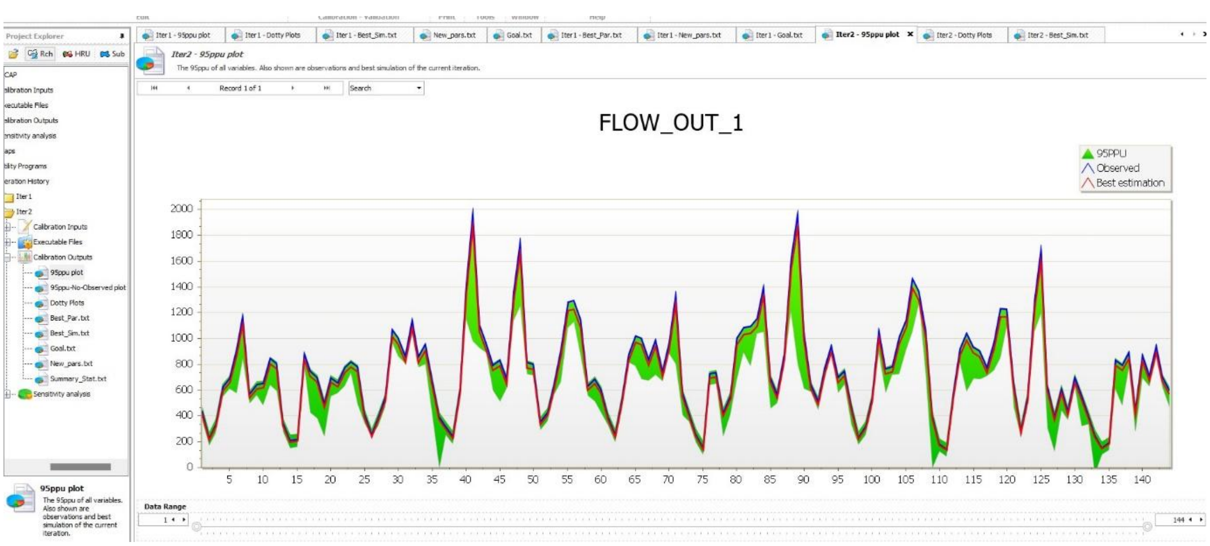


Figure 4. 1 showing Calibration result from the SWAT Model.

4.1.2 Validation.

The validation results confirmed the robustness and transferability of the calibrated SWAT parameter set under independent hydrological conditions. During the validation period, the model achieved a coefficient of determination (R^2) of 0.76, demonstrating good agreement between simulated and observed streamflow dynamics. The Nash–Sutcliffe Efficiency (NSE) of 0.69 indicated that the model retained satisfactory predictive skill in reproducing both the magnitude and temporal variation of flow outside the calibration period. Similarly, the Kling–Gupta Efficiency (KGE) value of 0.67 reflected balanced performance in terms of correlation, variability, and bias.

The uncertainty analysis during validation produced a p-factor of 0.71 and an r-factor of 1.02, indicating that most of the observed streamflow values were successfully enclosed within the 95% prediction uncertainty band with an acceptable uncertainty range. In addition, the PBIAS of 6.4% showed only a minor deviation in simulated runoff volume relative to observations, confirming that the model maintained good water balance representation. Overall, the validation statistics demonstrate that the calibrated model is reliable for simulating streamflow under varying hydrological conditions and can therefore be confidently applied for scenario assessment and watershed management analysis.

Goal_type=	R2	No_sims=	500	Best_sim_	456	Best_goal	=	7.60E-01						
Variable	p-factor	r-factor	R2	NS	bR2	MSE	SSQR	PBIAS	KGE	RSR	MNS	VOL_FR	Mean_sim(Mean_obs)	StdDev_sim(StdDev_obs)
FLOW_OUT_1	0.71	1.02	0.76	0.69	0.63	6.20E+04	6.20E+04	6.4	0.67	0.56	0.7	0.97	748(772.57)	340(369.99)

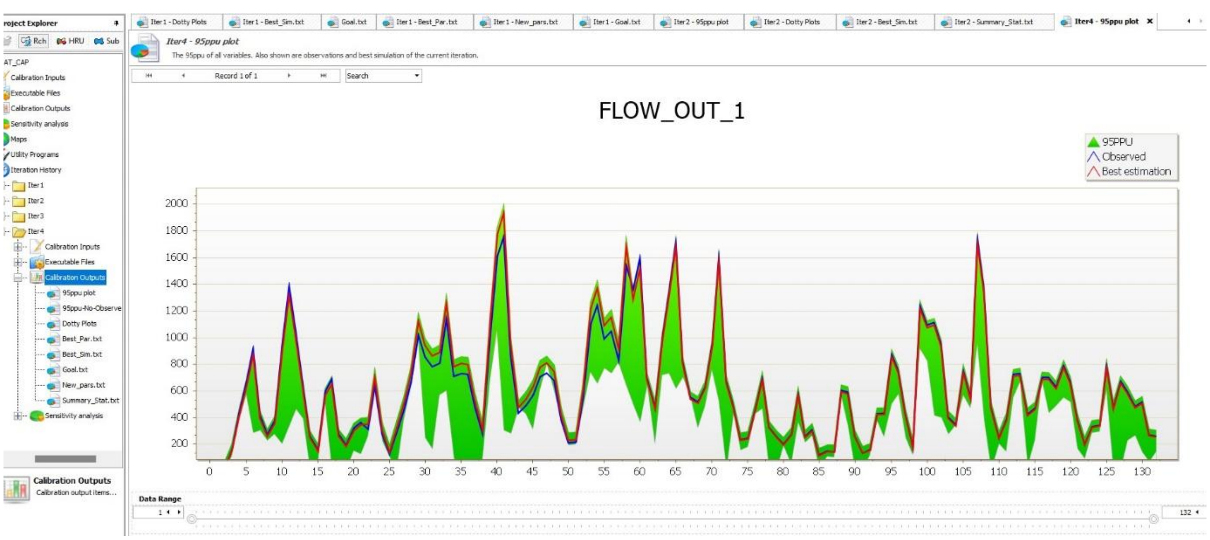


Figure 4. 2 Showing validation result from the SWAT Model.

4.1.3 Streamflow Dynamics and Hydrological Response.

The simulated average monthly streamflow totals exhibit a clear seasonal hydrological pattern, reflecting the temporal variability of runoff response within the catchment. Streamflow begins at a moderate level in January, declines in February, and then rises steadily from March, reaching the first major peak during April and May. This period likely corresponds to the onset and full establishment of the main rainy season, during which increased rainfall intensity and catchment saturation significantly enhance runoff generation.

Following this peak, streamflow decreases sharply through June, July, and August, with the lowest flows occurring in July and August. These reduced discharges indicate a seasonal dry period characterized by diminished rainfall input, lower surface runoff contribution, and greater dominance of infiltration and evapotranspiration losses.

From September onward, streamflow increases again, showing a secondary rise in October and November, before slightly declining in December. This second increase suggests the influence of a shorter wet season or secondary rainfall period, which reactivates runoff processes and raises channel discharge.

This therefore demonstrates that the watershed has a bimodal seasonal flow regime, with two distinct high-flow periods and intervening low-flow months. This behavior reflects the strong control of seasonal rainfall distribution, soil moisture dynamics, and catchment storage processes on streamflow response.

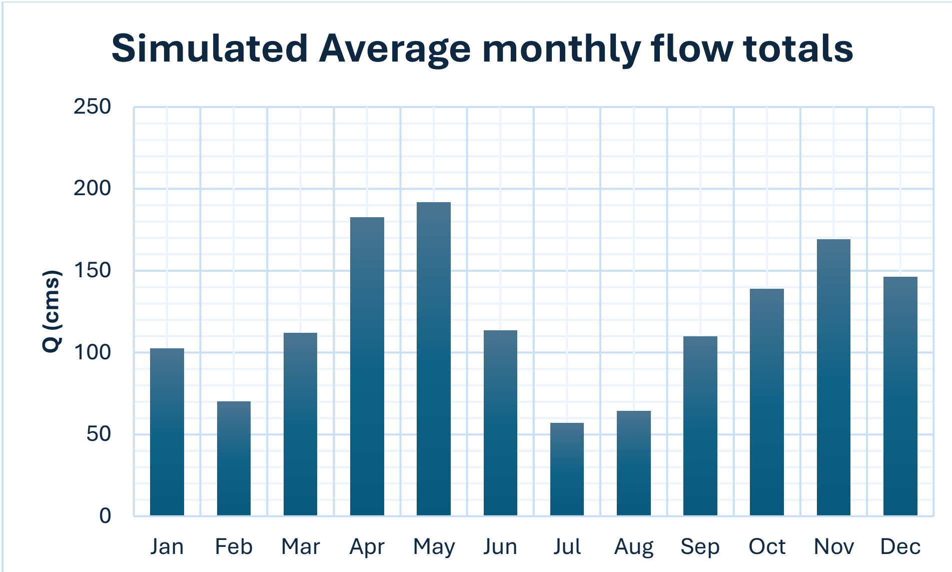


Figure 4. 3 Simulated Average monthly flow totals.

