



UGANDA CHRISTIAN
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Department of Computing & Technology

**A Machine Learning Framework for Flood Risk
Classification and Early warning in River Catchment
Areas.**

By

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23 August 2026

Declaration

I, *Namakula Martha Frances*, declare to the best of my knowledge that the work in this dissertation is original and has not been submitted before to any university/institution. It is the result of my effort.

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Ethical Generative AI Usage Declaration

I, *Namakula Martha Frances*, declare that no content generated by AI technologies has been used in this dissertation.

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Abstract

Flooding remains one of the most destructive natural hazards in Uganda, with the River Manafwa catchment area on the slopes of Mount Elgon experiencing recurrent and severe flood events that displace communities, destroy infrastructure, and disrupt livelihoods. Existing flood forecasting in Uganda relies heavily on global systems such as GloFAS and ECMWF, which operate at low spatial resolution and are often unreliable for small catchments, limiting their effectiveness for local early warning and disaster preparedness. This study developed a machine learning framework for flood risk classification in the River Manafwa catchment, using historical rainfall data (CHIRPS satellite, 1989–2024) and observed river discharge data (Ministry of Water and Environment, 1989–2024). Hydrological features were engineered, including antecedent rainfall accumulations (1, 3, 5, and 7-day windows), lagged and rolling-mean discharge variables, discharge differencing and acceleration terms, and seasonal cyclical indicators. A locally calibrated four-level flood risk classification (Normal, Mild, Advanced, Extreme) was developed based on discharge percentile thresholds (Q75, Q90, and Q95). Five machine learning models, Logistic Regression, Decision Tree, Random Forest, Gradient Boosting, and MLP Neural Network, were trained and evaluated using Macro F1-score, Extreme F1-scores, and AUC-ROC, with SMOTE applied to address class imbalance in the training data. Gradient Boosting achieved the strongest overall performance, recording the highest Macro F1-score and Extreme-class F1-score following SMOTE application, and was selected as the most suitable model for this study. SHAP analysis identified short-term lagged discharge, particularly the previous day’s discharge, as the dominant indicator of flood risk across all classes, while same-day rainfall and short-term cumulative rainfall accumulations retained comparatively greater influence specifically within the Extreme risk class. The model was validated against three documented historical flood events (June 2019, October 2019, and September 2021), with the model successfully flagging Extreme risk conditions several days ahead of officially reported flood dates. The resulting framework offers a low-cost, replicable, data-driven approach to strengthen flood early warning systems for the Manafwa catchment and other flood-prone rivers in Uganda, supporting disaster preparedness agencies including URCS, UNMA, and the OPM’s Department of Relief and Disaster Preparedness.

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Chapter 1

Introduction

1.1 Background

Flooding is among the recurring devastating natural hazards, causing tremendous loss of lives, agriculture, and property[1]. Floods usually occur when rainfall increases around drainage patterns, leading to increased surface runoff or river flow that exceeds channel capacity[2]. The increased variation in the climatic and socioeconomic conditions have also contributed to the increase in the frequency of flood events.

Over the course of the 20th century, flood events were linked to approximately 6.8 million fatalities across the globe. Between the years 2008 and 2017, flooding accounted for the highest proportion of recorded disasters in the World, resulting in about 51,002 deaths and \$371.8 billion in damage, contributing to about 41% of all the world's disasters[3]&[4]. Notably, nearly half of these deaths occurred in Asia during the final 25 years of that century[5].

In African countries, extensive flooding occurred in more than two dozen countries due to higher-than-average rainfall, resulting in thousands of fatalities roughly 11 million people, 2,500 fatalities, 4 million people displaced, and hundreds of health facilities and schools were made inaccessible. The high affected countries in 2024 were Nigeria, Cameroon, Niger, Chad, and South Sudan[6].

In recent years, climate change has induced many weather hazard phenomena, particularly flooding across the globe. According to the IPCC 2021 report, it is confirmed that the diversity in climate change has induced intensified rainfall patterns, causing pluvial and fluvial flooding in parts of the World[7]. In addition, the IPCC indicates that the induction of flooding especially in low lying areas, is mostly linked to human activities. These include uncontrolled settlement patterns, deforestation, soil silting in the river banks, greenhouse gas emissions, which alter the hydrological processes, increasing the frequency of the extreme flood events.

Furthermore, intense and recurrent extreme weather and climate events in East Africa, influenced by phenomena like the El Niño-triggered heavy rains and severe flooding, have devastated East Africa and the Great Lakes region, triggering mass displacement and impacting hundreds of thousands of refugees, internally displaced persons[8]. These conditions have continued to wreck developmental gains and subject hardship for communities across the region. In the years 2016, 2018, and 2023, the region experienced several heavy precipitation events, causing flood events with devastating impacts on agriculture, infrastructure, settlements, property, and life[9]. In Tanzania, weeks of rainfall in March and April 2024 resulted in 155 human deaths and a further 200,000 adversely affected, as well as massive damage, with floods sweeping away houses, roads, bridges, schools, and farmland[9].

In April 2024, floods killed over 200 people and displaced over 150,000 people in Kenya. A dam burst on 29 April in Nakuru County, killing at least 50 people, among them 17 children. Over 4,824 livestock had been lost, 27,717 acres of croplands damaged, with 264 small businesses and 24 schools adversely affected[9].

Over the years, Uganda has also experienced flooding occurrences due to the El-Nino rains that led to rivers overflowing and bursting their banks into the neighbourhood[10]. The study by [11] reported a likely general increase in precipitation across the country in the 2050s, 2070s, and 2090s. Despite observable changes in rainfall patterns, the occurrence and severity of floods continue to rise—largely due to a combination of natural and human-induced factors such as deforestation, poor land-use practices, settlement in floodplains, and inadequate drainage systems.

The positive trends in rainfall have already resulted in more recurrent floods, particularly between 2010 and 2019, compared to the period from 1960 to 2009[11]. The most affected areas are the mountainous subregions of Rwenzori and Elgon. Between September–December 2019, Uganda received unprecedented rains that caused devastating floods, displacing over 65,250 people[12]. In May 2020, Kasese district, in the Rwenzori region, faced new devastating rains that ravaged homes, infrastructures such as hospitals, roads, bridges, and water points, forcing the population to migrate to different areas[12]. From the recent IOM report, between August and October 2025, floods were the second reported hazardous weather event that affected 52,800 people, displacing about 11,678 people in the country. The most affected region is the Eastern region in the districts of Pallisa, Sironko, Bulambuli, Alebtong, Otuke, and Abim[13]. Reports indicate that heavy rainfall in the Eastern Region has led to severe flooding, flash floods, river overflows, and landslides, resulting in loss of lives and destruction of property. For instance, floods in Mbale City and surrounding districts such as Sironko and Kapchorwa have caused at least 29 fatalities, damaged about 80 houses, nine educational centers, and 14 bridges, and affected approximately 20,000 people across 4,000 households[14]. Therefore, this study focuses on flood risk classification in river catchments relying on historical rainfall and discharge patterns to improve flood disaster preparedness.

In relation to the study area, River Manafwa, which is located on the slopes of Mount Elgon and flows through Bududa, Manafwa, Mbale, and Butaleja districts before joining the Mpologoma River. The catchment has been subjected to frequency analyses based on long-term discharge records to characterize the magnitude of extreme flood events and provide a statistical basis for understanding the return periods of high-flow events[5],[15]. Over the last two decades, several major flood and landslide disasters have been documented within the catchment. In 2010, more than 3,000 people were relocated from Bududa following landslides that devastated villages in the Mount Elgon sub-region. In October 2018, at least 41 people lost their lives after the river burst its banks in Bududa[10]. In October 2019, the Manafwa River overflowed, damaging or destroying approximately 100 homes and affecting about 950 households across the wider Mount Elgon region. Furthermore, between May and June 2019, flooding and landslides in Bududa, Mbale, Sironko, and Butaleja directly affected nearly 2,850 people[16]. These recurring events demonstrate the persistent vulnerability of communities within the Manafwa catchment to flood-related hazards, with consequences for lives, households, property, and livelihoods. The occurrence of these events has been associated with variations in rainfall patterns and catchment-level factors such as land degradation. Therefore, there is a need for improved flood risk classification based on historical rainfall and discharge patterns to support timely flood preparedness and disaster risk reduction.

1.2 Problem Statement

Uganda faces several flood events which result into damage to crops, infrastructure, disruption of livelihood, displacement of people, loss of lives, and destruction of property[11]. These devastating floods are driven by climate variability, lack of early warning systems, weak infrastructure, and topography, including rivers, lakes, wetlands, and lowlands in some parts of the country[15]. Particularly, the River Manafwa catchment area is located on the gentle slopes of Mount Elgon, which experiences frequent flooding during both the short rainy season (October-November) and the long rainy season (March-May)[16].

Between the years 2014 and 2016, Flood early warning and response in the areas of Butaleja district relied on a solar-powered siren with a river gauge reading and reactive community alerts. The siren had a limited range and covered only a small part of the area that is prone to flooding. The system was not automated and therefore could not be remotely monitored[17]. The system was also reported to have broken down, causing insufficient lead time for effective evacuation and flood response.

The country currently depends on global forecasting models by GloFAS and ECMWF, which operate at a low spatial resolution, especially in small catchment areas like River Manafwa. Despite this challenge, the URCS developed the Early Action Protocol (EAP), which sources flood forecasts from GloFAS to predict flood impacts. For instance, when forecasts indicate higher-than-normal rainfall and elevated flood risk, URCS activates early warning systems[18], which can lead to unreliable flood predictions and weaken the triangulation process on which the EAP relies.

To address these gaps, this study proposes a flood risk classification using rainfall and discharge patterns with machine learning models to improve the accuracy and lead time of flood forecasts at the local catchment scale. The system helps to strengthen the EAP's triggering mechanism and support URCS in delivering timely early actions.

1.3 Research Objectives

The following are Specific, SMART (Specific, Measurable, Achievable, Relevant, Time-bound) goals the project aims to address.

1.3.1 Main Objective

To determine the flood risk classification and early warning in the River Manafwa catchment area using machine learning models.

1.3.2 Specific Objective 1

To examine and analyze the historical rainfall and river discharge patterns using satellite and gauging data, causing flooding around the Manafwa river catchment areas.

1.3.3 Specific Objective 2

To generate a hydrological flood risk classification percentile based on discharge for use in machine learning model training.

1.3.4 Specific Objective 3

To derive and identify hydrological variables from rainfall and river discharge data, which will be used as input features in flood risk classification models.

1.3.5 Specific Objective 4

To validate the selected model against historically documented flood events and assess model accuracy and reliability.

1.4 Research questions

In this research, the following questions are addressed:

- What are the historical rainfall and discharge patterns that are associated with flooding in the Manafwa catchment area? When does most rainfall and discharge occur in the catchment area? Which years experienced more rainfall, and how is this related to the discharge patterns during the same years? Is rainfall and discharge increasing, or decreasing over the study period?
- How do seasonal rainfall patterns in Uganda's two rainy seasons influence discharge patterns along the Manafwa river?
- Which engineered hydrological features mostly influence flooding along the River Manafwa catchment area: rainfall intensity, discharge anomalies, seasonal indicators, or lag time?
- Which machine learning algorithm performs best in flood risk classification under the data constraints of the Manafwa catchment?
- How flood risk classification align with documented historical flood events in the Manafwa catchment?

1.5 Significance

Improved flood prediction protects the lives of the communities and minimizes losses of properties. Given variability in rainfall patterns and extreme weather events, there is an urgent need to strengthen early warning systems, particularly in catchments where traditional hydrological modelling approaches are constrained by limited data availability. While global flood forecasting systems such as GloFAS provide discharge percentile thresholds for predicting flood events in Uganda, the forecasts made are at a global scale with a low resolution for small catchment areas like the River Manafwa. This study will contribute to a flood risk classification system for the Manafwa River. In addition, this research will add to the already existing body of knowledge around flood monitoring and early warning systems by demonstrating the impact of machine learning models on flood risk classification using rainfall and discharge data. Through hydrological features derived from rainfall and discharge data, which include antecedent rainfall accumulations, discharge anomalies, seasonal indicators, and rainfall-discharge lag time, from commonly available datasets, this study will offer a replicable and low-cost methodological framework applicable to other flood-prone rivers across Uganda.

The findings of this study will be particularly valuable to the Uganda National Meteorological Authority (UNMA), which provides real-time weather information and rainfall data. By generating cumulative rainfall (3, 5, and 7 days) and rainfall lag for the last three days, this research will enable UNMA to monitor evolving weather conditions more effectively and issue

timely warnings for different parts of the country. Furthermore, the discharge percentile-based flood risk classification system developed in this study provides a practical, locally calibrated tool that can be integrated into Uganda’s national early warning systems.

The study will provide information on the most vulnerable seasons, which is important information for the Department of Relief and Disaster Preparedness (DRDP) within the Office of the Prime Minister (OPM), as it supports improved planning, preparedness, and response. The DRDP can then guide land-use planning, community preparedness, and the strategic placement of critical infrastructure to prevent flood-related damages by discouraging settlement or development in high-risk zones and guiding the relocation of communities when necessary.

The study’s outputs are also valuable for infrastructure planning. Agencies such as the Uganda National Roads Authority (UNRA) can apply the findings to design and construct resilient roads, bridges, and drainage systems. Understanding flood magnitudes and rainfall–discharge relationships help engineers determine appropriate building materials and structural standards, reducing long-term maintenance costs and preventing severe infrastructure failures during heavy rainfall events.

The Department of Lands and Physical Planning will benefit from the study in making informed decisions on land zoning and the identification of suitable sites for relocating flood-affected communities. The insights may guide recommendations on flood-proofing existing buildings and improving the design standards for new developments in risk-prone areas. Because the methodology developed in this study relies only on rainfall and discharge data, the most commonly available hydrological measurements in Uganda, the approach can be readily scaled and replicated for other flood-prone rivers in the country.

The study will further support government institutions, non-governmental organisations, development agencies, and local communities by providing a scientific basis for informed decision-making, climate adaptation, and disaster preparedness. By improving flood prediction accuracy, the study contributes to safeguarding lives, reducing economic losses, enhancing community resilience, and promoting sustainable development within Uganda.

