MAKERERE UNIVERSITY

COLLEGE OF ENGINEERING, DESIGN, ART AND TECHNOLOGY

SCHOOL OF ENGINEERING

DEPARTMENT OF CIVIL AND ENVIRONMENTAL ENGINEERING

CIV 4200: CIVIL ENGINEERING PROJECT II

FLOOD FORECASTING AND EARLY WARNING IN NYAMWAMBA RIVER CATCHMENT USING MACHINE LEARNING

BY

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Submitted in Partial Fulfilment of the Requirements for the Award of a Degree of Bachelor of Science in Civil Engineering

……………………………25/06/2026 ……………………………..26/06/26

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JUNE 2026

DECLARATION

I Ndawula Joel, hereby declare that this research report has been carried out as part of my academic requirements for the award of the Degree of Bachelor of Science in Civil Engineering at Makerere University. I affirm that this work is original and represents the results of independent research efforts conducted under supervision. All information sources and data used in the preparation of this report have been duly acknowledged. This report has not been submitted in whole or in part to any other institution for any academic award.

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LIST OF ABBREVIATIONS

WRDs	Water-Related Disasters
UNDRR	United Nations office for Disaster Risk Reduction
WMO	World Mereological Organization
EM-DAT	Emergency Events Database
UNISDR	United Nations International Strategy for Disaster Reduction
DEM	Digital Elevation Model
DWRM	Directorate of Water Resources Management
GIS	Geographic Information System
GloFAS	Global Flood Awareness System
SDGs	Sustainable Development Goals
UNMA	Uganda National Metrological Authority
EFAS	European Flood Awareness System
EWS	Early Warning Systems
AFFS	African Flood Forecasting System
EAP	Early Action Protocol
HEC RAS	Hydrologic Engineering Center - River Analysis System
ANN	Artificial Neural Networks
SVM	Support Vector Machinery
URCS	Uganda Red Cross Society
NDVI	Normalized Difference Vegetation Index
ROC	Receiver Operating Characteristics Curve
MAE	Mean Absolute Error
RMSE	Root Mean Square Error
AUC	Area Under Curve

1 INTRODUCTION

1.1 Background

Water related disasters (WRDs) remain the most widespread and destructive class of natural hazards globally estimating 85–90% of all recorded disaster events over the past decades (UNDRR, 2024). Among these, floods are the leading cause of WRDs, representing almost half of annual events and generating the highest socio-economic costs globally (World Bank, 2024). Between 2000 and 2019, floods and related water hazards affected over 1.6 billion people worldwide, underscoring their far-reaching humanitarian and economic implications that 650 billion Us Dollars (Dr. Ilona Auer Frege, 2025). Current assessments further estimate the average annual global economic loss from water-related disasters at USD 388 billion, a figure projected to rise steeply as climate change intensifies the frequency and severity of extreme hydro-meteorological events.

The WRD events show that no region is immune to flood devastation. In 2024, Africa recorded the highest flood-related fatalities globally, with Chad reporting 576 deaths and Niger registering 396 (EM-DAT, 2024). The same year in South Asia, torrential monsoon rains and flash floods disrupted millions of lives affecting over 8 million people in India and 5.8 million in Bangladesh. Europe and the Americas also suffered significant losses. Spain's Valencia floods were listed among the world's ten costliest disasters, exceeding USD 11 billion in damages, while the May 2024 floods and landslides in Brazil's Rio Grande do Sul inflicted approximately USD 7 billion in economic losses (WMO, 2025).

The escalating frequency and intensity of such events are closely linked to climate change, which drives more extreme rainfall patterns, and land-use transformations such as deforestation, rapid urbanization, and poor drainage planning. These factors reduce infiltration, increase surface runoff and amplify flood peaks producing diverse flood types that include riverine, flash, pluvial and urban floods each with distinct effects on people and ecosystems (Thieken et al., 2023).

In Uganda, the realities of climate variability are increasingly visible through recurrent floods, prolonged droughts, and landslides. The International Organization for Migration (IOM, 2020) reported that between September and December 2019, the country experienced exceptional rainfall that triggered destructive floods and landslides across the eastern, western and northern regions displacing more than 65,000 individuals. Similar disasters have since recurred with the western region emerging as one of the country's most affected areas due to its mountainous terrain, proximity to the Rwenzori ranges and growing human settlement along floodplains.

While the Government of Uganda and partner institutions such as the Uganda National Meteorological Authority (UNMA) have made strides in weather forecasting, effective flood risk management remains constrained by sparse hydrological data, inadequate forecasting capacity and insufficient systems for community-level warning dissemination (Rentschler et al., 2022). Much of the existing response still lies on structural interventions such as dykes and embankments which although beneficial, are costly to maintain, limited in coverage and sometimes shift flood risk downstream.

In contrast, non-structural approaches such as data-driven flood forecasting and early warning systems (EWSs), are increasingly recognized as more adaptable, timely and cost-effective alternatives especially in resource-limited settings (Jain et al., 2018). They enable early detection and communication of impending floods giving communities the opportunity to act before disaster strikes.

Against this backdrop, this study seeks to develop a machine learning-based flood forecasting model and early warning system, focusing on the Nyamwamba River catchment which has experienced severe flooding events. The proposed system will apply the Extreme Gradient Boosting (XGBoost) algorithm to model hydrological and meteorological variables and integrate its outputs with a mobile alert platform for rapid community dissemination. By leveraging satellite imagery and local hydro-meteorological data, the research aims to provide accurate, location-specific and timely flood warnings enhancing preparedness and resilience among flood-prone communities in Kasese and contributing to Uganda's broader climate adaptation agenda.

1.2 Problem Statement

Uganda continues to experience an increasing frequency and intensity of flooding, resulting in loss of life, destruction of infrastructure and severe socio-economic disruption. This growing threat exposes a major weakness in the country's disaster management framework due to the absence of effective, operational and localized flood early warning systems. Kasese District exemplifies this challenge as recurrent floods along River Nyamwamba have caused widespread damages, displacements and economic losses.

Among the problems affecting flood risk management in Nyamwamba is the lack of a reliable data-driven flood forecasting models, customized to the hydro-climatic and geomorphological characteristics of the catchment. This problem is exacerbated by hydrological data scarcity due to sparse or non-functional gauging networks which hinders the calibration and validation of traditional hydrological models that depend on continuous in-situ data. As a result, flood management in Uganda remains predominantly reactive with responses initiated only after disaster impacts occur.

To address the problem, this study develops a forecasting and early warning system that utilizes the Extreme Gradient Boosting (XGBoost) algorithm. The proposed framework integrates remote sensing data, real-time environmental indicators and geospatial analysis within a machine learning model to significantly improve predictive accuracy. By coupling these advanced predictions with a mobile-based alert platform, the system ensures timely dissemination of warnings to at-risk communities.

This approach of fusing artificial intelligence, remote sensing and communication technologies aims to transition flood management in Kasese from a reactive to a proactive stance, thereby improving preparedness, response and community resilience within the Nyamwamba Catchment.

1.3 Objectives

1.3.1 Main Objective

To investigate the application of machine learning approaches for flood forecasting and early warning in the Nyamwamba River Catchment.

1.3.2 Specific Objectives

i. To evaluate the predictive capability of the XGBoost model using local hydrological and meteorological datasets against baseline models.
ii. To assess the effectiveness of integrating predictive modeling with community-based alert systems in improving early warning responsiveness.

1.4 Research Question

a) How can machine learning, remote sensing and geospatial analysis be integrated to develop an accurate and reliable flood forecasting model for the Nyamwamba River Catchment in Kasese District?
b) How effective is the proposed flood forecasting model and mobile early warning system in forecasting flood events and improving community preparedness in the Nyamwamba River Catchment?

1.5 Justification

The increasing frequency of flood events driven by climate change, glacier retreat and land degradation call for intelligent and adaptive systems capable of predicting floods accurately and timely alert dissemination, a transition from reactive recovery mechanism to predictive resilience strategies. The research is justified on the following grounds:

i. **Scientific relevance**: The study applies XGBoost algorithm, an advanced method for flood forecasting contributing to the growing body of research on ML-based hydrological forecasting under data constraints.
ii. **Technological Innovation:** It introduces an integrated framework where predictive analytics directly trigger community alerts via SMS and mobile apps, bringing the gap between model output and user action.
iii. **Society value**: By providing timely and localized warnings through SMS and Android platforms, the project empowers communities to make informed decisions and thereby reducing loss of life and property.
iv. **Policy alignment**: The project supports Uganda's National Development Plan (NDP III) objective of improving climate resilience and aligns with Sustainable Development Goal

(SDG) 13 -Climate Action thus promoting proactive climate adaptation at the community level.

v. **Replicability and scalability**: The system design can be implemented in other flood-prone districts such as Bududa, Butaleja and Mbale, fostering a national framework for data-driven disaster risk reduction.

1.6 Scope

This study focuses on enhancing flood risk management through the development of a data-driven flood forecasting model and early warning system for the Nyamwamba River Catchment in Kasese District. It applies the Extreme Gradient Boosting (XGBoost) machine learning algorithm to forecast flood events using both remote sensing and hydro-meteorological data.

Geospatial analysis through GIS tools will support catchment delineation, flood-prone area mapping and visualization of forecasting results. The scope is therefore confined to applying machine learning, remote sensing and mobile communication technologies for flood forecasting and warning dissemination.

1.6.1 Study Area

Nyamwamba River Catchment is located in Western Uganda, Kasese District. The river originates from the Mountains of Rwenzori flowing to Lake George through towns of Kilembe and Kasese.

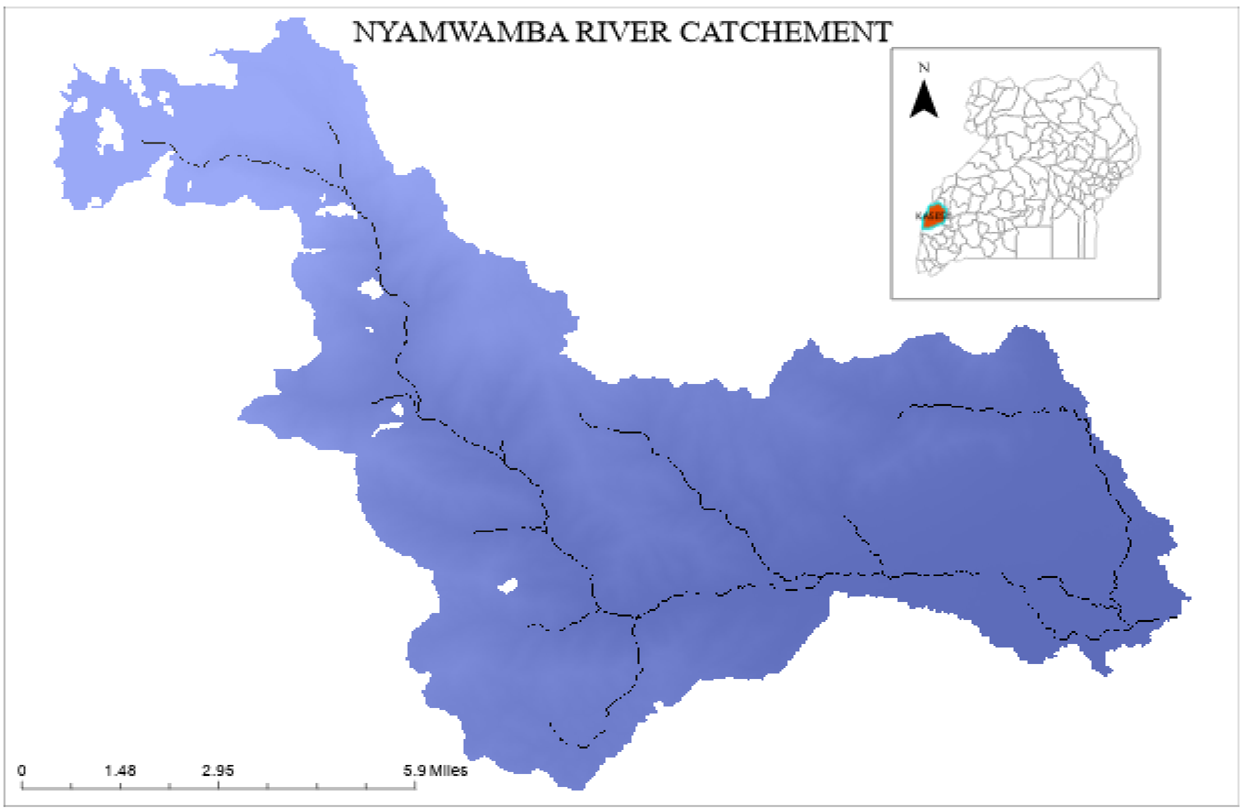

Figure 1: Nyamwamba River Catchment

2 LITERATURE REVIEW

2.1 Introduction

Floods are among the most destructive natural hazards globally, causing immense human and economic losses every year. According to the UN Office for Disaster Risk Reduction, floods account for nearly 45% of all weather-related disasters affecting over two billion people between 1998 and 2017 (UNISDR, 2017). The growing frequency and intensity of floods have been linked to climate change, rapid urbanization and poor land-use management (Tibara et al., 2022).

