Improvement of Streamflow Forecasting for Flood Management and Mitigation in the White Volta Basin, Northern Ghana

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Abstract

Flooding in Ghana's White Volta basin has led to severe human displacement, fatalities, and extensive property damage. The region's heavy dependence on agriculture exacerbates these impacts, posing significant threats to food security and livelihoods. In Ghana, institutions such as the Ghana Meteorological Agency (GMet) and the Ghana Hydrological Authority (GHA) are mandated to provide flood forecasts. However, their forecast remains inadequate, prompting many communities to rely on traditional knowledge and informal coping mechanisms. This study qualitatively assesses the operational state of Flood Early Warning Systems (FEWS) in the White Volta basin, focusing on their effectiveness, limitations, and opportunities for improvement. Using semi-structured interviews with 18 key stakeholders, including representatives from government agencies, technical experts, and community leaders, the study analysed the institutional and technical dynamics of Ghana's FEWS through thematic analysis. Findings reveal that although the myDEWETRA-VOLTALARM platform offers 5-day flood forecasts through social media, SMS, and radio, its warnings are often mistrusted or inaccessible to rural populations. Thematic analysis identified four critical gaps: institutional fragmentation, exclusion of local knowledge, inadequate data infrastructure, and last-mile communication failures. These are complicated by the basin's unique environmental conditions, including transboundary dam releases, intense seasonal rainfall, flat terrain, and poor drainage. These findings suggest that the current FEWS framework remains insufficient for proactive flood risk governance. Strengthening institutional coordination, integrating community-based adaptation practices, and investing in localised data and communication infrastructure are essential to improving system legitimacy and resilience. The study contributes to broader discourses on early warning systems in resource-constrained settings.

The study explored alternative data sources for building a robust and reliable FEWS in the White Volta basin. Satellite and reanalysis data were compared with ground-based observations in Northern Ghana. This surrogate data assumes prominence as an alternative predictor amid the scarcity of ground-based data for streamflow forecasting to manage and mitigate floods in the basin. Rainfall and mean temperature span from 1998 to 2019, and soil moisture from 2019 to 2019. Data were sourced from GMet, ISMN (ground-based), CHIRPS, PERSIANN-CDR, ERA5, ARC2, MERRA-2, TRMM, and CFSR (satellite and reanalysis). Using performance metrics, namely standard deviation, mean absolute error (MAE), and mean bias error (MBE), the accuracy of these datasets was thoroughly evaluated. The results revealed that CHIRPS and PERSIANN-CDR exhibited superior accuracy in rainfall simulation, with CHIRPS demonstrating particularly consistent congruence with observed data. ERA5 outperformed MERRA-2 and CFSR in predicting average temperatures. For soil moisture, both ERA5 and CFSR gave reliable results. Based on these findings, CHIRPS is recommended for rainfall, ERA5 for temperature, and either ERA5 or CFSR for soil moisture. These datasets are suitable for streamflow modelling, drought and flood forecasting, and managing water resources in Northern Ghana.

The study also examines an operational Flood Early Warning System (FEWS) in the White Volta basin, aimed at delivering accurate streamflow forecasts critical for effective flood management and mitigation. For the first time, this research applies machine learning algorithms, specifically Long Short-Term Memory (LSTM) and Random Forest (RF), trained on rainfall, temperature, soil moisture, and evapotranspiration data to predict streamflow at 1-, 5-, and 10-day intervals within the basin. The study further used these models (RF and LSTM) to forecast future streamflow using CMIP6 SSP5-8.5 scenario data. The model's output was evaluated using Mean Absolute Error, Mean Bias Error, and Kling-Gupta Efficiency. The result showed high variability in the streamflow, and both models performed well in capturing these variabilities. LSTM showed superiority in capturing peak flows, and RF provided stable long-term predictions for up to 10 days. The future predictions also showed high variability in the streamflow, suggesting an increased risk of floods and droughts in the basin. Given that these models are able to capture the timings (seasonal patterns and peaks), they are well-positioned to provide accurate and reliable streamflow forecasts to support effective flood risk management and mitigation in the basin. The models can be extended to similar ungauged basins, offering a replicable and sustainable framework for proactive flood early warnings.

Zusammenfassung

Die Überschwemmungen im White-Volta-Becken in Ghana haben zu massiven Vertreibungen, Todesfällen und erheblichen Sachschäden geführt. Eine starke Abhängigkeit der Region von der Landwirtschaft verschärft diese Auswirkungen und stellt eine erhebliche Bedrohung für die Ernährungssicherheit und die Lebensgrundlagen der Bevölkerung in diesem Gebiet dar. In Ghana sind Institutionen wie die Ghana Meteorological Agency (GMet) und die Ghana Hydrological Authority (GHA) mit der Erstellung von Hochwasservorhersagen beauftragt. Ihre Vorhersagen sind jedoch nach wie vor unzureichend, so dass sich viele Gemeinden auf traditionelles Wissen und informelle Bewältigungsmechanismen verlassen. Um diese Lücke zu schließen, wurde in dieser Arbeit der aktuelle Zustand des Frühwarnsystems für Überschwemmungen (FEWS) im White-Volta-Becken qualitativ bewertet und seine Wirksamkeit, Herausforderungen und mögliche Verbesserungen untersucht. Konkret wurde die operative Landschaft des FEWS anhand von ausführlichen Interviews mit zentralen staatlichen und nichtstaatlichen Akteuren analysiert. Im Zuge der Untersuchung wurde das myDEWETRA-VOLTALARM-Systems betrachtet, welches Hochwasserwarnungen über soziale Medien, Radio und Textnachrichten verbreitet. Die Warnungen dieses Systems waren jedoch nicht flächendeckend für alle Betroffene zugänglich. Weitere zentrale Schwächen des FEWS im Becken betrafen die begrenzte Einbindung der Gemeinden, finanzielle Einschränkungen, veraltete Technologien, unzureichende Echtzeitdaten, Lücken in der Überwachungsinfrastruktur sowie eine schwache institutionelle Koordination. Die Studie kommt zu dem Schluss, dass das derzeitige FEWS-Rahmenwerk im White-Volta-Becken für ein proaktives Hochwasserrisikomanagement unzureichend ist.

Zur Ermittlung alternativer Datenquellen für den Aufbau eines robusten und zuverlässigen FEWS im White-Volta-Becken bewertete die Studie in einem zweiten Schritt die Genauigkeit von Satelliten- und Reanalysedaten im Vergleich zu bodengestützten Daten in Nordghana. Diese Daten gewinnen an Bedeutung als alternative Prädiktoren angesichts des Mangels an bodengestützten Daten für Abflussvorhersagen zur Steuerung und Minderung von Überschwemmungen im White-Volta-Becken. Niederschlags- und Durchschnittstemperaturdaten von 1998 bis 2019 sowie Bodenfeuchtigkeitsdaten von 2019 bis 2022 wurden von GMet, ISMN (bodenbasiert), CHIRPS, PERSIANN-CDR, ERA5, ARC2, MERRA-2, TRMM und CFSR (Satelliten- und Reanalysequellen) erhoben. Die Genauigkeit dieser Datensätze wurde mithilfe strenger statistischer Maße – Standardabweichung, mittlerer absoluter Fehler (MAE) und mittlerer Bias-Fehler (MBE) – umfassend bewertet. Die Ergebnisse zeigten, dass CHIRPS und PERSIANN-CDR eine überlegene Genauigkeit bei der

Niederschlagssimulation aufwiesen, wobei CHIRPS eine besonders konsistente Übereinstimmung mit den beobachteten Daten zeigte. Bei der Vorhersage der Durchschnittstemperatur übertraf ERA5 sowohl MERRA-2 als auch CFSR. In Bezug auf Bodenfeuchtigkeit lieferten sowohl ERA5 als auch CFSR zufriedenstellende Simulationen. Die Ergebnisse sprechen daher für CHIRPS (für Niederschlagsdaten), ERA5 (für Temperaturdaten) und eine Kombination aus CFSR/ERA5 (für Bodenfeuchtedaten) als zuverlässige primäre Datenquellen für Abflussmodellierung, Dürrenanalyse, Hochwasservorhersage und Wasserressourcenmanagement im Kontext Nordghanas.

Zur Entwicklung eines operativen FEWS im White-Volta-Becken, das genaue Abflussinformationen für das Hochwassermanagement bereitstellt, setzte die Studie erstmals maschinelle Lernalgorithmen ein, insbesondere Long Short-Term Memory (LSTM) und Random Forest (RF), die mit Niederschlags-, Temperatur, Bodenfeuchte und Evapotranspirationsdaten trainiert wurden, um den Abfluss in Intervallen von 1, 5 und 10 Tagen im Becken vorherzusagen. Darüber hinaus wurden in der Studie die Modelle (RF und LSTM) eingesetzt, um den zukünftigen Abfluss mithilfe von Daten aus dem CMIP6 SSP5-8.5-Szenario zu prognostizieren. Die Modellleistung wurde anhand von MAE, MBE und der Kling-Gupta-Effizienz bewertet. Die Ergebnisse zeigten hohe Variabilitäten im Abfluss, wobei beide Modelle diese gut abbildeten. LSTM erwies sich jedoch als überlegen bei der Erfassung von Spitzenabflüssen, während RF stabile Langzeitvorhersagen über einen Zeitraum bis zu 10 Tagen lieferte. Auch die Zukunftsprognosen zeigten starke Schwankungen im Abfluss und deuten auf ein erhöhtes Risiko von Überschwemmungen und Dürren im White-Volta-Becken hin. Aufgrund dessen das die Modelle in der Lage sind, zeitliche Muster (saisonale Trends und Spitzen) zuverlässig zu erfassen, sind sie gut geeignet, präzise und zuverlässige Abflussvorhersagen bereitzustellen, die ein effektives Hochwasserrisikomanagement und eine vorausschauende Schadensminderung im Becken unterstützen. Die Modelle lassen sich auch auf ähnliche, nicht überwachte Einzugsgebiete übertragen und bieten einen replizierbaren und nachhaltigen Rahmen für frühzeitige Hochwasserwarnsysteme.

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CHAPTER 1

1 Introduction

1.1 Study Background and Problem Statement

Over the past 100 years, human activities, particularly the reliance on fossil fuels and inefficient use of land and energy, have driven a rise in global temperatures, now approximately 1.1°C above levels seen before industrialization (IPCC, 2023; Valavanidis, 2022). This temperature increase has led to a surge in extreme weather events, placing growing pressure on both the environment and human societies worldwide (IPCC, 2023). With each degree of warming, hazards such as heatwaves, heavy rainfall, and other extreme weather events intensify, posing further threats to human health and ecosystems (Seneviratne et al., 2021). Climate-related food and water shortages are expected to worsen as global warming continues (Wheeler & von Braun, 2013). The climate crisis has caused significant disruptions to human societies, with profound impacts on fundamental aspects of human livelihoods and social structures (IPCC, 2023). Throughout history, floods have consistently been recognised as one of the most significant climate crises on record, capable of causing extensive harm to individuals through physical injuries as well as property damage (Smith & Smith, 2013).

According to Asumadu-Sarkodie & Owusu (2015), global flood phenomenon has affected 65 million people, and it is projected to increase to 132 million by 2030 and 292 million by 2080 (Islam & Wang, 2024). Additionally, urbanisation is accelerating, leading to exposure and vulnerability of people and properties to floods. Between 1950 and 2011, the number of people living in urban areas increased almost five times, with the majority of this expansion taking place in less developed parts of the world (Cardona et al., 2012; United Nations Human Settlements Programme (UN-Habitat), 2011). On average, less developed countries are more vulnerable to floods, which often cause damage that heavily impacts their national GDP (Tanoue et al., 2016).

In Africa, over 27,000 fatalities attributed to flooding have been recorded between 1950 and 2019 (Tramblay et al., 2020). According to predictions about climate change, there will be significant reductions in the production of essential food crops due to increased drought and floods (Ayanlade et al., 2022). This will be particularly severe in sub-Saharan Africa, where it is estimated that by 2060, a total of US$26 million will be lost due to the impact of climate change on Arable lands (Gemeda & Sima, 2015). This decline in agricultural output will have a direct impact on food security and the risk of malnutrition, particularly among children (Ringler et al., 2010). West Africa has recently experienced an increase in floods, especially along the banks of the Niger and Volta Rivers, affecting approximately 1.5 million people and destroying many hectares of farmland (Atubiga & Donkor, 2022).