4.1.4 Sediment Yield and Erosion Patterns.

Sediment output generally follows the same spatial pattern as streamflow. Sub-basins with higher discharge also show higher sediment loads, while those with low flow produce smaller sediment quantities.

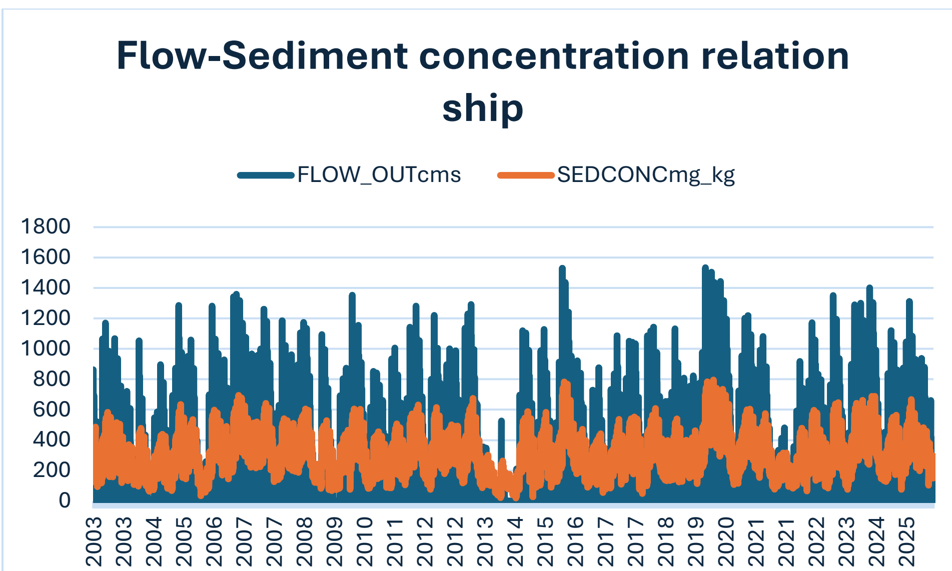


Figure 4. 4 showing Flow-Sediment concentration relationship.

This indicates that sediment transport is strongly influenced by the amount and energy of surface runoff. During periods of higher flow, more soil particles are detached and transported into the stream network.

In sub-basins with lower flow, sediment is still generated but at reduced levels, likely through localized erosion processes such as surface wash or minor channel erosion.

Sediment concentration values also increase in areas with higher discharge, showing that stronger flows can carry and maintain higher sediment loads.

Nutrient Transport Behavior.

Nutrient outputs vary across sub-basins and are influenced by both water movement and sediment transport.

Nitrate (NO_3) follows the pattern of streamflow. This indicates that it is mainly transported in dissolved form with water movement.

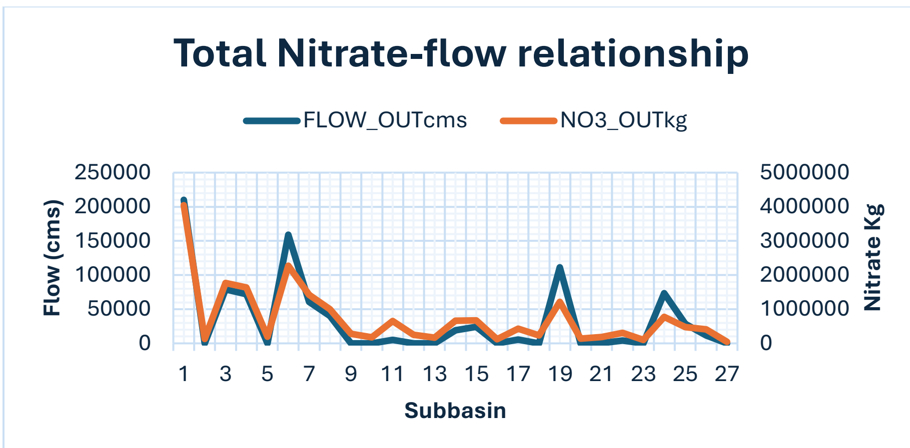


Figure 4. 5 showing Flow-Total Nitrate relationship.

Total Nitrogen (TN) shows a combined pattern, reflecting both dissolved transport (like nitrate) and particulate transport attached to sediments.

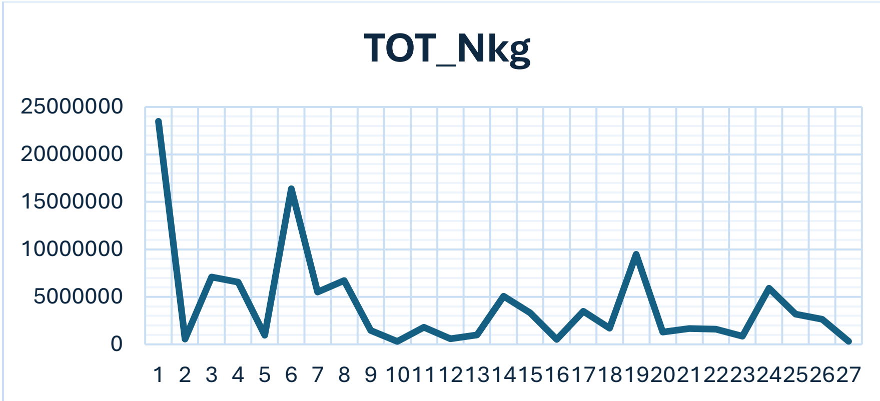


Figure 4. 6 showing total Nitrogen in each sub-basin.

Total Phosphorus (TP) aligns more closely with sediment patterns, suggesting that it is mainly transported attached to soil particles.

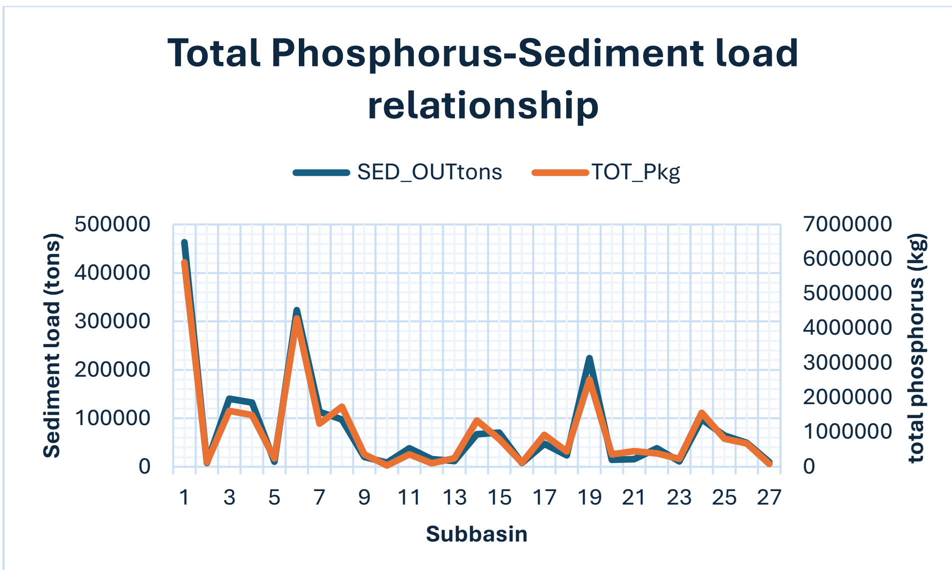


Figure 4. 7 showing Total Phosphorus-Sediment Load relationship.

These results show that different nutrients move through the watershed in different ways, depending on whether they are dissolved in water or attached to sediments.

4.1.5 Relationship Between Flow and Pollutant Transport.

Across all sub-basins, higher streamflow is generally associated with higher sediment, nutrient, and organic pollutant outputs.