In this context, accurate and timely flood forecasting has become central to disaster risk reduction. However, in data-scarce regions such as Uganda, the absence of dense hydrological monitoring networks severely constrains model calibration and operational forecasting (Anand et al., 2024). The rise of machine learning (ML), remote sensing (RS) and mobile communication technologies now provides new opportunities to overcome these limitations.

2.2 Global trends in flood forecasting systems

Globally, flood forecasting has evolved from deterministic, process-based hydrological models towards integrated and probabilistic early warning systems (EWS). Advanced systems such as the Global Flood Awareness System (GloFAS) and the European Flood Awareness System (EFAS) exemplify large-scale platforms that couple meteorological inputs with hydrological simulations to generate near-real-time flood probability forecasts. GloFAS for instance, provides 30-day probabilistic forecasts using the Lisflood model and ECMWF climate data (Harrigan et al., 2023)

These systems demonstrate the benefits of ensemble modelling and multi-agency data integration, which improve accuracy and lead time. However, they rely on dense observation networks and long historical datasets which are rarely available in developing regions (Emerton et al., 2016)

2.3 Flood forecasting in sub-Saharan Africa

Across Sub-Saharan Africa, flood forecasting remains limited by sparse gauging infrastructure, poor data sharing and low institutional capacity. Regional initiatives such as the African Flood Forecasting System (AFFS) modeled after GloFAS, have improved continental-scale awareness (Thiemig et al., 2015). However, their resolution remains too coarse for localized decision-making (Jos et al., 2023).

(Hoedjes et al., 2014) proposed a conceptual flash-flood EWS for Kenya using microwave links and satellite rainfall, demonstrating that cost-effective alternatives can be designed for low-resource contexts. Similarly, (Shoko & Dube, 2024) emphasized the importance of integrating remote sensing and hydrological models for flood detection across southern Africa.

Despite these efforts, most systems operate at regional or catchment scale, with limited downscaling to community or district levels. Furthermore, while ML techniques have been introduced in hydrological modeling in Africa, they remain underutilized for operational flood forecasting and rarely linked to community-based alert mechanisms.

2.4 Flood Forecasting and Early Warning in Uganda

The Uganda National Meteorological Authority (UNMA) provides rainfall forecasts, while the Uganda Red Cross Society (URCS) utilizes GloFAS outputs in its Early Action Protocol (EAP) to trigger community preparedness.

Although these initiatives mark progress, they remain limited by weak hydrological integration and minimal local customization. A solar-powered EWS established in Butaleja in 2014 ceased operation by 2016 due to technical failure and community distrust (Atyang, 2014).Studies have also used GIS to map flood-prone areas in Manafwa and Kyoga catchment s, yet these are primarily reactive spatial analyses, not predictive systems.

2.5 Overview of flood forecasting models

With the rise of artificial intelligence, machine learning algorithms now provide flexible nonlinear alternatives that can perform well even with incomplete. The flood forecasting models can be broadly categorized as physically based or data-driven (Mosavi et al., 2018) and these are defined below.

Physically based models: like HEC-RAS, SWAT simulate physical processes using equations of flow, infiltration, and storage. Their accuracy depends heavily on input data, often unavailable in developing countries (Jain et al., 2018).

Data-driven models: These use empirical relationships between input and output variables. Early statistical approaches like Linear Regression, ARIMA assume linearity, failing to capture the nonlinearity of rainfall–runoff interactions.

2.6 Machine learning for hydrological forecasting

Machine learning (ML) techniques such as Artificial Neural Networks (ANNs), Support Vector Machines (SVMs), Random Forests (RFs) and Gradient Boosting Machines (GBMs) have proven effective in hydrological forecasting(Gude et al., 2020). Among them, Extreme Gradient Boosting (XGBoost) stands out for its computational efficiency, robustness against missing data and capacity to model complex nonlinear relationships (Chen & Guestrin, 2016). (Tova-izquierdo, 2020) found that XGBoost outperformed ANN models in forecasting while (Waleed & Sajjad, 2025) reported superior flood susceptibility mapping accuracy compared to traditional ensemble methods. The XGBoost, based on its capabilities of gradient boosting, optimized speed, regulation and handling of complex data structures (Chen & Guestrin, 2016) makes it outperform other algorithms. Its ability to nonlinear relationships makes it well suited to processes influenced by multiple interacting factors such as rainfall-runoff dynamics, soil saturation and topographic controls. The tree-based structure also allows to model variable importance, identify key flood drivers and maintain high performance even in incomplete data sets. Although global literature confirms the algorithms strong performance, its application within East Africa is still limited. Most Uganda studies rely on deterministic hydrological models or GIS-based methods.

2.7 Technological advances in Remote Sensing, GIS and Communication

Remote sensing (RS) and GIS provide spatially continuous datasets vital for flood analysis in ungauged catchment s. Platforms such as MODIS, Sentinel-1, CHIRPS, and GPM offer real-time rainfall and terrain data. When coupled with ML models, RS data can enhance accuracy and compensate for missing ground observations (Abid et al., 2022). In Uganda, (Kabenge et al., 2017) demonstrated that satellite-derived precipitation can improve runoff estimation, yet integration with predictive modelling remains scarce.

The inclusion of mobile communication technologies further strengthens early warning dissemination. Studies in Asia and Africa have shown the effectiveness of SMS and Android-based alerts in bridging the gap between scientific forecasts and community response (Asmara & Aziz, 2011).

2.8 Research gaps

A synthesis of the reviewed literature reveals key methodological and practical gaps limiting effective flood forecasting in data-scarce environments.

Current reliance on data-intensive hydrological models reduces reliability where gauging networks are sparse. To address this, the study employs the Extreme Gradient Boosting (XGBoost) algorithm, a data-efficient machine learning method suited to heterogeneous datasets.

The limited use of remote sensing in existing models constrains spatial accuracy hence, this research integrates multi-source satellite and geospatial data for improved feature representation.

The absence of locally trained models has led to forecasts that overlook Uganda's unique hydrological dynamics. This study addresses the issue by training and validating a local model using past flood data.

Lastly, weak connections between predictive outputs and community alerts delay response actions. The study incorporates a mobile-based Early Warning System (EWS) to enhance communication and strengthen community-level flood preparedness.

This research presents a hybrid flood forecasting and communication framework that integrates XGBoost-based forecasting, remote sensing data assimilation and mobile alert dissemination. This approach not only addresses Uganda's data scarcity challenge but also operationalizes predictive outputs into an actionable early warning tool.

3 METHODOLOGY

3.1 Introduction

This chapter outlines a comprehensive step followed to achieve the study's objective to developing a flood forecast model using machine learning. The framework, data collection, design approach and validation strategies are presented with explanations of procedures that were undertaken.

3.2 Overview

The process is a sequential workflow that begins with data collection, where relevant hydrological, metrological, topographic and historical flood data are gathered. This is followed by preprocessing and feature engineering during which collected raw data is cleaned, normalized and transformed into meaningful input data for model training. The Extreme Gradient Boost modeling phase is employed to build a machine learning model capable of forecasting real flood events based on the trained data. The model then undergoes validation to ensure its accuracy, recall abilities and precision. Finaly, the validated model is employed within an early warning system to generate timely flood forecasts. This step-by-step process is as shown in the figure below.

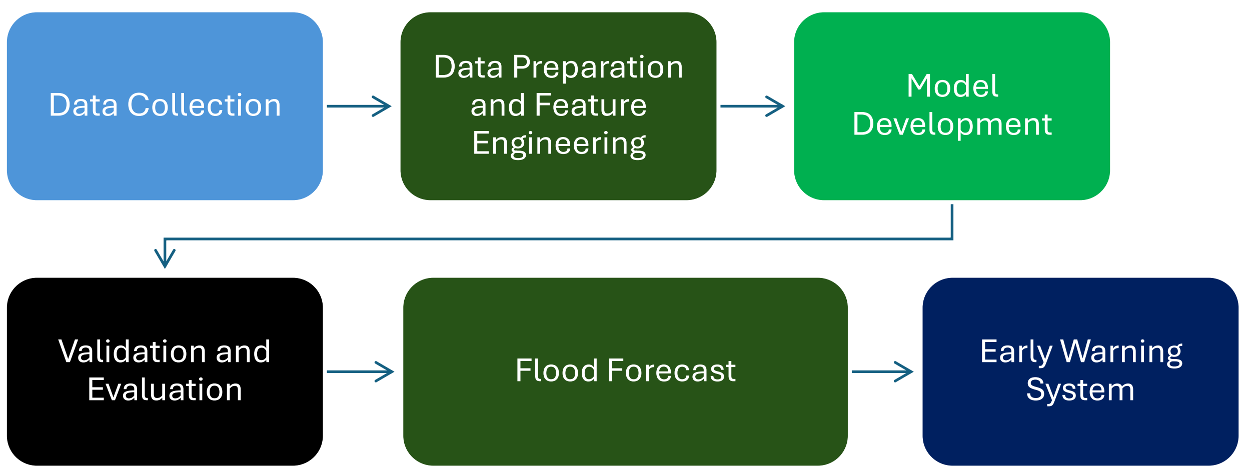

Figure 2: Model Framework for Early Warning System

3.3 Data Collection

3.3.1 Meteorological Data

Daily Rainfall, temperature, humidity and windspeed data were collected from the ERA5-Land satellite at 0.25° resolution for the entire catchment. The downloaded data is grouped together in one excel format file to serve as the driving climatic forces for the model. For continuous model training and learning, data for the past 25 years, (2000-2026) was used to study the various storm events.

3.3.2 Hydrological Data

Daily discharge volumes were obtained from GeoGlows Hydroviewer satellite, utilizing three points along river Nyamwamba and for good data quality, a mean discharge for these three points was calculated to obtain discharge input for the entire river stream as one for the model.

3.3.3 Topographic Data

The STRM DEM (30m resolution) was processed in Arc-GIS environment to derive slope and drainage density (stream length per unit area). The catchment boundary was used to extract the values as static attributes which were replicated across all time steps during the merging phase.