In Ghana, the National Disaster Management Organisation (NADMO), Ghana Hydrological Authority (GHA), Ghana Meteorological Agency (GMet), the Water Resources Commission (WRC), and Engineers assist in flood forecasting and management. They focus on developing early warning systems, monitoring, and forecasting, as well as assessing hazards (Organization for Economic Cooperation and Development (OECD), 2020). The Global Facility for Disaster Risk Reduction (GFDRR) and the World Bank initiated a flood hazard assessment for the White Volta basin to generate hazard maps, make flood predictions, and lay a foundation for an operational Flood Early Warning System (FEWS). This project integrated meteorological, river monitoring, and modelling data with defined institutional responsibilities to facilitate prompt evacuation decisions during flood events

However, despite the involvement of organisations such as NADMO, GMet, GHA, WRC, GFDRR, and the World Bank, the impact of flooding remains a recurring issue in Northern Ghana, affecting many residents each year. In 2007, over 260,000 people were affected, with more than 35 fatalities and over 3,000 hectares of farmland submerged in the Northern part of the country (Ahadzie & Proverbs, 2011). In 2018, heavy rains and overflow from Burkina Faso's Bagre Dam led to flooding that impacted 100,000 people, causing 34 deaths and destroying 196 square kilometers of farmland (Evers et al., 2024; Katsekpor et al., 2024a). In 2021, eight lives were lost, coupled with the destruction of homes and properties (FloodList, 2021). Moreover, in 2023, floods displaced approximately 26,000 people with significant damage to properties (International Federation of Red Cross and Red Crescent Societies, 2024), while Africanews (2024) reported a recent flood in 2024 that killed 8 people and collapsed major roads and bridges.

Figure 1.1: Floods in Nawuni, September 2023 (Source: Picture taken by Title Man, 2023).

In this region, agriculture is the main source of livelihood and is highly susceptible to flood damage, which poses significant risks to both food security and economic stability in Ghana (Ntim-Amo et al., 2022). For instance, about 60% of the labour force in Kumbungu, a community along the White Volta basin, depends largely on agriculture as the main source of livelihood (Ayereka & Jaman, 2023). Nonetheless, the combined effects of climate change and the recurring release of water from the Bagre Dam have heightened their exposure to risk and intensified food insecurity. Li et al. (2022) revealed that population exposure to flood hazards in communities along the basin increased from 2016 to 2020. While Abubakari et al. (2019) and Smits et al. (2024) projected rising flood exposure during the wet season throughout the 21st century. Given the growing intensity and frequency of these events, the implementation of an effective FEWS is essential to safeguard lives and property (Kuller et al., 2021). The United Nations has highlighted the critical role of early warning systems (EWS) through key frameworks such as the Paris Agreement and the Sustainable Development Goals (World Meteorological Organization, 2023) and further detailed in the Sendai Framework for Disaster Risk Reduction (Kuller et al., 2021; UNDRR, 2023b; World Meteorological Organisation, 2023).

Institutions, in their effort to forecast floods, face significant challenges. These challenges include inadequate technologies, personnel capacity, weak planning systems, ineffective EWS, inadequate vulnerability and hazard maps, and non-cooperation and non-compliance among some community members (Almoradie et al., 2020). The findings by Almoradie et al. (2020)

revealed that existing models for flood predictions have a coarse resolution, hindering effective flood management and adaptation practices. Computational power, capacity, and data availability hampered the attempt to run models at a higher resolution. The White Volta especially suffers from inadequate data and sparse gauge station locations, hindering water level monitoring, resource management, and flood prediction in the area (Almoradie et al., 2020; Li et al., 2022). The lack of station data and gaps in the existing ones introduce uncertainty, especially when using spatial interpolation with limited data. This interpolation is necessary for obtaining hydrological model input, but can lead to significant errors. Furthermore, this uncertainty affects model calibration and validation results (Jung et al., 2012). It has become important to find complementary methodological approaches in developing EWS with improvement in the lead-time and spatiotemporal resolution (Almoradie et al., 2020).

Satellite and reanalysis data, such as CHIRPS, ERA5, ARC2, CFSR, PERSIANN-CDR, and GloFAS discharge data, can complement limited ground-based data. However, these surrogate data contain biases and uncertainties that must be validated against ground-based data. Moreover, Challenges associated with flood risk management are being aided by the advancement in Earth Observations (EO) with more precise, higher resolution data in real-time (Avalon-Cullen et al., 2023) and machine learning (ML) models (Hunt et al., 2022; Nevo et al., 2022). ML methods like Random Forest (RF), Artificial Neural Networks (ANN), Long Short-Term Memory (LSTM), and Convolutional Neural Networks (CNN) have aided in making flood forecasting more promising with higher accuracy (Khairudin et al., 2022; Nevo et al., 2022). ML can adjust its boundary conditions with changing hydrological conditions and also learn from past data, predicting water levels accurately and quickly, even with scarce amounts of data (Huang et al., 2022). That is not to say that machine learning does not need data. They are as good as their training data, and their performance depends on the quantity and quality of the training data (Bayat & Tavakkoli, 2022). The use of ML models for flood-related research in regions with data scarcity is often promoted compared to the physically-based models, which require larger datasets (Mosavi et al., 2018; Nevo et al., 2022; Sellami et al., 2022; Yang et al., 2023).

To improve the accuracy of streamflow forecasting, researchers have explored hybrid models that integrate the advantages of different approaches to offset their individual weaknesses (Hunt et al., 2022; Roy et al., 2023). For example, physically based hydrodynamic models, remote sensing technologies, and data-driven approaches such as deep learning and ML (ANN, CNN, ConvLSTM) have been combined in flood forecasting (Estébanez-Camarena et al., 2023; Kim et al., 2019; Sampurno et al., 2022). Puttinaovarat & Horkaew (2020) combined geospatial, meteorological, and hydrological data obtained from the Global Flood Awareness System (GloFAS), hourly rainfall prediction, and crowdsource (or volunteer) data for flood forecasting in Thailand, aided by ML. Combining machine learning, remote sensing, and global flood forecasting systems like GloFAS offers promising avenues for improving flood prediction and risk management. However, their application in the White Volta basin remains underexplored, necessitating further research to develop an effective flood mitigation strategy for the area.

A significant gap exists in current studies. While prior literature has delved into flood perception, preparedness, and impact assessments in Southern Ghana, particularly Accra and Kumasi (Abass, 2022; Amaglo et al., 2022; Antwi-Agyei et al., 2023; Osei et al., 2021; Poku-Boansi et al., 2020; Yin et al., 2021), limited attention has been given to flood forecasting and FEWS in Northern and, specifically, the White Volta basin, suggesting potential for streamflow forecasting (Almoradie et al., 2020).

To address this gap, the present study examines the effectiveness of frameworks for Flood Early Warning Systems (FEWS) and validates satellite and reanalysis data against ground-based measurements. Additionally, the study simulates and forecasts streamflow at 1-, 5-, and 10-day intervals using Random Forest (RF) and Long Short-Term Memory (LSTM) driven mainly by rainfall, temperature, and soil moisture. Furthermore, the study incorporates the Coupled Model Intercomparison Project Phase 6 (CMIP6) - Shared Socioeconomic Pathway SSP5-8.5 scenario to project streamflow from 2020 to 2050.

1.2 Aim of the Study

This study investigates and predicts streamflow and flood events in the White Volta basin of Ghana.

1.3 Specific Objectives

Specifically, the study seeks to:

- Evaluate the current state of the Flood Early Warning Systems (FEWS) in the White Volta basin.
- Validate satellite and reanalysis products with ground-based observations in the White Volta basin of Ghana.

- Predict and evaluate streamflow using a shallow model (RF) and a deep learning model (LSTM) for flood mitigation and management in the White Volta basin of Ghana.

1.4 Research Questions

The research seeks to address the following questions:

- How effective are the current FEWS in the White Volta basin?
- What is the reliability and consistency of reanalysis and satellite data for flood forecasting in the White Volta basin of Ghana?
- How does the performance of a shallow model (RF) compare to a deep learning model (LSTM) in forecasting streamflow in the White Volta basin of Ghana?

1.5 Research Hypothesis

Given the limited progress in climate policy implementation in Ghana, it is hypothesized that climate projections under the SSP5-8.5 scenario will provide a more realistic basis for assessing future climate impacts in Ghana.

1.6 Significance of the Study/Expected Result

By assessing the current structure of FEWS in the White Volta basin, the study draws attention to key strengths, weaknesses, opportunities, and threats that are important for policy implementation in the field of flood management.

By validating open-source satellite and reanalysis data from ERA5, CHIRPS, MERRA-2, TRMM, ARC2, CSFR, and PERSIANN-CDR, this study provides reliable data sources for flood predictions and water management in the basin faced with limited ground data.

By developing an ML LSTM and RF, this study improves on the current streamflow and flood forecasting in the basin, Northern Ghana. These models are important for more accurate and timely flood forecasts, leading to improved preparedness and mitigation measures by strengthening the capacity of early warnings.

Lastly, this study serves as a reference for policy guidelines and frameworks as well as future research. Thus, it provides a practical approach to managing flood risk and can serve as a model for similar regions facing similar challenges. Managing flood occurrences in the basin is central to securing livelihood sources and addressing food insecurity.

1.7 Conceptual Framework

Flood risk management is essential for ensuring the safety and sustainability of communities, especially in areas prone to flooding. An effective FEWS is required as extreme weather events become more frequent and intense. This system should adopt a holistic approach that includes stakeholder involvement, policy implementation, and robust streamflow/flood monitoring and forecasting. Stakeholders play a crucial role in developing and executing policies, monitoring and forecasting floods, and disseminating early warnings, which are vital for disaster risk reduction. For instance, local communities provide essential knowledge that aids in policy formulation and enhances the accuracy of flood forecasting.

Leveraging open-source satellite and reanalysis data, as well as ML models, is critical for predicting water levels and monitoring potential flood risks in data-scarce regions. This enables authorities to implement timely and targeted measures for flood mitigation and response, which ultimately reduces the hazard, exposure, and vulnerability of the population.

Streamflow forecasting is key to predicting water levels and monitoring potential flood risks. This allows authorities to enact timely and precise interventions. Additionally, ground-based monitoring stations offer crucial localised data on water levels, river flow rates, and soil moisture. These stations complement satellite observations and improve their accuracy in streamflow forecasting. Enhancing ground data collection policies and installing telemetric systems and radar are essential for improving flood and streamflow monitoring. Suppose the government fails to implement policies or enhance the existing infrastructure for ground data collection for developing operational models and optimising existing ones, the risk of flood hazard, exposure, and vulnerability is likely to increase.

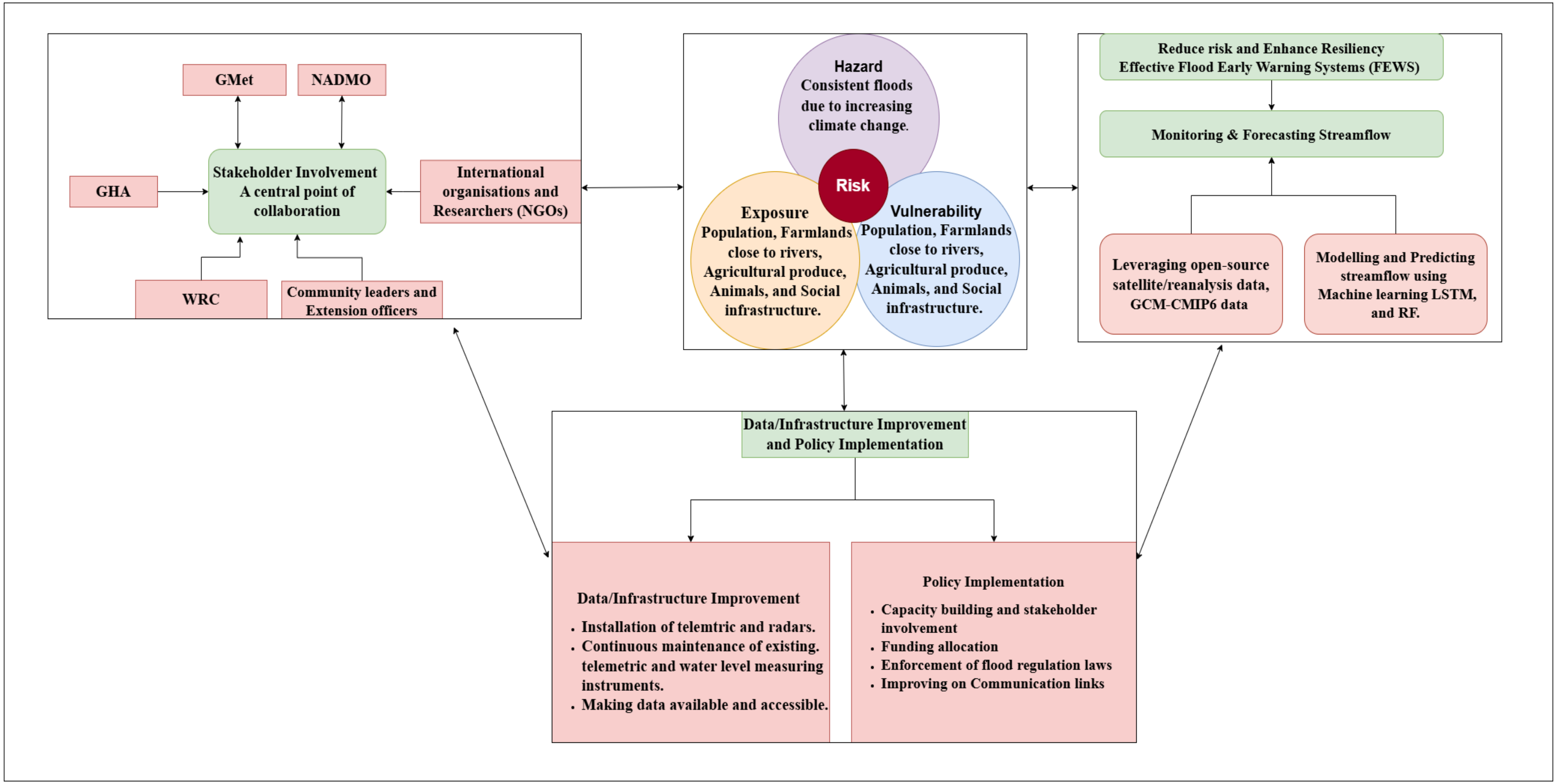

Figure 1.2: Conceptual framework illustrating the key components and relationships underpinning the study (Source: Author's own construct).