1.6 Justification

The Manafwa catchment has experienced repeated catastrophic flooding, with events recorded in 2007, 2010, 2011, 2018, and subsequent years, causing significant loss of life and displacement of thousands of households. The frequency and severity of flooding in this region is expected to increase with climate change, making the development of reliable flood prediction tools an urgent need to improve early warning and disaster preparedness.

Traditional flood forecasting approaches in Uganda, including physically based hydrological models such as HEC-HMS and HEC-RAS[45], require dense spatial datasets detailed digital elevation models, soil characteristics, and land-cover classifications at high resolution, that are rarely available for small, ungauged or sparsely gauged catchments such as the Manafwa[58]. Simpler statistical approaches, including linear regression and fixed discharge-threshold rules, assume that flood-generating processes are stationary and linearly related to rainfall; however, the analysis in this study (Section 4.1.3) shows that the rainfall–discharge relationship in the Manafwa catchment is neither immediate nor linear: some periods of heavy rainfall produce comparatively low discharge, while moderate rainfall following a saturated antecedent period produces sharp discharge increases. This behaviour reflects nonlinear interactions between antecedent soil moisture, cumulative rainfall, and lagged discharge response, which conventional threshold-based or linear methods cannot adequately represent.

Machine learning models are well suited to this context because they can learn nonlinear, interacting relationships directly from historical rainfall–discharge observations without requiring an explicit physical representation of the catchment. This makes ML particularly appropriate for data-scarce, small-catchment settings like the Manafwa, where the two most consistently available hydrological records of the daily rainfall and discharge are exploited as fully as possible. The use of ML in this study is therefore not simply a matter of predictive convenience, but a direct response to the physical evidence of nonlinearity and lagged response uncovered in the exploratory analysis, combined with the practical constraint of limited spatial data availability.

This study demonstrates that these commonly available datasets, when combined with appropriate feature engineering advances in machine learning models, are sufficient to build a meaningful flood risk classification framework.

Chapter 2

Literature Review

2.1 Introduction

Floods are among the disasters that cause widespread destruction to human lives, properties, and the environment every year and occur at different places with varied scales across the globe[19]. In Uganda, floods have become one of the most persistent hazardous events affecting lives, property, infrastructure, and other forms of livelihoods, particularly in low-lying, flat, wetland areas. This chapter reviews existing literature on flood types in Uganda, the causes of flooding, the role of rainfall and discharge patterns in the cause of flooding, hydrological modelling approaches, and the application of machine learning to flood prediction. The review identifies gaps in existing research and how to address them.

A flood is rapidly flowing water which have a significant concern to agriculture, engineering, public health, and economic patterns of life. Different words like inundation, swamping, deluge, torrent, overflow, freshet, downpour, cloudburst, spate, outpouring, torrent, rush, stream, gush, surge, cascade, flow etc. are all used to refer to floods[19]. There are different types of floods, each driven by different hydrological and meteorological processes and carrying different impacts on the livelihoods and their surroundings.

2.2 Flood types in Uganda

2.2.1 Flash floods

Flash floods are among the most destructive flood types and are usually difficult to predict. They are characterized by a rapid onset, which occurs within hours of intense rainfall events. The Mt. Elgon region was susceptible for flash flooding. According to[20]. After a dry spell in the Eastern region for almost half of the year in 2019, from June to December 2019, flash floods occurred regularly around Mount Elgon, including at least in Bulambuli district (one of the catchment areas of River Manafwa). This impacted people's livelihoods due to the loss of seeds, crops, or food stored, increasing their vulnerabilities.

2.2.2 Surface water floods

Areal floods can happen on flat or low-lying areas when water is supplied by rainfall or snowmelt more rapidly than it can either infiltrate or run off. The excess accumulates in place, sometimes to hazardous depths. Surface soil can become saturated, which effectively stops infiltration,

where the water table is shallow, such as a floodplain, or from intense rain from one or a series of storms.

2.2.3 River floods

River floods occur when river discharge exceeds the bankfull capacity of a channel, causing water to spill onto adjacent floodplains or the collapse of large water retention structures[21],[22]. Rivers in Uganda are prone to river flooding during and immediately following periods of sustained or intense rainfall. In April 2024, heavy rainfall caused rivers, including the Manafwa, Lwakhakha, Sironko, Mpologoma, Awoja, Nabuyonga, and Namatala, to overflow, displacing thousands of families and destroying houses[23].

2.2.4 Urban floods

Flood risk analysis in urban areas is caused by rapid urbanisation and poor drainage systems in a city that fail to absorb the water from heavy rain[24],[25], and [26]. Hence, water flowing into the street makes driving very dangerous. Studies noted that given Uganda's current population growth, an overload of sewer and stormwater drainage systems is inevitable, with floods projected to increase in some parts of the country at significant economic cost[9]. For instance, rivers like Manafwa and Nabuyonga that lie at the edge of Mbale City introduce urban flood dynamics that interact with the broader hydrological system of the catchment areas.

2.2.5 Landslide-induced floods

In the Mt. Elgon region, flooding is frequently accompanied by or triggered by landslides, creating a compound hazard[27]. In the Rwenzori Mountains, Uganda, demonstrated how the combined occurrence of intense rainfall and the occurrence of landslides providing debris to the river system induced a debris-rich and highly destructive flash flood, causing several fatalities and destruction of infrastructure and farms, which also makes these floods challenging to predict[28].

2.3 Causes of flooding

2.3.1 Rainfall characteristics

Rainfall is important in the hydrological cycle, providing water for agriculture, and is used for most of the human activities. However, heavy, intense rainfall for a prolonged period of time, becomes responsible for the deadly and destructive flooding[29].

In recent years, climate change has significantly led to the increasing precipitation, its frequency, and severity globally[30]. Rainfall impacts, for instance, are particularly noticeable in Sub-Saharan Africa, where rainfall variability contributes to heightened vulnerability. The East Africa zone experienced severe flood disasters in 2019 and 2020 that affected 4 to 6 million people[31]. Similarly, Uganda, has witnessed an increase in extreme rainfall events, with increasing flood events in many parts of the country[32]. Between September and December 2019, extreme rainfall caused devastating floods and landslides that affected most districts in the Eastern, Western, and Northern regions, resulting in widespread damage and displacement of communities.[33].

According to the Uganda Department of Meteorology, Uganda's rainfall patterns have become more variable compared to historical norms. Traditionally, the country experienced two major

rainfall seasons: March to June, followed by a short dry spell in July; and August to November, followed by a longer dry period from December to February. These seasons are influenced by the Intertropical Convergence Zone (ITCZ), monsoon systems, and moist westerly winds from the Congo Basin. However, recent observations by the Uganda Department of Meteorology indicate increasing variability in the onset, cessation, and distribution of rainfall, making prediction and planning more challenging. These variabilities depend on the nature of the rainfall and the catchment areas[34]. Studies by [35], [36] Investigating rainfall patterns in Uganda indicate that September, October, and November consistently record the highest count of extreme rainfall days, with this understanding of these extreme rainfall characteristics identified as crucial for effective flood management planning.

Rainfall characteristics are key determinants of the flood inundation risk. These include: rainfall amount, duration, Intensity, extreme rainfall, and rainfall frequency. A spatial uniform rainfall of higher intensities on shorter duration leads to worse floods compared to the rainfall of long duration but with low intensities. Understanding the rainfall patterns and their characteristic can help in assessing flood risk and designing improved early warning systems.

2.3.2 Climate change

Several studies [37], [38], [39] indicate that climate change has increased both the frequency and intensity of precipitation events, contributing to more frequent hydrometeorological extremes worldwide, including flooding. In Uganda, the most significant climate-related impacts have been linked to increased rainfall intensity. Reports from the Intergovernmental Panel on Climate Change (IPCC) project that extreme rainfall events are likely to intensify across many regions of East Africa, including Uganda. More specifically, rainfall is expected to increase significantly in areas such as the western shores of Lake Victoria, the Mount Elgon region, the central western belt, and the Rwenzori–Kyoga corridor[40]. These changes imply that climate-driven flood risk will continue to rise, making flooding one of the most pressing sectoral threats facing the country.

Research by [41], [42], [43], [44] on hydrological extremes in East Africa highlights the heterogeneous distribution of extremes in space and time, with El Niño capable of causing droughts in one part of the region and floods in another, and notes that concurrent extremes will become the norm rather than the exception, emphasising the importance of antecedent conditions in understanding flood generation.

Beyond climatic factors, human activities also play a major role in amplifying flood severity. Land-use changes such as deforestation, agricultural encroachment on steep slopes, degradation of wetlands, and unregulated settlement in floodplains reduce natural water retention capacity and accelerate surface runoff. Modifications to river channels, poor drainage planning in urban areas, and inadequate flood control infrastructure further compound the problem[19].

2.4 Role of River Discharge Patterns in Flooding

River discharge is the most direct measurable indicator of flood conditions in a river system. When the drainage system capacity is exceeded by surface runoff discharge, flooding is inevitable during periods of intense rainfall downpour[21]. Accurate prediction of rainfall and river discharge predictions at different temporal and spatial scales remains a major concern to hydrologists, particularly in data-scarce tropical catchments [29]. According to [10] an upward trend in discharge across all probability distributions along the Manafwa River is attributable to climate change and rapid land-use change within the catchment. These changes are pro-

jected to worsen, with a considerable increase in peak discharge, inundation areas, and water elevation levels under future scenarios[45] , making reliable flood prediction increasingly critical for the protection of livelihoods and infrastructure in the Manafwa catchment area.

The Global Flood Awareness System (GloFAS) represents one of the most widely used global flood forecasting platforms, designed to provide flood warnings for large river basins worldwide, including in data-scarce regions of Sub-Saharan Africa, such as Uganda[46]. GloFAS forecasts are globally generalised models that offer complementary, probabilistic early warning information about upcoming and ongoing flood events[47]. While global flood forecasting systems provide a valuable baseline capability, they are insufficient as standalone tools for catchment-specific flood risk prediction in small-scale and data-scarce areas.

According to [48]report, When the GloFAS performance is compared to the climatology, the results are less encouraging, with the climatology performing very similarly to the forecast and occasionally outperforming the forecast. This indicates that the model peak discharge predicted tends to come earlier than observed peak discharge, therefore misrepresenting flood risk at the catchment scale. Accurately characterising the rainfall-discharge lag time for the Manafwa catchment is therefore an important step in developing a reliable flood classification model.

2.5 Machine learning models

Machine learning (ML), deep learning (DL), and artificial intelligence (AI) are some of the most popular information technology (IT) fields that are increasingly receiving attention in academia[49]. Machine learning models have recently received much attention in flood risk assessment due to their ability to capture relationships efficiently[45] and their self-learning capabilities from data without incorporating any complex physical processes, with a comprehensive review of approaches that can automatically analyze and build appropriate models, which improve the effectiveness of mitigation strategies.

Over the years, the mode of flood prediction has shifted from traditional hydrological methods to Artificial Intelligence and Machine learning predictive models. According to [45], traditional models often fall short of capturing the complex interplay of diverse variables contributing to flood susceptibility in changing environments. On the other hand, machine learning models have the ability to manage large volumes of data, learn from historical data, and forecast future floods which aids in developing safety measures[50]. Machine learning uses a series of scientific methods and techniques, including Natural Language Processing, artificial neural network analysis, algorithms, and other mathematical tools, to receive training based on big data[51] providing valuable insights for flood mitigation strategies.

In the context of flood prediction, several ML algorithms have been successfully applied worldwide. For instance, the FNN and Long Short-Term Memory (LSTM) models exhibited high accuracy and stable loss, indicating minimal overfitting[52]. Additionally, [53]used the Long Short-Term Memory (LSTM) model to predict flash floods, demonstrating stability and effectiveness in simulating large floods. Similarly, [54] found Long Short-Term Memory (LSTM) more stable than traditional Artificial Neural Network (ANN) and both superior to physical models, but did not consider extended rainfall accumulation and relied heavily on gauging stations, issues addressed in this research.

A number of Machine learning (ML) algorithms such as Random Forest (RF), Support Vector Machines (SVMs), and deep neural networks have demonstrated strong capabilities in processing large-scale, meteorological time series and topographic features. For instance, [55] employed

four supervised models based on ML algorithms: Random Forest (RF), KNN, Artificial Neural Networks (ANN), and XGBoost for flood susceptibility in the watershed of Morocco. According to the dynamics[7] RF is widely adopted for its robustness, interpretability, and suitability for spatial risk mapping, while deep learning architectures such as Long Short-Term Memory (LSTM) networks and Convolutional Neural Networks (CNNs) are increasingly employed to model temporal dependencies and spatial patterns in flood dynamics[7]. In another study of the state of Kansas, [45] employed classification algorithms, including Logistic Regression (LR), Random Forest (RF), Support Vector Machine (SVM), K-nearest neighbor (KNN), Adaptive Boosting (Ada Boost), and extreme Gradient Boosting (XGB) to model the study area as flood or non-flooded cells using the historical flood inventory.

According to, [52] the relationship between discharge, return period, and year is examined using the Gamma and log-normal methods, with Annual Exceedance Probabilities (AEP) considered at 5%, 1%, 0.1% and 0.01%. These AEP thresholds are crucial for identifying significant flood events with high return periods, which aligns with common practices in flood risk management, providing valuable insights for water resource planning and flood mitigation strategies

2.5.1 Flood forecasting with machine learning in Uganda

Uganda is primarily affected by data limitations, insufficient hydrological monitoring networks, and significant cost constraints, which limits the establishment and maintenance of flood risk early warning systems. For instance, according to the report issued by the Prime Minister’s office, there existed a solar-powered flood early warning system in Butaleja district consisting of a water sensor, a siren, and back-up computers, which was commissioned in 2014 to monitor flood[17]. The system, however, broke down in 2016. The lack of gauged stations affects prediction and forecasting systems. According to Mitheu, Uganda has no localized forecasting systems as it relies on the forecasts issued by the Uganda National Meteorological Authority, and global forecasts developed by GloFAS, ECMWF, used by the Red Cross to guide timely preparedness for disaster management[56].