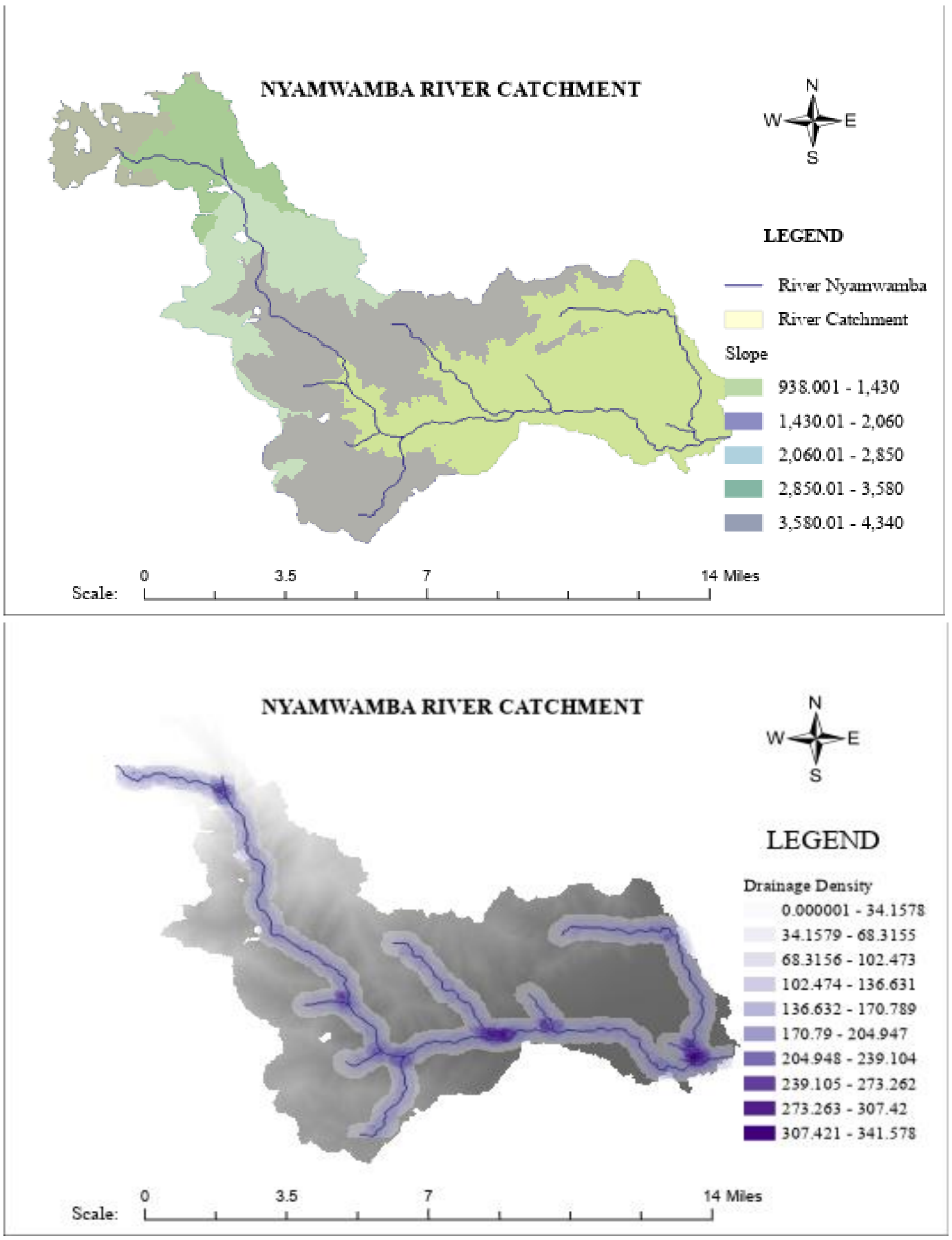

Figure 3: Slope and Drainage Density

The ESA CCI Land Cover product (300m resolution) for the years was used to compute the fraction of the urban area impervious cover and the average Normalized Difference Vegetation Index (NDVI). The soil moisture was obtained from the ERA5-Land satellite 0 to 70cm mean (m^3/ m^3) daily product (9km resolution) and averaged over the entire catchment.

Since these variables change slowly, they were aggregated to monthly means and then linearly interpolated to daily values.

3.3.4 Flood Events

This being the target variable, the flood events were constructed by a list of known flood dates. The flood data was compiled from historical archives and media archives for the Nyamwamba catchment into an excel file format covering a period 25 year-event from 2000-2025. The dates with confirmed flood events were labelled as 1 and all others labelled as 0.

3.3.5 Real Time Data Sources

The operational forecasting system uses two free Application Program Interface (APIs) from Open-Meteo.

Weather API: This provides hourly forecasts of temperature, humidity, rainfall and the wind speed for early, 3–7-day window. Open-Meteo API weather is utilized for live data fetching.

Flood API: This provides daily river discharge forecasts from the Global Flood Awareness System (GloFAS) fetched through open Meteo monitoring satellite.

The system also allows recovery of the last 14 days of historical data to compute rolling features like 3-day cumulative rainfall for the forecast period.

3.4 Data Analysis

All processing steps for the input data are implemented in Data Preparation class. During training, the pipeline fits imputers and scalers. Similarly, during live forecast, it is applied also to the fetched data.

3.4.1 Missing Values

For numeric columns excluding the target flood events, missing values are imputed using K-Nearest Neighbors (KNN) imputation with n_neighbors = 5. This method estimates missing values based on the five most similar records. During inference, the fitted KNN imputer is reused. Any new column missing from the inference data is filled with zero.

3.4.2 Handling of Outliers

Outliers are data points that differ significantly from the rest of the observational datasets. In the meteorological variables of temperature, humidity and wind speed, outliers are removed using the method of interquartile range (IQR). Below are the two boundary methods that were applied on the datasets.

Lower bound = Q1 - 1.5*IQR

Upper bound = Q3 - 1.5*IQR

The values outside this range are therefore dropped from the training sets. During live forecasts, outlier values are not removed to avoid dropping real extreme events.

3.4.3 Data Normalization

All the numeric features except for flood events, are normalized using StandardScaler method which uses the Z-score normalization technique. The process recalibrates every data point by subtracting the mean of the feature and then dividing the standard deviation. This is because the machine learning algorithms are poor at data with different scales. Therefore, the formula for the transformed value z is given by;

$Z = \frac{x-\mu}{\sigma}$ Where, x is the original value,

μ is mean value of the data and

σ is the standard deviation

3.4.4 Datetime Data Extraction

The dates in the datasets are inherently non-numeric and cannot be directly passed and processed by the model. To capture the temporal patterns and seasonal variables, the following steps were taken.

Decomposition of Temporal Components. The primary date attribute was decomposed into discrete numeric features that include Year, Month, Day and Day of the year. This allows the model to identify long-term trends i.e., annual changes and specific periods within a month where for example discharge levels may fluctuate due to localized weather patterns.

Categorical and Binary Indicators. To provide the model with environmental defined contexts like season, the months are mapped to specific seasonal categories like March – May, Jun – Aug and others. This acts as a high-level grouping that aligns with major rainy and dry seasons as observed in the Rwenzori region. This helps to provide climatic shifts as a shortcut to the model.

Seasonal Periodicity. In a linear scale of 1-12, December and January appear far apart despite being adjacent. To preserve continuity, the months are transformed into two-dimensional space using sine and cosine functions. This allows to reduce the effect of boundary of in months. The functions are as below;

month_sin = $\sin\left(2\pi \frac{month}{12}\right)$

month_cos = $\cos\left(2\pi \frac{month}{12}\right)$

The transformation therefore allows the model to map the temporal data onto a unit circle to recognize the cylindrical nature of the calendar year, capturing recurring hydrological cycles.

3.5 Feature Transformation

This phase allows construction of the hydrological variables. The raw datasets are expanded to derive features specifically designed to capture the memory of the catchment and the non-linear relationships between precipitation and river responses.

Cumulative Rainfall: By calculating the 3-, 7-and 14-day windows, the model accounts for the gradual saturation of the catchment.

$$\text{Cumulative rainfall in d-days} = \sum_{i=0}^{d-1} rainfall_{t-i}$$

Lag features: Lagged values for rainfall and discharge e.g., 1, 2 and 3days are created to allow the model observe the propagation delay i.e., the time it takes for runoff to travel from the upper stream of Rwenzori mountains to the downstream.

$$\text{Rainfall lag\_k} = rainfall_{t-k} (\text{k} = 1, 2, 3)$$

Antecedent Precipitation Index (API): When the soils are saturated with water, they cannot absorb more water and therefore, subsequent rainfall will contribute to immediate runoff and flash flooding. A decay factor (**k**) which represents the rate at which soil moisture depletes over time is taken as 0.85 and used to ensure that the recent rainfall is weighted more heavily than rain from two weeks ago. The antecedent precipitation index is therefore defined by the formula below.

$$API_t = k * API_{t-1} + rainfall$$

- if k = 1, the soil never dries and hence the ground has an infinite memory.
- If k = 0, the soil dries instantly hence the ground has no memory.
- For the value of k = 0.85, the soil retains about 85% of its moisture influence from one day to the next.

Rolling Statistics: The rolling means and standard deviations over a 7-day window are used to smooth sensor noise and identify significant deviations from the weekly baseline. The rolling maximum particularly important as it captures the peak intensity of a storm event, often the primary driver of flash floods.

$$rolling\ mean\ in\ 7\ days = \frac{1}{7}\sum_{i=0}^{6} x_{t-1}$$

$$rollind\ standard\ devidation\ in\ 7\ days = \sqrt{\frac{1}{6}\sum_{i=0}^{6}(x_{t-i} - mean)^2}$$

$$rolling\ maximum\ in\ 7\ days = \max\left(x_t, x_{t-1}, \dots \dots \dots \dots, x_{t-6}\right)$$

Interaction of Hydrological Indicators

These are created to capture the non-linear relationships between the hydrological processes.

i. **Relative Rainfall Intensity**
This interaction indicates how much the current rain exceeds the recent average.

$$relative\ rainfall\ intensity = \frac{rainfall}{rolling\ mean\ in\ 3days + 0.1}$$

ii. **Short-term runoff potential**
This multiplies the 3day rain by soil moisture to identify high-risk saturation levels. It's obtained by the formula below.

$$short\ term\ runoff = cumulative\ rainfall\ in\ 3day\ X\ soil\ moisture$$

iii. **Surge Momentum**
This combines the rate of discharge with rainfall intensity to detect rapidly rising waters.

$$surge\ momentum = (discharge_t - discharge_{t-}1)\ X\ rainfall\ intensity$$

iv. **Flash Flood Threat**
This feature is one of the most significant predictors in the model validating, the hypothesis that floods in the Nyamwamba Catchment are driven by the interaction of soil saturation and high intensity rainfalls.

3.6 Model Development

The modeling phase was divided into two distinct tasks, the Binary Classification and Regression. The Binary Classification is set to predict the occurrence of a flood while the Regression is responsible for predicting the specific water discharges.

3.6.1 Data Splitting

Unlike standard datasets where data can be shuffled, hydrological data is a time series. To prevent data leakages where the model accidentally learns from the future to predict the past, a data split was taken. The data fed into the model was partitioned as below.

1. **Training Set**: For initial model learning, the 70% of the data is used for training.
2. **Validation Set**: This set was purposely set for hyperparameter tunning and early stopping. 15% of data is set for validation.

3. **Tests Set**: This data is set aside to help in evaluation of the final performance on unseen future data. It's also set at 15%.

3.6.2 XGBoost Classification Model

The primary objective of this model is to determine the probability of a flood event. The model utilizes the Binary Logistic Loss function (Log-Loss) as its objective. This function penalizes the model based on how far the predicted probability (p_i) is from the actual label (y_i).

$$l = \frac{1}{n}\sum_{i=1}^{n}[y_i \log(p_i) + (1 - y_i)\log(1 - p_i)]$$

y_i represents the actual observed river discharge, (the ground data)
where the predicted probability is derived from the logistic sigmoid function given as;

$$p_{i=}\frac{1}{1+e^{-\hat{y}i}}$$

The following are taken into account while setting up the classification model.

Class Imbalance Handling

Because the floods account for a smaller percentage in the training dataset, a class imbalance exists. These imbalances can cause the model simply predict No flood every time to achieve accuracy. The scale_pos_weight parameter is applied by setting the ratio samples of negatives to positives, forcing the model to penalize errors on flood days more heavily.

$$scale\ pos\ weight = \frac{count\ (y)}{count\ (y = 1)}$$

Optimization and Evaluation Metric

The model utilizes early stopping on the validation set. This prevents overfitting by halting once the performance on unseen data stops improving. Given the class imbalance, AUC-PR (Area Under the Precision Recall Curve) is selected as the primary evaluation metric during training, as it provides a more realistic assessment of performance on the minority class than standard ROC-AUC.

Model Calibration

This was performed using a grid search with 3-fold StratifiedKFold cross validation method. The search space and values are as shown in the table below.

Table 1: Model Calibration results for XGBoost Classifier

Parameter	**Search Space**	**Best Value**
Learning rate	0.01, 0.05, 0.3	0.1
Max-depth	3, 5, 7, 9	6
n-estimators	50, 100, 200	100
Subsample	0.6, 0.8, 1.0	0.8
Column-sample-bytree	0.6, 0.8, 1.0	0.8

The learning rate determines how much weight is given to each new tree. A small learning rate means the model learns slowly and carefully while a high learning rate like 0.4 makes the model learn fast but might cause it to jump over the best solution. The max depth defines how deep each individual tree can grow ensuring that the model can capture complex flood patterns.