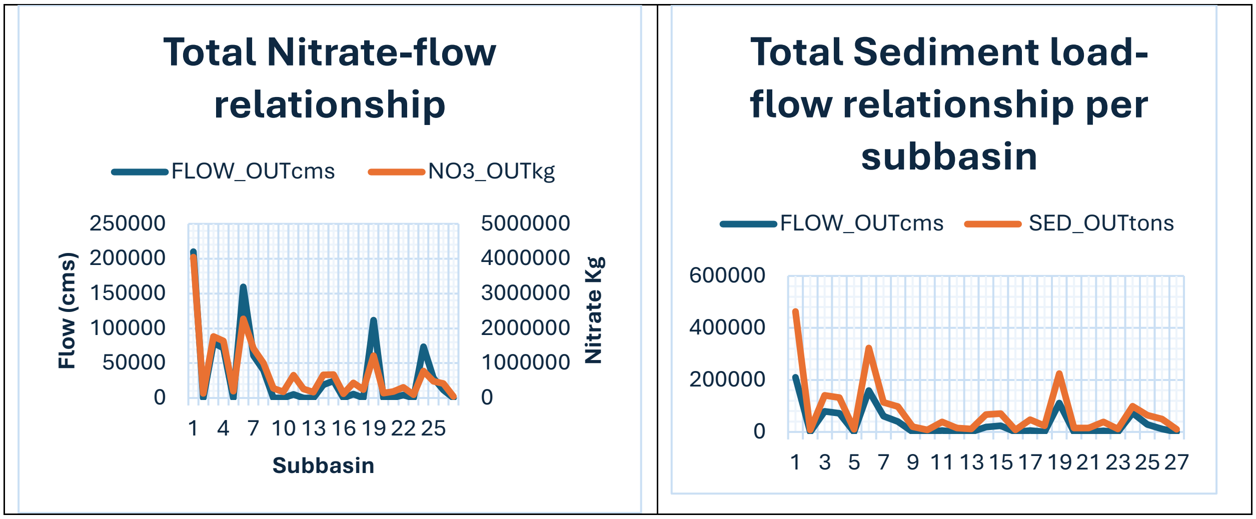


Figure 4. 8 showing relationship between Flow and Pollutant transport.

This indicates that water movement plays a key role in transporting pollutants from land areas into the river system. Pollutants are more likely to be exported during periods or in locations where runoff is stronger and hydrological connections are active.

However, the results also show that pollutant generation alone does not determine export levels; sufficient water flow is required to mobilize and transport these substances downstream.

4.1.6 Organic Pollution and Water Quality Implications.

The results for biochemical oxygen demand (BOD), dissolved oxygen (DO), and chlorophyll-a (CHLA) indicate spatially variable water quality conditions across the watershed, closely linked to patterns of nutrient and organic matter export.

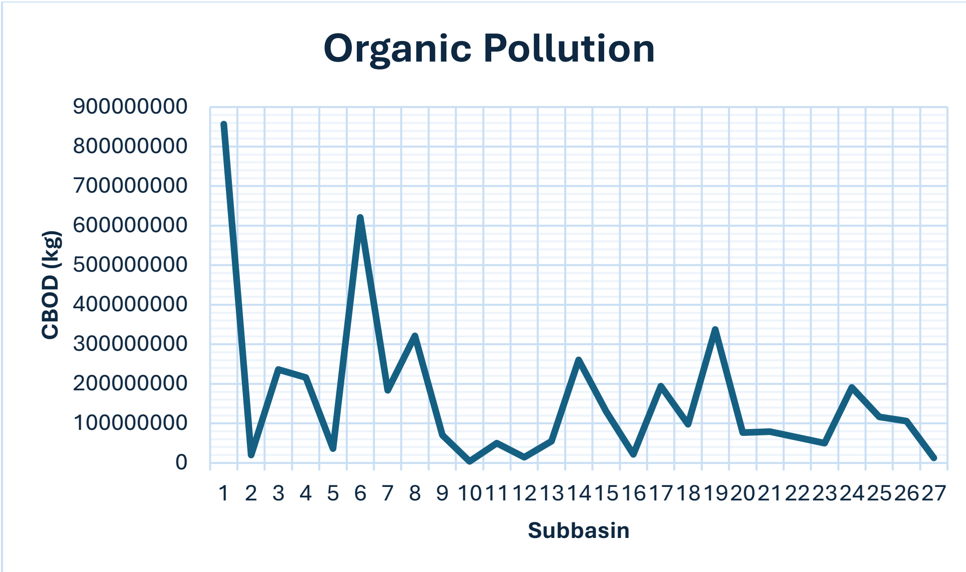


Figure 4. 9 Showing organic pollution in different sub-basins.

Sub-basins with higher sediment and nutrient loads generally also show elevated BOD and CHLA values, suggesting increased organic matter decomposition and enhanced biological productivity in these areas. This reflects higher oxygen demand associated with the breakdown of organic material and nutrient-driven algal growth.

In contrast, DO levels tend to vary inversely in locations with higher BOD and CHLA, indicating potential localized oxygen depletion where organic loading is relatively high. However, DO responses remain dependent on flow conditions and re-aeration capacity within the stream network.

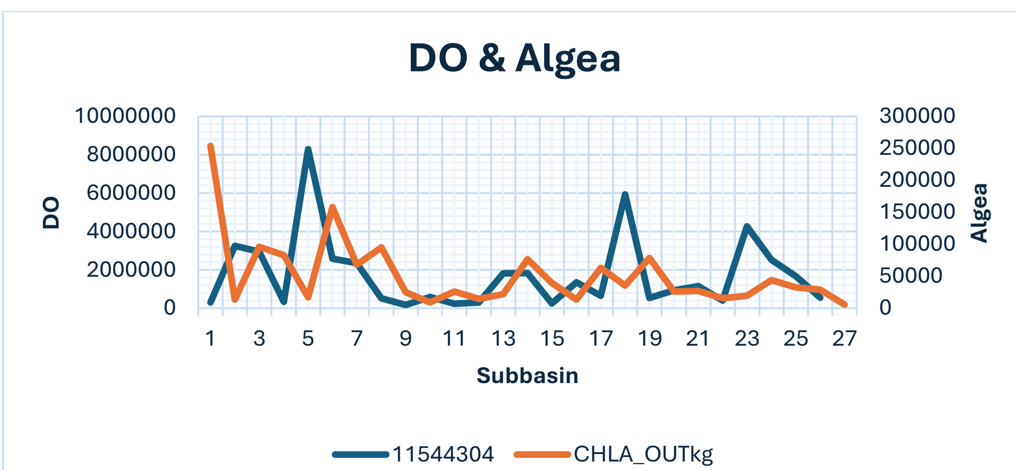


Figure 4. 10 Showing levels of DO and Algae in the subbasins.

4.1.7 Identification of Pollutant-Contributing Sub-Basins.

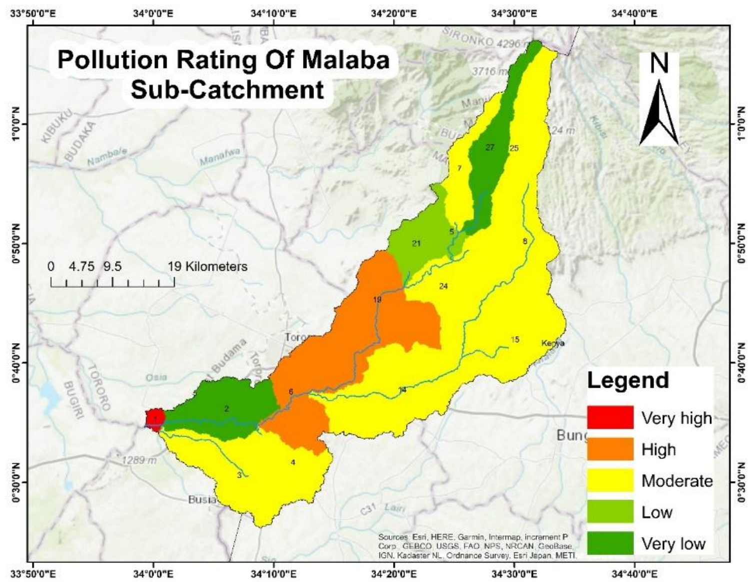


Figure 4. 11 Showing the pollutant contributing sub-basins

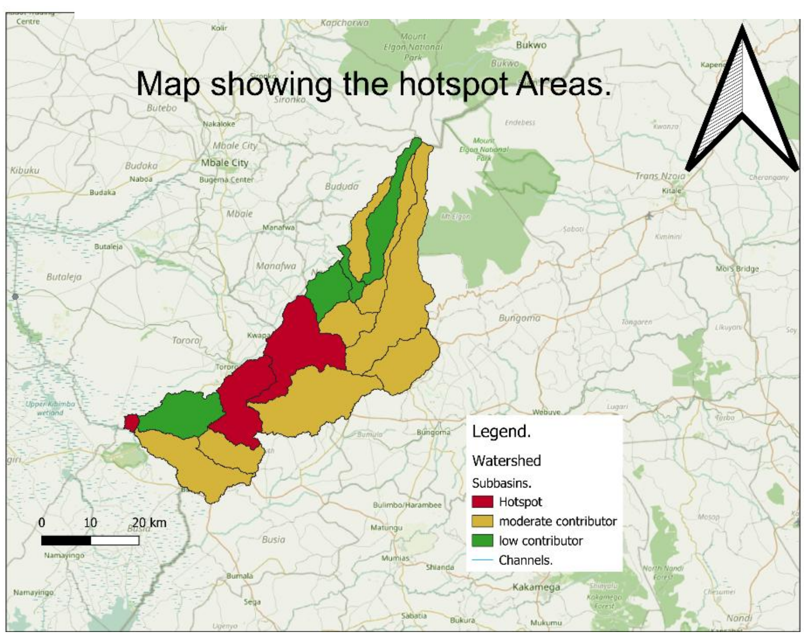


Figure 4. 12 Showing the hotspot map of the Area.