1.8 Structure of the Thesis

Chapter 1 outlined the flood challenges in the White Volta basin, justified the significance of the research, identified existing knowledge gaps, and stated both the overall aim and specific objectives of the study. Chapter 2 gives a broader view of the topic focusing on the state of floods as a disaster, flood risk management, and flood early warning system in Ghana with key challenges, streamflow monitoring as an early warning system, the role of physical models, ML (LSTM and RF), and open source satellite, reanalysis data as well as the CMIP6 data. Chapter 3 assessed the current state of the FEWS in the basin, along with its potential opportunities and challenges. This work forms the basis of the first manuscript submitted to the Journal of Flood Risk Management, titled ‘Flood early warning systems in the White Volta basin, Ghana: challenges and opportunities’, which has undergone the first revision process. Chapter 4 focused on validating various open-source satellite and reanalysis datasets, specifically rainfall, mean temperature, and soil moisture, using ground-based observations from locations near gauge stations in the basin. This chapter has been published in Meteorological Applications (Katsekpor et al., 2024a) under the title ‘Comparative analysis of satellite and reanalysis data with ground-based observations in Northern Ghana.’ Chapter 5 applied ML models specifically, LSTM and RF, using the validated data from Chapter 4 to forecast streamflow at 1-, 5-, and 10-day intervals for flood management and mitigation. The models were also trained with CMIP6 SSP5-8.5 scenario data to project streamflow up to the 2050s. This study has been published in Environmental Challenges (Katsekpor et al., 2025). The manuscript is titled ‘Streamflow forecasting using machine learning for flood management and mitigation in the White Volta basin of Ghana.’ Chapter 6 concludes the work and gives recommendations for further research and policy directions.

CHAPTER 2

2 Literature Review

2.1 Introduction

This chapter provides a theoretical and conceptual review of flood risk reduction strategies, examines the significance of streamflow forecasting, and explores the influence of climate change on future streamflow patterns and associated flood risks. The study also reviewed the role of open-source satellite and reanalysis, as well as physical-based and data-driven machine learning models in streamflow predictions.

2.2 Examining the Concept of Disasters

Disasters have been an integral part of the Earth's history (Veenema, 2018). The number of disasters has increased fivefold over the past 50 years, partly due to human-induced climate change (World Meteorological Organisation, 2023). In 2010, there were 435 natural disasters resulting in 329,880 deaths, over 26 million people injured or homeless, and around $143 billion in material damages, according to the Annual Disaster Review (Guha-Sapir et al., 2016). Future disasters are projected to rise due to the convergence of global warming, climate change, sea level rise, resource depletion, and social factors (Alexander, 2006).

The term 'disaster' has no universal definition. Their definition are dependent on the discipline using them, as a result, different terms have been used to define disaster. A disaster is characterised as a sudden natural or human-induced event, including technological malfunctions, that temporarily overwhelms the response capacity of individuals, communities, or ecosystems, leading to significant harm, economic loss, social disruption, injuries, or loss of life (Parker, 1992). The World Health Organisation and the Pan American Health Organisation provide the following definition for a disaster: it is an occurrence that typically happens suddenly and unexpectedly, leading to significant disturbances for the affected individuals and objects. This leads to loss of life, public health impacts, destruction of community property, and significant environmental damage. Such a situation disrupts normal life, causing misfortune, helplessness, and suffering. It also negatively impacts the socioeconomic structure of a region or country and may require outside assistance and immediate intervention due to environmental modifications (Severin & Jacobson, 2020). Similarly, the Centre for Research on the Epidemiology of Disasters (CRED) describes a disaster as a sudden and unforeseen event that results in substantial damage and human suffering, surpassing the ability of local systems to cope and necessitating support from national or international sources (CRED, 2020).

While often natural, disasters can also result from human actions (CRED, 2020). The three definitions share the core idea that a disaster is an unexpected event causing significant damage, harm to people, disruption, and suffering. They all emphasise the overwhelming nature of the event and the need for external assistance. The main differences lie in specific aspects and focus: Parker's definition highlights the role of technological failures, the WHO and PAHO's definition emphasizes disturbances and impact on the environment, while CRED's definition includes the possibility of disasters having human origins.

A review of the types of disasters by Shaluf et al. (2003), has categorised them into natural, man-made, and hybrid. Natural disasters are devastating occurrences caused by natural hazards, which stem from internal, external, weather-related, and biological factors. These disasters are uncontrollable by humans and are often termed as 'Act of God' (Shaluf et al., 2003). The International Federation of Red Cross and Red Crescent Societies (IFRC) (2014) classifies natural disasters into five types: geophysical (such as earthquakes, landslides, tsunamis, and volcanic eruptions), hydrological (including avalanches and floods), climatological (like droughts, extreme temperatures, wildfires, and floods), meteorological (such as storms, cyclones, wave surges, and floods), and biological (including disease outbreaks and plagues caused by insects or animals) (Shaluf et al., 2003). On the other hand, Man-made disasters are catastrophic events caused by human decisions. They can be either sudden or long-term, with sudden ones referred to as socio-technical disasters. Man-made disasters include environmental degradation, pollution, and accidents, such as industrial, technological, or transport-related incidents, often involving hazardous materials. Hybrid disasters fall in between natural and man-made and are often viewed as a result of both human choices and natural forces, sharing the common element of causing significant harm to people, property, and the environment. However, this thesis focuses extensively on flood occurrences and how they can be managed.

2.3 Floods

The Intergovernmental Panel on Climate Change Special Report (IPCC SREX) report cited in Kundzewicz et al. (2014) defines a flood as 'the overflowing of the normal confines of a stream or other body of water or the accumulation of water over areas that are not normally submerged'. According to Seneviratne et al. (2012), floods are caused by extreme excesses of precipitation or unexpected releases of excess water from storage, like dams or snow packs. Compared to drought, they are normally confined to small areas. Types of floods include river (fluvial/riverine) floods, flash floods, urban floods, pluvial floods, sewer floods, coastal floods, and glacial lake outburst floods.

Floods are the most common and destructive natural disasters, making up almost half of all disasters in the last ten years, and are responsible for 6.8 million deaths in the 20th century (Jonkman, 2005). For example, the 2005 and 2009 floods in Cumbria and the 2007 flooding across England resulted in loss of lives and major economic impacts. The summer 2007 floods alone cost over £3.2 billion (Thorne, 2014). Between 1998 and 2017, floods accounted for 43.4% of recorded natural disasters, with 45% of people being impacted by weather-related disasters (UNDRR & CRED, 2018). Developing countries suffered nearly 50% of flood-related fatalities during the last quarter of that century. The impact of flooding, which is projected to increase, can be far-reaching, causing extensive damage to infrastructure, homes, agriculture, and posing a significant threat to human lives and wildlife (Tanoue et al., 2016; United Nations Office for Disaster Risk Reduction, 2015). With the onset of global warming and climate change, the frequency and intensity of flood events have been projected to increase (Petrova, 2022). This is primarily due to several interconnected factors, including rising sea levels, increased precipitation, changing weather patterns, urbanisation, and storm surges (Ali et al., 2020).

According to Rentschler et al. (2022), many developing nations in Africa, Asia, and Latin America experience frequent flooding. As indicated by Douglas (2017) and Rentschler et al. (2022) Africa, particularly sub-Saharan Africa, is highly susceptible to floods, a situation usually triggered by a combination of erratic rainfall patterns and inadequate drainage infrastructure, which increases the region's vulnerability to these disasters. The UNDRR's data reveals that in the last two decades, floods accounted for 43% of all reported natural disasters in Africa, impacting the lives and livelihoods of millions of people (UNDRR, 2023a). Agriculture, which is a cornerstone of many developing economies, is usually affected as flooding destroys crops and farmlands, leading to food scarcity and economic instability (Armah et al., 2010; Atanga & Tankpa, 2021; UNDRR, 2023a). The Food and Agriculture Organisation (FAO) highlights that flood events in Africa cause approximately $11 billion in damage to crops annually (United Nations Economic Commission for Africa & Food and Agriculture Organization of the United Nations, 2018). Furthermore, floods often compromise the safety of drinking water sources and sanitation facilities, thereby facilitating the spread of waterborne diseases such as cholera (Ntajal et al., 2022).

Ghana, situated in West Africa, also grapples with a significant flood risk, predominantly during the rainy season. Aside from epidemics, flood is the second highest natural disaster, causing devastation in the country (Ansah et al., 2020). The capital city, Accra, has been especially vulnerable to annual flooding events over the years (Okyere et al., 2013). Amoako & Frimpong Boamah (2015) explain that the city's topography, coupled with inadequate drainage systems and unplanned urbanisation, has contributed significantly to the recurrent flooding events experienced in the nation's capital. Riverine flooding is another common cause of floods, affecting especially the White Volta basin with annual occurrences. These floods are a result of torrential rainfall and the release of the Bagre dam, causing the displacement of people and large hectares of agricultural land. Intense rainfall in 2018, with the Bagre Dam spillage in Burkina Faso, affected 100,000 individuals, resulting in 34 fatalities and the destruction of 196 km^2 of agricultural land in the basin (Armah et al., 2010; Atanga & Tankpa, 2021; Katsekpor et al., 2024a). In 2021, floods in the Upper East of Ghana killed 5 people and destroyed homes, roads, and bridges (FloodList, 2021). In 2024, floods killed two people and caused further damage to roads and bridges (Africanews, 2024). The PARADeS project identified Accra, Kumasi, and the White Volta basin to be the most critical (highly vulnerable) areas affected by floods (Almoradie et al., 2020). Floods in Ghana also have environmental repercussions, affecting ecosystems and water resources, leading to the contamination of water bodies and their attendant long-term risks to the health of the population (Ntajal et al., 2022).

2.3.1 Flood Risk Management

Understanding the relationship between hazards, flood disasters, risk, vulnerability, exposure, and resiliency is essential for flood disaster management (UNISDR, 2017). A hazard is a potential human or natural threat that can cause harm (Schneiderbauer & Ehrlich, 2004; UNISDR, 2017). A disaster occurs when a hazard materialises. Risk is the likelihood of a hazardous event and its impact, influenced by the hazard's probability, vulnerability of exposed elements, and their capacity to cope (Peduzzi et al., 2009; Schneiderbauer & Ehrlich, 2004). Vulnerability is the susceptibility of a community to harm, while exposure is the presence of people or assets in hazard-prone areas (Schneiderbauer & Ehrlich, 2004). Exposure alone does not equate to risk; vulnerability must also be present. Resilience is the ability to recover from difficulties, reducing damage and speeding recovery (Woods, 2015). In summary, hazards trigger disasters and risks, but vulnerability, resilience, and adaptation measures shape the extent of losses.