The n-estimators refers to the total number of trees the model builds. This is controlled by early stopping strategy that tells the model to stop adding trees once the performance on the validation set stops improving.

Subsamples and column sample by tree tell the model to only look at a random fraction of the data (rows) and features (columns) for each tree. This prevents the model from relying too heavily on a single historical year. It forces the model to be more alert by learning the patterns from different perspective.

3.6.3 Model Benchmarking using Baseline Models

To establish a performance benchmark for the proposed classifiers, two baseline classifiers were trained on the identical training dataset. Evaluating advanced architectures against standard algorithm is critical to ensure that any increase in model complexity yields a justified improvement in predictive performance. The baselines implemented for this analysis are as below:

Logistic Regression

This model was configured with balanced class weights and l2 regularization. In the context of flood forecasting, data imbalance is a challenge as flood events are inherently minority classes compared to normal non-flood conditions. The application of balanced class weights mitigates this imbalance, preventing the model from developing predictive bias towards the majority class. Furthermore, l2 regularization was applied to prevent overfitting ensuring the model maintains its ability to generalize when exposed to unseen meteorological data.

K-Nearest Neighbours (KNN)

This model was implemented with k = 5 and distance weighting. As an instance-based learning algorithm, KNN classifies new environmental data points based on their proximity to historical weather and hydrological records. The inclusion of distance weighting ensures that most similar historical conditions, exert a proportionality greater influence on the final classification outcome than more distant data points.

3.6.4 XGBoost Regression Model (Discharge Prediction)

This model is responsible for river discharge. The regressor is optimized using the Squared Error Loss function with the objective of calculating the average of the squares of the errors, the differences between the predicted value ($\hat{y}_i$) and the actual river discharge (y_i).

$Q = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^{2}$ Where;

n is the total number if observations in the dataset.

$\hat{y}_i$ represents the predicted river discharge generated by the model.

y_i represents the actual observed discharge, (the ground data).

3.7 Evaluation Metrics for Developed Models

To assess the predictive capabilities of the developed models, an evaluation metric is employed. This is because the proposed system encompasses both discrete event classifications i.e., the flood risk and continuous variable regression i.e., discharge. The evaluation framework is divided into two corresponding categories.

3.7.1 Classification Metrics

For the baseline classification models evaluating categorical flood risk, performance cannot be determined by accuracy alone given class imbalances that exist in meteorological data where no flood days heavily out number flood days. Therefore, the following metrics were utilized.

1. **Accuracy:** This is the ratio of correctly predicted observation to the total number of observations. It's useful but insufficient on its own while dealing with imbalanced datasets.
2. **Precision:** This is mathematically defined as the ratio of true positive values to the sum of true positive values and false positive. A high precision is vital for avoiding false alarms. Precision = $\frac{TP}{TP+FP}$
3. **Recall (Sensitivity):** This measures the proportion of actual positive cases that where correctly identified. Optimization of this metric ensures that the model captures all impeding flood events, as a missed (False Negative) posse a severe risk to human life and property.
4. **F1-Score:** This is the harmonic mean of precision and recall. This metric is used to provide a balanced evaluation of the model's performance, penalizing extreme disparities between precision and recall.
5. **Receiver Operating Characteristics (ROC-AUC):** This metric is also used to evaluate the model's ability to distinguish between the flood and non-flood classes across the

decision threshold. An AUC close to 1.0 indicates that the model has a high true positive rate and a low false positive rate.

3.7.2 Regression Metrics

To evaluate the precision of the XGBoost model in predicting continuous discharge, standard statistical error metrics were applied to quantify the deviation between the predicted values and the ground truth.

Mean Absolute Error (MAE)

This metric calculates the average magnitude of the errors in a set of predictions, without considering their direction. It provides a highly interpretable measure of average absolute deviation.

$$MAE = \frac{1}{n}\sum_{i=1}^{n} |y_i - \hat{y}_i|$$

Root Mean Square Error (RMSE)

By squaring the errors before averaging them, RMSE assigns a disproportionately higher penalty to larger errors relevant for river discharge forecasting, where a massive under estimation of a flood peak is significantly more dangerous than a minor fluctuation.

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^{2}}$$

n is the total number if observations in the dataset.

$\hat{y}_i$ represents the predicted discharge generated by the model.

y_i represents the actual observed discharges, (the ground data).

Coefficient of Determination (R^2)

This represents the proportion of the variance in the dependent variable i.e., discharge that is predictable from the independent variables, meteorological features. It therefore serves as an indicator of the model's overall goodness of fit.

Mean Absolute Percentage Error (MAPE)

This metric expresses the prediction accuracy as a percentage. It is scale independent, making it highly effective for communicating model reliability.

3.8 Real-Time Forecasting and Early Warning System

3.8.1 Live Forecasting

The operational workflow of the live forecasting module executes a sequential automated connection designed to transform raw meteorological data into structured and actionable risk assessments. The real-time inference process consists of the following seven stages.

1. **Meteorological data acquisition**

The system queries the Open Meteo Weather API to retrieve hourly meteorological data specifically temperature, humidity, rainfall and wind speed variables for a subsequent 24-hour window. Concurrently, it fetches data for predicting 14 days earlier to provide the necessary historical context for computing rolling window features i.e., antecedent conditions.

2. **Hydrological Data Acquisition**

Daily forecasted river discharge metrics are fetched via Open Meteo API, providing the primary hydrological inputs required for model inferencing.

3. **Historical Data Integration**

The newly acquired data is merged with static catchment characteristics i.e., slope gradient and drainage density. Additionally, the most recent observed river discharge is carried forward to establish the current hydrological baseline.

4. **Data Preparation**

To ensure that the live data conforms the exact distribution of the training data, pre-fitted transformation of objects are applied in inference mode. This includes deploying the saved StandardScaler for feature normalization and the K-Nearest Neighbours (KNN) imputer to handle any missing values in the live API feed.

5. **Variable Transformation**

The prepared data is passed through the data preparation pipeline allowing application of the same transformations utilized during model training, generating predictive variables such as lagged features, rolling averages and interactions that capture the cumulative effects of recent weather patterns.

6. **Model Inference**

The created variable set is fed into the finalized predictive models. The XGBoost classifier calculates the probability of a flood event occurring, while the XGBoost regressor simultaneously estimates the continuous river discharge for each forecasted hour.

7. **Output Merging**

The forecasting pipeline culminates the generated structured Data Frame. This output aggregates timestamps, expected rainfall, predicted discharge, the computed flood probability and categorical risk severity classification i.e., low, moderate or high.

3.8.2 Lead Time

The efficiency of an early warning system is heavily dependent of the lead time it provides to vulnerable populations. Due to the specific topographic characteristics of the Nyamwamba Catchment i.e., steep slopes and short time concentrations, the hydrological response to intense precipitation is characteristically rapid resulting into flash floods.

By levering the 24-hour forecasting window provided by external meteorological API's, the system is designed to detect pre-conditions for flooding well before surface runoff accumulates. This integration of predictive modeling with continuous API monitoring extends the operational lead, granting emergency management teams a critical temporal buffer to execute evacuation protocols and deploy flood mitigation resources before the catchment reaches its critical threshold.

3.8.3 Alert Manager

The dissemination of early warnings is governed by the Alert manager module. To prioritize public safety and mitigate the risk of missed detections, the system utilizes a conservative decision boundary. When the calculated flood probability exceeds the defined threshold, the system automatically triggers a multi-channel alert protocol. The notification design incorporates the following mechanism;

- **Short Message Service (SMS)**: Automated text alerts are dispatched via Twilio to a designated registry of stakeholders i.e., community members and emergency respondents maintained within the localized directory.
- **Electronic Mail (Email):** Detailed warning reports are transmitted via SMTP protocols to the email addresses of relevant disaster management authorities and the community members able to access the media platform.
- **Physical Hardware Integration:** The system includes a place hold for triggering a localized physical siren sound system. While not physically in place, the logic trigger is fully integrated for future hardware scalability. With this being the most appropriate method in the area as it alerts the community via sound.

To ensure actionable communication, the alert payload explicitly details the calculated flood probability, the anticipated peak river level and prescribed mitigation actions e.g., evacuate and move to higher grounds. Furthermore, all triggered alerts are persistently recorded in an audit log to facilitate post-event analysis and system performance reviews.

4 RESULTS AND DISCUSSION

4.1 Feature Importance Analysis

A feature importance analysis was conducted to extract the underlying drivers of the model's predictions quantifying the importance of each input variable and this was to ensure the model's predictive logic aligns with established hydrological principles. The plot shows that the model is using physical and temporal signals. The graph below shows the plot of feature importance.

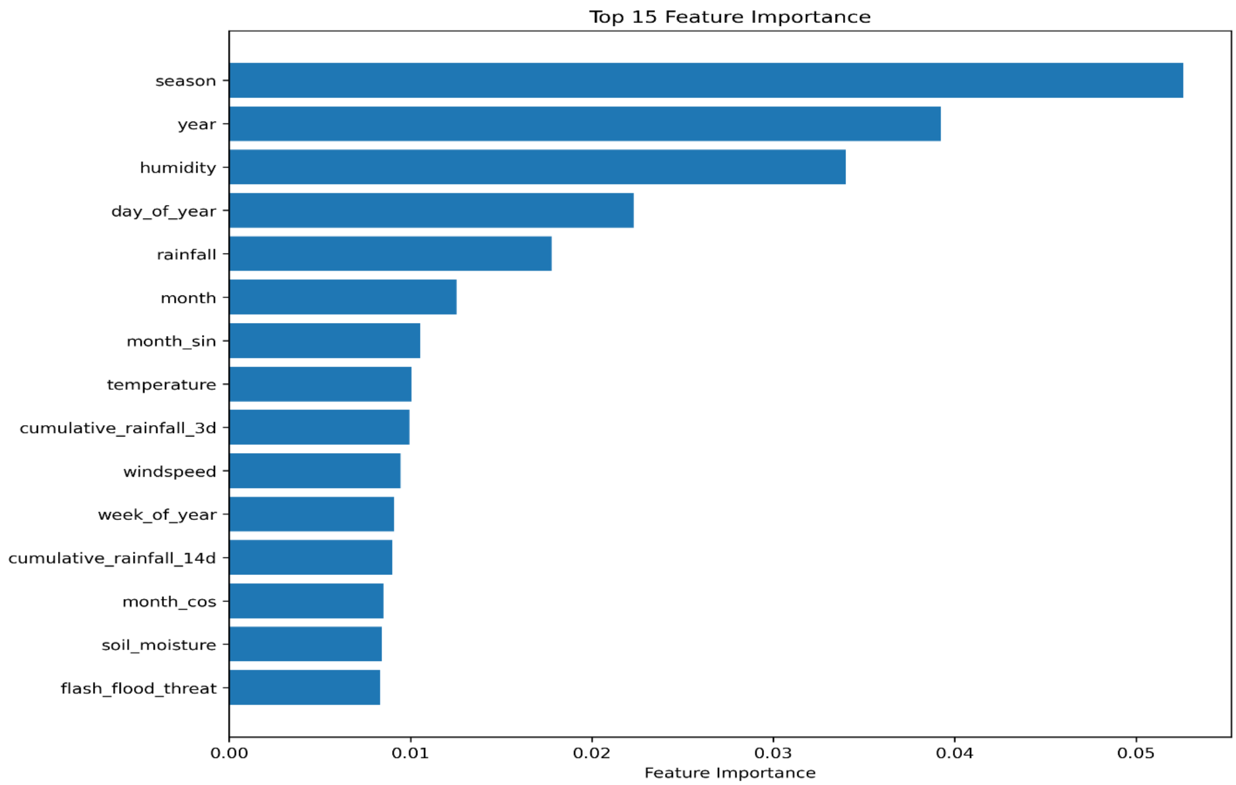

Figure 4: Feature Importance -Top15 Predictive Variables

The season, year and month indicate the bimodal rainy season of the catchment providing the context of the hydrological data being the top drivers. This indicates that flood occurrences in this catchment are highly cyclical and heavily dependent on broader seasonal trends.