However, there have been some studies by [10],[57],[5], and [58] that address flood forecasting using hydrological and GIS to address flooding problems around the River Manafwa. Ceci-nati and Okoth provide a statistical flood frequency analysis using historical annual maximum discharge data, evaluating four probability distribution models and identifying the best-fit distribution for characterising extreme flow events[10], [57]. On the other hand, Nabusayi takes an applied engineering approach, integrating satellite-based weather forecasting, GIS-based watershed analysis, hydrological modelling (HEC-HMS), and hydraulic modelling (HEC-RAS) to develop an operational flood forecasting and inundation mapping system for the basin. Both Okoth and Nabirye observe an upward trend in extreme Manafwa discharge magnitudes, attributing this to climate change and land use transformation. Yet both studies use stationary frequency analysis methods that assume annual maximum flows are independently and identically distributed over time.

A study by Miiro, which developed and implemented a machine learning-based flood forecasting prototype in Kasese District, Uganda. The linear regression model was fitted on five days of collected data and produced the following equation: Flood level = $0.25 \times \text{Rainfall} - 0.4 \times \text{Temperature} + 0.1 \times \text{Humidity} + 2$. The system was programmed to trigger a flood alert when the predicted flood level exceeded 5 cm. This threshold was determined by the researchers rather than derived from hydrological analysis of the Kasese basin. The alert mechanism used the Arduino GSM SIM900 module to send SMS notifications and was also designed to post alerts on Twitter/social media[47]. However, the model is limited by the linear regression model is less advanced compared to more complex machine learning models like Random Forest and

Neural Networks that can capture nonlinear relationships. These limitations may have caused deficiencies in the predictive accuracy of the prototype.

2.6 Research Gaps

A significant gap exists in Ugandan flood management, as no machine learning (ML) framework currently learns flood risk directly from observed rainfall–discharge patterns within the Manafwa River Basin or any other Ugandan catchment. While advanced ML approaches have demonstrated strong predictive performance in other African regions, such as the Perkerra River in Kenya[2] and the Imo River in Nigeria[29], such frameworks have not yet been applied to Ugandan river basins using historical hydrological data.

Furthermore, the region suffers from sparse gauge networks and short data records, leaving many flood-prone rivers ungauged and limiting the accuracy of conventional modelling[47]. Current initiatives are often limited in spatial and temporal coverage, lack integration with community-based monitoring, and struggle to accurately predict extreme flood peaks. Additionally, there is a distinct lack of locally calibrated discharge percentile classifications and replicable ML methodologies specifically designed for these data-scarce environments.

This research addresses these gaps by developing a data-driven, ML-based flood risk classification framework for rivers based on the Manafwa River Basin using long-term rainfall–river discharge records. The proposed methodology provides a statistically validated and computationally efficient approach that is uniquely suited to the data-limited conditions of Ugandan catchments. By utilizing ML models that inherently capture shifts in rainfall–discharge relationships over time, the research eliminates the need for explicit non-stationary statistical modelling.

To ensure the results are practical for disaster response, the framework is designed to output structured, interpretable flood risk levels (e.g., Normal, Mild, Advanced, and Extreme) rather than raw discharge values, making the data useful for local authorities and communities. Finally, the research will strengthen model confidence by validating performance across multiple historical flood events of varying magnitudes, such as the major floods of 2010 and 2019.

2.7 Conceptual framework

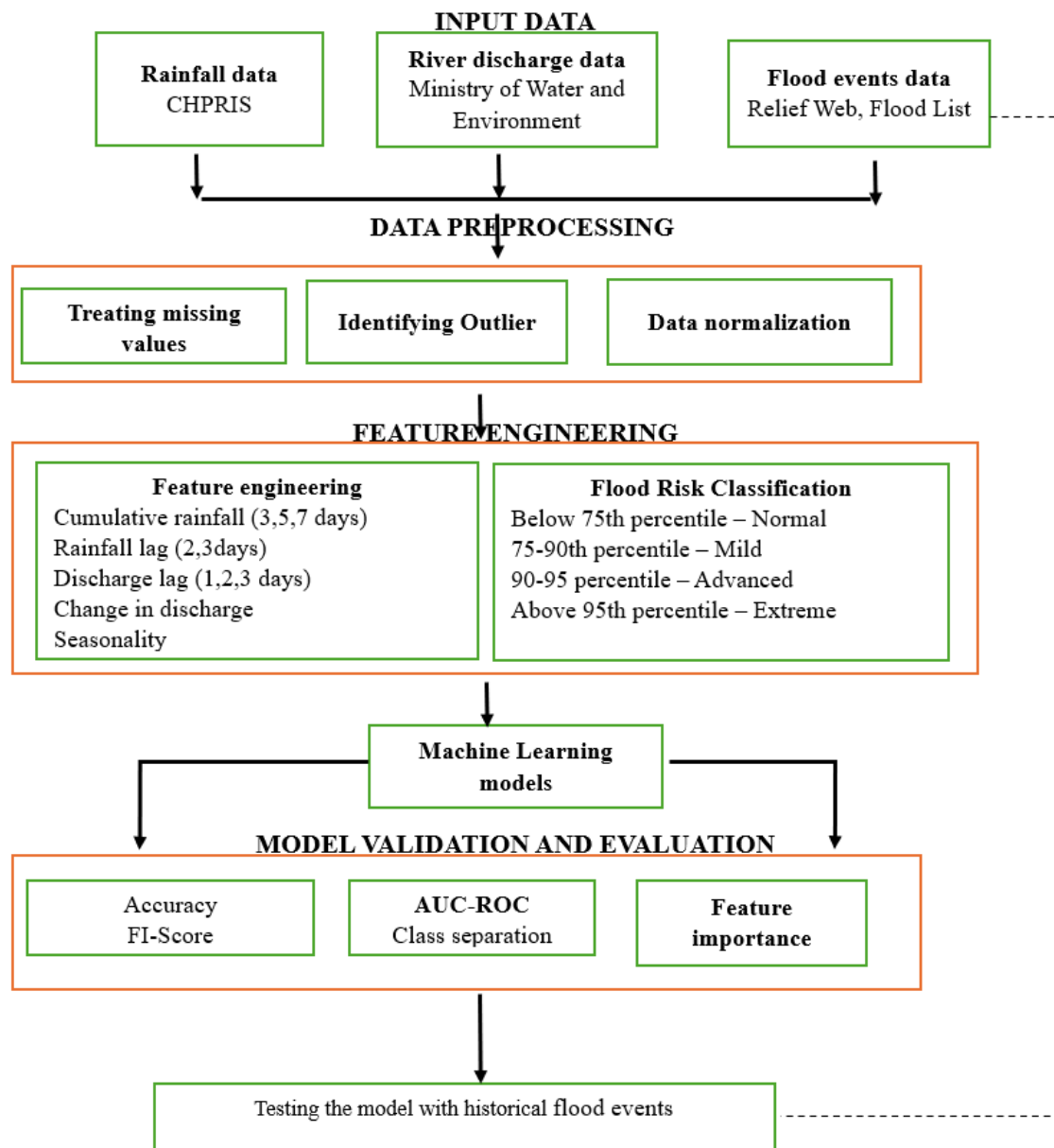


Figure 2.1: Flow of the Conceptual Framework

Chapter 3

Methodology

3.1 Introduction

The chapter shows the systematic approach of the study, which include: the research design, area of study, data sources, data preparation, data analysis, classification, and presentation

3.2 Research design

The research takes a data-driven approach with the aid of machine learning frameworks to classify flood risk in the Manafwa River. Attention was focused on the rainfall and discharge patterns. The methodology combines feature-engineered variables from rainfall and discharge patterns with machine learning to analyze rainfall-discharge patterns and classify flood risks along the Manafwa River.

3.3 Study Area

River Manafwa catchment area is located along the slopes of Mountain Elgon, in Eastern Uganda. The river primarily originates from Mountain Elgon and flows into River Kyoga. It crosses through the districts of Mbale, Butaleja, and Manafwa, which have been prone areas of floods for the past several years. The catchment area is about 2,280 square kilometers and densely populated, with most of its inhabitants engaging in agricultural practices.

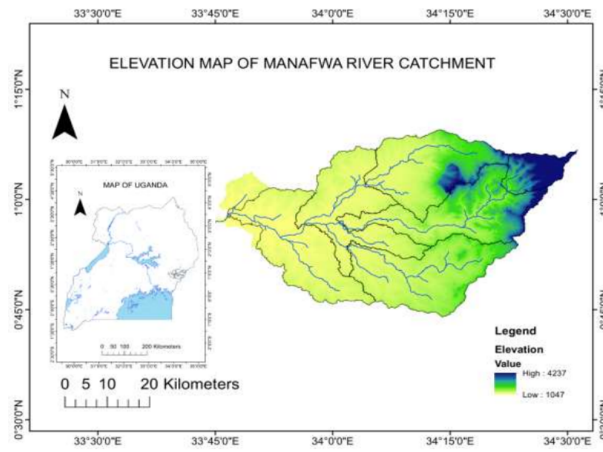


Figure 3.1: River Manafwa catchment area

3.4 Data sources

The model input parameters include daily rainfall data from 1989 to 2024 from the CHIRPS satellite. The observed river discharge data were obtained from the Ministry of Water and Environment for the period of 1989 to 2024. While the Historical flood event records were collected from the Uganda Red Cross Society, the Flood List, and UNDRR.

3.5 Data preparation

3.5.1 Handling missing data and outliers

There were over 2300 missing data points, which were handled by applying a tiered machine learning imputation strategy. Short gaps of up to five consecutive days were addressed using KNN imputation, which estimates missing values from the K most similar observations. For gaps between six and thirty days, the MICE (Multiple Imputation by Chained Equations) algorithm was applied, iteratively modelling each variable with missing values as a function of all remaining features. This helped to handle different missing data patterns.

3.5.2 Data analysis

To analyze the patterns in the rainfall and discharge data. Quantitative methods was used to analyze the collected data. Some of the analyses that was conducted include;

- Annual average Rainfall analysis
- Annual Rainfall intensity
- Analysis of the precipitation patterns separated by the different seasons.
- River discharge patterns in relation to flood frequency
- Analyzing the relationship between the rainfall peaks with the discharge peaks

3.5.3 Computation of the Flood Risk Classification threshold

Four-level risk classification criteria will be developed in terms of percentiles to make the model's output more action oriented as follows;

- Normal: Below the 65th percentile.
- Mild: 75th to 90th percentile.
- Advanced: 90th to 95th percentile.
- Extreme: Above the 95th percentile.

3.5.4 Feature Engineering

To capture the complex hydrological relationships within the basin, five categories of derived variables are computed. This specific use of feature engineering from rainfall and discharge data alone represents a novel application for flood modeling in Uganda;

- Antecedent Rainfall: Calculated over 3, 5 and 7-day windows to account for soil saturation.
- Discharge Anomalies: Identifies deviations from standard flow patterns.
- Lag Time: Incorporates rainfall-discharge intervals of 1 to 7 days to account for the response time.

3.6 Machine Learning

The application of machine learning (ML) algorithms has significantly improved the precision and efficiency of flood prediction by capturing complex relationships among environmental and hydrological factors.

The following algorithms have been selected because of their ability to work with non-linear hydrological variables over time. In this case, each offers a range of techniques to address classification modeling challenges. These include: Logistic regression, Random Forest, Gradient Boosting, Decision Tree, MLP Neural and Networks.

3.6.1 Logistic Regression (LR)

Logistic Regression is a linear baseline model which computes the probability of the class variable helping to reveal the extent to which flood risk in the Manafwa catchment is linearly separable from engineered hydrological features. The maximum number of iterations was set to 2,000 to allow sufficient convergence, while the regularization parameter was set to ($C=0.5$). The class-balanced weighting was applied to account for differences in the frequency of the flood-risk classes.

3.6.2 Decision Tree (DT)

A decision tree is a hierarchy-based model that uses a set of rules to generate predictions from training data. Due to its rule-based architecture, the Decision Tree provides thresholds and variable importance rankings, allowing for clear interpretation of what triggers flood events. The Decision Tree was restricted to a maximum depth of eight levels, with a minimum of 20 observations required at each terminal leaf. Class-balanced weighting was applied to reduce the influence of class imbalance.

3.6.3 Random Forest (RF)

Random Forest is an ensemble of decision trees that combines and averages across all trees to improve model prediction and reduce overfitting. RF is included because of its robustness to overfitting, its ability to handle nonlinear relationships and feature interactions inherent in rainfall-discharge patterns. The Random Forest consisted of 200 decision trees, with each tree restricted to a maximum depth of 12 and a minimum of 10 observations per leaf. Class-balanced weighting was applied to improve the representation of less frequent flood-risk classes. The ensemble approach was used to improve prediction stability and capture nonlinear relationships between the predictor variables and flood-risk classes.

3.6.4 Gradient Boosting (GB)

Gradient Boosting constructs an ensemble of decision trees sequentially, with each successive tree fitted to the residuals of the previous ensemble. GB is included because it is a powerful machine learning algorithm that is known for its speed, accuracy, and efficiency in handling rainfall-discharge relationships, and it has demonstrated strong performance in flood susceptibility studies globally. The Gradient Boosting classifier was configured with 200 boosting stages, a learning rate of 0.05, and a maximum tree depth of five. A subsampling fraction of 0.8 was used, meaning that 80% of the available training observations were used at each boosting stage. These settings provided a controlled balance between model complexity, learning rate, and generalization.

3.6.5 MLP Neural Network (MLP)

A Multi-Layer Perceptron is an artificial neural network with multiple hidden layers and activation functions. This helps it to model relationships between rainfall and discharge patterns. This is achieved through learning hierarchical features that can capture interactions among the antecedent rainfall, discharge anomalies, and seasonal patterns. The MLP Neural Network consisted of three hidden layers containing 128, 64, and 32 neurons, respectively, with the ReLU activation function. Training was allowed for a maximum of 500 iterations, with early stopping enabled to terminate training when performance on the validation subset ceased to improve. Ten percent of the training data was used as the validation fraction, while the initial learning rate was set to 0.001. This architecture was selected to allow the model to learn nonlinear interactions among the rainfall, discharge, and derived lagged and cumulative predictors.