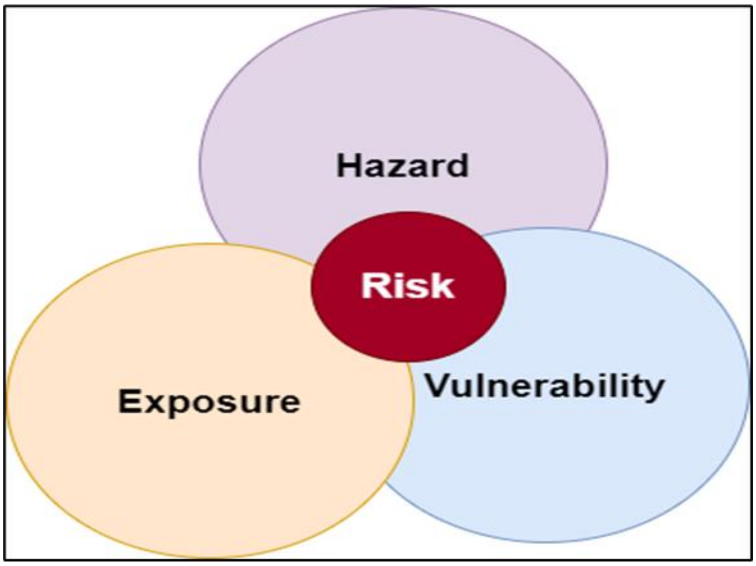

Figure 2.1: Relationship between risk, hazard, exposure, and vulnerability (Sayers et al., 2013).

Managing flood risks efficiently maximizes benefits with limited resources. Flood risk management is a comprehensive, practical method combining various strategies to reduce flood risks by addressing community exposure and vulnerability (Sayers et al., 2013). This approach encompasses prevention, emergency preparedness, response, and recovery, aiming to minimise flood impacts rather than eliminate them. As climate change increases the frequency and severity of extreme weather events, effective flood risk management becomes increasingly critical (Sayers et al., 2013). The general approach to managing floods includes structural and non-structural measures (Sayers et al., 2013; Wang et al., 2022). Structural measures involve constructing physical infrastructures like levees, floodwalls, reservoirs, and stormwater systems to alter the natural environment and manage water flow, thus reducing flood risks (Sayers et al., 2013). However, these measures can be costly and may have negative environmental impacts, such as increased erosion and decreased ecological health (Amoateng et al., 2018). Non-structural measures focus on policies, regulations, and planning to reduce vulnerabilities and enhance resilience. These measures include land-use planning, floodplain management, early warning systems, emergency preparedness, and community engagement (Wang et al., 2020). They aim to raise awareness, provide timely alerts, and involve communities in decision-making, fostering a culture of resilience and sustainable development. An integrated approach combining both structural and non-structural measures, such as early warning systems and proper land-use planning, is essential for effective flood risk management (Chan et al., 2020). This holistic method enhances adaptive capacity, preserves natural floodplains, and promotes ecological integrity while empowering communities to better handle flood risks.

2.3.2 Flood Management in Ghana, Stakeholder Involvement, and Challenges

As a result of climate change, Ghana is expected to experience more frequent and severe flood events, calling for urgent, sustainable flood risk management (FRM) strategies with full participation from community members, government institutions, and other stakeholders. One of the approaches of sustainable FRM is actively developing systems to communicate and forecast floods to communities. If effectively communicated and comprehended, FEWS can enhance the accuracy of contingency planning and evacuation, thus safeguarding people and potentially valuable economic assets from harm.

NADMO, GHA, WRC, and GMet are the primary entities developing FEWS. GHA plays a key role in monitoring rivers and other water levels, and WRC acts as a coordinating agency in managing water bodies, including transboundary ones (Amoako & Frimpong Boamah, 2015). NADMO's responsibilities include managing disasters like floods by coordinating government and non-governmental resources and building community capacity to respond to this while improving livelihoods through social mobilisation, job creation, and poverty reduction initiatives (UNDP & NADMO, 2012). GMet is tasked with monitoring meteorological and climate conditions and issuing forecasts of rainfall and storms (IFRC, 2023). Together, both GMet and GHA issue early warnings on floods, which are then communicated to NADMO, who are closer to the community members, especially during the flood event (UNDP & NADMO, 2012).

The Ghana government has actively implemented the National Water Policy, which advocates for measures such as community consultation in implementing mitigation strategies in the form of early flood warnings and enforcement of buffer zone laws to prevent settlement near river banks (Almoradie et al., 2020). Another significant strategy taken is the implementation of the Blue Agenda, which targets flooding and associated threats through initiatives like enforcement of building regulations and public education (Danso & Addo, 2017). Aside from these Governmental institutions, there are also non-profit organisations like STAR-Ghana that collaborate with NADMO. They provide sensitisation programs to communities within the White Volta basin, namely Sugu Tampia in the Kumbungu District, Nawuni in the Savelugu District, Chama Janga in West Mamprusi, and Kubugu-Yagaba in the Mampurugu Moaduri District. Sensitisation programs include identifying risk factors of floods in their communities and how they can be managed to reduce the impact. Generally, the foundation strengthens flood risk management structures at the local and regional levels by serving as a middle person between the communities and the philanthropies, mobilising local resources, and enhancing EWS, among others.

Despite these interventions, findings by Almoradie et al. (2020), Amoako & Frimpong Boamah (2015) and Yiwo et al. (2022) shows the weak coordination between agencies and inadequate participation of community members in FRM. Another challenge identified in Ghana's effort is that strategies for managing floods tend to be more focused on responding to and addressing the consequences of floods after they occur, rather than proactively preventing them from happening in the first place (Almoradie et al., 2020; Amoateng et al., 2018; Danso & Addo, 2017).

Policies on Flood Management in the White Volta Basin

Although Ghana has undertaken efforts to implement several flood risk management policies within the White Volta basin, as outlined in Table 2.1, substantial challenges continue to hinder their effective implementation. For example, the White Volta Flood Hazard Assessment, which seeks to establish an operational FEWS with modern hydrological and meteorological systems, faces significant challenges, which include inadequate funds, community engagement, data accessibility and quality, transboundary cooperation, and technical capacity (Klutse, 2022).

The Government of Ghana in partnership with the Ministry of Sanitation and Water Resources in April 2024 developed a policy that seeks to mitigate the effects of climate change and prevent damage caused by extreme floods and droughts on people and agriculture, facilitate intra-institutional collaboration to address overarching climate change challenges in an integrated manner, build institutional capacity to manage climate change, define and implement adaptation and mitigation programs and measures as well as engage marginalised groups, especially women and youth (Ministry of Sanitation and Water Resources, 2024). The Government seeks to develop an operational framework for a FEWS, promote the construction of structures for flood protection, and promote rainwater harvesting (Ministry of Sanitation and Water Resources, 2024).

Table 2.1: Policies on water resources and flood management in the White Volta basin.

<table>
<tr><th>Policies</th><th>Strengths of these Policies</th><th>Challenges faced</th></tr>
<tr><td>Volta River Development Act, 1961 (Act 46)</td><td rowspan="8">Emphasizes integrated water management in the Volta basin
Collaborate actively with neighbouring countries in managing the transboundary Volta basin.
The policies cover various flood risk management, including water resource management, riparian buffer protection, and climate change adaptations.</td><td rowspan="8">Limited funds and logistical challenges often lead to differences between policy objectives and practical life implementation.
Limited infrastructure, capacity training, and technical know-how often affect the implementation of these policies.
Bureaucratic systems and officers’ lack of willingness to coordinate at the local and national agencies impeded particularly effective flood management.
The increasing threat of climate change and weather variability poses challenges in accurately predicting extreme events.
Community/ Public engagement and awareness.
Data accessibility and quality.
Making flood management a key priority.</td></tr>
<tr><td>National Water Policy (2007)</td></tr>
<tr><td>National Riparian Buffer Zone Policy (2011)</td></tr>
<tr><td>National Integrated Water Resources Management Plan (2012)</td></tr>
<tr><td>National Climate Change Policy (NCCP)</td></tr>
<tr><td>Master Plan for Development and Sustainable Water Management (MPSDM)</td></tr>
<tr><td>White Volta Flood Hazard Assessment</td></tr>
<tr><td>ECOWAS Flood Management Plan and Strategies</td></tr>
</table>

Adapted from Klutse (2022).

2.4 Flood Early Warning System (FEWS)

Providing an effective Early Warning System (EWS) is key to saving lives and properties and consequently reducing flood impact, especially on the poorest in society. For instance, nations with limited EWS experience six times higher disaster-related mortality rates than nations with advanced EWS (UNISDR &WMO, 2023). According to UNISDR (2017), an EWS is a coordinated framework that integrates hazard monitoring, forecasting, risk evaluation, communication, and preparedness to support timely actions that reduce disaster risk. Similarly, WMO (2023) views FEWS as interconnected structures that provide rainfall forecasts, operate hydrometric networks, run real-time flood modelling software, and issue early flood alerts. From the two definitions above, it is important to note that FEWS is broad, which includes forecasting and monitoring floods, risk assessment, communicating hazards to the public, ensuring an adequate response to floods, and conducting evaluations after flood events. Evidence further indicates that countries with comprehensive multi-hazard early warning systems experience lower mortality rates compared to those with minimal or no such systems (WMO, 2023). Although the importance of EWS for climate adaptation is widely acknowledged, less than half of the least developed countries and only about one-third of small island developing states report having such systems in place. To address this, the UN has launched the 'Early Warning for All' Initiative, aiming to ensure that EWS protects everyone within five years. Countries in West Africa including Ghana, Nigeria, Gambia Libera, Togo, Niger, and others recently implemented early warning for all (WMO, 2023). In recent times, Global Flood Awareness System (GloFAS), the Global Flood Detection System (GFDS), the Global Forecast System (GFS), the African Flood Forecasting System (AFFS), and others have provided weather forecasts that facilitate the FEWS in Africa. For instance, A study conducted in Africa revealed that the African Flood Forecasting System (AFFS) accurately identified approximately 70% of reported flood events (Thiemig et al., 2015). The system was particularly effective in forecasting prolonged riverine floods lasting over a week and impacting areas larger than 10,000 square kilometers (Fofana et al., 2023; Thiemig et al., 2015). In West Africa, particularly Ghana, some active FEWS include FANFAR and GloFAS embedded in myDEWETRA-VOLTALARM. FANFAR provides reliable and timely flood forecasts and alerts through web visualisations, SMS, email, and APIs. It uses an open-source hydrological model in a cloud-based Information Communication Technology (ICT) environment to maintain robustness despite frequent power and internet outages in West Africa (Lienert et al., 2022). The myDEWETRA -VOLTALARM FEWS brings together different data from local, national, and international sources to monitor and predict real-time floods and droughts

(Reggiani et al., 2022). This platform is shared among six countries, which include Togo, Cote d'Ivoire, Burkina Faso, Benin, Mali, and Ghana, who forms part of the Volta River basin. For instance, Ghana forecasters can see Burkina Faso's (upstream) situation, provide warnings, and take necessary preparedness measures. Key limitations of FEWS include delays in data transmission and frequently inaccurate information, which are mainly due to inadequate tools to collect data (Reggiani et al., 2022).

2.4.1 Streamflow Monitoring and Forecasting

Streamflow refers to the volume of water flowing through a channel per unit of time, and it exhibits temporal and spatial variability (Wiche & Holmes, 2016). While excess streamflow is essential for the ecosystem, it may pose a flood hazard that threatens settlements around it. Understanding the amount of streamflow and how it varies over time and space is essential for hydrology, flood forecasting, emergency response, and areas such as water resource planning and environmental protection.

2.4.2 History of Streamflow Forecasting

Streamflow forecasting is a very important aspect of river flood management. It involves predicting the flow of water in rivers and streams, allowing authorities and communities to make informed decisions and take preventive measures in the face of potential flood events (Yaseen et al., 2015). Historically, one of the first attempts to forecast streamflow can be attributed to the work of Mulvaney (1851), which comprised a linear regression relationship between catchment rain and streamflow. He laid the foundation for the concept of hydrograph and estimating runoff. Likewise, the work of Imbeaux (1892), cited in Hunt et al. (2022), was among the first attempts to quantitatively predict a flood hydrograph adopting a semi-distributed model of snowmelt and runoff generation in France. His methodology played a key role in the field of Hydrology and flood prediction. Ross (1921), as referenced in Hunt et al. (2022), advanced this work in the United States by integrating Mulvaney's (1851) simple rational method for estimating peak flow. In addition, the Muskingum-Cunge method developed by Albert R. Robinson and Ven Te Chow significantly improved the accuracy of flood prediction and river flow routing (Moglen, 2015). The work of Horton (1933) also contributed to physics-based streamflow models with his insight into how soil properties and infiltration capacity affect runoff generation (Beven, 2004). His work laid the foundation for understanding how land surface characteristics and rainfall patterns influence runoff in watersheds, which is fundamental in hydrology and the study of water resources management.

Additionally, Edward A. Thomas pioneered the use of physics-based models and computer simulations to predict streamflow. His work made a significant contribution to the development of physically based models, which are now widely used for flood forecasting and water resource management. In recent years, data-driven models like the application of ML algorithms have gained much attention in streamflow forecasting due to the drawbacks of the physical-based models (Mosavi et al., 2018).