Humidity and rainfall are the physical primary triggers of the flash floods. Because rainfall feature looks small relative to humidity on the plot, it remains the main trigger of the flooding. This is because the rainfall data was split into numerous different columns like cumulative rainfall in given windows i.e., 3-, 7-, 14 making each individual rainfall feature have a smaller importance. Humidity however, likely remains a single feature with no splits. Therefore, if the rainfall derived features are added-up, they would almost outweigh humidity.

Also, the cumulative rainfalls indicate that the model successfully accounted for soil saturation, which is why even a moderate rain can cause a flood if the ground is already saturated.

4.2 Residual Analysis for River Discharge Prediction

The residual plots evaluate the performance of the model regression in predicting continuous river discharge. The model achieved a high coefficient of determination (R^2) score of 0.9949. The residual distribution histogram on the right is heavily centered at zero with very narrow spread. This demonstrated that the vast majority of the predictions deviated minimally from the observed values, which is consistent with the recorded Mean Absolute Error (MAE) of 0.2515.

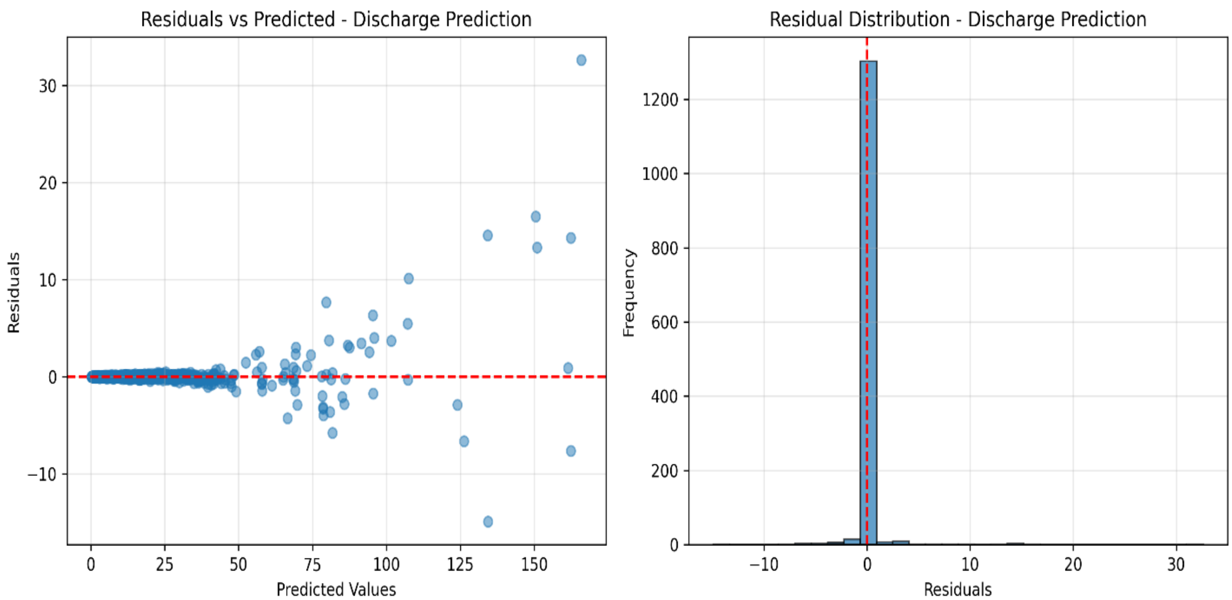

Figure 5: Discharge prediction curves

The residuals vs the predicted scatter plot on the left exhibited a degree of non-constant variance. While the predicted discharges are below 100, we observe a residual congestion. As the predicted discharge values increase beyond 100, the spread of the residual widens. This behavior indicates baseline and moderate river flows predicted with high precision. Because the high-flow events carry a larger margin for error, the system is incorporated with wider dynamic confidence intervals to issue peak flood warnings.

4.3 Receiver Operating Characteristics (ROC) Curve

The curve illustrates the diagnostic ability of the XGBoost Classifier in distinguishing between a flood and no flood conditions. The model achieves an area under the curve of 0.776, demonstrating a strong predictive capability that significantly outperforms the random classifier baseline. The curve is illustrated in the figure below.

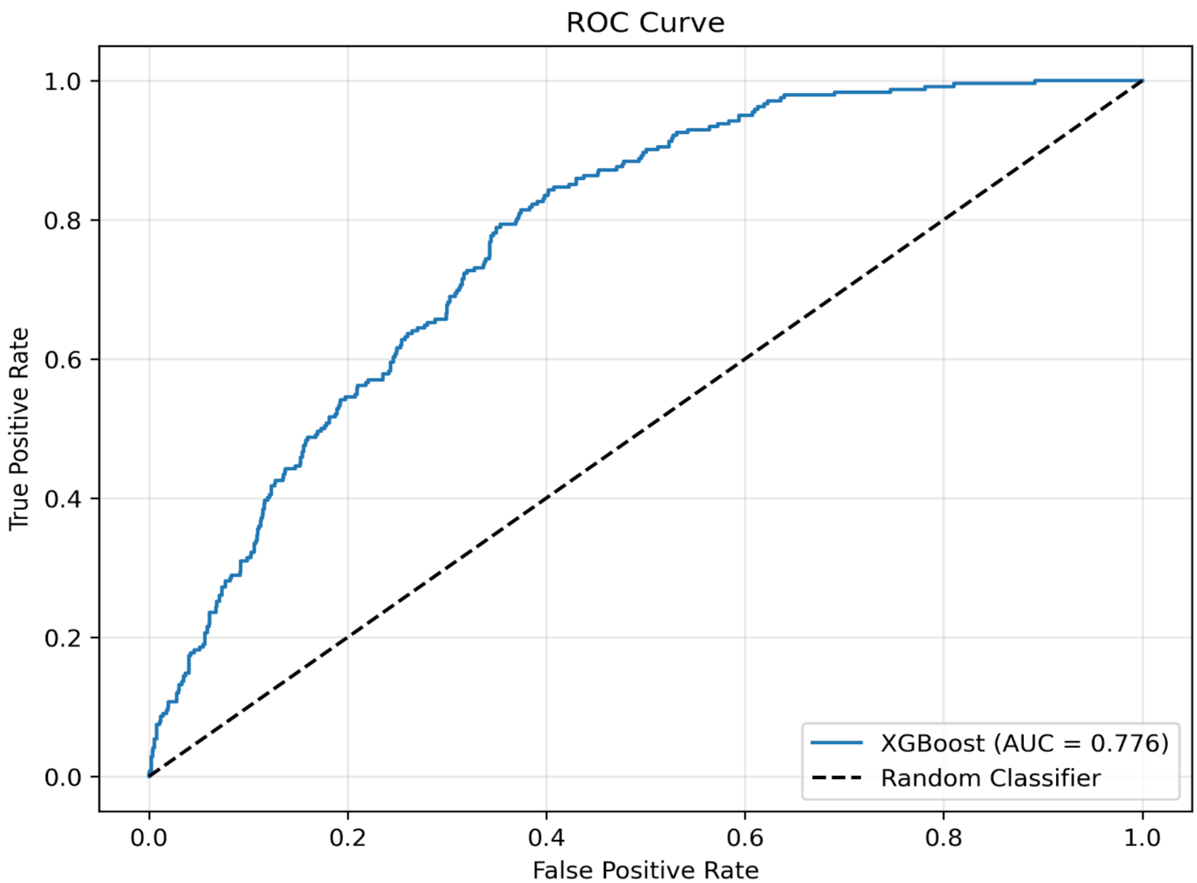

Figure 6: Receiver Operating Characteristics Curve

The sharp upward slope at the beginning of the curve demonstrates that when the model is highly confident, it correctly identifies floods with very few false alarms. Because the floods in the catchment are driven by season, the made up 17.8% of the training data. Even with this imbalance, the score shows that the model effectively learnt the physical patterns that cause floods rather than relying on the fact that No flood is the most common outcome.

Therefore, the system must be calibrated to prioritize finding as many as real floods as possible. This is by lowering the probability threshold required to trigger the alert helping the models recall performance improve and with such an adjustment, the model can capture a more percentage of all actual floods.

4.4 Classification Model Performance

The classification performance was evaluated across three primary algorithms that included the logistic Regression, K-Nearest Neighbors (KNN) and XGBoost. The results demonstrated a clear tradeoff between overall accuracy and the ability to correctly identify actual flood events. The table below summarizes the performance metrics for each model after the training phase.

Table 2: Performance metrics of flood classification models

Model	Accuracy	Precision	Recall	F1-Score	ROC-AUC
Logistic Regression	0.6849	0.3211	0.6860	0.4374	0.7607
K-Nearest Neighbours	0.7970	0.3721	0.1983	0.2588	0.7057
XGBoost	0.817	0.4674	0.1777	0.2575	0.7757

The XGBoost model achieved the highest overall accuracy and precision, meaning it was the most reliable at correctly identifying the No flood days and had the lowest rate of false alarms at the default threshold.

While it was the most accurate overall, the Logistic regression showed significantly a higher recall at the default threshold. This indicated that the baseline Logistic model was naturally more sensitive to flood events, where the XGBoost was more conservative.

The ROC-AUC scores that measures the model's ability to distinguish between classes regardless of the set threshold, showed that the XGBoost and Logistic Regression Models performed similarly and both outperformed KNN.

Although the XGBoost had a low recall initially, its high ROC AUC indicates that it had the best potential for improvement. This justified the selection of the XGBoost with aim of further calibration.

4.4.1 Confusion Matrix

The confusion matrix was generated to provide a granular view of how each model handles the classification of Floods and No Floods. By examining the raw counts of True Negative (TN), False Positive (FP), False Negative (FN) and True Positives (TP), specific behavior patterns in each algorithm were identified. At a threshold of 0.5, the obtained results for the models are in the table.

Table 3: Summary of Confusion Matrices

Model	True Negatives No Flood)	False Positives (Type I Error)	False Negatives (Type II Error)	True Positives Flood
Logistic Regression	762	351	76	166
KNN	1032	81	194	48
XGBoost	1064	49	199	43

The Logistic Regression shows most aggressiveness correctly identifying the highest number of floods but at the cost of 351 false alarms. This indicates a bias towards predicting a flood whenever a slight indicator is present. While the XGBoost is the most conservative model, it produces the fewest false alarms but missing actual floods i.e., 199. This makes it reliable when it does predict a flood, however if not well calibrated it may be not good for a critical system.

The high number of False Negatives across all the models reflected the difficulty of the algorithms in identifying the minority of class events for the floods as a result of class imbalance. The models leaned towards the majority class (non-flood instances) in order to maintain a high accuracy.

4.5 Spatial Simulation

While the model provides a temporal and magnitude of the flood events, an ArcGIS based spatial simulation was conducted to visualize the likelihood of the hazard within the catchment when it rains in the upper stream.

4.5.1 Flood Simulation

The simulation utilized an online resolution basemap, and world topography. By applying the necessary calibrations, a rainfall of 40mm was created and simulated for about 30 minutes. In addition, parameters like infiltration were set for dry sand around the river banks.

Figure 7: Upper Kilembe Rainfall Boundary

Figure 8: Rainfall simulation after 10 min of precipitation

4.5.2 Observation of the Simulation

In the earliest stages of the simulation (observed around 00:00:45), the 40 mm/hr rainfall intensity quickly begins to interact with the terrain. Given the steep gradient of the valley walls, there is minimal opportunity for water to pool or infiltrate deeply into the soil before overland flow begins.

By the second image, distinct drainage patterns emerge on the hillsides. The water (represented by the blue polygons) rapidly finds the paths of least resistance, forming fast-moving streams down the steep slopes. The high-resolution surface model (0.468 m cell size) accurately captures how micro-topography funnels water directly toward the valley floor.

By just over 4 minutes into the simulation, significant water volume has already reached the main channel of River Nyamwamba. The tributaries and hillside gullies are actively dumping concentrated runoff into the primary riverbed. The speed at which surface water transitions from the slopes to the main channel demonstrates an extremely short time of concentration i.e., the time it takes for water to travel from the furthest point in the watershed to the watershed outlet.

Figure 9: Rapidly filling of River Nyamwamba

When the 40 mm/hr. intensities were sustained for 30 minutes resulting in 20 mm of total accumulated rainfall in a very short window, the main channel rapidly filled. The steep slopes continuously shed water with almost zero lag time leading to a sharp, sudden spike in the river's flash flooding.