3.7 Model Training, optimization and evaluation

All models were trained on a chronological 80/20 split rather than a random split: the first 80% (1989–2015) daily record was used for training, and the most recent 20% (2016–2024) was considered as the test set. This ordering ensures no future information leaks into the training process and that model evaluation reflects a realistic operational scenario in which the model is trained on historical data and evaluated on subsequently occurring, unseen periods.

To address class imbalance arising from extreme flood events in the historical record, SMOTE (Synthetic Minority Over-sampling Technique) was applied to the training dataset only, generating synthetic samples for underrepresented risk classes without contaminating the test set.

Model performance was assessed using Classification metrics. This will include Accuracy, Precision, Recall, F1-score, and AUC-ROC, evaluated across all four risk classes to ensure reliable

performance at each level of flood severity.

Given the imbalanced distribution of the flood-risk classes, greater emphasis was placed on macro-averaged F1-score, macro AUC-ROC, and the class-specific F1-score for the extreme flood-risk class to assess balanced performance across all four flood-risk categories. The best-performing model was subsequently interpreted using SHapley Additive explanations (SHAP) to identify the most influential variables contributing to flood-risk classification.

3.8 Model Validation Against Historical Flood Events

Model was validated against historically documented flood events in the Manafwa catchment, including the major floods of June 2019, October 2019, and September 2021, sourced from URCS records, Flood List, and Daily Monitor archives. Validation assessed whether predicted risk levels correctly identify documented flood periods.

Chapter 4

Results

This chapter outlines the expected outcomes of the proposed machine learning framework for flood risk classification in the River Manafwa catchment. The expected results are organized around the four specific objectives of the study and methodology for analysing the rainfall and discharge pattern analysis, outcomes and findings.

4.1 Objective 1: Historical Rainfall and Discharge Pattern Analysis

4.1.1 Rainfall analysis

Rainfall patterns surrounding the Manafwa catchment area, figure 4.1 indicates that the area experiences rainfall at least each year for the last 35 years. The total annual rainfall spans from 175 mm/yr to 367 mm/yr. (Please see the figure below);

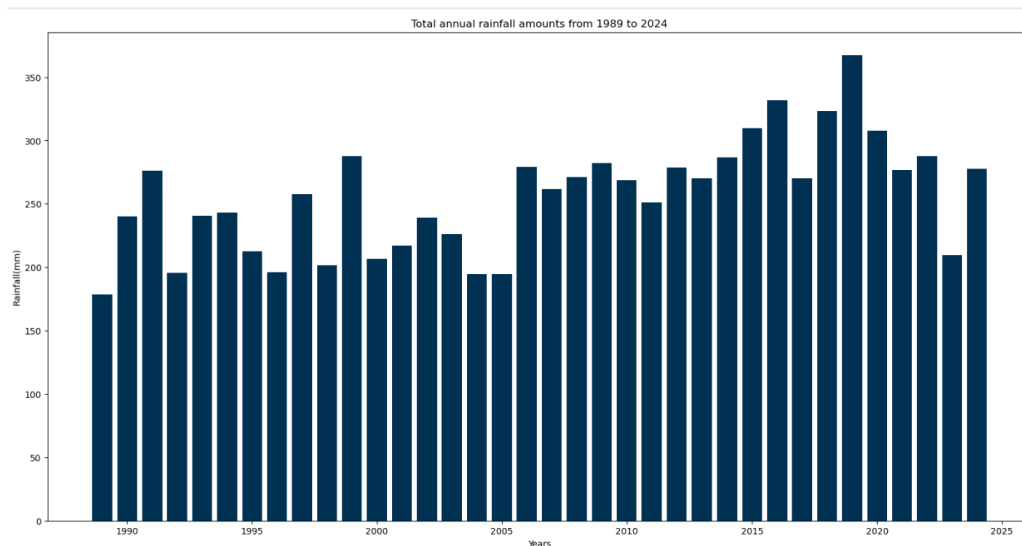


Figure 4.1: Total rainfall per year

The monthly average rainfall for the period 1989 to 2024 coincides with the seasonal patterns for the Eastern Africa region of March-April-May (MAM)—Wet season, June-July-August (JJA)—dry season, September-October-November (SON)—wet season, and December-January-February (DJF)—dry season. At the outset, the low average rainfall is observed in the DJF months,

which is attributed to the dry season. On the other hand, the high average rainfall amounts are more pronounced in MAM and SON, and the highest amounts were recorded in April of approximately 6.9 mm/day, followed by another average peak in May 6.7mm/day and October with 6.2 mm/day, please see the figure 4.2 below;

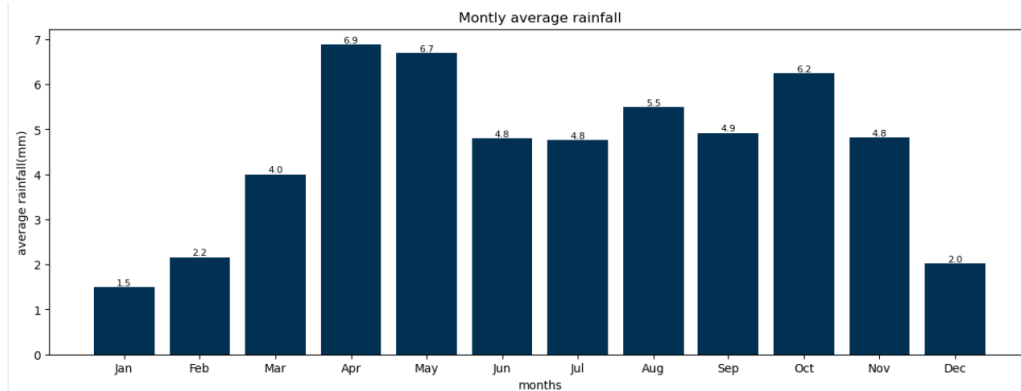


Figure 4.2: Daily average rainfall per month

Annual maximum daily rainfall

The monthly maximum daily rainfall, similar to the monthly average rainfall, the maximum daily rainfall patterns still align with the seasonality, whereby, the highest rainfall intensities occur during two distinct peak periods: March–June, with values rising from 46.9 mm/day in March to a peak of 48.3 mm/day in June, and September–November, followed by the year's highest average maximum of 49.9 mm/day in October. However, it is observed that the dry season, there were also peak rainfall amounts at least ranging from 27 to 35 mm, indicating a relatively short and mild dry interlude rather than a prolonged dry season. The lowest rainfall intensities occur from December through February, reaching a minimum of 27.0 mm/day in January, which aligns with the Eastern region primary dry season as indicated in figure 4.4. The rainfall seasonality also justifies the historical flood events that occurred in the window of September 2011 and October 2019.

From Figure 4.4, it is apparent that the maximum daily rainfall over the years (1989-2024) ranges from 27mm/day to 50mm/day. Please see the figure below;

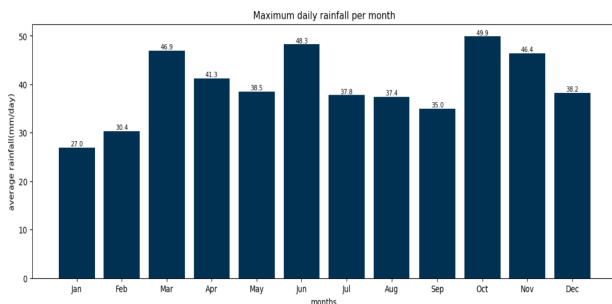


Figure 4.3: Daily Maximum rainfall per month

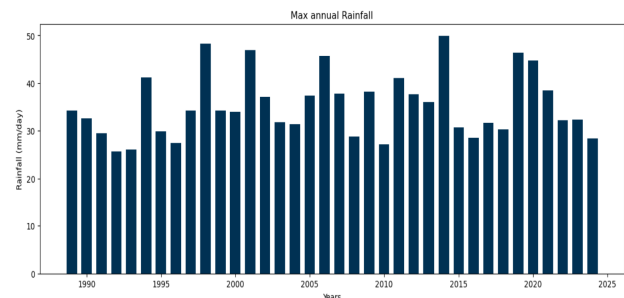


Figure 4.4: Maximum daily rainfall per year

4.1.2 Discharge analysis

Monthly distribution of daily peak discharge

The discharge pattern along the River Manafwa catchment as referred to in Figure 4.6 which indicates that the highest January at 103 m³/s, however, based on the rainfall analysis, this falls in the dry season, where low rainfall amounts are received. This was followed by discharge of 84 and 94 m³/s in April and May, respectively, which correspond to the MAM wet season. The lowest discharge peak was recorded in September at about 45 m³/s, with a later gradually rise in October to December. This indicates that there were anomalies in the discharge patterns in relation to the seasonality as compared to the rainfall patterns.

For the average discharge patterns Figure 4.6, it shows a range of 5.8 m³/s in February to 12.8 m³/s in May, which also aligns with the seasonal patterns of DJF and MAM, please see the figure below;

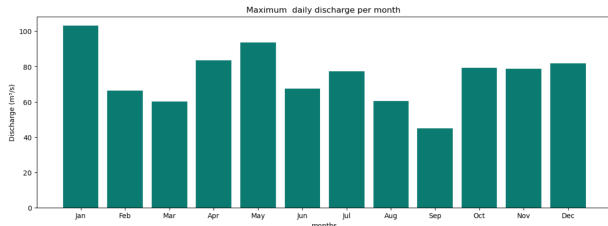


Figure 4.5: Maximum discharge per month

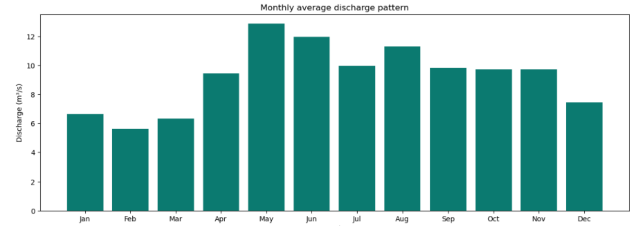


Figure 4.6: Average discharge per month

Relationship between the rainfall patterns and discharge patterns

The figures below show the relationship between daily rainfall and river discharge in the Manafwa catchment from 1989 to 2024. The discharge generally follows the rainfall pattern, but with a noticeable delay and lower intensity. This reflects the effects of soil infiltration, water storage, and the movement of water through the river network. The steep and degraded terrain in the catchment, together with reduced vegetation cover and siltation, may also affect how rainfall is converted into river discharge.

The relationship between rainfall and discharge is not always direct. Some periods of heavy rainfall do not result in very high discharge, while moderate rainfall sometimes produces sharp increases in discharge. This suggests that flood response depends not only on rainfall on a given day but also on conditions such as soil moisture, previous rainfall, and cumulative rainfall. These factors support the use of machine learning methods such as Gradient Boosting, which can capture complex and nonlinear relationships between rainfall, discharge, and flood risk.

The highest discharge peaks also occur around several known flood periods, including the early 1990s, mid-2000s, and 2014–2021. This supports the use of discharge as an important classification of flood risk, alongside rainfall.

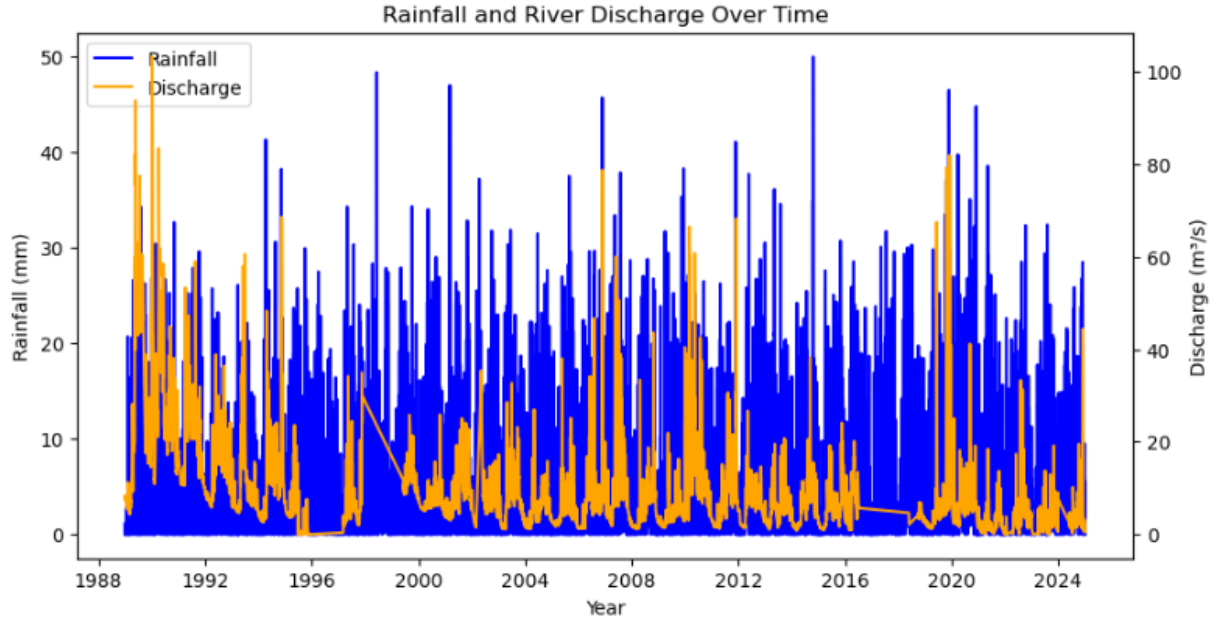


Figure 4.7: Daily rainfall and discharge

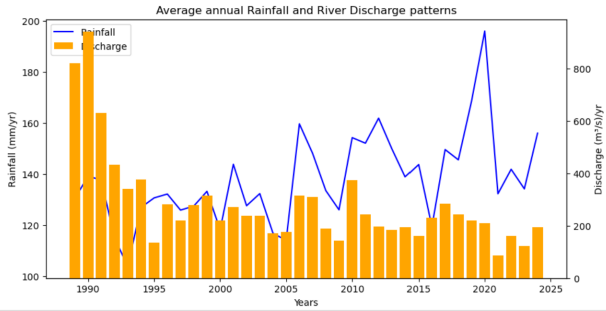


Figure 4.8: Average rainfall and discharge

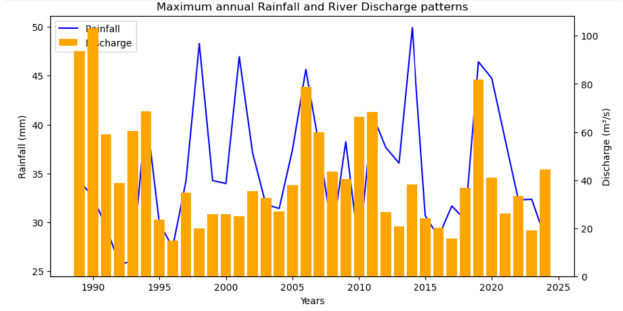


Figure 4.9: Maximum rainfall and discharge

Return periods and Gumbel analysis

Return period estimates for both discharge and rainfall extremes, derived from the ranked annual maxima, calculated with the Weibull formula and fitted to a Gumbel distribution, revealed a consistent increase in magnitude with increasing return period for both variables.