2.4.3 Streamflow Forecasting in Ghana

Ghana is endowed with many streams and rivers (White Volta, Black Volta, Pra, Ayensu, Densu Rivers, among others), making riverine flooding one of the most common types of floods experienced in the country (Mensah & Ahadzie, 2020). Streamflow forecasting is a crucial tool in river flood management, providing communities with the knowledge and time to prepare for and respond to flooding events (Kankam-Yeboah et al., 2013). Its historical evolution, range of forecasting approaches, and importance in infrastructure planning and disaster response make it a pivotal component in flood-prone regions globally, particularly in developing nations like Ghana and across Africa (Gaisie & Cobbinah, 2023).

Streamflow forecasting in Ghana has become increasingly important due to the recurring threat of riverine floods, particularly in the White Volta basin during the rainy season and spillage of the dams upstream. As a result, the government and relevant agencies like the Water Resource Commission (WRC) have been working to enhance the country's streamflow forecasting capabilities by investing in early warning systems (Kankam-Yeboah et al., 2013). The Ghana Meteorological Agency (GMet), being primarily responsible for monitoring and forecasting weather-related events in the country, often collaborates with the Ghana Hydrological Authority (GHA) and NADMO to provide timely flood warnings (Agyekum et al., 2023). GMet utilises data from rain gauges, river gauges, and weather radar strategically placed in various parts of the country to track rainfall patterns and river levels (IFRC, 2023). According to IFRC (2023), Ghana is making significant efforts to develop and implement early warning systems for floods, particularly in high-risk areas. These early warning systems typically involve the collection of real-time data on rainfall, river levels, and weather conditions, which is used to make forecasts, after which alerts and warnings are issued to the general public and relevant authorities based on these forecasts (IFRC, 2023).

Challenges

GMet and GHA, in their effort to make forecasts, face limited equipment and technical capacity. These institutions lack the necessary equipment and technical capacity to monitor the weather, collect hydrometeorological data, calibrate models, and provide early warnings with adequate lead time, which is crucial for preparing for extreme weather events (Almoradie et al., 2020; UNDP & NADMO, 2012). Gauge stations are sparsely distributed with inadequate telemetric and radar instruments. The second challenge has to do with inadequate lead time. Effective flood forecasting and early warning systems require the ability to predict extreme weather events with sufficient lead time. Currently, GMet cannot offer this, limiting the time available for preparation and response (Almoradie et al., 2020; UNDP & NADMO, 2012).

2.4.4 Models for Streamflow Forecasting

Streamflow forecasting plays a pivotal role in enhancing preparedness and reducing the adverse effects of flooding by allowing authorities to continually monitor water levels. Furthermore, precise streamflow forecasting is crucial not only for effective water resource management but also for informed environmental planning. Models for streamflow forecasting are categorised into physical-based, conceptual, and black-box/data-driven models (Abba et al., 2020). However, in recent years, hydrological models have generally been classified into process-based (physical) and data-driven models.

Physics-based model

Physical-based models are commonly used in predicting hydrological events like rainfall/runoff, storms, floods, shallow water conditions, hydraulic models of flow, etc. (Mosavi et al., 2018). These models are also referred to as the white box or process-based model. Sharma & Machiwal (2021) define these models as using differential equations to describe the physical laws of mass, energy, and momentum conservation, thereby giving a detailed description of the hydrologic system. According to Ahmadi et al. (2023), the physical-based models provide an accurate estimate of hydrologic variables. Beven (2020) added that physical-based models are created from field data such as soil texture, land use, and vegetation cover, among others, and are based on pre-existing mathematical correlations between various hydrological processes. Simply put, the physical-based model is a description method of the hydrologic variables of the targeted basin (Khairudin et al., 2022). Examples of these models include Geospatial Hydrologic Modelling (HEC-GeoHMS) (Darko et al., 2021; Haile et al., 2016), Soil and Water Assessment Tool (SWAT), (Obuobie & Diekkrüger, 2023; Osei et al., 2021; Senent-Aparicio et al., 2021), MIKE (Ghosh et al., 2019), physically based distributed hydrological models (PBDHMs) (Chen et al., 2016), LISFLOOD (Harrigan et al., 2020), etc. These models are also effective in capturing the physics of the hydrological cycle, characterised by the basin's response to rainfall events (Roy et al., 2023). For instance, the LISFLOOD uses static maps in generating discharge for the Global Flood Awareness System (GloFAS). While physics-based models have seen significant advancements, they are presently constrained by a lack of understanding of processes, insufficient data, especially regarding the subsurface, and inadequate grid resolution (Hunt et al., 2022). Hydrological-hydrodynamic models for flood forecasting suffer from coarse resolution, inadequate data in the White Volta region, and sparse gauge station locations (Almoradie et al. 2020). Moreover, these models fail to account for the random variability inherent in hydrologic systems, and linear regression models overlook the nonlinear behaviour of hydrologic processes (Ahmadi et al., 2023).

LISVAP model

LISVAP is a pre-processor for LISFLOOD that calculates potential evapotranspiration grids using the Penman-Monteith or Hargreaves equations (Burek et al., 2013). The model is implemented in PCRaster Environmental Modelling language with a Python interface. This study ran the model using Linux with installed PCRaster and Python. The model's primary output includes evaporation of open water bodies (e0), evaporation from bare soil (es), and potential evapotranspiration (et) (Burek et al., 2013). The formula of the main output of the LISVAP model are shown below:

$$et = \frac{\Delta R_{na} + \gamma EA}{\Delta + \gamma}$$

$$es = \frac{\Delta R_{na,s} + \gamma EA_s}{\Delta + \gamma}$$

$$e0 = \frac{\Delta R_{na,w} + \gamma EA_w}{\Delta + \gamma}$$

where :

es is potential evapotranspiration for reference crop $mm\ day^{-1}$, es is potential evaporation for bare soil surface $mm\ day^{-1}$, e0 is potential evaporation for open water surface $mm\ day^{-1}$, R_{na} is net absorbed radiation, reference crop $mm\ day^{-1}$, $R_{na,s}$ is net absorbed radiation - bare soil surface $mm\ day^{-1}$, $R_{na,w}$ is net absorbed radiation - open water surface $mm\ day^{-1}$, EA is evaporative demand - reference crop $mm\ day^{-1}$, EA_s is evaporative demand - bare soil surface $mm\ day^{-1}$, EA_w is evaporative demand - open water surface $mm\ day^{-1}$, Δ is slope of the saturation vapour pressure curve $mbar\,^{\circ}C^{-1}$, γ is Psychrometric constant $mbar\,^{\circ}C^{-1}$ (Burek et al., 2013).

LISFLOOD – Distributed Water Balance and Flood Simulation

Developed in 1997 by the Joint Research Centre (JRC) of the European Commission, the LISFLOOD model is a semi-distributed, physically based tool used for applications including flood forecasting, drought analysis, and evaluating the effects of land use and climate change on water resources (Burek et al., 2013; Knijff et al., 2010). The model is normally used in simulating trans-national catchment water balance and is applied in flood forecasting (as in the case of GloFAS), drought and soil moisture assessment and forecasting, assessing the impact of land use and climate changes on water resources, assessment of water balance between water demand, consumption, and availability. The LISFLOOD model's spatial resolution can vary between 10 meters and 5 kilometers, determined by the resolution of input data and computational resources available (Gai et al., 2018). It allows simulating both long-term water balance over several decades with user-defined time steps and individual flood events. Inputs required to run the LISFLOOD model are categorised into meteorological forcings and static maps. Meteorological forcings include information on precipitation and temperature, as well as reference values for evaporation from water and open water bodies, and evapotranspiration for each pixel derived by running the LISVAP model (Cantoni et al., 2022; Hirpa et al., 2018). Static maps provide information on morphological, topographic, soil, and land use properties, river channels, and reservoirs for each pixel of the computational domain (Cantoni et al., 2022; Gai et al., 2018; Hirpa et al., 2018). The primary output of LISFLOOD is river discharge, and it also allows users to rewrite inputs as outputs. The LISFLOOD model comprises multiple elements, including a two-layer soil moisture balance component, modules for simulating both groundwater and subsurface flow, a component that directs surface runoff to the closest river channel, and another that handles the routing of flow within the river network (Burek et al., 2013; Knijff et al., 2010).

LISFLOOD simulates processes that include snowmelt, infiltration, rainfall interception, leaf drainage, evaporation and water absorption by vegetation, surface runoff, preferential flow (bypassing the soil layer), moisture exchange between two soil layers, drainage to groundwater, sub-surface and groundwater flow, and river channel flow (Burek et al., 2013; Knijff et al., 2010). The Xinanjiang model is employed to simulate the soil's infiltration capacity (Ren-Jun, 1992). Sub-surface storage and movement are modelled using a two-parallel linear reservoirs approach, where the upper zone represents rapid runoff and the lower zone represents slow groundwater flow, contributing to base flow. Kinematic wave equations handle surface runoff and channel routing. Reservoirs are modelled as points within the channel network, with inflow equal to the upstream channel flow and outflow determined by various parameters (Burek et al., 2013; Knijff et al., 2010).

All precipitation is considered snow when the average daily temperature drops below 1°C. A snow correction factor may be used to adjust for the underestimation of snowfall. Unlike rain, snow remains on the ground until it melts, and the rate of snowmelt can be calculated based on the complete surface radiation balance. Due to the data demands of radiation balance models, LISFLOOD uses a degree-day factor equation for snowmelt.

$$M = C_M(1 + 0.01 \cdot R\Delta t)\left(T_{avg} - T_m\right) \cdot \Delta t$$

where:

M represents the snowmelt rate (mm), calculated using several variables: C_M is the degree-day factor (mm/°C/day), R is the rainfall intensity (mm/day), Δt is the time interval (days), T_{avg} is the average daily temperature (°C), and T_m is the temperature threshold above which snowmelt occurs (°C).

Interception

Rainfall interception is modelled following Aston (1979) and Merriam (1960), requiring only two parameters. Interception is calculated as:

$$Int - S_{max}[1 - exp(-kR\Delta t \,/\, S_{max})]$$

where:

Int (mm) is the interception per time step, S_{max} (mm) is the maximum interception capacity, R is the rainfall intensity ($mm\ day^{-1}$), k is the density of the vegetation.

Furthermore, The equations show that S_{max} is influenced by the LAI, which represents the vegetation density in each grid cell. The higher the LAI, the greater the maximum interception capacity, up to a certain point. S_{max} is calculated using the empirical relation (von Hoyningen-Huene 1981).

$$S_{max} = \begin{cases} 0.935 + 0.498 \cdot LAI - 0.00575 \cdot LAI^2 & ifLAI > 0 \cdot 1 \\ 0 & ifLAI \leq 0 \cdot 1 \end{cases}$$

Where:

where LAI is the average Leaf Area Index ($m^2\ m^{-2}$) of each grid cell. K constant is given by:

k = 0.046·LAI

The interception value (Int) cannot exceed the storage capacity, defined as the difference between the maximum interception (S_{max}) and the accumulated intercepted water (Int_{cum}). Evaporation of intercepted water (EW_{int}) occurs at the potential evaporation rate from an open water surface ($E0$). The maximum evaporation during each time step is determined by the proportion of vegetated area within each pixel.

$$EW_{max} = E0 \cdot \left[1 - exp\left(-k_{gb} \cdot LAI\right)\right] \Delta t$$

where E0 is the potential evaporation rate (mm/day), k_{gb} is the extinction coefficient for global solar radiation, LAI is the Leaf Area Index, and Δt is the time step. The actual evaporation from the interception store is limited by the amount of water stored on the leaves and is given by the minimum of EW_{max} and Int_{cum} (Supit et al., 1994).

$$EW_{int} = min(EW_{max}\, \Delta t, Int_{cum})$$

Here, EW_{int} represents the evaporation from the interception store, measured in millimeters per time step. It is assumed that all intercepted water either evaporates or reaches the soil surface as leaf drainage within a day. Leaf drainage is modeled using a linear reservoir with a one-day time constant.

$$D_{int} = \frac{1}{T_{int}} \cdot Int_{cum} \Delta t$$

Where:

D_{int} is the amount of leaf drainage per time step (mm) and T_{int} is the time constant for the interception store, set to one day. Further elaborations like the treatment of impervious areas, evapotranspiration, Infiltration, preferential flow and surface runoff, Soil moisture flow, Subsurface flow, hillslope and channel routing are found in the works of (Burek et al., 2013; Knijff et al., 2010).