4.5.3 Lead Time Analysis

Based on the simulations, the calibration of an Early Warning System (EWS) for low-lying areas in Kasese must focus on the following two conclusions regarding lead time:

The Zero-Lag Constraint: The simulation proves that the upper Kilembe area has a minimal Time of Concentration. This is because the slopes are so steep and the drainage density is so high, the lead time provided by downstream river gauges is essentially zero. To provide low-lying areas with a usable lead time, the system must be calibrated to Rainfall Intensity Thresholds as for this project did rather than river levels. An alarm is triggered the moment the model detects sustained precipitation exceeding 40mm/hr.

This 3D view also suggests that for low-lying downstream communities, this window is compressed to less than 30–45 minutes from the start of a peak rainfall event. Calibration must therefore prioritize Automated Dissemination. Any delay caused by manual data verification in decision-making may likely result in the warning arriving simultaneously with the flood wave, rendering the EWS ineffective for saving lives in high-risk zones.

4.5.4 Predictive lead time

The spatial modelling in ArcGIS estimated exactly how long surface runoff takes to transit from the steep upper reaches of the Kilembe sub-catchments to the main river channel. Because the physical topography dictates an extremely short travel time often under 45 minutes during the simulation, relying solely on physical water movement provides insufficient warning. By utilizing a 3-day rainfall forecast window, the modelling system shifts from a reactive posture.

Figure 10: 30 min 40mm/hr. Rainfall in Kasese municipality. ArcGIS simulation

The XGBoost model system successfully generated a critically extended lead time for the downstream communities of Kasese Municipality. Because the XGBoost model calculates risk based on impending meteorological data rather than waiting for physical water accumulation, the system triggers automated pre-alerts well before surface runoff begins. As shown in the figure 9, the most rapid hydrologic response occurs in the high-gradient zones of upper Kilembe.

Table 4: Lead Time Enhancement via Predictive Modeling

Zone	Physical Lead Time (ArcGIS),	Predictive Lead Time (XGBoost)	Warning Strategy
Upper Kilembe (Steep Slopes)	< 15 Minutes	12 - 24 Hours	Automated sirens
Middle Catchment	15 - 30 Minutes	12 - 24 Hours	SMS alerts Community radio broadcasts. Sirens
Kasese Municipality (Downstream)	30 - 45 Minutes	24 - 72 Hours	Multi-channel

4.6 Overall System Calibration

This part focuses on calibration which is the process of tuning the model so that its predictions match the actual events recorded on the ground. The calibration of the model ensures that the system is not just a mathematical formula but a tool for real world in making safety decisions.

4.6.1 Finding the Best Settings

The first step of calibration involved searching for the best internal setting. A method known as StratifiedKFold cross-validation was used with three splits of data. This meant that the model was tested multiple times on different parts of the data., making sure it could handle both dry days and flood days equally well. Through the process, a learning rate of 0.1 and maximum depth of learning 6 which gave us reliable reliance was quiet identified as a good effective setting. These settings however can be adjusted to obtain a better performing model.

4.6.2 Threshold Adjustment

Most models use a default setting of 0.5 to decide if a flood is happening, meaning they only trigger an alert if they are more than 50% sure. However, when the setting of 0.5 was used, they model showed that this default setting was too strict and missed many actual flood events. To make models more effective, this value was lowered to 0.1. The adjustment means the model becomes sensitive prioritizing catching as many floods as possible.

4.6.3 Accuracy Proof with Ground Data

To prove that the models' predictions were correct, it was compared to its results directly against the actual measured river discharge. Two main pieces of evidence for verification were used.

1. The residual plot: The difference between the model's prediction and real-world measurements i.e., residuals, was examined. As seen in figure (Figure 5: Discharge prediction curves), majority of these errors are clustered very close to zero proving that the model's prediction is almost identical to what was observed on the ground.
2. The discharge model achieved R^2 score of 0.9949 a very strong proof of accuracy, as it showed that the model can explain over 99% of the changes and movements seen in the actual river data.

4.7 Real Time Forecasting Output

The validated models were subsequently deployed into a live forecasting pipeline, continuously fetching real time meteorological data from the Open Meteo API and GloFAS discharge forecasts. The figure below shows a next 24-hour forecast as the model is deployed on live data fecthing.

FORECAST FOR THE NEXT 24 HOURS:

Timestamp	Expected_Rainfall_mm	Predicted_Discharge_m3s	Flood_Probability	Alert_Level
2026-05-01 10:00:00	1.000000e-01	15.076573	0.054648	LOW
2026-05-01 11:00:00	1.000000e-01	15.076573	0.030233	LOW
2026-05-01 12:00:00	9.000000e-01	15.071975	0.049238	LOW
2026-05-01 13:00:00	1.000000e-01	15.071975	0.038081	LOW
2026-05-01 14:00:00	4.440892e-16	15.073711	0.076973	MODERATE
2026-05-01 15:00:00	4.440892e-16	15.071975	0.042046	LOW
2026-05-01 16:00:00	4.440892e-16	15.067698	0.067491	LOW
2026-05-01 17:00:00	4.440892e-16	15.067698	0.072148	LOW
2026-05-01 18:00:00	4.440892e-16	15.089183	0.035810	LOW
2026-05-01 19:00:00	4.440892e-16	15.102142	0.052126	LOW
2026-05-01 20:00:00	4.440892e-16	15.104208	0.050061	LOW
2026-05-01 21:00:00	4.440892e-16	15.104208	0.042033	LOW

Figure 11: next 24-hour forecast

The live output demonstrated the model's sensitivity to dynamic inputs. During periods of minor rainfall, the predicted river discharge fluctuates relatively by a small amount and the system dynamically shifts the alert status mode. While probabilities remained below the critical threshold during this specific dry window, the calibration dataset proved that when the probabilities exceed the 0.15 threshold, the system autonomously dispatches a high alert.

4.8 Discussion of Key Findings

The study shows that the Nyamwamba River's behavior is driven by clear seasonal patterns and immediate weather changes. One of the most important findings is that while long time weather matters, the rainfalls from just the last three days is much stronger indicator in an upcoming flood. This tells us that the river catchment reacts very quickly to new rain.

In terms of technology, the models proved to be highly effective at different tasks. The model that was used to predict the actual amount of water in the river (discharge) was accurate showing that it can follow the river natural trend of rise and fall with over 99% precision. However, it was noticed that the model's prediction becomes less certain when the water levels are at their highest.

This means that while the system is reliable for daily monitoring, extra care should be taken when it predicts extreme peaks.

Finally, it was found out that using the default setting for the flood detection model would lead to missing of too many dangerous events. By manually adjusting these settings, it allows the model to be more sensitive. This finding prioritizes detecting as many floods as possible and therefore it has to be taken into consideration while performing the calibration process.

5 CONCLUSION AND RECOMMENDATIONS

5.1 Conclusion

The project successfully developed a dual-layered forecasting system for the Nyamwamba River Catchment, capable of predicting both flood probabilities and specific river discharge levels. Powered by an XGBoost model, the system accurately captures the region's unique seasonal and rainfall patterns.

With a 6-hour warning window and an automated alert system, this project provides practical solution for flood mitigation strategies. While there is still room to improve how the model handles extremely high-water levels, the current system offers a reliable foundation for protecting lives and property.

5.2 Recommendation

The Directorate of Water Resources Management, Ministry of Water and Environment should prioritize the installation of automated real time stream gauges within the Kasese region at large. This helps in reducing reliance on secondary APIs and continuously improves the forecasts within the region. In addition, the ministry should ensure daily data recording for the Nyamwamba River to allow acquisition of high ground data quality for well simulation of the river behavior.

Currently, static topographic features were excluded to help the model perform better. Future research can explore integrating dynamic spatial data rather than relying on only point measures as this could help the model better understand exactly how saturated the ground is before a storm hits.

It’s also required to explore advanced calibration techniques to reduce false positives. Minimizing these false alarms is critical in preventing warning fatigue.

The implementation of such systems is accompanied by community workshops to educate the residents on interpreting the alert tiers and establishing a clear localized evacuation protocols to ensure orderly responses during emergencies.

A further study should be done to assess the impact of rock (debris) transportation from the upper streams of the river to the downstream. In addition, the impact of future land uses and further climate changes on the flood vulnerability in the area.

This model is not perfect and therefore, there is always a scope for refining the model. The model can be refined by incorporating real observed data, higher resolution digital elevations, recent flood scenarios and real time weather forecast for the region.

5.3 Challenges

The study area had no rainfall gauges making it hard to collect the necessary data to be used in the modelling process.

Similarly, the Ministry of Water and Environment confirmed absence of river discharge data and daily data records of the river levels. This limited the actual understand of the river responses during a storm by real ground data.

Some areas where too remote to be accessed during the site visit. This hindered clear observation to some parts of the river there by limiting to only accessible parts of the river.

The model tends to memorize the data thereby trying to skip the learning process, therefore it's important to re-run the model to avoid data memorization and enable it perform the learning before live forecasting.

During the site visit and questionnaire, some residents where not willing to provide information and those who were willing, there was a challenge of language. However, managed to collect from the willing residents.

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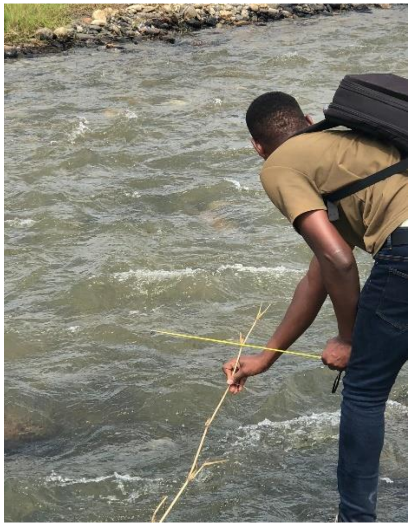
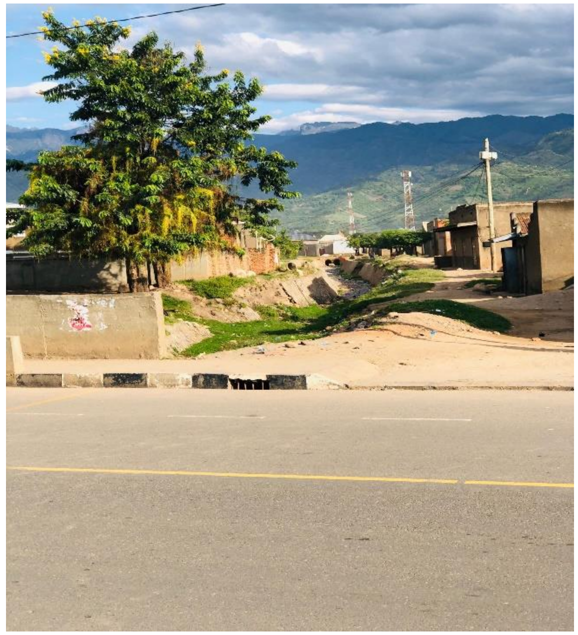
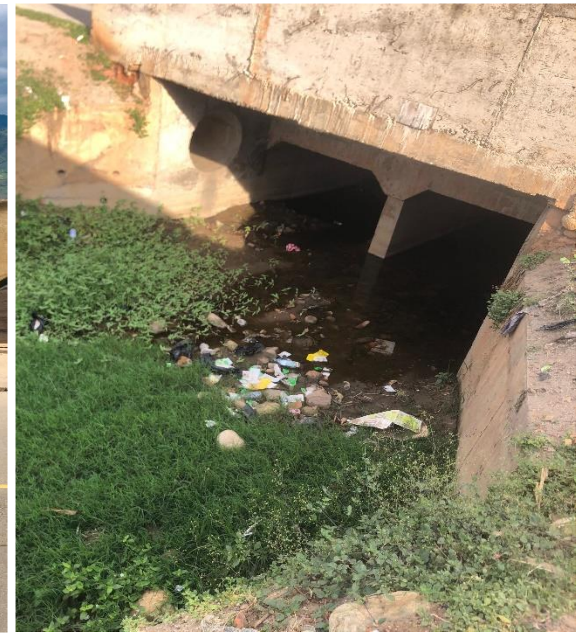
APPENDIX A1