The return period, $T = \frac{N+1}{M}$, where N is the total number of years and M is the rank(1,2,... 100).

In relation to the discharge patterns, the frequency curve(Figure 4.12) indicates that the return period spans from approximately 37 m³/s for a 2-year return period, rising to 54 m³/s (5-year), 67 m³/s (10-year), 81 m³/s (25-year), 91 m³/s (50-year), and 101 m³/s (100-year), exhibiting the characteristic Gumbel shape of steep initial growth followed by a flattening tail at longer return periods.

Similarly, the resulting frequency curve (Figure 4.10) indicates that a rainfall maximum return period is approximately 34 mm is expected to be equaled or exceeded roughly once every 2 years, rising to approximately 40 mm for a 5-year return period, 45 mm for 10 years, 50 mm for 25 years, 54 mm for 50 years, and 58 mm for a 100-year return period. The curve shows a steep initial rise at shorter return periods that progressively flattens as return period

increases, reflecting the diminishing marginal increase in rainfall magnitude, please see the figures below;

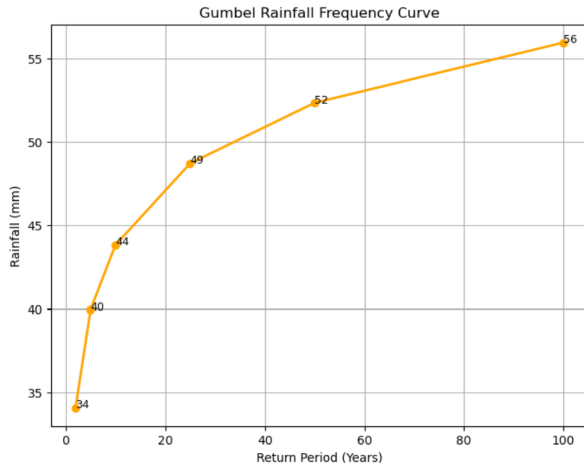


Figure 4.10: Gumbel rainfall

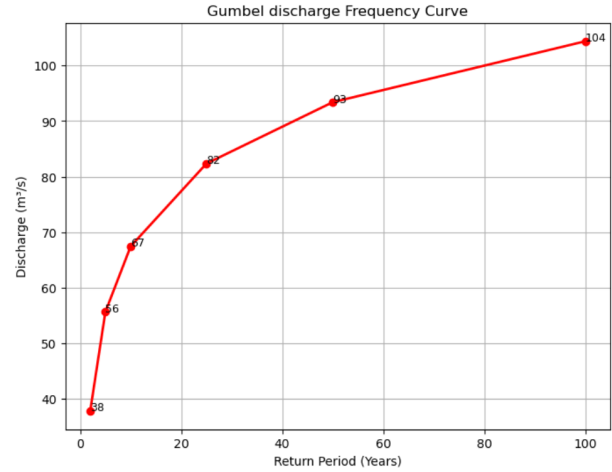


Figure 4.11: Gumbel discharge

4.2 Objective 2: Flood Risk Classification

In effort to determine the flood risk score, we used the daily discharge records (13,635) for the period of 1989 to 2024. This was based on quantile discharge thresholds. That is 75th percentile ($Q75 = 10.33 \text{ m}^3/\text{s}$), 90th percentile ($Q90 = 17.39 \text{ m}^3/\text{s}$), and 95th percentile ($Q95 = 25.31 \text{ m}^3/\text{s}$) of the discharge distribution, yielding four risk classes: Normal (below $Q75$), Mild ($Q75$ – $Q90$), Advanced ($Q90$ – $Q95$), and extreme (above $Q95$),

Flood class Number	Flood class	Number of events
0	Normal	7,741
1	Mild	1,582
2	Advanced	646
3	Extreme	654

Table 4.1: Flood risk classification

From these results, each day was encoded based on Normal—0 Mild—1, Advanced—2, and extreme—3. The normal days showed 72% of the data, while Mild 14% and advanced 6% & extreme with 6% . This indicates that majority of the days along the catchment area are normal days, and occasionally Mild flood events occur.

Figure 4.13 illustrates the relationship between daily precipitation, discharge, and assigned flood risk class. A number of extreme flood events occur at low or moderate rainfall, while some normal events are classified with extreme rainfall. This indicates that instantaneous rainfall alone cannot entirely lead to flooding. It also calls for feature engineering to derive additional variables, such as discharge lags and cumulative rainfall, which can provide a more comprehensive understanding of the factors influencing flooding; please refer to the figures below;

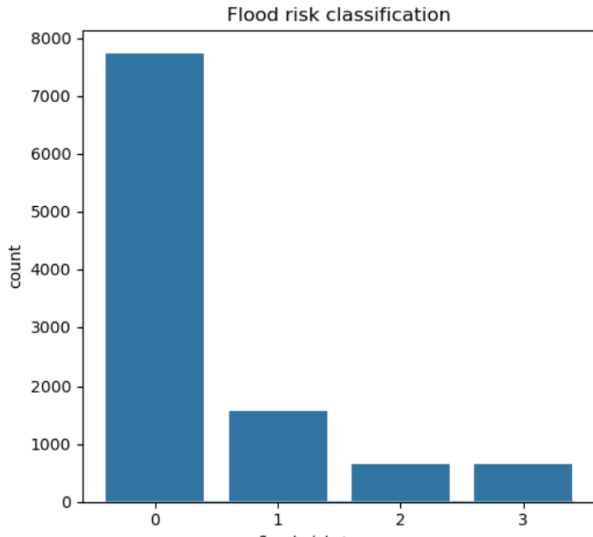


Figure 4.12: Flood risk classification

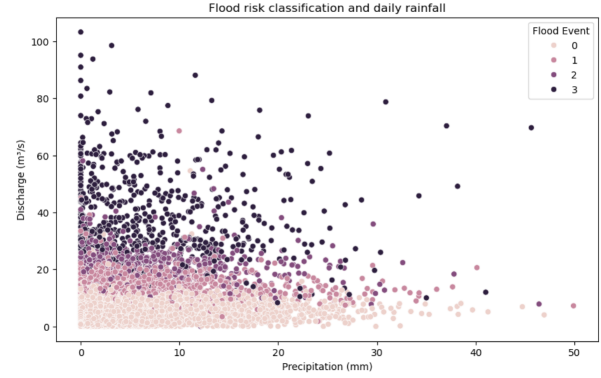


Figure 4.13: Flood class and rainfall and discharge

4.3 Objective 3: Hydrological feature engineering and importance

Feature engineering was applied to derive additional hydrological variables from the rainfall and discharge data, capturing lags and cumulative relationships. These included lagged discharge variables (`discharge_lag1`, `discharge_lag2`, `discharge_lag3`, `discharge_lag7`), a 7-day rolling mean discharge, discharge differencing and acceleration terms, cumulative rainfall accumulations over 1, 3, 5, and 7-day windows, and seasonal cyclical indicators (`season_sin`, `season_cos`).

Discharge lag: Lagged discharge variables were derived to capture the watershed memory effect, whereby current-day discharge reflects the cumulative influence of antecedent rainfall, soil moisture, and groundwater conditions rather than instantaneous inputs alone. This was motivated by the observation that reported flood dates do not always coincide with the actual onset of elevated discharge, with some events showing a lag of two to three days between the true hydrological peak and the officially recorded flood date.

Cumulative rainfall: Cumulative rainfall accumulations were derived on the basis that a single day's rainfall is insufficient to explain flood occurrence, since progressive rainfall over several consecutive days contributes to soil saturation, which in turn drives increases in discharge. Four accumulation windows (1, 3, 5, and 7 days) were computed to capture this progressive saturation effect at different timescales.

Figure 4.14 illustrates the June 2019 flood event in relation to antecedent catchment conditions. Discharge reached its peak (approximately $68 \text{ m}^3/\text{s}$) around 7 June, five to seven days ahead of the officially reported flood date of 12 June. Although there was a record of high rainfall amounts in May and July, no flood events were reported during those periods. This provides direct empirical support for the antecedent saturation whereby flood generating discharge is governed less by the intensity of a single rainfall event than by the cumulative rainfall based on the state of the catchment area.

Following the flood event, discharge gradually decreased despite several rainfall events in the subsequent month July, which indicated a reduced runoff and recovery storage conditions along the catchment area.

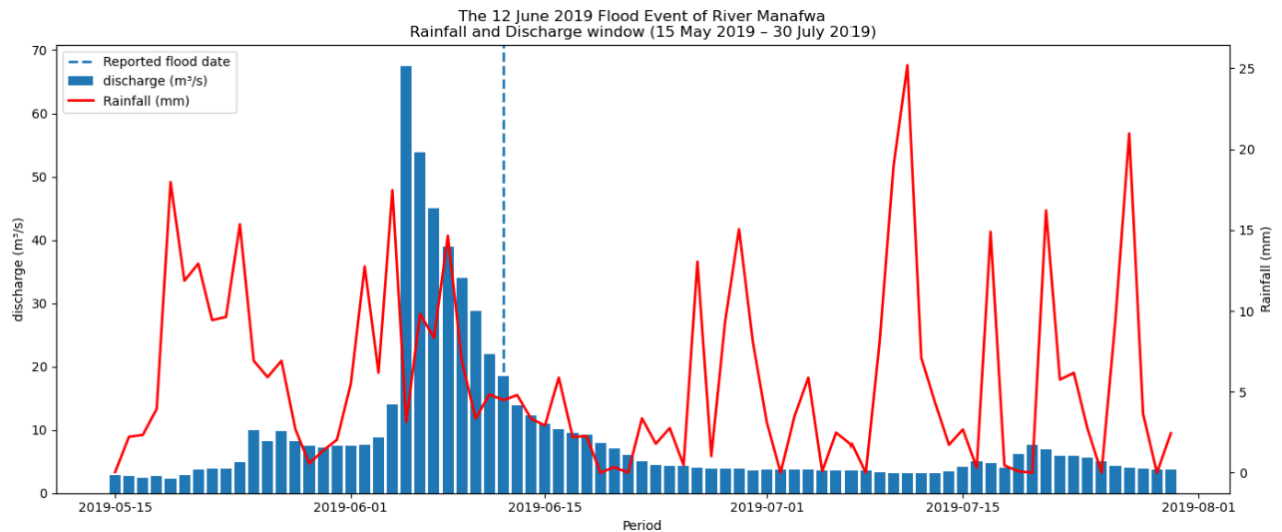


Figure 4.14: June flood event

Machine learning model training and validation In this research five machine learning models were used included MLP, gradient boost, logistic regression, random forest and decision tree, these were selected because of their ability to predict non linear data.

The data was split into training 80% and test 20%. It was thereafter standardized, and each taken through the model. Initial model evaluation using the original imbalanced dataset showed that gradient Boost and MLP were the best performing models, please see the figure below

	Accuracy	Macro F1	Flood F1 (Extreme)	Flood Precision	Flood Recall
Model					
Logistic Regression	0.875000	0.486000	0.429000	0.450000	0.409000
Decision Tree	0.848000	0.471000	0.449000	0.407000	0.500000
Random Forest	0.903000	0.504000	0.439000	0.474000	0.409000
Gradient Boosting	0.927000	0.511000	0.389000	0.500000	0.318000
MLP Neural Network	0.920000	0.473000	0.250000	0.400000	0.182000

Figure 4.15: Model accuracy

Area Under Curve

In terms of macro-averaged Area Under the Curve (AUC), gradient boost scored the highest AUC accuracy of 0.918% followed by MLP with 0.909% as shown in Figure 4.17. The gradient Boost also improved on extreme events specifically with 0.97% relative to that of Logistic regression. In conclusion, the results indicate that advanced ensemble methods, and particularly gradient boosting are quite effective in rainfall-driven flood classification and early warning, as shown in the figures below;