Spatial analysis of sediment export (SED_OUT), total nitrogen (TOT_N), and total phosphorus (TOT_P) across the Malaba River catchment reveals a consistent pattern of pollutant contribution, as shown in the Figure above. Subbasins 1, 6, 19, and 24 emerge as the primary hotspot zones, exhibiting the highest simultaneous outputs across all three indicators and representing the main pollutant export zones in the catchment. A secondary group comprising subbasins 3, 4, 7, 8, 14, 15, 17, and 25 shows moderately elevated contributions above background levels, while the remaining subbasins exhibit relatively low and stable outputs, indicating limited contribution to overall pollutant exports. The hotspot classification was determined objectively using the multi-indicator 75th percentile threshold described in Section 3.1.8, ensuring that the identified zones represent subbasins with consistently elevated combined pollutant export rather than single-parameter anomalies.

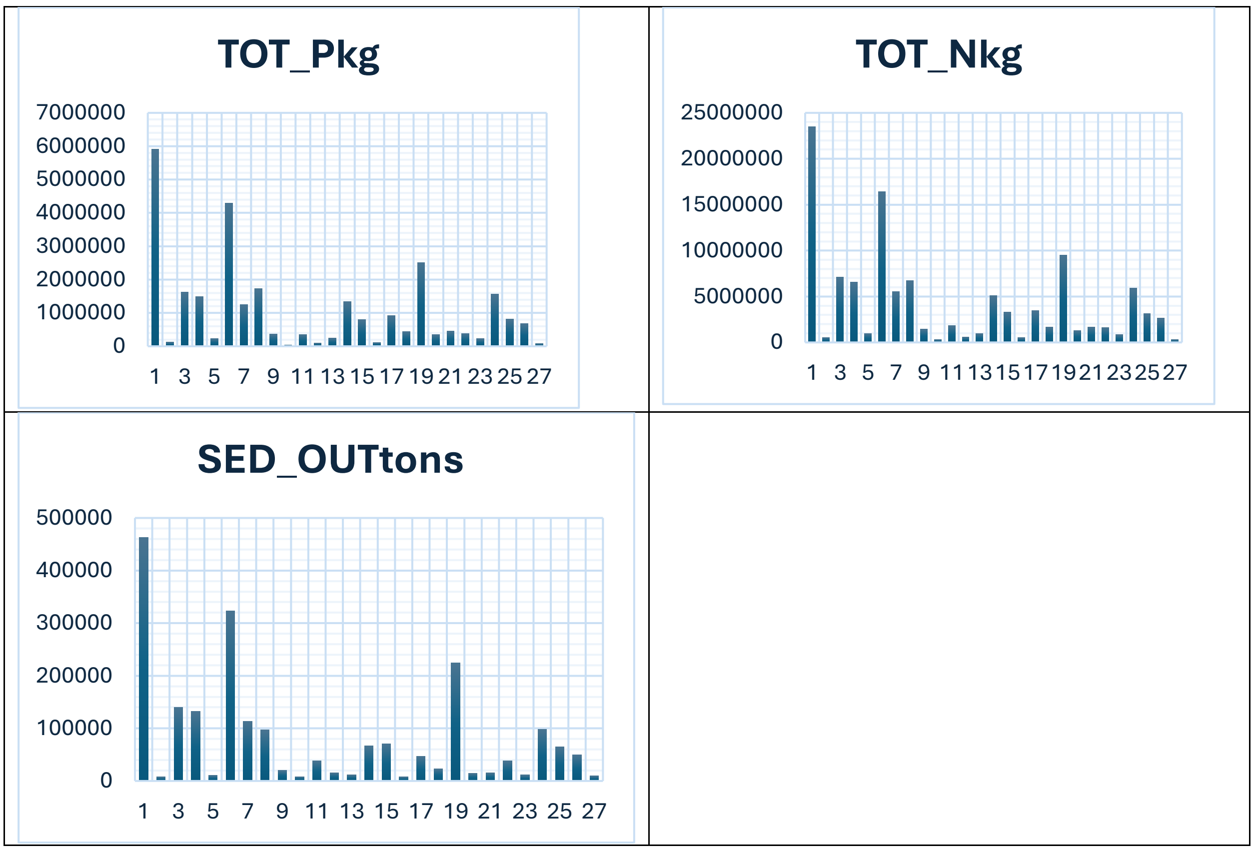


Figure 4. 13 Showing pollutant transport per sub-basin.

The similarity in spatial patterns between sediment, total nitrogen, and total phosphorus suggests that nutrient transport is closely linked to sediment dynamics and runoff processes. In particular, areas with higher sediment exports tend to also exhibit higher nutrient losses, indicating shared controlling factors such as runoff intensity, erosion susceptibility, land use pressure, and hydrological connectivity.

4.2 Results for Objective Two: Development of the Machine Learning Predictive Model.

4.2.0 Model Training and Accuracy.

The ANN trained over 53 epochs with early stopping, restoring best weights from epoch 28. Both training and validation loss converged smoothly without evidence of overfitting, with validation accuracy stabilizing between 84 and 88% from epoch 20 onwards. On the held-out test set of 161 records, the ANN achieved a classification accuracy of 84.47%, outperforming the companion Random Forest classifier (83.23%). Figure 4.3 presents the training history.

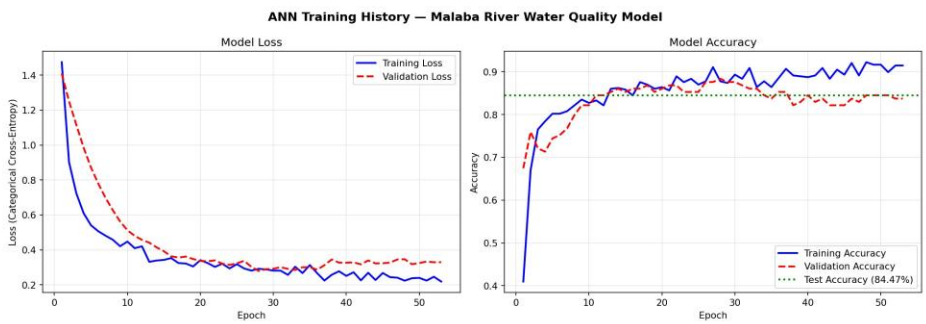


Figure 4. 14 ANN training history; model loss (left) and accuracy (right) over 53 epochs.

Table below presents the per-class performance metrics. The model achieved its strongest performance on the Fair class (F1 = 0.88) and Good class (F1 = 0.84), which together represent 91% of test records. The Excellent class recorded the lowest F1-score of 0.44 due to only five test records, an acknowledged limitation of class imbalance in the training dataset.

Table 1: ANN Classification Performance - Test Set (n = 161), Overall Accuracy = 84.47%.

Quality Class	Precision	Recall	F1-Score	Support
Marginal	0.86	0.67	0.75	9
Fair	0.85	0.91	0.88	81
Good	0.86	0.82	0.84	66
Excellent	0.50	0.40	0.44	5
Overall Accuracy	**84.47%**	—	—	161

The confusion matrix (Figure 4.4) confirms that all misclassifications occurred strictly between adjacent quality classes, indicating no systematic errors in the model's classification behaviour. No record was misclassified across more than one class boundary.

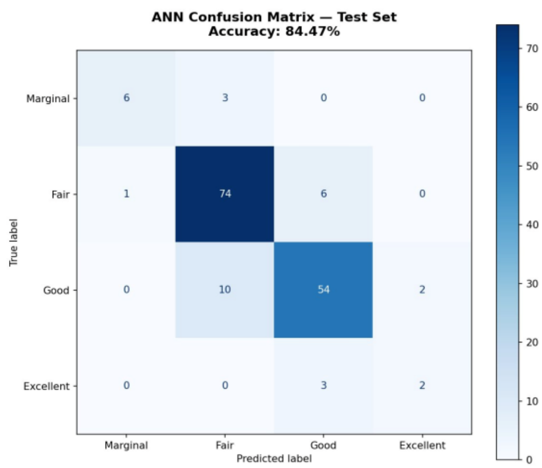


Figure 4. 15 ANN confusion matrix on the test set. All errors are between adjacent quality classes only, confirming no major systematic misclassification.