Depth measurement along points of the river

Vegetation Cover along the river (Nyamwamba Division)



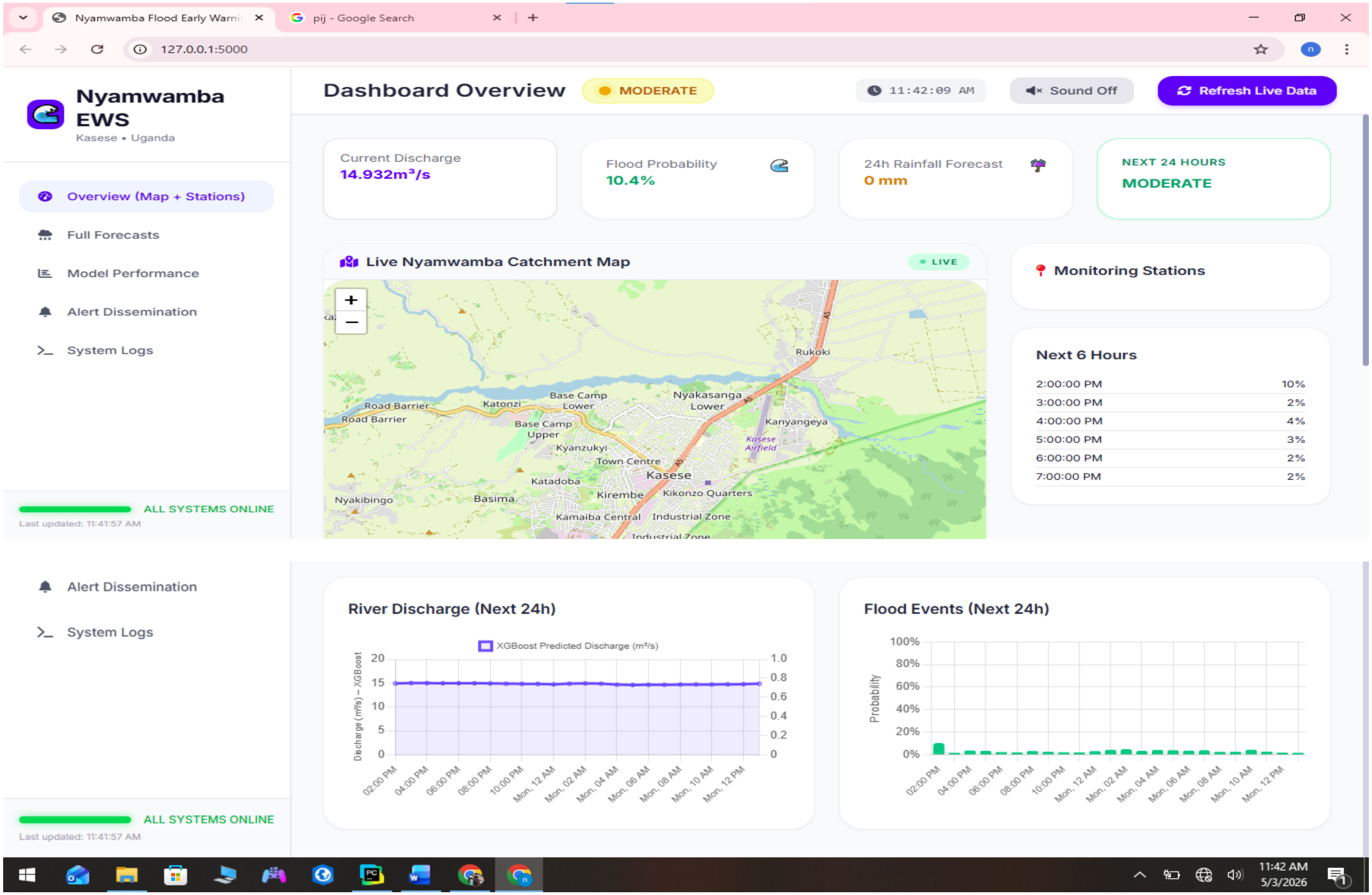


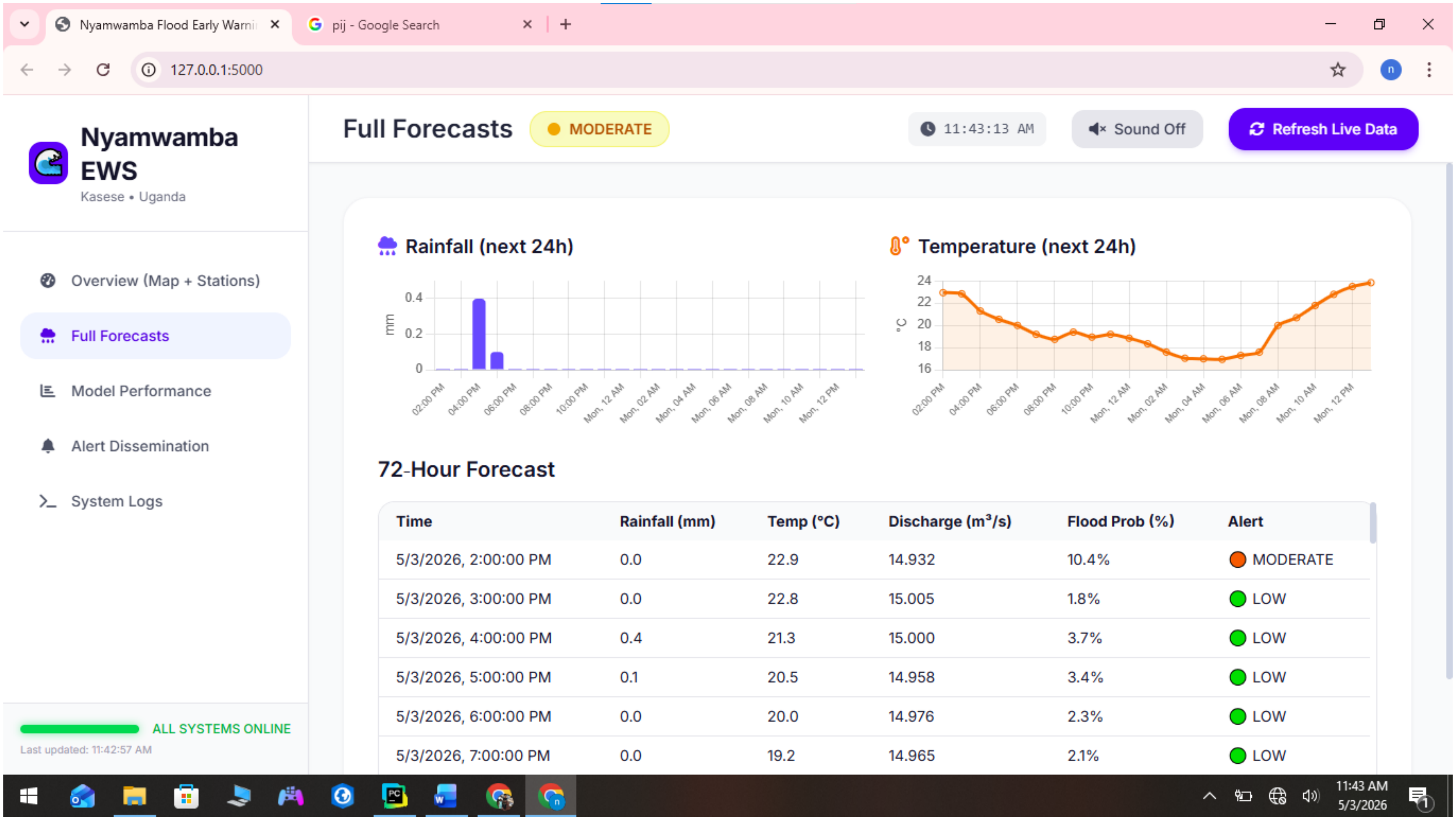
Rocks along the river banks

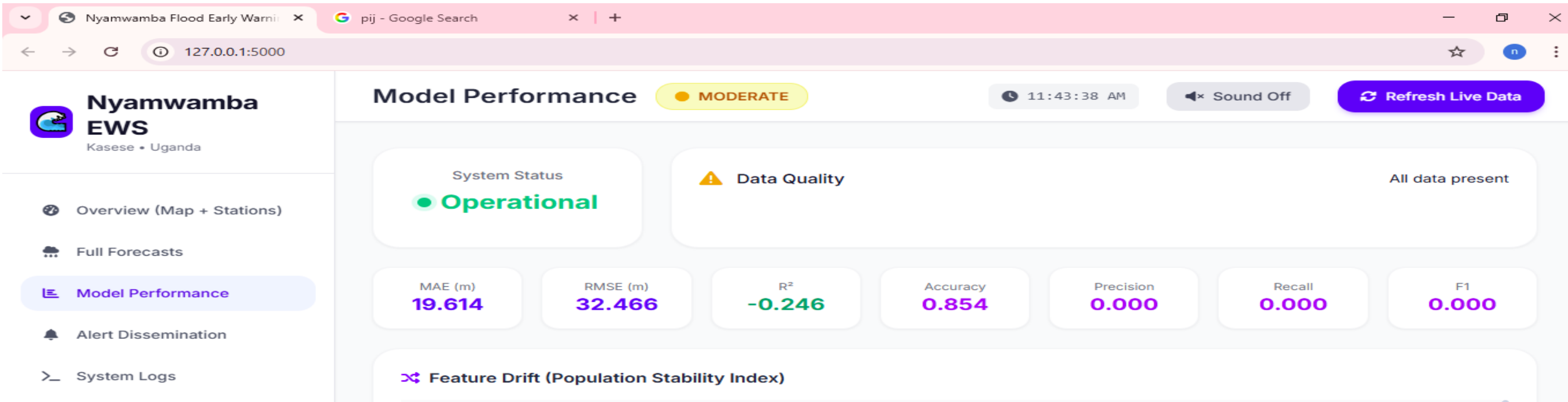
Conveying Channels for surface runoff during flooding (Kasese Municipality)