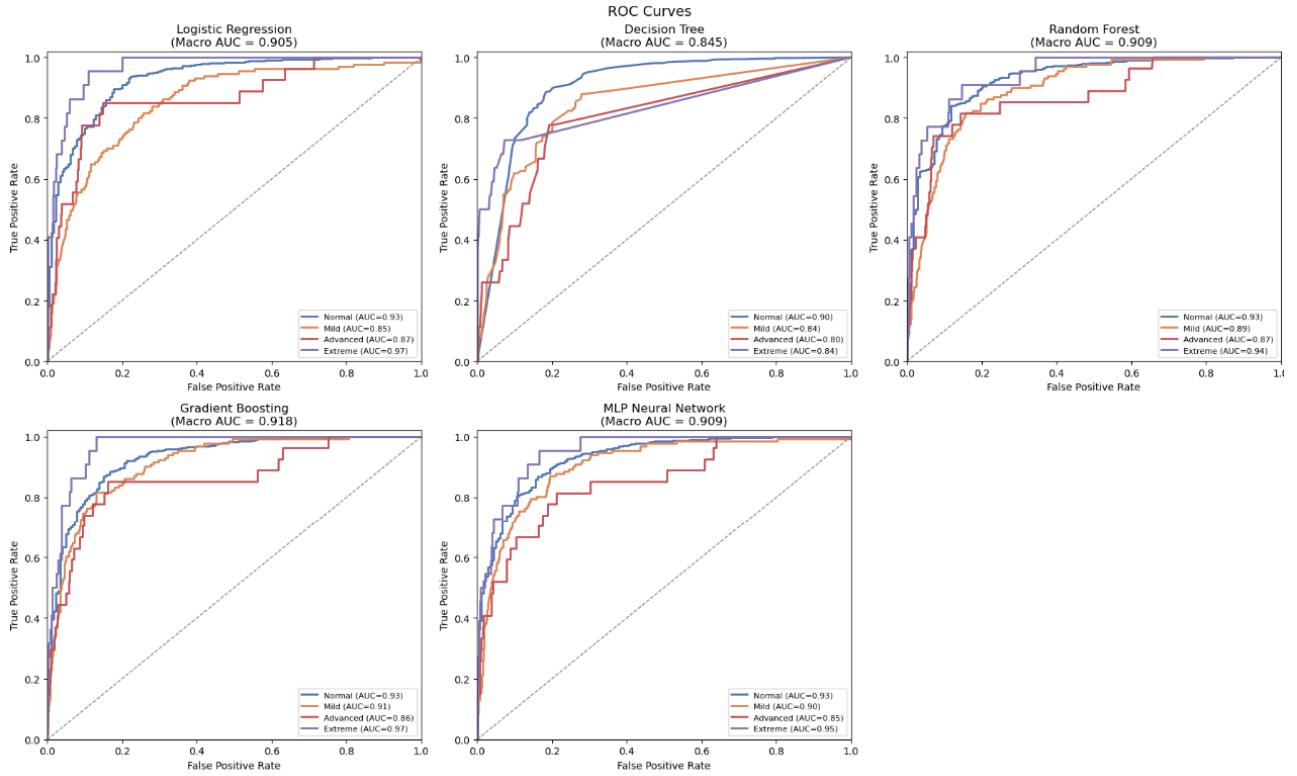


Figure 4.16: Area Under Curve

Comparison of Classification Performance Metrics for Baseline and SMOTE Balanced Models.

Following the application of SMOTE to address class imbalance, model performance was reassessed across five models using macro-averaged F1-score, class-specific F1-scores for the Advanced and extreme risk categories, and macro-averaged AUC (Figure 4.18). Gradient Boosting achieved the strongest overall performance, with the highest Macro F1-score under both baseline (0.511) and SMOTE-balanced training (0.541), as well as the highest macro AUC on the baseline data (0.918). Critically, Gradient Boosting also achieved the highest extreme-class F1-score after SMOTE application (0.471), improving substantially from its baseline value (0.389) and surpassing all other models, including Random Forest (0.410) and Logistic Regression (0.419). A similar pattern was observed for the Advanced class, where Gradient Boosting again achieved the highest SMOTE-based F1-score (0.291), improving from 0.227 at baseline.

These results indicate that SMOTE was particularly effective for Gradient Boosting, meaningfully improving its ability to correctly identify both Advanced and extreme flood risk days without degrading its overall macro AUC (0.918 to 0.906).

On the contrast, SMOTE affected other models apart from Logistic regression where the AUC Macro SMOTE declined. However, Given the consistent improvement of gradient boosting across the Macro, Advanced, and extreme F1-scores following SMOTE application, combined with the highest overall AUC among all five models, it was selected as the best-performing model for this study, particularly in its capacity to identify the extreme flood risk classes most relevant to early warning applications.

Model	F1 Macro (Base)	F1 Macro (SMOTE)	F1 Advanced (Base)	F1 Advanced (SMOTE)	F1 Extreme (Base)	F1 Extreme (SMOTE)	AUC Macro (Base)	AUC Macro (SMOTE)
Logistic Regression	0.486	0.488	0.188	0.200	0.429	0.419	0.905	0.906
Decision Tree	0.471	0.426	0.088	0.151	0.449	0.273	0.845	0.850
Random Forest	0.504	0.509	0.174	0.213	0.439	0.410	0.909	0.903
Gradient Boosting	0.511	0.541	0.227	0.291	0.389	0.471	0.918	0.906
MLP Neural Network	0.473	0.455	0.200	0.141	0.250	0.318	0.909	0.861

Figure 4.17: Comparison of Classification Performance Metrics for Baseline and SMOTE-Balanced Models

The final model was selected using a composite criterion combining Macro F1-score and extreme-class F1-score, rather than overall accuracy. This choice reflects the operational purpose of the study: because Normal-risk days vastly outnumber extreme-risk days (72% vs. 6% of records), accuracy alone is dominated by correct classification of the majority class and would reward a model that performs well on ordinary days while failing to flag rare, high-consequence flood events — the very events an early warning system exists to catch. Macro F1 was used because it weights all four risk classes equally regardless of frequency, while the extreme-class F1-score was tracked explicitly because correctly identifying extreme-risk days carries the highest operational value for disaster preparedness. Gradient Boosting was selected because it achieved the best score on both criteria simultaneously (Macro F1 = 0.541; extreme F1 = 0.471, post-SMOTE), while also maintaining the highest overall macro AUC among the five candidate models, indicating that its advantage was not confined to a single metric or class.

Comparison of gradient Boosting with traditional hydrological approaches

To situate the performance of the selected ensemble methods, three additional hydrological approaches were considered. First, a **climatology-based classifier** was constructed by assigning each test-period day the most frequently occurring flood-risk class historically observed for that calendar month in the training data, without reference to that day’s actual rainfall or discharge. This approach mirrors the seasonal-averaging logic embedded in global forecasting systems such as GloFAS, which the literature review (Section 2.4) identifies as offering limited resolution for small, ungauged catchments. Second, a **linear regression model** was fitted to classify discharge from same-day rainfall, with discharge subsequently converted into a flood-risk class using the study’s training-derived percentile thresholds (Q75, Q90, Q95); this reflects a classical statistical hydrology approach comparable to the linear regression prototype reported by Miirio [50] for flood-level prediction in Kasese District.

All comparators were evaluated on the identical chronologically-split test set and target variable (next-day flood-risk class) used for the primary Gradient Boosting model, to ensure a fair comparison. Results are summarized in Table [4.2]:

Model	Accuracy	Macro F	extreme F
Climatology (seasonal average)	0.821	0.225	0.000
Linear Regression (rainfall → discharge)	0.691	0.265	0.000
Gradient Boosting — full engineered features (post-SMOTE)	0.927	0.541	0.471

Table 4.2: Gradient Boost and Hydrological models

The Machine learning based approach outperformed the two traditional approaches especially on Macro F1, and, critically, neither the climatology nor the linear regression baseline correctly

classified a single extreme-risk day in the test period ($F1 = 0.000$ for both). Notably, climatology achieved higher raw accuracy (0.821) than linear regression (0.691), since climatology was not able to predict the majority Normal class for most months; this illustrates that accuracy alone is a misleading indicator of flood-classification skill under severe class imbalance, and directly supports this study’s decision to prioritize Macro F1 and extreme-class F1 as model-selection criteria (Section 4.2) rather than accuracy. These results empirically reinforce the limitation of coarse, climatology-comparable global systems for catchment-specific extreme event detection raised in Section 2.4.

SHAP analysis

In order to understand the variables that the Gradient Boosting model considered, SHAP analysis was conducted across all the four flood risk classes, which are Normal, mild, advanced and extreme, which assisted to quantify each variable’s contribution towards each class.

In reference to figure 4.19, the beeswarm plot indicated discharge lag 1 was that most influential predictor across all classes, with elevated discharge values (shown in pink) consistently pushing predictions toward higher-risk classes, while low discharge values (blue) pushed predictions toward lower-risk classes.

Secondary contributors, including rainfall_lag0, discharge_lag2, and discharge_accel, showed moderate influence, with narrower SHAP value ranges and less distinct separation by feature value, while cumulative rainfall accumulations and seasonal cyclical indicators (season_sin, season_cos) indicated minimal spread across all four classes, contributing little to model predictions, please see the figure below;

SHAP Beeswarm feature Contributions per Risk Class by
(Gradient Boosting)

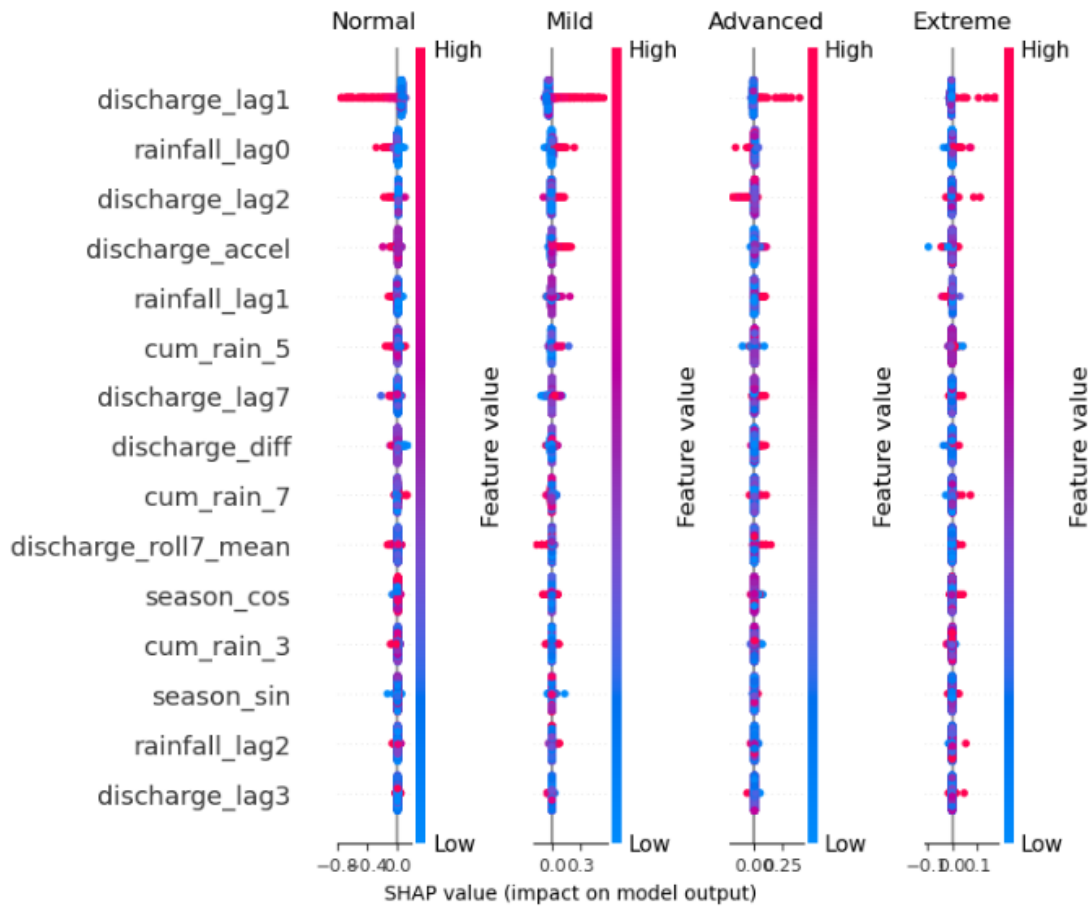


Figure 4.18: SHAP beeswarm

Mean SHAP Value Comparison Across Risk Classes

To complement the beeswarm plot analysis, mean absolute SHAP values were computed for each feature across all four risk classes. Figure 4.18 presents the mean absolute SHAP value for each engineered feature, broken down by flood risk class, using the selected Gradient Boosting model. The results show that discharge_lag1 recorded the highest mean SHAP values overall, but its influence was concentrated predominantly within the Normal (0.073) and Mild (0.055) classes, with smaller contributions to the Advanced (0.014) and extreme (0.005) classes. This declining pattern of importance, decreasing from Normal through to extreme was observed consistently across nearly all features, including discharge_lag2, rainfall_lag0, and discharge_roll7_mean, indicating that feature signals are generally strongest for identifying the Normal risk class and comparatively weaker for identifying rarer, extreme flood days.

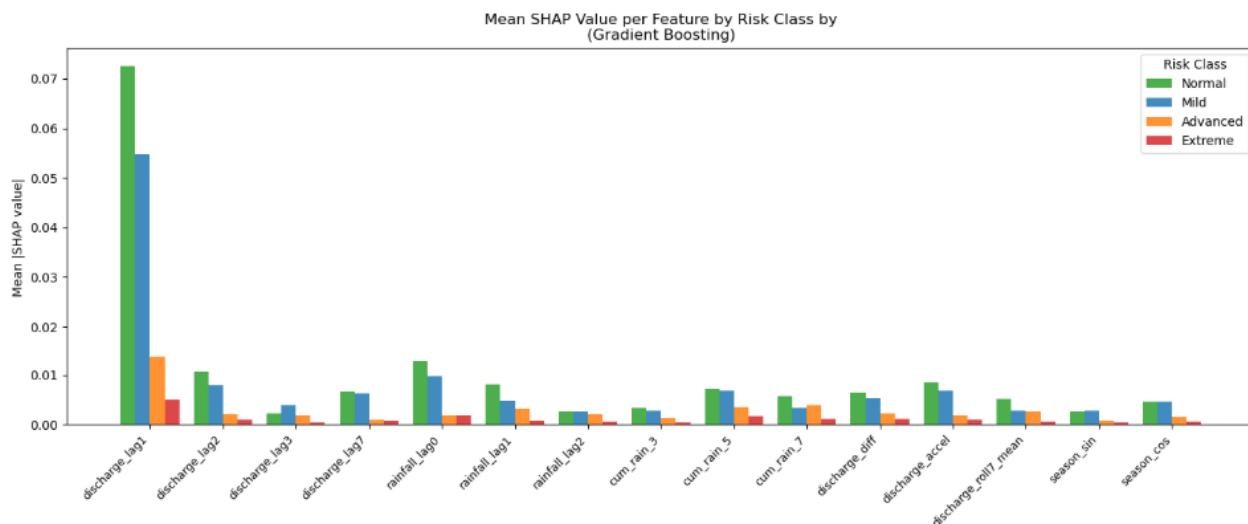


Figure 4.19: SHAP mean per class

Regarding the extreme flood risk class, given its central importance for early warning systems, variables were examined independently from other risk classes. Figure [4.19] presents the mean absolute SHAP values for the extreme risk class specifically, confirming `discharge_lag1` as the single dominant feature, with a mean SHAP value (0.005). Notably, for the extreme class specifically, same-day rainfall (`rainfall_lag0`) and the 5-day cumulative rainfall accumulation (`cum_rain_5`) ranked as the second and third most influential features respectively, ahead of several shorter discharge-lag variables. This suggests that while discharge history remains the primary driver of flood risk classification overall, short-term rainfall intensity and accumulation play a significant role in distinguishing the most severe flood conditions. Seasonal cyclical indicators and longer discharge lags (`lag3`, `lag7`) contributed the least across all fourteen features.