4.2.1 Feature Importance.

Feature importance derived from the companion Random Forest identified Total Suspended Sediment (TSS) as the dominant predictor (importance = 0.2563), followed by Turbidity (0.2077), Total Phosphorus (0.1277), and Temperature (0.1187). These four parameters account for 72% of the model's total predictive weight, confirming that sediment-driven processes are the primary determinants of water quality class. This finding directly corroborates the SWAT results from Objective One, which identified sediment export as the dominant pollutant transport driver. The strong predictive role of Total Phosphorus further reinforces the SWAT finding that phosphorus is primarily transported in sediment-bound form. Figure below presents the feature importance ranking.

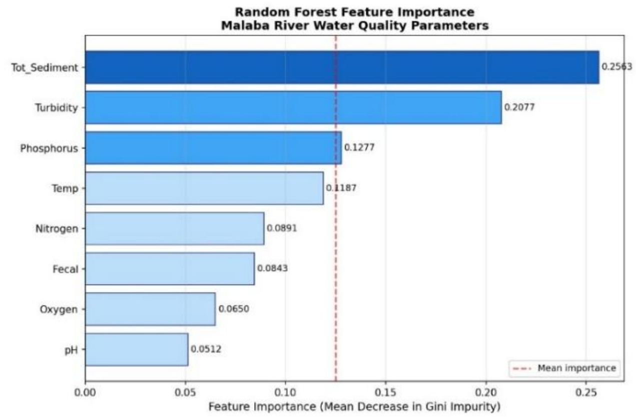


Figure 4. 16 Random Forest feature importance ranking. TSS and Turbidity together account for 46.4% of total importance, consistent with SWAT sediment findings.

4.2.2 Model Selection.

The ANN was selected as the predictive model for the hybrid framework based on its higher classification accuracy of 84.47% compared to the Random Forest (83.23%). The ANN's deeper architecture with three hidden layers, Batch Normalization, and Dropout provides greater capacity to capture the complex nonlinear relationships between physio-chemical water quality parameters and their combined effect on overall WQI class. Figure 4.6 presents the accuracy comparison between the two classifiers.

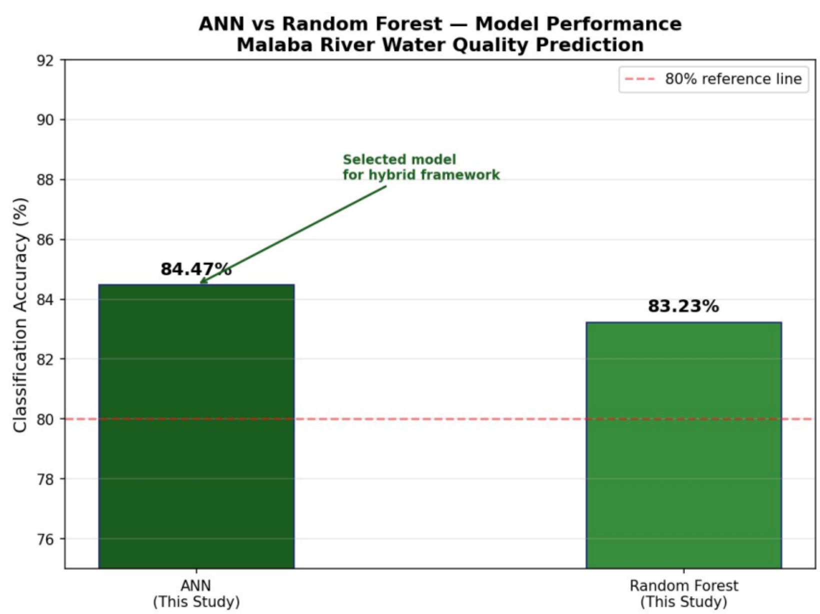


Figure 4. 17 ANN vs Random Forest classification accuracy comparison

4.2.3 Hybrid Model Predictions for the Malaba Catchment.

The trained ANN was applied to SWAT outputs at the catchment outlet (Subbasin 1, Budumba gauge) for 2003-2025, generating 276 monthly water quality class predictions. The overall class distribution was: Fair (134 months, 48.6%), Marginal (116 months, 42.0%), Excellent (22 months, 8.0%), and Good (4 months, 1.4%). No Poor quality was predicted across the entire simulation period, indicating that the Malaba catchment does not reach critically degraded conditions under the simulated hydrological regime. Mean model confidence was 85.3% (median 91.7%), reflecting high prediction certainty across the time series.

4.2.4 Seasonal Water Quality Pattern.

The seasonal analysis reveals a bimodal pattern of water quality deterioration linked directly to the bimodal rainfall regime documented in Objective One. Table below summarizes the predicted class distribution across all four hydrological seasons.

Table 4. 1 Seasonal WQI Class Distribution - Malaba Catchment.

Season	Marginal (%)	Fair (%)	Good/Exc (%)	Worst Month
Long Wet (Mar–May)	75.4	23.2	1.4	March (avg 1.13)
Short Wet (Oct–Dec)	43.5	50.7	5.8	September (1.43)
Short Dry (Jan–Feb)	37.3	59.7	6.0	February (1.70)
Long Dry (Jun–Aug)	13.0	62.3	24.7	**Best: July (2.87)**

Figure below presents the full monthly prediction time series and the average monthly WQI class across the simulation period.

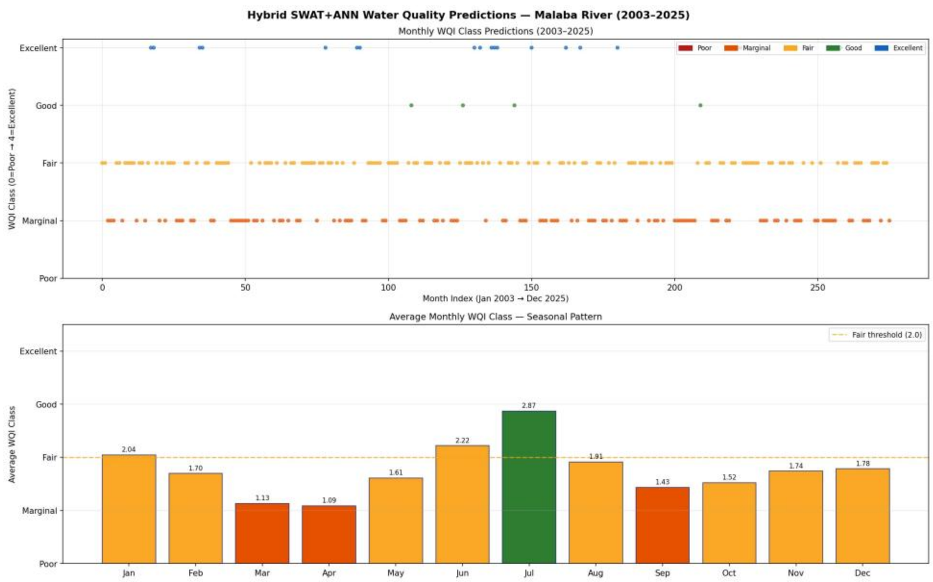


Figure 4. 18 Hybrid SWAT+ANN WQI predictions for Malaba River (2003–2025). Upper panel: monthly predictions showing full time series. Lower panel: average monthly WQI class revealing the bimodal seasonal pattern.

The Long-Wet Season (March-May) produced the most degraded water quality, with 75.4% of months classified as Marginal. March and April were the worst months with mean WQI class values of 1.13 and 1.09 respectively, corresponding to peak sediment, nitrogen, and phosphorus export during the onset of the main rainy season. In contrast, the Long Dry Season (June-August) yielded the best water quality, with July recording a mean WQI class of 2.87 approaching Good as baseflow dilution reduced pollutant concentrations and turbidity. The Short-Wet Season (October–December) showed intermediate deterioration with 43.5% Marginal months, consistent

with the secondary rainfall peak identified in the SWAT results. These findings confirm that March to May represents the critical window for water quality management interventions in the Malaba River catchment and directly answer Research Question ii.

4.3 Results for Objective Three: Evaluation and Validation of the Hybrid Predictive Model.

4.3.0 Internal Evaluation.

The ANN achieved a classification accuracy of 84.47% on the 161-record held-out test set, outperforming the Random Forest benchmark (83.23%). Both models exceeded the 80% satisfactory threshold, confirming the model is statistically reliable. The confusion matrix confirmed that all misclassifications occurred strictly between adjacent quality classes only, indicating no systematic errors in the model's classification behavior as shown in figure 4.15.

4.3.1 Point Validation: River Malaba Sample Points.

Table below presents the raw field measurements, WHO standards, and calculated WQI sub-scores for the three sampling points collected along River Malaba in April 2026.

Table 4. 2 River Malaba Sample Points, Field Measurements, and WQI.