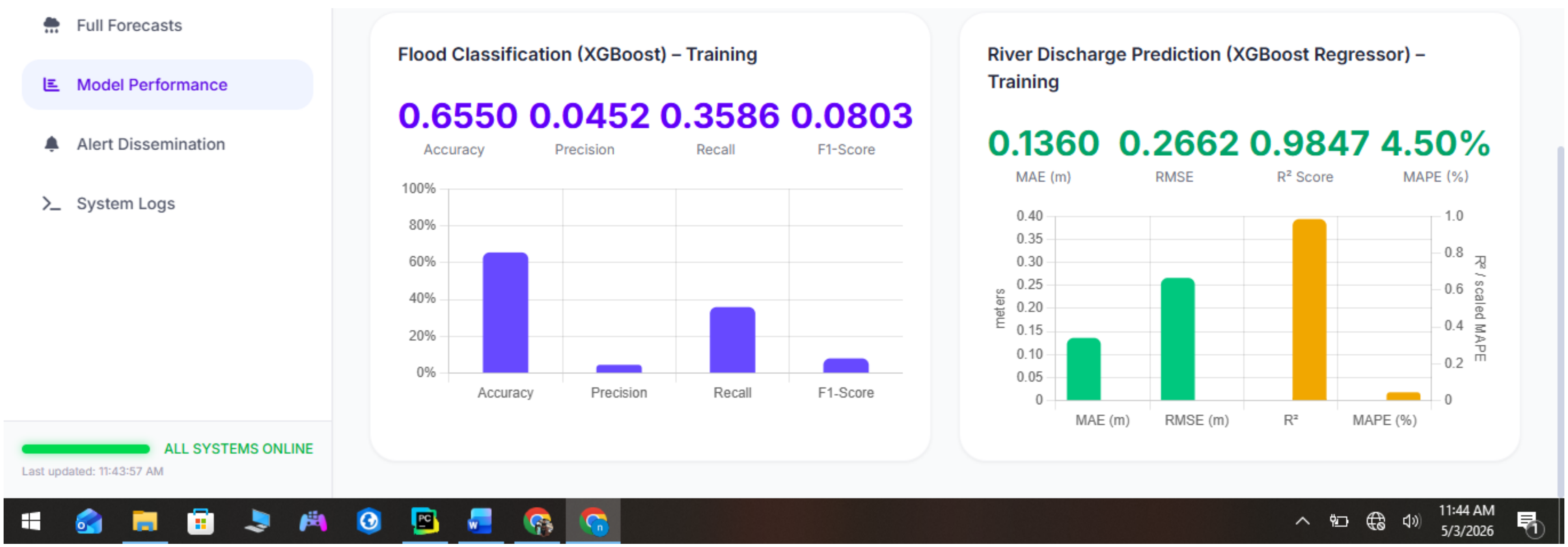
APPENDIX A2

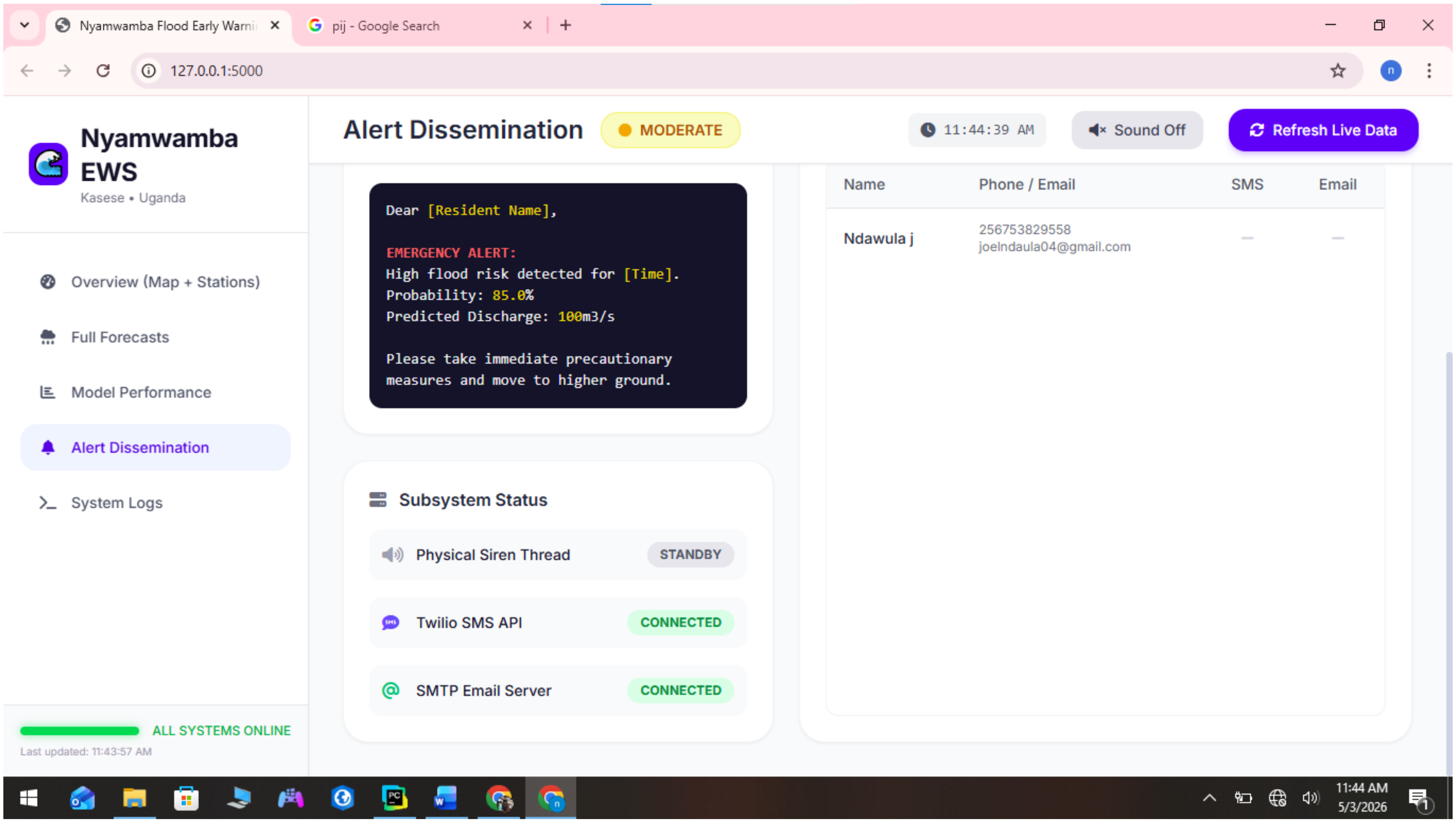
Flood early warning system interface

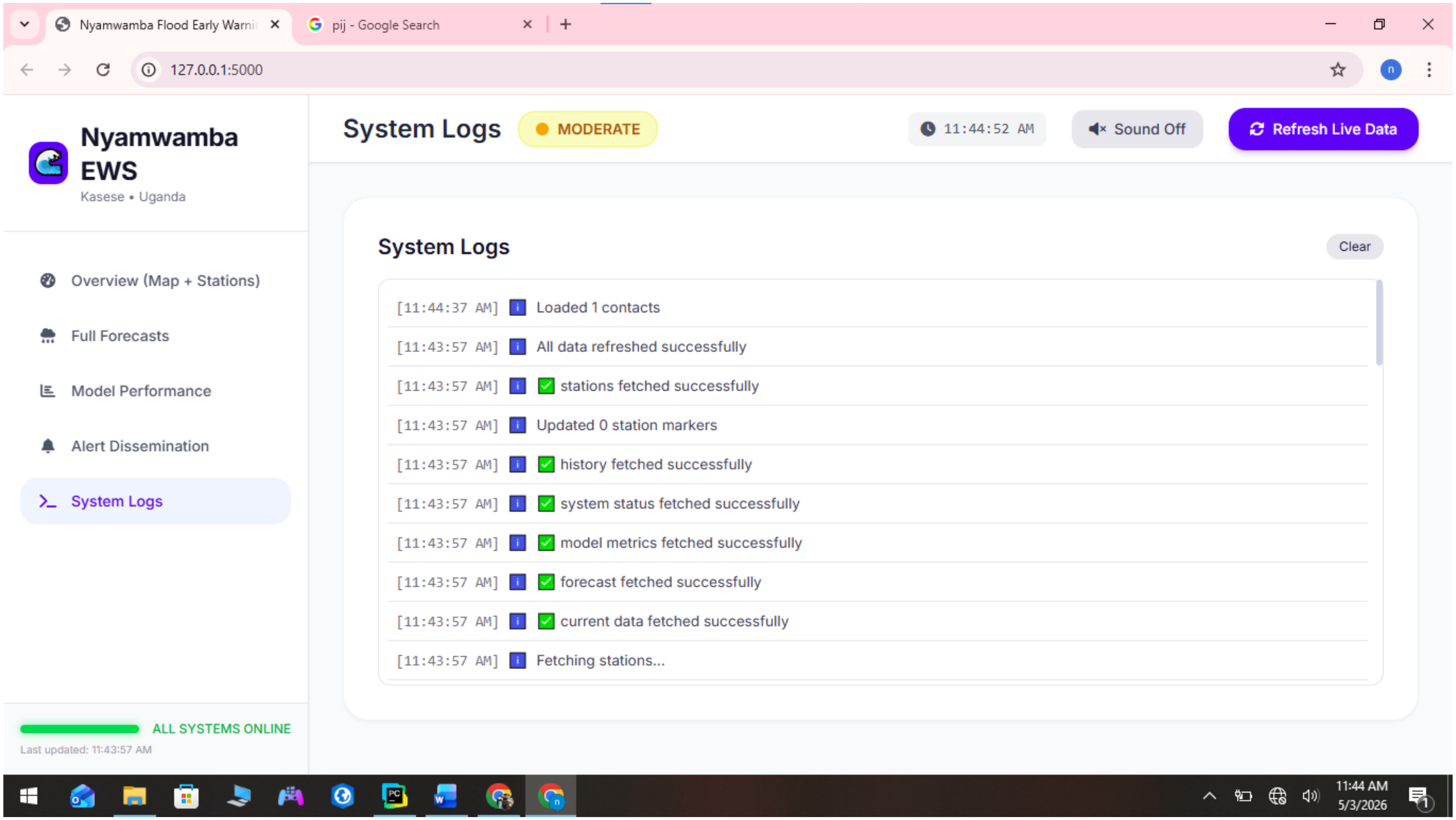



Nyamwamba Flood Early Warni
pij - Google Search
127.0.0.1:5000
Nyamwamba EWS
Kasese • Uganda
Overview (Map + Stations)
Full Forecasts
Model Performance
Alert Dissemination
System Logs
ALL SYSTEMS ONLINE
Last updated: 11:42:57 AM
Full Forecasts
MODERATE
11:43:13 AM
Sound Off
Refresh Live Data
Rainfall (next 24h)
Temperature (next 24h)
mm
°C
72-Hour Forecast
Time
Rainfall (mm)
Temp (°C)
Discharge (m³/s)
Flood Prob (%)
Alert
5/3/2026, 2:00:00 PM 0.0 22.9 14.932 10.4% MODERATE
5/3/2026, 3:00:00 PM 0.0 22.8 15.005 1.8% LOW
5/3/2026, 4:00:00 PM 0.4 21.3 15.000 3.7% LOW
5/3/2026, 5:00:00 PM 0.1 20.5 14.958 3.4% LOW
5/3/2026, 6:00:00 PM 0.0 20.0 14.976 2.3% LOW
5/3/2026, 7:00:00 PM 0.0 19.2 14.965 2.1% LOW
11:43 AM
5/3/2026


Nyamwamba Flood Early Warni
pij - Google Search
127.0.0.1:5000
Nyamwamba EWS
Kasese • Uganda
Overview (Map + Stations)
Full Forecasts
Model Performance
Alert Dissemination
System Logs
Model Performance
MODERATE
11:43:38 AM
Sound Off
Refresh Live Data
System Status
Operational
Data Quality
All data present
MAE (m)
19.614
RMSE (m)
32.466
R²
-0.246
Accuracy
0.854
Precision
0.000
Recall
0.000
F1
0.000
Feature Drift (Population Stability Index)


Full Forecasts
Model Performance
Alert Dissemination
System Logs
ALL SYSTEMS ONLINE
Last updated: 11:43:57 AM
Flood Classification (XGBoost) – Training
0.6550 0.0452 0.3586 0.0803
Accuracy Precision Recall F1-Score
River Discharge Prediction (XGBoost Regressor) – Training
0.1360 0.2662 0.9847 4.50%
MAE (m) RMSE R² Score MAPE (%)
meters
R² / scaled MAPE
11:44 AM
5/3/2026


Nyamwamba Flood Early Warni
pij - Google Search
127.0.0.1:5000
Nyamwamba EWS
Kasese • Uganda
Overview (Map + Stations)
Full Forecasts
Model Performance
Alert Dissemination
System Logs
ALL SYSTEMS ONLINE
Last updated: 11:43:57 AM
Alert Dissemination
MODERATE
11:44:39 AM
Sound Off
Refresh Live Data
Dear [Resident Name],
EMERGENCY ALERT:
High flood risk detected for [Time].
Probability: 85.0%
Predicted Discharge: 100m3/s
Please take immediate precautionary measures and move to higher ground.
Subsystem Status
Physical Siren Thread
STANDBY
Twilio SMS API
CONNECTED
SMTP Email Server
CONNECTED
Name
Phone / Email
SMS
Email
Ndawula j
256753829558
joelndaula04@gmail.com
11:44 AM
5/3/2026


Nyamwamba Flood Early Warni
pij - Google Search
127.0.0.1:5000
Nyamwamba EWS
Kasese • Uganda
Overview (Map + Stations)
Full Forecasts
Model Performance
Alert Dissemination
System Logs
ALL SYSTEMS ONLINE
Last updated: 11:43:57 AM
System Logs
MODERATE
11:44:52 AM
Sound Off
Refresh Live Data
System Logs
Clear
[11:44:37 AM] Loaded 1 contacts
[11:43:57 AM] All data refreshed successfully
[11:43:57 AM] stations fetched successfully
[11:43:57 AM] Updated 0 station markers
[11:43:57 AM] history fetched successfully
[11:43:57 AM] system status fetched successfully
[11:43:57 AM] model metrics fetched successfully
[11:43:57 AM] forecast fetched successfully
[11:43:57 AM] current data fetched successfully
[11:43:57 AM] Fetching stations...
11:44 AM
5/3/2026