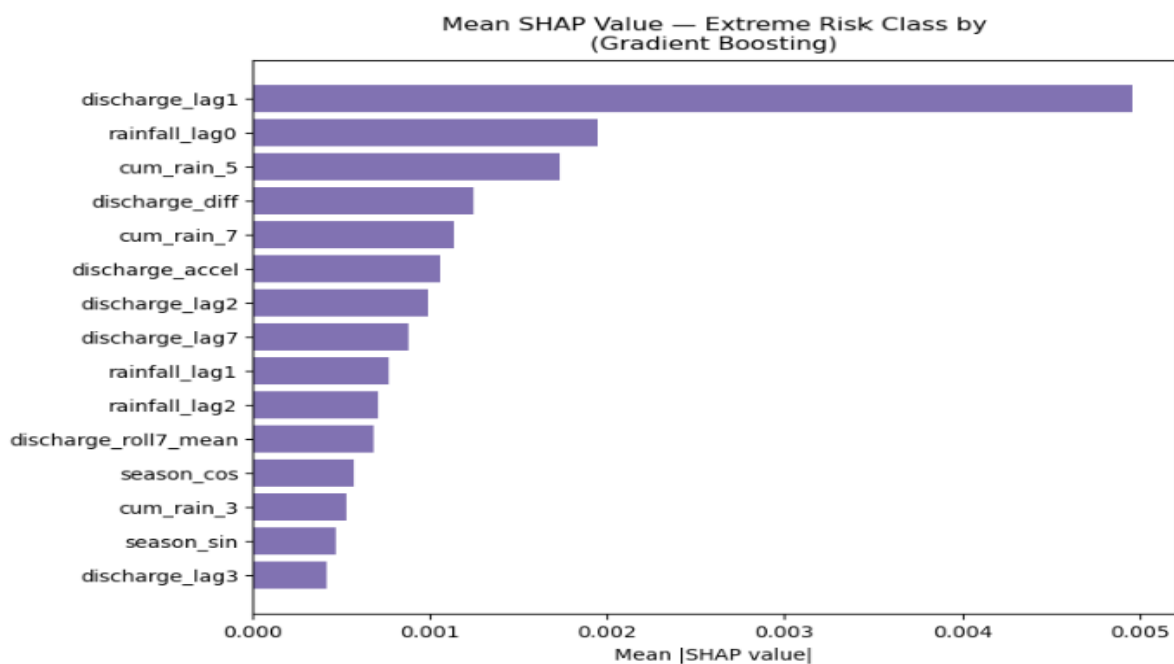


Figure 4.20: SHAP mean

4.4 Objective 4: Validation Against Historical Flood Events

Flood events based on the models' output of the discharge and rainfall patterns

Across all three identified flood events, the model achieved moderate success in identifying flood occurrences, while missing some flood days. The accuracy spanned from (59-90)%, whereby the June 2019 event emerged as the highest while the September 2021 event was challenging. Since non-flood events are usually more expected as compared to flood days, accuracy is more influenced by larger numbers of correctly non flood days, which overestimates model performance.

Flood event	Window period	Actual flood days	Predicted Food days	Extreme risk class	Accur acy	Macro F1
12 June 2019	77	6	4	3	0.90	0.60
October 2019	77	4	3	1	0.82	0.42
September 2021	122	9	8	2	0.57	0.42

Figure 4.21: Historical flood event validation

Chapter 5

Discussion

5.1 Historical Rainfall and Discharge Pattern Analysis

The analysis of rainfall and discharge patterns revealed that the River Manafwa catchment shows a bimodal rainfall pattern, characterized by two major wet seasons occurring between March and June and between September and November. Maximum daily rainfall ranged from approximately 27 to 50 mm/day, with peak rainfall recorded in June (48.3 mm/day) and October (49.9 mm/day). This pattern is primarily caused by the seasonal Inter-Tropical Convergence Zone (ITCZ), which is the East African climate system[35],[36], together with local convectional rainfall processes that enhance precipitation over the catchment.

The occurrence of maximum discharge during relatively low rainfall periods, particularly the January peak of approximately 103 m³/s, highlights the importance of antecedent catchment conditions rather than rainfall intensity alone[59]. Therefore, flood events can occur following moderate rainfall conditions, whereby when soils are saturated and antecedent discharge conditions are elevated, even relatively small rainfall inputs may generate substantial runoff and rapid river level increases. This suggests that accumulated rainfall, soil moisture conditions, catchment saturation, and land surface characteristics influence flood generation processes. The results further demonstrate that flood classification approaches based solely on rainfall intensity may underestimate flood likelihood in catchments where delayed runoff responses dominate.

Notably[29], flood magnitudes are influenced by interactions between climatic variability, hydrological processes, and catchment modifications. In addition, increasing flood occurrences are usually attributed by the local communities to climate change, especially increasing rainfall over time. Although Uganda experiences impacts of climate change, this alone is not enough to explain the influence of increasing flood events. For instance, the report issued in 2012 by the U.S. Geological Survey (USGS) noted that the rainfall patterns in Uganda are decreasing with increasing temperatures despite the increase in flood events.

5.2 Flood frequency analysis and flood risk classification

The Gumbel flood frequency analysis indicates that the estimated peak discharge increases progressively with return period, ranging from approximately 37 m³/s for the 2-year event to about 101 m³/s for the 100-year event.

The observed-versus-fitted comparison demonstrates that the observed annual maximum discharges and the fitted probability distributions exhibit a similar increasing trend. However, the observed annual maxima consistently exceed the fitted values, indicating that the fitted Gumbel distributions underestimate the magnitude of the most extreme discharge events. Overall, the increasing trend in extreme discharges suggests that the flood hazard within the Manafwa River floodplains has intensified, likely as a result of climate change and increased land-use changes within the catchment area.

It was also observed that flood risk within the catchment is predominantly classified as Normal(Fig 4.12), with relatively few occurrences of the extreme risk class. This suggests that, under typical conditions, the catchment effectively regulates runoff and river flow, thereby limiting the likelihood of severe flooding. However, occasional extreme hydrometeorological and other related conditions such as land use changes can overwhelm the catchment’s capacity, resulting in catastrophic flood events[29].

5.3 Machine learning Model evaluation

In this study five models were used that is Logistic Regression, Decision Tree, Random Forest, Gradient Boosting and MLP Neural Network. The comparison of the five machine learning models showed a clear and consistent pattern across several performance metrics, providing confidence in the final model selection. Under both the original and SMOTE-balanced datasets, Gradient Boosting achieved the highest Macro F1-score, increasing from 0.511 to 0.541 after SMOTE. This performance was better than that of Random Forest (0.504–0.509), Logistic Regression (0.486–0.488), MLP Neural Network (0.473–0.455), and Decision Tree (0.471–0.426). Gradient Boosting also performed best in identifying the extreme flood events. Its F1-score for the extreme flood class improved from 0.389 to 0.471 after SMOTE, exceeding the performance of Random Forest (0.410), Logistic Regression (0.419), MLP Neural Network (0.345), and Decision Tree (0.273). A similar improvement was observed for the extreme flood class, where the F1-score increased from 0.227 to 0.291, again ranking highest among all models. In addition, Gradient Boosting achieved the highest macro AUC on the original dataset (0.918) and maintained strong performance after SMOTE (0.906), remaining comparable to Random Forest (0.903).

Overall, Gradient Boosting demonstrated the most balanced and reliable performance across all evaluation metrics[7]. While some models experienced reduced performance after SMOTE for example, the Decision Tree showed a marked decline in extreme class F1-score (0.449 to 0.273), Random Forest also decreased slightly (0.439 to 0.410), and the MLP Neural Network recorded a lower macro AUC (0.909 to 0.861)—Gradient Boosting improved across nearly all key measures. This suggests that it benefited from the balanced training data without losing its ability to distinguish between flood risk classes. Since the main aim of this study was to accurately identify classification of flood risks for early warning, the consistent performance of Gradient Boosting, together with its results for the extreme flood class, makes it the most suitable model for flood risk classification in the River Manafwa catchment.

5.4 SHAP analysis

The SHAP analysis(Fig 4.19) showed that the Gradient Boosting model based its predictions on meaningful hydrological relationships. Across all flood risk classes, discharge.lag1 was the most influential feature. Lower discharge values were mainly associated with the Normal flood class, while higher discharge values increased the likelihood of Advanced and extreme flood conditions.

This indicates that flood risk is influenced not only by current weather conditions but also by the recent hydrological state of the catchment. In comparison, the seasonal variables contributed less to the model, suggesting that recent river conditions provide more useful information for classifying flood risk than the time of year alone.

The SHAP results for each flood risk class revealed some important differences. Although `discharge_lag1` remained the dominant feature for the Normal and Mild classes, its influence was lower for the Advanced and extreme classes. Instead, same-day rainfall (`rainfall_lag0`) and 5-day cumulative rainfall (`cum_rain_5`) became relatively more important for predicting these higher-risk conditions (Fig. 4.20). This suggests that the factors influencing common, low-risk flood conditions are not exactly the same as those driving severe flood events. It also helps explain why the model found the Advanced and extreme classes more difficult to classify accurately. Because fewer variables strongly distinguish these less frequent events, the model has less information to separate them from other flood risk classes.

5.5 Analysis of historical Flood Events

Overall, the validation results from the three historical flood events show that the Gradient Boosting model has a good ability to classify real flood occurrences. The model has the capability to correctly identify most flood days within the selected periods and was able to detect some extreme flood risk conditions in all three events. However, differences in performance between the events, especially the lower Macro F1-score observed for October 2019 and September 2021 compared with June 2019, show that the model does not perform equally well under all flood conditions. This variation may be related to differences in flood characteristics, including the length of the evaluation period, rainfall and discharge patterns, and the intensity and duration of each flood event.

These findings support the overall results of the study, showing that although the model performs well and provides useful early warning information, predicting less frequent and more complex flood events remains challenging. The ability of the model to identify extreme risk conditions before reported flood dates demonstrates its potential application in flood early warning systems. However, improving future predictions will require additional historical flood cases, and the inclusion of other factors can help to improve the classification of severe floods.

Chapter 6

Conclusion and Recommendation

6.1 Conclusion

This study focused on developing and evaluating a machine learning framework for flood risk classification in the River Manafwa catchment using 35 years (1989–2024) of historical daily rainfall and river discharge data. Based on discharge percentile thresholds, four flood risk categories were established: Normal, Mild, Advanced, and extreme.

The hydrological analysis showed that the catchment experiences a bimodal rainfall pattern, which is typical of the Eastern Africa climate region. The analysis also confirmed a delayed response between rainfall and river discharge. Cross-correlation analysis showed the strongest relationship occurring at a two-day lag. This finding provided important insight into the catchment response and guided the development of lag-based features used in the machine learning models.

Five machine learning algorithms—Logistic Regression, Decision Tree, Random Forest, Gradient Boosting, and MLP Neural Network—were assessed for flood risk classification. Among the evaluated models, Gradient Boosting produced the best overall performance, achieving the highest Macro F1-score under both baseline (0.511) and SMOTE-balanced training (0.541). It also achieved the highest extreme-class F1-score after SMOTE application (0.471). The consistent improvement of Gradient Boosting after data balancing suggests that it was better able to identify minority flood classes without reducing overall model performance. However, all models experienced challenges in distinguishing the Advanced risk class, mainly due to its smaller number of observations and narrow discharge range compared with the more frequent Normal and Mild classes.

The SHAP analysis provided further understanding of the factors influencing model predictions. Discharge_lag1 was identified as the most important feature across all risk classes, showing that recent river conditions play a major role in determining flood risk. However, for extreme flood conditions, rainfall on the current day and short-term accumulated rainfall became relatively more influential. This demonstrates that while previous discharge conditions are important for general flood classification, severe flood events are also strongly influenced by recent rainfall inputs. These results highlight the importance of considering multiple hydrological factors when predicting extreme flood events.

Validation using three documented flood events—June 2019, October 2019, and September 2021—confirmed the practical value of the model, with prediction accuracy ranging from 0.57 to 0.90. The June 2019 event showed the strongest performance, where the model successfully identified extreme flood risk several days before the reported flood occurrence and achieved an

accuracy of 0.90 and Macro F1-score of 0.60. Combined with the Gumbel frequency analysis, which supported the selected discharge thresholds, these findings demonstrate that a discharge-based, lag-informed classification approach provides a useful and interpretable method for flood risk prediction in the Manafwa catchment.

Overall, this study achieved its objective of developing a data-driven flood risk classification early warning framework based on rainfall and river discharge characteristics. The integration of hydrological analysis, machine learning, SHAP interpretation, and historical event validation provides a practical approach for supporting flood early warning. Although challenges remain, particularly in predicting Advanced-level risks and improving consistency across different flood events, the developed framework provides a foundation that can be further improved and applied to other flood-prone catchments in Uganda with similar data limitations and hydrological conditions.