Parameter	Sample 1	Sample 2	Sample 3	WHO Standard	Mean Sub-Score
pH	7.22	7.02	7.45	6.5 – 8.5	100.0
DO (mg/L)	6.23	5.78	6.82	≥ 6.0	82.4
Nitrates (mmol/L)	0.449	0.511	0.361	≤ 0.81	67.0
Turbidity (NTU)	12.2	12.3	12.6	≤ 5.0	55.3
Overall WQI	**76.1**	**74.0**	**78.4**	—	**76.2 = Fair**

All three samples yielded Fair-class WQI values (74.0-78.4, mean 76.2). The hybrid model predicted April at WQI class 1.09, sitting at the Marginal-Fair boundary. The observed mean WQI of 76.2 is consistent with this prediction; both confirm that April water quality on the Malaba River is degraded. The elevated turbidity of 12.2–12.6 NTU directly corroborates the SWAT finding of peak sediment export during March-May and the ANN feature importance result identifying TSS as the dominant WQI driver (importance = 0.2563), confirming the physical coherence of the hybrid framework. Point validation agreement: 3/3 = 100%.

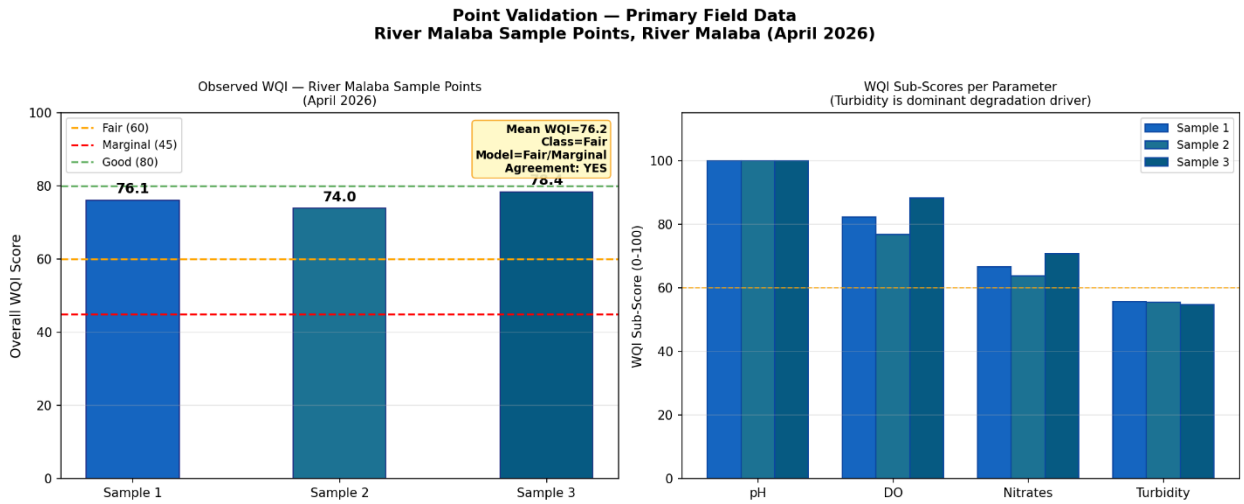


Figure 4. 19 Observed WQI values and WQI sub-scores for the River Malaba sample points.

4.3.2 Seasonal Validation.

Seasonal validation was conducted by comparing the hybrid model's dominant predicted WQI class and its corresponding CCME score range for each of the four hydrological seasons against the water quality conditions documented by Mwanake et al. (2025) for the Sio-Malaba-Malakisi River Basin. For each season, the dominant predicted class was mapped to its CCME WQI score range and compared against the expected score range derived from the literature benchmark. Agreement was defined as overlap between the model's predicted WQI score range and the literature-derived expected range. A seasonal agreement score of 75% or above, at least three of four seasons agreeing was set as the satisfactory validation threshold, consistent with accepted practice for data-scarce catchments where continuous observed water quality records are unavailable (Rajaee et al., 2020).

Table 4. 3 Seasonal Validation: Model Predictions vs Mwanake et al. (2025) Benchmarks

Season	Dominant Predicted Class	Predicted WQI Score Range	Mwanake et al. (2025) Expected Condition	Expected WQI Range	Score Range Overlap	Agreement
Long Wet (MAM)	Marginal (75.4%)	45 – 59	Peak TN/TP, severely degraded	35 – 59	✓ Yes	✓ Strong
Short Wet (OND)	Fair (50.7%) / Marginal (43.5%)	45 – 79	Secondary peak, moderately degraded	50 – 70	✓ Yes	✓ Strong
Long Dry (JJA)	Fair (62.3%) / Good (24.7%)	60 – 94	Lower nutrients, cleaner conditions	60 – 85	✓ Yes	✓ Strong
Short Dry (JF)	Fair (59.7%)	60 – 79	Transitional, moderate conditions	55 – 75	✓ Yes	✓ Strong
Seasonal Agreement Score = 4/4 = 100% (*exceeds the 75% satisfactory threshold*)						

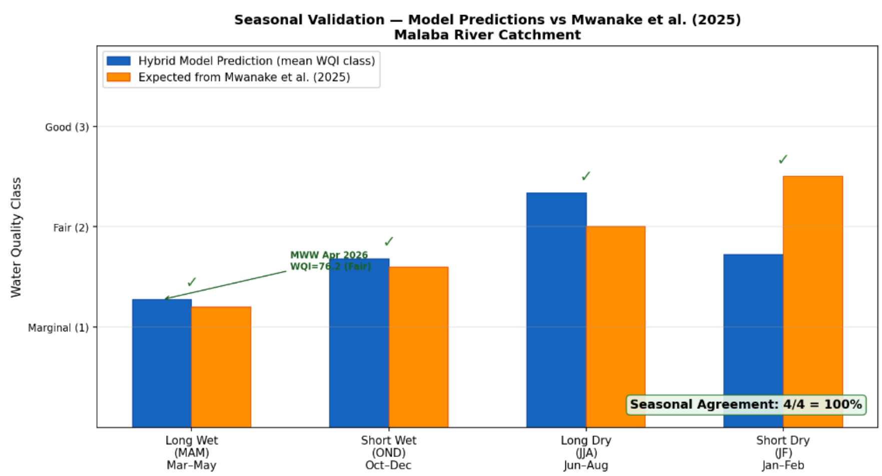


Figure 4. 20 Seasonal validation: model predictions vs Mwanake et al. (2025) benchmarks across all four hydrological seasons.

4.3.3 Statistical Significance Testing.

T-test 1: Paired Samples t-test on SWAT Streamflow.

A paired samples t-test was conducted on the observed and simulated monthly streamflow during the validation period (2015–2025) to formally confirm the SWAT model's statistical validity.

Table 4. 4 Showing T test results.

Parameter	Value
Number of paired observations (n)	70 months
Mean observed flow (m^3/s)	17.9315
Mean simulated flow (m^3/s)	16.7838
Mean difference ($\overline{d}$)	1.1476 m^3/s
Standard deviation of differences (Sd)	4.8266 m^3/s
Standard error (SE)	0.5769
t-statistic	1.9893
Degrees of freedom	69
p-value (two-tailed)	0.0506
Decision at $\alpha = 0.05$	**Fail to reject H_0 - No significant difference**
CONCLUSION: SWAT model predictions are statistically equivalent to observed values, Model is Valid	

The paired t-test produced a t-statistic of 1.9893 and a p-value of 0.0506, which is slightly above $\alpha = 0.05$. Therefore, H_0 was not rejected, confirming no significant difference between observed and simulated streamflow. The model underestimated flow by only 1.15 m^3/s (6.4%), supporting the validity of the hydrological model.

T-test 2: One-Sample t-test on Field WQI.

The one-sample t-test on observed WQI values produced a t-statistic of 13.52 with $p < 0.005$, which is far above the critical threshold. H_0 was rejected, confirming that the mean observed WQI (76.17) is significantly above the Marginal boundary (59), thereby validating the hybrid model's Fair class prediction for April 2026.