Empirical Studies on LISFLOOD-OS and GloFAS

The GloFAS, operated by the Copernicus Emergency Management Service, provides flood forecasts and early warning information to aid decision-making at various levels (Harrigan et al., 2020). It employs hydrological models utilising meteorological data, satellite-derived maps, and specific parameter settings to deliver global probabilistic flood forecasts (Alfieri et al., 2020; Harrigan et al., 2020; Hirpa et al., 2018). Key data sources for GloFAS include precipitation estimates, river delineations, soil properties, land use and cover, and digital elevation models, with data drawn from multiple organisations such as MERIT DEM (Multi-Error-Removed Improved-Terrain Digital Elevation Model), FAO (Food and Agriculture

Organisation), CGLS (Copernicus Global Land Service), ISRIC (World Soil Information), and AQUASTAT (Choulga et al., 2024). GloFAS uses LISFLOOD-OS (open source) described in the previous paragraphs as a hydrological model to generate hourly discharge at a 24-hourly timestep. It adopts a data assimilation process to integrate observations from various sources with model outputs, enhancing the accuracy of initial conditions and subsequent flood forecasts. This system uses ensemble forecasting to manage the uncertainties inherent in flood predictions, providing a range of scenarios to help decision-makers understand potential flood magnitudes, timings, and extents. Additionally, GloFAS emphasizes effective communication of flood risks through user-friendly interfaces and interactive tools that present flood forecasts and hydrological information (Harrigan et al., 2020).

The real-time land data assimilation used in GloFAS may cause biases (Harrigan et al. 2020; Zsoter et al., 2019). Calibrating model parameters and validating them with observed data is one way to enhance model performance. Cantoni et al. (2022) showed that calibrating LISFLOOD parameters improved simulated streamflow in ungauged basins in Tunisia, focusing on Xb (Xinanjiang b), PPF (power preferential bypass flow), UZTC (upper zone time constant), GWPV (groundwater percolation value), LZTC (lower zone time constant), CMM, GwLoss, and lower zone threshold (LZT) parameter tuning. Senent-Aparicio et al. (2021) recommended discharge data from GloFAS as a suitable option for calibrating hydrological models in the absence of observed streamflow data. Similarly, GloFAS has been used in flood research in West Africa, Komi et al. (2017) simulated flood extent and flood inundation using the LISFLOOD-OS and the LISFLOOD-FP, respectively, in the Oti basin. The study's methodology enabled the identification and prediction of flood-prone areas that are ungauged.

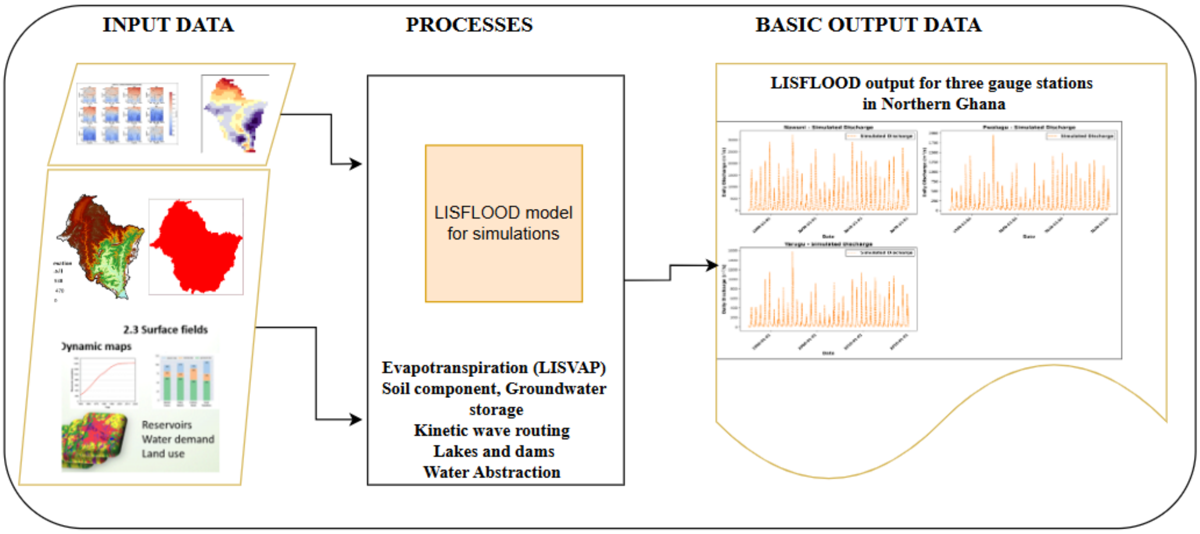

Figure 2.2: Generating daily streamflow with the help of LISFLOOD-OS (adapted from Choulga et al. (2024)).

Data-driven models

Data-driven models have gained prominence in hydrological studies like flood and streamflow prediction due to their significant advancements in computational techniques and capacities over recent decades (Özdoğan-Sarıkoç & Dadaser-Celik, 2024). Data-driven model, as mentioned earlier, does not rely entirely on physical characteristics to simulate streamflow. They can be trained relatively easily without the need for deep knowledge about the physical processes occurring within the hydrological basin (Mosavi et al., 2018; Özdoğan-Sarıkoç & Dadaser-Celik, 2024). This makes them particularly important in the White Volta basin, where there is inadequate and incomplete ground-based data. Data-driven methods include artificial intelligence, machine learning (ML), computational intelligence (CI), and soft computing (SC) that are used as a complement or replacement to the physically based models (Solomatine et al., 2008)

Machine Learning (ML)

The term 'machine learning' was first introduced by Arthur Samuel in 1959, who described it as a field that enables computers to learn without being explicitly programmed (Alzubi et al., 2018). According to Sarker (2021), machine learning is the science of creating algorithms that can learn from and make predictions or decisions based on data. This allows computers to identify patterns, make decisions, learn, and improve from experience without explicit programming, using statistical techniques to enable systems to improve their performance over time (Sarker, 2021). It encompasses a diverse range of algorithms and methodologies, each tailored for specific tasks.

The history of ML has seen several key milestones. It can be traced back to 1950, where Alan Turing proposed the 'Turing Test,' which later gave birth to Artificial Intelligence (AI) at the Dartmouth Conference in 1956 (Muggleton, 2014). In 1958, the work of Frank Rosenblatt's 'Perceptron' laid the foundation of ANN (Sheikh et al., 2023). ML shifted from knowledge-driven to data-driven approaches in the 1990s. Notable achievements in this period include IBM's Deep Blue defeating a World chess champion in 1997 and the coining of 'Deep Learning' in 2006 by Geoffrey Hinton. Breakthroughs like Google's AlphaGo in 2016 marked the combination of ML and tree-searching techniques. Recent developments include Google's Lens, Facebook's DeepFace, and advancements in distributed ML (Sheikh et al., 2023). The timeline illustrates the continuous evolution of ML, from foundational concepts to transformative applications across various domains.

ML models can be predictive, where they perform prediction, or descriptive, gaining knowledge. In certain situations, they could be both (Taffese & Sistonen, 2017). ML models are typically categorized into supervised, unsupervised, and reinforcement learning (Akinsola, 2017). Supervised learning relies on labelled datasets, where each input is matched with a known output; common techniques include linear regression, support vector machines (SVM), and decision trees (Akinsola, 2017). In contrast, unsupervised learning works with unlabelled data, enabling models to detect underlying patterns using methods such as k-means clustering and principal component analysis (Akinsola, 2017). Reinforcement learning involves training models to make sequential decisions within an environment by optimising actions based on feedback in the form of rewards or penalties. Algorithms like Q-learning and Deep Q Networks (DQNs) are widely used in this domain, especially in robotics and gaming applications. These models are not commonly used, unlike supervised and unsupervised learning. It is very important to identify the difference between supervised and unsupervised learning in this study. According to Taffese & Sistonen (2017), the key difference between supervised and unsupervised learning is whether labelled output data is available. In supervised learning, the model is trained with both input and corresponding output labels, allowing the model to learn the correlation between inputs and outputs. This learned relationship can then be applied to predict new cases. On the other hand, unsupervised learning aims at uncovering patterns or structures within the data without the use of labelled output information. Instead, it seeks to discover inherent relationships or similarities among input instances, often through techniques like clustering.

Random Forest (RF)

RF is a popular ML model for classification and regression tasks. RF is an ensemble learning method used for classification and regression tasks (Kim & Han, 2020). This model is created out of multiple decision trees through techniques of bootstrapping and aggregating, often known as bagging, to improve predictive performance (Adnan et al., 2023; Blandini et al., 2023). To Tyralis et al. (2019) bagging decision trees reduces the variance and generally boosts the performance of the final model. The algorithm also introduces some randomness during the construction of the individual trees, ensuring sturdiness and variety in the model (Cutler et al., 2011). This model achieves diversity by generating multiple decision trees during training, with each tree built from a randomly selected subset of features (Blandini et al., 2023; Cutler et al., 2011). For prediction, the outputs of these trees are combined, either by averaging in regression tasks or by majority voting in classification scenarios (Breiman, 2001, cited in Blandini et al. (2023)). RF finds applications in various fields like land cover classification, remote sensing, and flood frequency analysis (Desai & Ouarda, 2021; Park et al., 2020; Tyralis et al., 2019). Their robustness, accuracy, and ability to handle large datasets make them a popular choice for complex problems with multi-dimensional datasets (Salman et al., 2024). Tyralis et al. (2019) defined RF as 'bagging of CARTs (Classification And Regression Trees) with some additional degree of randomisation.'

Features of an RF: according to Kim & Han (2020) key parameters of the RF include max_features for determining the maximum attributes in each node, bootstrap for data overlap, and n_estimators for the number of decision trees. These authors went further to identify the algorithm of RF to include: extracting bootstrap samples, generating decision trees by selecting characteristics, and repeating the process multiple times, with predictions aggregated through majority vote. However, one major weakness suffered by the RF is that a large number of trees in the model can lead to computational inefficiency (Esteve et al., 2023).

Out-Of-Bag (OOB): When sampling data using bootstrapping, some of the data do not make it to the bootstrap datasets, and these are called 'out-of-bag data'. These OOB are very key in estimating the generalisation error. According to Janitza & Hornung (2018), OOB plays a significant role in estimating the prediction error of RF, called the OOB error. This OOB error thus helps in assessing the accuracy of the RF model. One advantage of the OOB error is that it can be used in validating and tuning the hyperparameters of the RF.

Tuning: This is one of the most important things to consider when training an RF to improve accuracy. The key parameters in tuning a Random Forest model include: 'm', the number of features randomly selected at each split; 'J', the total number of trees in the forest; and the depth or size of each tree. RF shows some sensitivity to the parameter m, with defaults based on √M for classification and N/3 for regression. While tuning using out-of-bag error is possible, it introduces bias in estimating generalisation error. However, RF models typically exhibit low sensitivity to the value of 'm', reducing the need for precise tuning and helping to mitigate the risk of overfitting (Cutler et al., 2011).

Long Short-Term Memory (LSTM)

In theory, the hidden state in a recurrent neural network (RNN) should retain the memory of previous input data. However, in practice, traditional RNNs with artificial neurons as hidden units encounter problems with gradients that either vanish or explode during network training (Li et al., 2021). LSTM, on the other hand, is a type of RNN that is designed to capture long-term dependencies in sequential data (Van Houdt et al., 2020). This approach is widely used in fields such as natural language processing, speech recognition, and time series analysis due to its ability to retain information over extended sequences, making it particularly effective for capturing complex temporal dependencies (Van Houdt et al., 2020). LSTM networks consist of memory cells that can store and access information over long sequences. By incorporating gating mechanisms that can regulate the flow of information, LSTM models can retain relevant information and discard irrelevant data (Lu & Salem, 2017).

The original work of the standard LSTM cell concept dates back to 1997, wherein a simple RNN cell was improved by pioneering a memory block controlled by input and output multiplicative gates. The LSTM architecture features a self-connected linear component within its memory block, known as the 'constant error carousel' (CEC), which helps mitigate the vanishing and exploding gradient issues commonly associated with traditional RNNs (Staudemeyer & Morris, 2019). The LSTM cell incorporates input and output gates, each equipped with specific weight matrices and activation functions, which regulate the flow of pertinent information into and out of the cell. While a standard LSTM cell consists of an input layer, an output layer, and a self-connected hidden layer, the addition of a forget gate layer became necessary to address saturation issues and allow the cell to erase unnecessary information.

An LSTM model consists of three primary gates: the forget gate, input gate, and output gate. Each gate utilises a sigmoid activation function (σ) to regulate the amount of information retained, added, or released from the cell state C_t. The weights of the sigmoid functions are adjusted via gradient descent.

Forget Gate f_t: Forget gate determines whether to accept information from the cell state C_{t-1} or block it (Smagulova & James, 2019). Forget gates are vital for LSTM performance as they enable the network to selectively remember relevant information, addressing the need to avoid retaining every detail from the past (Chaturvedi et al., 2024; Smagulova & James, 2019). The model takes the prior hidden state h_{t-1} and the current input data x_t as inputs, generating a vector with variables between 0 to 1 through a sigmoid activation function (Aslam et al., 2021; Mikami, 2016; Smagulova & James, 2019). Distinctively, the forget gate network is programmed to be trained in a way that assigns values close to 0 for information considered irrelevant and close to 1 for relevant information (Mikami, 2016). These vector elements act as filters, permitting more information when their values approach 1.