In effort to support the community and disaster risk management, the findings, guided by the identified lagged discharge response and the four-level flood-risk classification, can support the development of graduated warning and preparedness procedures. Increasing risk levels can be linked to progressively stronger actions, including community awareness, monitoring of vulnerable locations, protection of household assets and livestock, preparation of evacuation routes, and timely relocation of highly exposed households where necessary. The findings can therefore contribute to strengthening community resilience and reducing the potential social and economic impacts of flooding in the Manafwa catchment.

The framework developed in this study is percentile-based discharge classification combined with lag- and accumulation-based feature engineering, is methodologically transferable to other Ugandan catchments, since it depends only on the two most commonly available hydrological records (rainfall and discharge) rather than dense spatial or physically based inputs. However, the trained model itself is catchment-specific and would require retraining on local discharge and rainfall records before being applied elsewhere; what generalizes is the modelling approach, not the fitted parameters.

For the approach to transfer meaningfully, the catchment area should share key characteristics with the Manafwa: (i) a comparable bimodal seasonal rainfall regime typical of the wider East African region, (ii) a broadly similar catchment size and hydrological response time, so that the same lag windows (1–7 days) remain hydrologically meaningful, and (iii) the availability of a sufficiently long historical rainfall–discharge record to support percentile-based risk classification and model training. Catchments lacking these similarities — for example, much larger basins with longer response times, or those with fundamentally different rainfall seasonality, would likely require re-derivation of the lag windows and risk thresholds rather than direct application of the Manafwa calibrated model.

6.2 Recommendation

Communities in flood-prone areas of the Manafwa catchment should strengthen household and community-level preparedness plans. These should include identification of safe areas and evacuation routes, household evacuation procedures, protection of important documents and household assets, and arrangements for the timely movement of livestock, food and agricultural inputs during periods of increasing flood risk. Community flood preparedness committees should work with local leaders and disaster-management authorities to ensure that warning information is understood and translated into practical actions.

The four flood-risk categories developed in this study should be considered as a basis for

developing graduated warning and response procedures. Rather than issuing a single flood warning, different levels of risk could be linked to progressively stronger preparedness actions. For example, Normal conditions could require routine monitoring; Mild conditions could trigger increased community awareness; Advanced conditions could trigger preparation for possible evacuation and protection of assets; while extreme conditions could support the activation of locally agreed emergency response and evacuation procedures. These action levels should be further validated against historical impacts and agreed upon with local communities and responsible authorities before operational implementation.

The developed framework should be explored for integration with existing flood early warning and anticipatory-action mechanisms in Uganda. The locally calibrated risk classification could complement existing forecasting information from national and global systems. However, operational implementation should involve validation of the thresholds, assessment of false alarms and missed events, and consultation with communities and disaster-management institutions to ensure that warnings are understandable, timely and actionable.

Local governments and relevant planning authorities should strengthen long-term flood-risk reduction measures in highly exposed areas. These should include appropriate land-use planning, protection of riverbanks and wetlands, improved drainage, erosion and sediment-control measures, and careful management of development within flood-prone areas. The identification of recurrently exposed areas should inform decisions concerning infrastructure placement and, where necessary, relocation of highly vulnerable households.

The findings of this study provide several opportunities for future research and practical application. To improve the precision and reliability of flood prediction models, future studies are encouraged to incorporate additional variables such as soil moisture, vegetation indices, land use and land cover, urban drainage characteristics, population size, and topographic attributes. Integrating these variables with rainfall and river discharge data would provide a more comprehensive representation of the processes influencing flood occurrence.

Future research should also consider the impacts of climate variability and long-term environmental change by integrating Global Climate Model (GCM) projections and applying non-stationary extreme value analysis. In addition, incorporating scenarios of future land use change would enable the assessment of evolving flood hazards and support the development of adaptive flood risk management strategies.

Rather than treating the River Manafwa catchment as a single system, future studies should investigate the upper, middle, and lower sections of the catchment independently. The considerable variation in elevation, slope, topography, land cover, and hydrological response across these geographic zones.

Although the evaluated machine learning models demonstrated promising performance, they exhibited limitations in differentiating advanced and extreme flood events. Future studies should therefore explore advanced and hybrid machine learning techniques, including deep learning approaches, while integrating physically based hydrological models to enhance both predictive performance.

Finally, effective flood risk management requires a multidisciplinary and collaborative approach. Future studies should actively involve government agencies, disaster management authorities, local communities, and other stakeholders in the selection and validation of flood-related variables to ensure that prediction models reflect local conditions and knowledge. Strengthening the integration of flood prediction models into disaster preparedness, land use planning, infrastructure development, and early warning systems will enhance their practical value and contribute to more resilient communities.

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Appendix A

Declaration of AI use

Declaration Statement:

I, *Namakula Martha Frances*, declare that I used

- i. **ChatGPT and Notebook LLM to summarize research papers and this helped to identify key aspects used in related research for flood prediction. I modified the outputs in I modified the output to suit the literature review.**
- ii. **Grammary to correct the grammatic errors and improve punctuation. I modified the outputs in a way that aligns with the flow of insights.**

Signature:  Date: 15/9/2026

Appendix B

Research alignment with national (NDPIV) and Global (SDGs) agenda

B.1 Alignment with NDPIV

Objective 1: Sustainably increase production, productivity, and value addition in agriculture, minerals, oil and gas, tourism, ICT, and financial services.

Objective 2: Enhance human capital development along the entire life cycle.

Objective 3: Build and maintain strategic sustainable infrastructure in transport, energy, water, and ICT.

B.2 Alignment with the Uganda Vision 2040

Science, technology, engineering, and innovation: Through the launching of the satellite, Uganda will be able to monitor changing discharge patterns at high resolution, which will improve on research advanced in Artificial Intelligence and Machine Learning, hence improving accurate prediction of flood events in catchment areas.

Agriculture opportunity: Improved flood prediction helps reduce agricultural losses, that is, crops and livestock, through early warning systems, thereby supporting Uganda's goal of transitioning from subsistence to commercial farming. This also helps to improve agricultural investment.

B.3 Alignment with global agenda

SDG 13 Climate Action: Effective flood risk prediction strengthens resilience, early mitigation, and adaptive measures among the communities, hence reducing the impact of severe floods to the community.

SDG 1 No poverty: Through improving the flood risk forecasting system, it helps to protect the livelihood of communities and their property, especially the farmers, which helps to reduce loss of lives, property, and improve food security, hence people falling back into extreme poverty.

SDG 6 Clean Water and Sanitation: Timely early warnings enable communities to evacuate and health facilities to prepare for flood-related injuries and deaths.

Appendix C

Algorithms, Code of interest

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import xarray as xr
import seaborn as sns
import calendar

from sklearn.impute import KNNImputer
from sklearn.experimental import enable_iterative_imputer
from sklearn.impute import IterativeImputer
from sklearn.preprocessing import StandardScaler
from sklearn.linear_model import LogisticRegression
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import RandomForestClassifier, GradientBoostingClassifier
from sklearn.neural_network import MLPClassifier
from sklearn.metrics import (
    classification_report, confusion_matrix,
    f1_score, precision_score, recall_score, accuracy_score,
)
from sklearn.utils.class_weight import compute_class_weight
from sklearn.preprocessing import LabelEncoder
```

Figure C.1: Imported Libraries

```
#choosing return periods
return_periods = np.array([2, 5, 10, 25, 50, 100])

#Compute the exceedance probability

prob = 1 - 1/return_periods

#Estimate the corresponding discharge

Q_return = gumbel_r.ppf(prob, loc=loc, scale=scale)
```

Figure C.2: Calculating Return period

```
# Calculating discharge thresholds
Q75 = Res["discharge"].quantile(0.75)
Q90 = Res["discharge"].quantile(0.90)
Q95 = Res["discharge"].quantile(0.95)

print(f"Records : {len(Res):,}")
print(f"Period : {Res['time'].min().date()} → {Res['time'].max().date()}")
print(f"\nDischarge thresholds")
print(f" Q75 = {Q75:.2f} m³/s (Normal-risk)")
print(f" Q90 = {Q90:.2f} m³/s (medium-risk)")
print(f" Q95 = {Q95:.2f} m³/s (High-Risk)")
print(f"\nDischarge stats:")
display(Res["discharge"].describe(percentiles=[.5,.75,.9,.95,.99]).to_frame().T.round(2))
```

Figure C.3: Discharge Thresholds

```
4. Feature Engineering

# Calculating Discharge lags
for lag in [1, 2, 3, 7]:
    Res[f"discharge_lag{lag}"] = Res["discharge"].shift(lag)

# Calculating rainfall lags (current + recent rain)
for lag in [0, 1, 2]:
    Res[f"rainfall_lag{lag}"] = Res["rainfall"].shift(lag)

# Cumulative rainfall windows
Res["cum_rain_3"] = Res["rainfall"].shift(1).rolling(3).sum()
Res["cum_rain_5"] = Res["rainfall"].shift(1).rolling(5).sum()
Res["cum_rain_7"] = Res["rainfall"].shift(1).rolling(7).sum()

# Rate of discharge change & acceleration
Res["discharge_diff"] = Res["discharge"].shift(1).diff()
Res["discharge_accel"] = Res["discharge_diff"].diff()

# 7-day rolling mean discharge
Res["discharge_roll7_mean"] = Res["discharge"].shift(1).rolling(7).mean()

# Cyclic seasonal encoding (captures annual flood seasonality)
day = Res["time"].dt.dayofyear
Res["season_sin"] = np.sin(2 * np.pi * day / 365.25)
Res["season_cos"] = np.cos(2 * np.pi * day / 365.25)

# Target: next-day flood risk class
Res["flood_risk_tomorrow"] = pd.cut(
    Res["discharge"].shift(1),
    bins=[-np.inf, Q75, Q90, Q95, np.inf],
    labels=[0, 1, 2, 3]
).astype("int64")
```

Figure C.4: Variable feature engineering

```
# Standardizing the features
from sklearn.preprocessing import StandardScaler, MinMaxScaler
PredictorScaler = MinMaxScaler()

# Storing the fit object for later reference
PredictorScalerFit = PredictorScaler.fit(X)

# Generating the standardized values of X
X = PredictorScalerFit.transform(X)

from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.2, random_state = 42)

MODELS = [
    "Logistic Regression": LogisticRegression(
        max_iter=2000, class_weight="balanced",
        C=0.5, solver="lbfgs", random_state=42
    ),
    "Decision Tree": DecisionTreeClassifier(
        max_depth=8, min_samples_leaf=10,
        class_weight="balanced", random_state=42
    ),
    "Random Forest": RandomForestClassifier(
        n_estimators=200, max_depth=12, min_samples_leaf=10,
        class_weight="balanced", n_jobs=-1, random_state=42
    ),
    "Gradient Boosting": GradientBoostingClassifier(
        n_estimators=200, learning_rate=0.05, max_depth=5,
        subsample=0.8, random_state=42
    ),
    "MLP Neural Network": MLPClassifier(
        hidden_layer_sizes=(128, 64, 32), activation="relu",
        max_iter=500, early_stopping=True, validation_fraction=0.1,
        learning_rate_init=0.001, random_state=42
    ),
]
```

Figure C.5: Machine Learning models

```
# SMOTE
try:
    from imblearn.over_sampling import SMOTE
except ImportError:
    import sys
    if sys.executable:
        -m pip install imbalanced-learn --quiet
    from imblearn.over_sampling import SMOTE

from collections import Counter

# Single chronological 80/20 split for the SMOTE experiment
split_idx = int(len(X) * 0.8)
X_train_sm = X[:split_idx]
X_test_sm = X[split_idx:]
y_train_sm = y[:split_idx].reset_index(drop=True)
y_test_sm = y[split_idx:].reset_index(drop=True)

scaler_sm = StandardScaler()
X_train_sm_sc = scaler_sm.fit_transform(X_train_sm)
X_test_sm_sc = scaler_sm.transform(X_test_sm)

print("Training class distribution BEFORE SMOTE:")
print(Counter(y_train_sm))

# Target counts: bring Class 2 and Class 3 up to Class 1's count.
# Adjust these numbers if your actual training counts differ.
class_counts = Counter(y_train_sm)
target_minor = class_counts[1] # use Mild-risk count as the ceiling for classes 2 & 3

smote = SMOTE(
    sampling_strategy={2: target_minor, 3: target_minor},
    k_neighbors=5,
    random_state=42
)

X_res, y_res = smote.fit_resample(X_train_sm_sc, y_train_sm)

print("\nTraining class distribution AFTER SMOTE:")
print(Counter(y_res))
```

Figure C.6: Computation of SMOTE

```
#SHAP Analysis

try:
    import shap
except ImportError:
    import sys
    !pip install shap --quiet
    import shap

feature_names = [
    'discharge_lag1', 'discharge_lag2', 'discharge_lag3', 'discharge_lag7',
    'rainfall_lag0', 'rainfall_lag1', 'rainfall_lag2',
    'cum_rain_3', 'cum_rain_5', 'cum_rain_7',
    'discharge_diff', 'discharge_acc01', 'discharge_rol17_mean',
    'season_sin', 'season_cos'
]

class_labels_shap = ['Normal', 'Mild', 'Advanced', 'Extreme']
model_type = type(best_clf).__name__

print("Model selected for SHAP:", best_model)
print("Model type: ", model_type)
print("Test set shape: ", X_test_xc2.shape)
```

Figure C.7: SHAP mean analysis

```
if isinstance(shap_vals, list) and len(shap_vals) == 4 and shap_vals[0].ndim == 2:
    vals = np.stack(shap_vals, axis=1) # (n_samples, n_features, n_classes)
else:
    vals = shap_vals[0]

extreme_mean_shap = pd.Series(
    np.abs(vals[:, :, 1]).mean(axis=0), # class index 3 = Extreme, assuming order matches
    index=feature_names
).sort_values(ascending=True)

fig, ax = plt.subplots(figsize=(8, 6))
bars = ax.bar(extreme_mean_shap.index, extreme_mean_shap.values, color="B0E7D2")
ax.set_xlabel("Mean SHAP value")
ax.set_title("Mean SHAP Value - Extreme Risk Class by n([best_model])")
plt.tight_layout()
plt.show()
```

Figure C.8: Computing SHAP for extreme classes