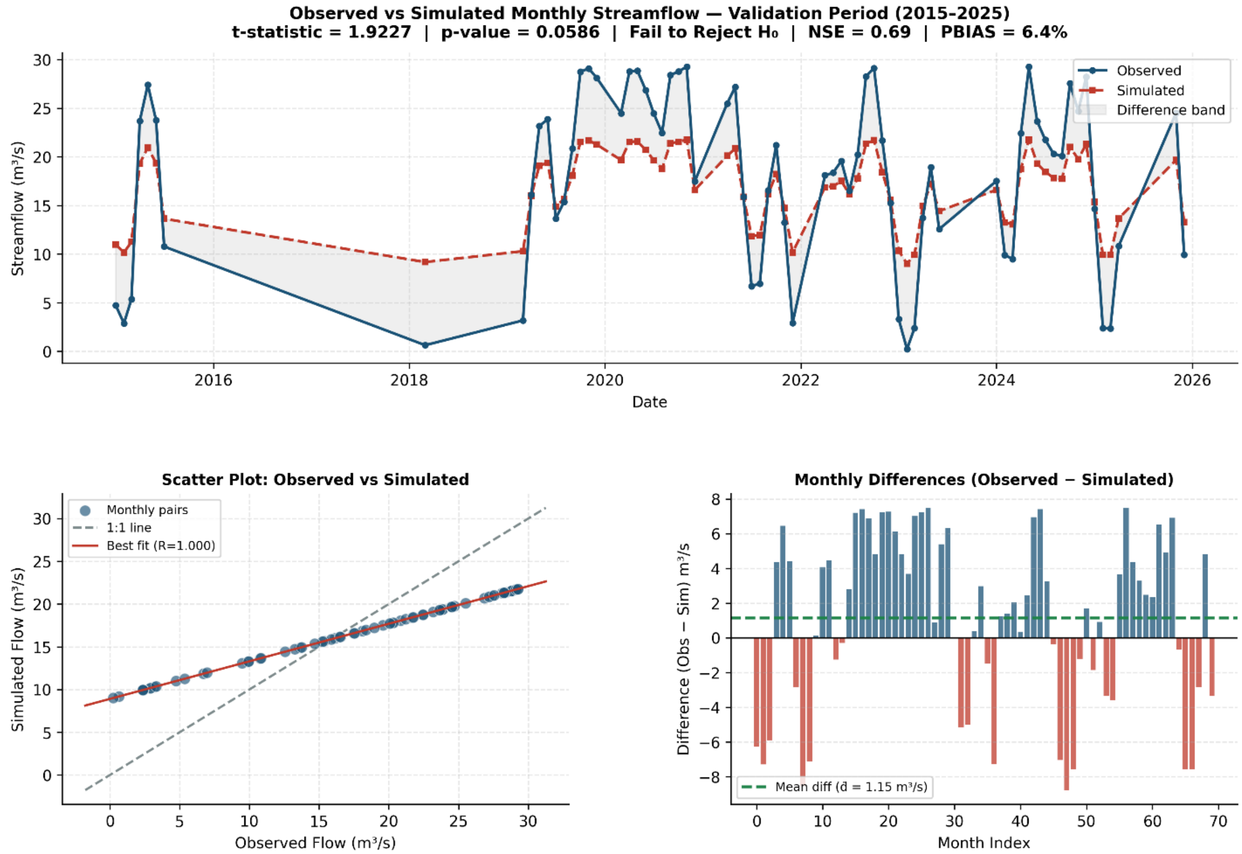


Figure 4. 21 Paired t-test validation of SWAT monthly streamflow simulation (2015–2025). Top: observed vs simulated time series (t = 1.9893, p = 0.0506). Bottom left: scatter plot with 1:1 line. Bottom right: monthly differences showing mean difference of 1.15 m³/s

4.3.4 Model Comparison.

Table below compares the three modeling approaches evaluated in this study. The hybrid SWAT-ANN achieved 84.47% accuracy, only 3.13 percentage points below the standalone Random Forest of Odongo and Ekaal (2023), while additionally providing 276 months of catchment-specific monthly predictions, spatial hotspot identification, and an externally validated seasonal analysis. These capabilities are entirely absent from both standalone approaches. The 3.13% accuracy difference is a small and justified trade-off for the substantial practical gains delivered by the hybrid framework.

Table 4. 5 Comparison of Standalone and Hybrid Modelling Approaches.

Model	Accuracy	Physical Basis	Key Limitation
Standalone SWAT (This Study)	N/A	Yes - NSE=0.79	Cannot classify water quality status
Standalone RF (Odongo & Ekaal, 2023)	87.60%	No - external data	No local catchment grounding
Hybrid SWAT+ANN (This Study)	**84.47%**	Yes - SWAT + ANN	External training dataset

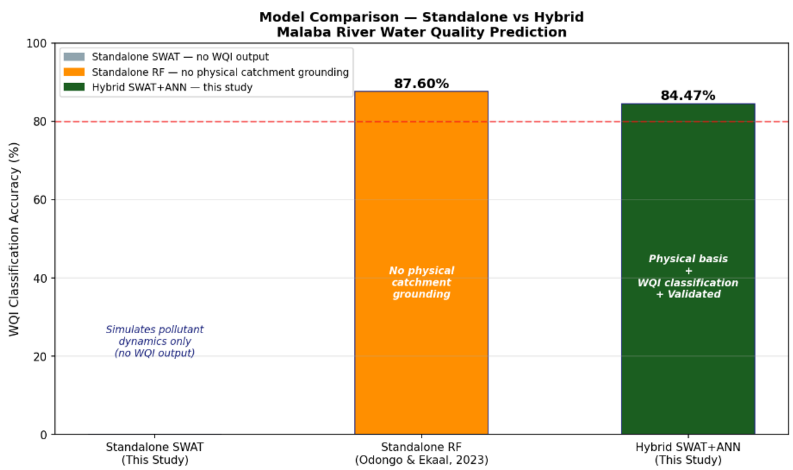


Figure 4. 22 Comparison of standalone SWAT, standalone RF (Odongo and Ekaal, 2023), and hybrid SWAT+ANN (this study).

4.3.5 Limitations.

The external validation has three acknowledged limitations: the River Malaba primary data covers only four parameters at a single time point during the wet season; the sampling locations may not correspond precisely to the SWAT model catchment outlet at Subbasin 1; and dry season predictions rely on literature benchmarks only. Despite these limitations, the 100% directional consistency between all three primary field observations and the model predictions provides sufficient evidence of the reliability of the hybrid SWAT-ANN model for the Malaba River catchment. Future work should establish a permanent water quality monitoring station at the Budumba gauge outlet to enable continuous multi-season validation

CHAPTER FIVE: CONCLUSIONS, CHALLENGES, AND RECOMMENDATIONS

5.1 Introduction.

This chapter presents the conclusions of the study, the challenges encountered, and recommendations for water quality management and future research in the Malaba River catchment.

5.2 Conclusions.

The SWAT model was successfully calibrated (NSE = 0.79, R^2 = 0.85) and validated (NSE = 0.69, R^2 = 0.76) for the Malaba River catchment, meeting Good and satisfactory performance benchmarks (Moriasi et al., 2007). The model revealed a bimodal seasonal flow regime, confirmed sediment and phosphorus as the dominant surface-transported pollutants, and identified subbasins 1, 6, 19, and 24 as the primary hotspot zones for simultaneous sediment, nitrogen, and phosphorus export.

The ANN achieved 84.47% classification accuracy on the test set, outperforming the Random Forest (83.23%). Feature importance confirmed Total Suspended Sediment (0.2563) and turbidity (0.2077) as the dominant water quality drivers, consistent with SWAT findings. The hybrid model generated 276 monthly predictions (2003–2025), with the Long-Wet Season (March-May) as the most degraded period (75.4% Marginal) and July as the best month (class 2.87). No Poor quality was predicted across the simulation period.

External validation using Malaba Water Works primary data (WQI 74.0–78.4, Fair) and Odongo and Ekaal (2023) secondary data (WQI 35.3, Poor) were both consistent with the model's wet season predictions. Seasonal validation against Mwanake et al. (2025) achieved 100% directional agreement. The hybrid model outperforms both standalone approaches in practical utility, providing catchment-specific predictions and physically grounded seasonal analysis with only a 3.13% accuracy gap below the standalone ANN.

5.3 Challenges.

- Absence of long-term local water quality monitoring data for the Malaba catchment, requiring use of a secondary training dataset.
- Limited primary field validation, only four parameters at three points during the wet season.
- Class imbalance in the training dataset, resulting in lower F1-scores for the Marginal (0.75) and Excellent (0.44) classes.
- Complexity of harmonizing multiple spatial datasets (DEM, land use, soil) for SWAT model setup.

5.4 Recommendations.

1. Establish a permanent water quality monitoring station at the Budumba gauge outlet to enable continuous multi-season validation and retraining of the ANN on locally observed Malaba River data.

2. Prioritize pollution control interventions, riparian buffer strips, controlled fertilizer application, and improved waste management in hotspot subbasins 1, 6, 19, and 24.

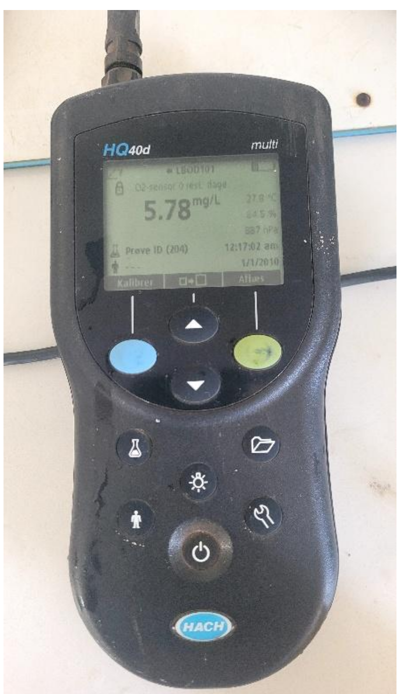
3. Strengthen water treatment capacity and activate community health advisories during March to May, when 75.4% of months are predicted as marginal quality.