Input Gate: first, the input gate identifies the new data to be stored in the memory cell determines whether the data should be retained or not. Secondly, the tanh layer generates a vector of new candidate values to augment the state.

Update cell States: the previous cell state C_{t-1} are updated to a new cell state C_t by utilising the input i_t and forget gates f_t with the new candidate cell states $\bar{C}_t$. To update the previous cell state C_{t-1}, multiply the vector f_t, add $i_t * \bar{C}_t$. The updated cell state reflects the updated long-term memory of the network.

Output: Output are normally dependent on the cell state $\bar{C}_t$ with filter from output gate o_t. The output gate controls whether the latest cell output $\bar{C}_t$ will be transmitted to the final state h_t (SHI et al., 2015). Thus the output gate o_t determines which part of cell state $\bar{C}_t$ will be the output. Furthermore, the final output is generated with the help of tanh-ed ell states filtered by o_t. Similarly, the sigmoid function is employed on the previous hidden state and current input to determine the output from the memory cell. The result is then multiplied by the tanh and applied to the new memory cell, ensuring values between -1 and 1 (Mikami, 2016).

$$f_t = \sigma\left(W_f * [h_{t-1}, x_t] + b_f\right)$$

$$i_t = \sigma(W_i * [h_{t-1}, x_t] + b_i)$$

$$o_t = \sigma(W_o * [h_{t-1}, x_t] + b_o)$$

$$C_t = f_t * C_{t-1} + i_t * \bar{C}_t$$

$$h_t = o_t * tanh(c_t)$$

Empirical Review of Machine Learning (ML) in Streamflow and Flood Forecasting

Machine learning models are important, particularly in the White Volta, because the computational costs and time of running them are low, and they can be used effectively in flood early warning systems (FEWS) (Kilsdonk et al., 2022). Most importantly, this model can learn from meteorological rainfall and temperature data without the physical characteristics of elevation.

LSTM is one of the widely used models in streamflow and flood forecasting (Fang et al., 2021; Hunt et al., 2022; Nevo et al., 2022; Ng et al., 2023). The work of Hunt et al. (2022) and Ng et al. (2023) show how the LSTM can handle and learn from the non-linear, complex relationships in data, crucial for time series like streamflow. ML models can also perform better than hydrological models, as mentioned by Liang et al. (2023). Recently, ML has been used to calibrate and optimise hydrological models. Alexander & Kumar (2024)adopted CNN in calibrating the Structure for Unifying Multiple Modelling Alternatives (SUMMA), Jiang et al. (2023) used the Multilayer Perceptrons (MLP) in calibrating the process-based Advanced Terrestrial Simulator (ATS) model, Zhao et al. (2023) adopted Gaussian process regression (GPR), Gaussian mixture copula (GMC), RF, and XGBoost to calibrate the RAPID river routing model. Yang et al. (2019) uses the LSTM to improve the Global Hydrological Models (GHMs).

ML models perform better when trained with more data, as shown in the findings of Nevo et al. (2022), where the model improved slightly after adding past precipitation data. Moreover, model performance in forecasting longer lead times on both a daily and monthly basis is influenced by the number of epochs and input data span (Cheng et al., 2020). The work of Cheng et al. (2020) shows that the LSTM performs better than ANN in forecasting a long lead time. Predictions using ML models for long lead times are less accurate in smaller basins as compared to larger basins (Farfán-Durán & Cea, 2024). A significant challenge identified in using ML models like RF and LSTM is that they are sensitive to the physical characteristics of terrain. For instance, the study of Catchment characteristics, such as the steepness of slopes and the sand content, negatively affect RF performance in certain flow regime groups (Pham et al., 2021).

Researchers have recently used the hybrid model, combining two or more models to optimise predictions. The study of Li et al. (2023) also showed that the Convolutional neural network (CNN)-LSTM performs better in mountainous basins. Fang et al. (2021) developed the local spatial sequential (LSS)-LSTM to capture local spatial data for flood monitoring and mitigation. Similarly, Ni et al. (2020) combined the wavelet transforms and the LSTM models to enable accuracy for a long time ahead of forecasting. Liu et al. (2020), used Empirical Mode Decomposition (EMD) to decompose streamflow time series to enhance LSTM's forecasting ability, achieving superior performance with different time lag inputs. The study of Wu et al.

(2009) adopted the crisp distributed support vectors regression (CDSVR) model for forecasting monthly streamflow, but saw a reduction in the model's performance as the forecast horizon increased.

2.4.5 The Role of Satellite and Reanalysis Data in Streamflow Prediction

To forecast streamflow or floods, in situ measurements such as temperature, rainfall, and soil moisture are recognised (Ling et al., 2021). These ground-based data are considered the most reliable data for predicting streamflow and floods because they provide direct measurements from the actual location of interest, enabling detailed insights into local hydrological conditions and dynamics (Corona et al., 2014; Ling et al., 2021). Hence, to develop EWS for flood monitoring in Northern Ghana, these ground-based measurements are key. However, there are significant challenges regarding the availability and quality of these in-situ data for regions such as Northern Ghana. Gauge stations are sparsely distributed, with significant areas lacking measurement stations (Abbam et al., 2018). Besides, available station measurements often lack coverage of continuous and comprehensive temporal data (Bliefernicht et al., 2022; Ling et al., 2021; Peng & Loew, 2017). These data challenges are making flood forecasting in the area difficult, given that accurate streamflow and flood forecasting often rely on data from a dense network of gauge stations and the completeness of data (Upadhyay et al., 2022). In the absence of in situ data, alternative data sources like high-resolution satellite and reanalysis data emerge as viable options for managing streamflow and floods (Upadhyay et al., 2022). These data are crucial for weather forecasting and climate studies. However, regardless of its source, these surrogate data inherently contain uncertainties, biases, and regional variations in accuracy. Therefore, validation of such data with ground-based measurements is necessary to examine their level of accuracy in predicting streamflow and floods (Upadhyay et al., 2022; Wiwoho et al., 2021). Additionally, validating satellite and reanalysis data against ground-based measurements enhances confidence in using surrogate data for streamflow and flood forecasting. It also serves as an assessment tool, enabling researchers to gauge the reliability of datasets and identify where they fall short. Water resource managers can rely on validated datasets to make informed decisions and develop robust flood management strategies.

Research conducted by Ahmed et al. (2024) in Ethiopia shows that CHIRPS data outperforms ERA5 in simulating rainfall, particularly in high altitudes. Similarly, the study of Mekonnen et al. (2023) recommended Multi-Source Weighted-Ensemble Precipitation (MSWEP), African Rainfall Estimation (RFE), ARC2, and CHIRPS rainfall data for Northern, Western, Central, and Eastern Africa regions, respectively. A study conducted by Dembélé & Zwart (2016) evaluated the performance of PERSIANN, ARC2, CHIRPS, RFE, Tropical Applications of Meteorology using Satellite (TAMSAT), African Rainfall Climatology and Timeseries (TARCAT), Tropical Rainfall Measuring Mission (TRMM) against ground-based gauges in Burkina Faso. The study recommended that for drought monitoring, ARC2, RFE, and TARCAT perform best, while for flood monitoring, PERSIANN, CHIRPS, and TRMM perform best. Logah et al. (2021) and Kouakou et al. (2023) also added that CHIRPS is the most reliable satellite in detecting rainfall and extreme rainfall indices. Aside from CHIRPS performance in detecting rainfall, PERSIANN-CDR, TAMSAT, CRU, TRMM, and TMPA 3B42 have also been recommended as a good alternative to rain gauge data (Dembélé & Zwart, 2016; Owusu et al., 2019; Atiah et al., 2020; Garba et al., 2023). However, all authors admitted that the performance of these products varies depending on the spatial and temporal scale of analysis, with daily data showing weaker performance compared to longer time scales. Most of this research validated rainfall data, and a few have covered temperature and soil moisture. Parsons et al. (2022) recently validated temperature data and found the CHIRTS to be good in Northern Ghana. In Ghana, the study of Oduro et al. (2024) shows that the Climate Research Unit (CRU), Climate Prediction Center (CPC), and TerraClimate outperform ERA5 and MERRA in simulating surface temperature. A study in China shows that ERA5 is good at simulating soil moisture in northern and northwestern China (Ling et al., 2021). Similarly, the work of Tian & Zhang (2023) shows ERA5 performs best in mimicking soil moisture at the root zone. To the best of the researcher's knowledge, no study has validated historical soil moisture with ground-based measurements in the White Volta.

2.4.6 Empirical Studies on GCM-CMIPs Data

According to the Intergovernmental Panel on Climate Change (IPCC) report, climate change will intensify globally in the coming decades, with global temperature rise expected to reach or exceed 1.5°C (IPCC, 2021). This effect is expected to substantially alter rainfall and temperature patterns, which in turn will influence global water systems, including streams and rivers (Deng et al., 2024). Understanding variations in catchment streamflow under future climate scenarios is crucial, especially in West Africa, where warming is expected to exceed the global average throughout the 21st century (Dembélé et al., 2022; Todzo et al., 2020). The Global Climate Models (GCMs) and the Regional Climate Models (RCMs) provide projected data under various local and regional adaptations, which can be used to model streamflow and other hydrological variables until the end of 2100.

Global Climate Models (GCMs) developed through the World Climate Research Programme's Coupled Model Intercomparison Projects, CMIP3, CMIP5, and CMIP6 are designed to simulate climate dynamics and adaptation responses on a global scale (Lakku & Behera, 2022). These models employ mathematical representations structured as 'grid boxes' to simulate the physical processes of the Earth's climate system, encompassing the atmosphere, oceans, land surfaces, and cryosphere (Virgilio et al., 2022). CMIP6 data encompass a broad range of experimental simulations designed to improve understanding of climate variability and change across historical, current, and future periods (Eyring et al., 2016). It significantly improves on the CMIP 3 and 5 by incorporating more detailed experiments and forcings. According to Singh et al. (2023), using scenarios from the latest CMIP6-GCMs can reduce the uncertainty in streamflow prediction. These models, which show significant advancements over earlier versions like CMIP3-GCMs and CMIP5-GCMs in simulating historical rainfall and temperature, provide a more accurate forecast of future hydrological regimes in catchments (Adib & Harun, 2022; O'Neill et al., 2016; Siabi et al., 2023; Singh et al., 2023). CMIP6-GCMs are fundamental for generating global climate projections and provide insights into climate dynamics under different greenhouse gas concentration (GHG) scenarios (Auffhammer et al., 2011). Different disciplines like geographers/hydrologists, sociologists, economists, and policymakers use GCM projections to evaluate the potential impacts of climate change on human systems and design adaptation practices (Auffhammer et al., 2011). One key challenge of the models is that they are coarse in resolution (grid cells of about 100–200 km), which limits their ability to capture fine-scale phenomena like local weather patterns and topographies (Auffhammer et al., 2011; Nguyen et al., 2022; Virgilio et al., 2022). Downscaling methods, such as dynamical or statistical approaches used by Regional Climate Models (RCMS), translate GCM outputs into higher-resolution context data. While these methods can effectively address local discrepancies in marginal statistics, they cannot correct large-scale inaccuracies like repositioning overarching patterns (e.g., the North Atlantic storm track). Kerr (2013) argued that using the output from GCMs and downscaling using the RCMs does not entirely improve data quality. Errors from the GCM can be transferred to the RCM (Dingamadji et al., 2024; Gudmundsson et al., 2012).

GCMs have been used in the Volta basin in West Africa to project flood and drought risk. Research conducted by Abubakari et al. (2019) about the influence of climate change on the streamflow of the White Volta basin, projected an increase in streamflow during the wet season by the mid-21st century using the SWAT model. The work of Todzo et al. (2020) indicates that the hydrological cycle is expected to intensify, resulting in an increase in droughts and floods.

Dembélé et al. (2022) assessed the impact of climate change on the Volta basin using bias-corrected GCM-RCM from CORDEX-Africa and the distributed mesoscale Hydrologic Model (mHM) in simulating future changes in the hydrological cycle. The study consequently projected an increase in floods under RCP 8.5 and a risk of drought under RCP 2.6 and 4.5. Similarly, Smits et al. (2024) projected a 19.3% increase in flood risk by 2100. The study of Smits et al. (2024) relied on historical data from GMet, which are very sparsely distributed and present challenges for an accurate analysis. Recently, Siabi et al. (2023) used the CMIP6 in monitoring future climate changes. However, the study focuses on rainfall and temperature changes in Accra. This makes data-driven tools like the LSTM and Random Forest attractive for futuristic streamflow in West Africa, specifically the White Volta basin, a valuable area for research.