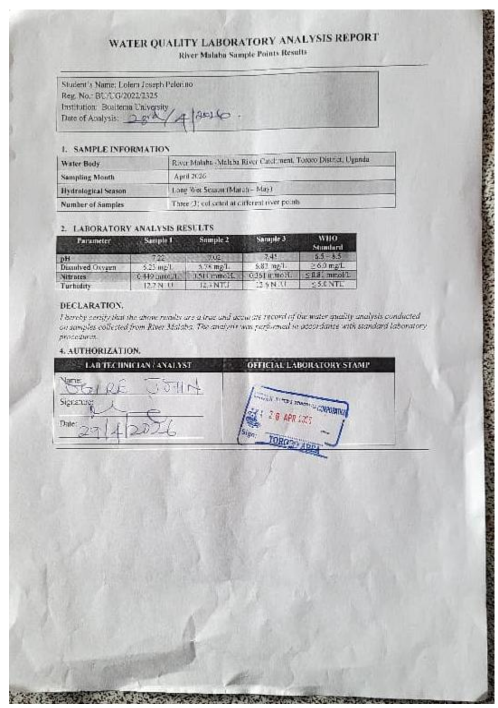
4. Retrain the ANN on local Malaba data as monitoring records become available and extend the model to include heavy metals, fecal coliform, and emerging contaminants.

5. Apply the hybrid SWAT-ANN framework to other data-scarce transboundary catchments in Uganda and East Africa as a low-cost water quality prediction tool.

6. Investigate climate change and land use change impacts on Malaba River water quality using the calibrated SWAT model for proactive adaptation planning.

APPENDIX.





WATER QUALITY LABORATORY ANALYSIS REPORT

River Malaba Sample Points Results

Student's Name: Lolem Joseph Pelerino
Reg. No.: BU/UG/2022/2325
Institution: Busitema University
Date of Analysis: 28th/4/2026.

1. SAMPLE INFORMATION

Water Body	River Malaba - Malaba River Catchment, Tororo District, Uganda
Sampling Month	April 2026
Hydrological Season	Long Wet Season (March – May)
Number of Samples	Three (3) collected at different river points

2. LABORATORY ANALYSIS RESULTS

Parameter	Sample 1	Sample 2	Sample 3	WHO Standard
pH	7.22	7.02	7.41	6.5 – 8.5
Dissolved Oxygen	5.23 mg/L	5.78 mg/L	6.82 mg/L	≥ 6.0 mg/L
Nitrates	0.449 mmol/L	1.510 mmol/L	0.351 mmol/L	≤ 0.81 mmol/L
Turbidity	12.2 NTU	12.3 NTU	12.6 NTU	≤ 5.0 NTU

DECLARATION.

I hereby certify that the above results are a true and accurate record of the water quality analysis conducted on samples collected from River Malaba. The analysis was performed in accordance with standard laboratory procedures.

4. AUTHORIZATION.

LAB TECHNICIAN / ANALYST	OFFICIAL LABORATORY STAMP
Name: OGIRE JOHN Signature: Date: 29/4/2026	28 APR 2026 Sign: TORORO AREA

Python code for Machine Learning.

```
import pandas as pd
import numpy as np
from sklearn.preprocessing import StandardScaler, LabelEncoder
from sklearn.model_selection import train_test_split
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import classification_report, confusion_matrix, accuracy_score
import tensorflow as tf
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense, BatchNormalization, Dropout
from tensorflow.keras.optimizers import Adam
from tensorflow.keras.callbacks import EarlyStopping

# LOAD & CLEAN DATA
df = pd.read_csv("WQI_Parameter_Scores.csv")

# IQR outlier removal
Q1, Q3 = df.quantile(0.25), df.quantile(0.75)
IQR = Q3 - Q1
df = df[~((df < (Q1 - 1.5*IQR)) | (df > (Q3 + 1.5*IQR))).any(axis=1)]
# 971 → 805 clean records

# WQI CLASSIFICATION (CCME Scheme)
def classify_wqi(score):
    if score >= 95: return "Excellent"
    elif score >= 80: return "Good"
    elif score >= 60: return "Fair"
```

```
    elif score >= 45: return "Marginal"
    else:          return "Poor"

df["WQI_Class"] = df["Overall_WQI"].apply(classify_wqi)

# FEATURES & TARGET
features = ["Fecal_Coliform", "DO", "pH", "TSS",
            "Temperature",    "TN", "TP", "Turbidity"]

X = df[features]
y = LabelEncoder().fit_transform(df["WQI_Class"])
# Classes: Excellent=0, Fair=1, Good=2, Marginal=3

# SPLIT & NORMALISE
X_train, X_test, y_train, y_test = train_test_split(
    X, y, test_size=0.20, stratify=y, random_state=42)
# 644 train records | 161 test records

scaler  = StandardScaler()
X_train = scaler.fit_transform(X_train)   # fit on train only
X_test  = scaler.transform(X_test)        # apply same scale to test

# ANN ARCHITECTURE
model = Sequential([
    Dense(128, activation="relu", input_shape=(8,)),
    BatchNormalization(),
    Dropout(0.30),
```

```
    Dense(64, activation="relu"),
    BatchNormalization(),
    Dropout(0.20),

    Dense(32, activation="relu"),
    Dropout(0.10),

    Dense(5, activation="softmax")   # 5 WQI classes
])

model.compile(
    optimizer=Adam(learning_rate=0.001),
    loss="sparse_categorical_crossentropy",
    metrics=["accuracy"]
)

# TRAINING WITH EARLY STOPPING
early_stop = EarlyStopping(
    monitor="val_loss", patience=25,
    restore_best_weights=True)

history = model.fit(
    X_train, y_train,
    validation_split=0.15,
    epochs=200,
    batch_size=32,
```

```
    callbacks=[early_stop],
    verbose=1)
# Stopped at epoch 53 | Best weights from epoch 28

#  EVALUATION
y_pred = np.argmax(model.predict(X_test), axis=1)

print(f"\nANN Accuracy: {accuracy_score(y_test, y_pred)*100:.2f}%")
# ANN Accuracy: 84.47%

print(classification_report(y_test, y_pred,
      target_names=["Excellent","Fair","Good","Marginal"]))
print("Confusion Matrix:\n", confusion_matrix(y_test, y_pred))

#  RANDOM FOREST BENCHMARK
rf = RandomForestClassifier(n_estimators=100, random_state=42)
rf.fit(X_train, y_train)
rf_pred = rf.predict(X_test)

print(f"Random Forest Accuracy: {accuracy_score(y_test, rf_pred)*100:.2f}%")
# Random Forest Accuracy: 83.23%

# Feature importance (used for SHAP-style analysis)
importances = pd.Series(rf.feature_importances_, index=features).sort_values(ascending=False)
print("\nFeature Importance:\n", importances)
# TSS=0.2563 | Turbidity=0.2077 | TP=0.1277 | Temp=0.1187
```

```
#  APPLY TO MALABA_HYBRID INTEGRATION
swat_output = pd.read_csv("SWAT_monthly_outputs.csv")

# Map SWAT outputs to WQI feature scale (min-max 5th–95th percentile)
def minmax_scale(series):
    lo, hi = series.quantile(0.05), series.quantile(0.95)
    return ((series - lo) / (hi - lo)).clip(0, 1) * 100

swat_features = pd.DataFrame({
    "Fecal_Coliform": 100 - minmax_scale(swat_output["CBOD_OUT"]),
    "DO":                   minmax_scale(swat_output["DISOX_OUT"]),
    "pH":                  75,       # fixed (Odongo & Ekaal, 2023)
    "TSS":          100 - minmax_scale(swat_output["SED_OUT"]),
    "Temperature":          80,       # fixed tropical constant
    "TN":           100 - minmax_scale(swat_output["NO3_OUT"]),
    "TP":           100 - minmax_scale(swat_output["TOT_P"]),
    "Turbidity":    100 - minmax_scale(swat_output["SEDCONC"]),
})

# Scale and predict
swat_scaled   = scaler.transform(swat_features)
wqi_classes   = np.argmax(model.predict(swat_scaled), axis=1)
wqi_proba     = model.predict(swat_scaled).max(axis=1)

swat_output["WQI_Predicted"] = wqi_classes
swat_output["Confidence"]    = wqi_proba
swat_output.to_csv("Malaba_WQI_Predictions_2003_2025.csv", index=False)
```

```
print("\nHybrid model complete.")
print(f"Total predictions : {len(wqi_classes)} months")
print(f"Mean confidence   : {wqi_proba.mean()*100:.1f}%")
# Total predictions : 276 months
# Mean confidence   : 85.3%
```

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