SSPs - Shared Socioeconomic Pathways

Future climate projections depend mainly on anthropogenic factors, including emissions of greenhouse gases, aerosols, chemical reactive gases, and land changes. The SSPs represent total radiative forcings, which largely stem from mixed greenhouse gases (GHG), moderated by radiative forcings from the troposphere aerosols (Meinshausen et al., 2020). SSP projections provide the GHG concentrations, with the dominant concentration being carbon dioxide for most of the SSP scenarios (Nazarenko et al., 2022). According to Riahi et al. (2017), the SSPs are future socioeconomic pathways designed for climate change research and policy analysis, covering a broad spectrum of challenges to mitigation and adaptation.

The SSP1-2.6 represents low climate forcing with global warming below 2°C by 2100. This scenario also supports an increase in global forest cover, supporting land use studies and low societal vulnerability. The SSP2-4.5 is a mid-range scenario corresponding with the RCP4.5 pathway, used widely for regional downscaling and near-term climate forecasts. It offers a balance of moderate land use changes and aerosol levels, ideal for studies on societal vulnerability and climate impacts. SSP3-7.0 represents a medium to high climate forcing, also focusing on higher societal vulnerability and significant land use changes, like decreased global forest cover. The SSP5-8.5 is the highest scenario and an update of the RCP8.5. It is assumed that humans are adamant about climate change and make no effort to mitigate it (Riahi et al., 2017). The World population is postulated to grow to 8.5 billion in the 2050s, with a sharp drop of 7 billion by 2100. The scenario represents a radiative forcing of 8.5 W/m^2 by 2100. It is crucial for studying extreme climate outcomes and impacts.

The SSP is further described below (Riahi et al., 2017):

In SSP1 (taking the green road), the world becomes conscious about climate change and adopts a sustainable approach, focusing on inclusive development within environmental limits, improving global commons management, and prioritising health and education to foster demographic shifts and enhance well-being, while reducing inequality and shifting consumption toward less material-intensive patterns. In SSP2 (middle of the road), the world continues on a path where social, economic, and technological trends largely follow historical patterns, leading to uneven development and moderate global population growth, with institutions making slow progress toward sustainable goals, persistent income inequality, and ongoing environmental degradation despite some improvements. In SSP 3 (a rocky road), there is a rise in security concerns, and countries tend to prioritise regional and domestic issues, implementing policies on security and regional self-sufficiency in energy and food. However, declining investment in education and technology, sluggish economic growth, resource-intensive consumption, persistent or growing inequalities, uneven population trends, and major environmental degradation, driven by weak international cooperation, remain pressing issues. In SSP4 (a road divided), increasing disparities in human capital, economic opportunities, and political power exacerbate inequalities and stratification globally, creating a divide between a well-connected, high-tech global economy and fragmented, low-income, low-tech societies, leading to social unrest, uneven technological development, and a diverse but divided energy sector focusing on both high-carbon and low-carbon investments, with environmental policies targeting local issues in more affluent areas. In SSP5 (taking the highway), the world optimistically relies on competitive markets, innovation, and participatory societies to drive rapid technological advances and human capital development for sustainable growth, integrating global markets and heavily investing in health, education, and institutions, while adopting resource-intensive lifestyles and exploiting fossil fuels, leading to a booming global economy and a peaking then declining global population, with successful management of local environmental issues and confidence in handling broader social and ecological challenges, potentially through geo-engineering.

2.5 Conclusion

This chapter provides a comprehensive review of floods as a global disaster, focusing particularly on flood disasters in Ghana. It discusses how floods are managed, highlighting the roles of organisations, policies, and various flood early warning systems (FEWS) that have been established. The chapter also examines streamflow forecasting as an early warning strategy, exploring different models adopted, including physical models such as LISFLOOD, which is used in generating GloFAS discharge, and data-driven models like RF and LSTM. Additionally, the chapter reviews literature on the use of satellite and reanalysis data in streamflow and flood forecasting, especially in regions with sparse ground-based data, Ghana. In light of ongoing climate change, the study further reviews literature on the potentials of GCMs-CMIPs data that could be adopted to simulate the responses of streamflow under the SSP scenarios.

CHAPTER 3

3 Flood Early Warning System in the White Volta Basin, Northern Ghana: Opportunities and Challenges

3.1 Introduction

This chapter evaluates the current state of FEWS in the White Volta basin of Northern Ghana. It is based on a paper submitted for publication in the 'Journal of Flood Risk Management'. Except for the Introduction section, which has been removed, and the conclusion, which has been replaced with a summary, the rest of the text remains unchanged from the submitted manuscript.

The study evaluates existing frameworks for effective FEWS by drawing on case studies from local government agencies and community leaders. The study focuses on the variables monitored, communication channels used, and the roles of various stakeholders in flood management. It also identifies key data gaps and technological challenges. These findings highlight both the potential and the limitations of the current FEWS, offering practical insights to enhance flood preparedness and resilience in one of Ghana's most flood-prone regions. Additionally, the study proposes a comprehensive framework for evaluating FEWS and underscores the critical role of community leaders in local flood management. Its novelty lies in providing context-specific evidence from a resource-limited setting, contributing to the global discourse by bridging the knowledge gap between developed and developing countries.

3.2 Methodology

3.2.1 Profile of the Study Area

The research primarily focuses on Northern Ghana and the lower White Volta basin, regions selected due to their susceptibility to consistent flooding. The White Volta basin (shown in Figure 3.1), a transboundary river basin shared predominantly by Ghana and Burkina Faso, is situated between latitudes 8°N and 15°N and longitudes 1°E and 4°W. The climate is marked by clearly defined wet and dry seasons, with the wet season occurring from April to October and the dry season from November to March. Reliance on agriculture, which is predominantly rain-fed, makes the region particularly susceptible to the adverse effects of climatic variability (Taylor et al., 2006). The economic activities in these communities extend beyond agriculture to include fishing and shea processing, yet these too are influenced by the seasonal climate and the availability of water resources (Katsekpor et al., 2024b). Persistent flooding and variable rainfall patterns pose significant challenges to the livelihoods of the local population, necessitating further research into FEWS to mitigate the impacts of climate change and enhance resilience in the White Volta basin (Awuni et al., 2023).

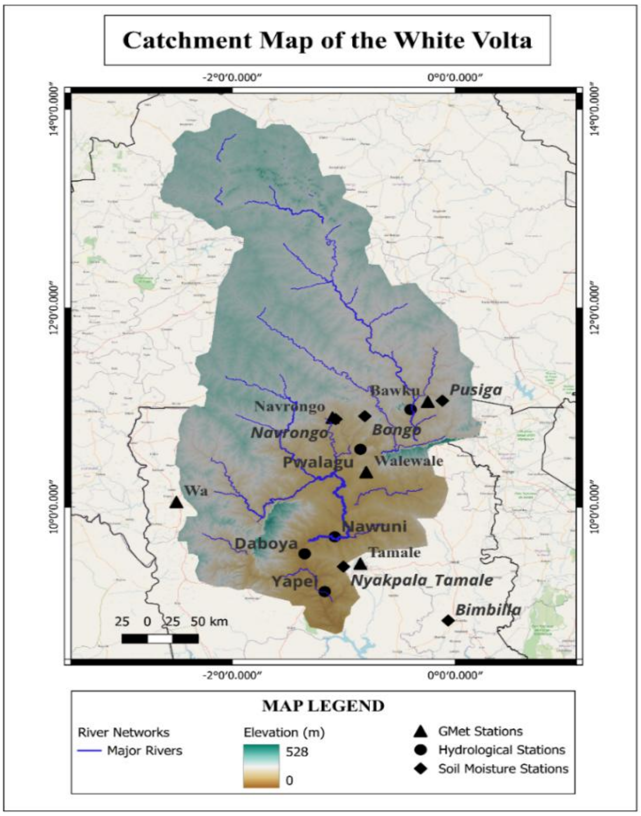

Figure 3.1 Study area map with elevation (m), adapted from Katsekpor et al. (2025) and Katsekpor et al. (2024a).

3.2.2 Research Design

The methodology is guided by a flowchart that visually outlines the research steps (see Figure 3.2). We employed a qualitative case study approach to investigate the effectiveness of FEWS and the management and monitoring of floods in the White Volta basin by stakeholders. This method is suited for investigating complex issues in real-world settings, especially where the context and subject are closely intertwined (Baxter & Jack, 2010; Creswell & Creswell, 2017). It allows us to explore local dynamics and stakeholder interactions, such as those between government agencies and community leaders, in depth. The study draws on multiple data sources, including semi-structured interviews and system analysis, to understand how FEWS functions on the ground and what challenges arise. This approach provides a rich, contextual understanding of how the system operates within Northern Ghana's social, geographical, and institutional landscape.

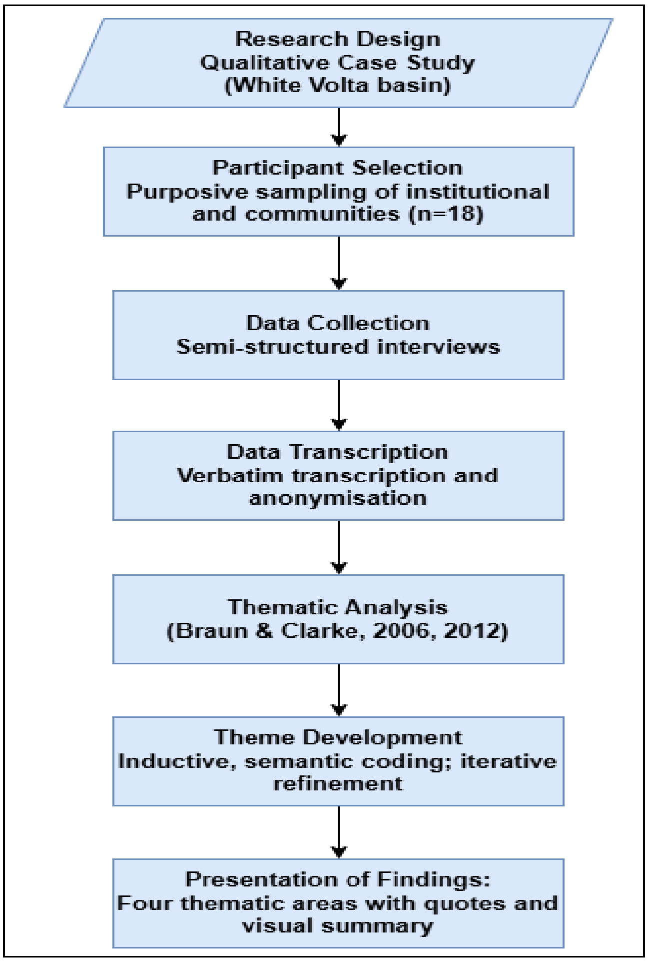

Figure 3.2: Methodological flowchart

3.2.3 Case Study Context

This study adopts a single case study design focused on the FEWS operating in the White Volta basin, Northern Ghana. The primary system under examination is the myDEWETRA-VOLTALARM platform, which became operational in 2020 under the Volta Flood and Drought Management (VFDM) project. This initiative was coordinated by the Volta Basin Authority (VBA), CIMA Research Foundation, and the World Meteorological Organisation (WMO), with funding from the Adaptation Fund (Reggiani et al., 2022). The platform represents part of a broader regional collaboration among national agencies from the six Volta basin countries.

What distinguishes this FEWS is its transboundary and multi-agency governance structure, as well as its technical integration of multiple forecasting models. These include the Global Flood Awareness System (GloFAS), Global Flood Monitoring (GFM), Flood Forecasting and Alert System for West Africa (FANFAR), and the Soil and Water Assessment Tool (SWAT) (Alfieri et al., 2013; Arnold et al., 1998; Lienert et al., 2022). The system delivers 5-day impact-based forecasts, colour-coded by severity level, and co-produced using both global satellite products and in-situ data from national agencies such as GMet and GHA (Reggiani et al., 2022).

Unlike urban-focused early warning systems in Southern Ghana, the White Volta FEWS operates in a rural, under-resourced environment, marked by infrastructural deficits, limited communication reach, and frequent flood threats from the Bagre Dam in Burkina Faso.

3.2.4 Data Collection

This study employed a purposive sampling strategy to identify and select participants who were directly involved in the design, management, or implementation of FEWS in the White Volta basin. The aim was to capture a diverse range of institutional, technical, and community-level perspectives on the functionality and effectiveness of the FEWS (Patton, 1999). A total of 18 participants were selected based on their operational roles, institutional affiliations, and geographic proximity to flood-prone areas. The sample included representatives from the National Disaster Management Organisation (NADMO) at national, regional, and district levels, as well as technical officers from the Ghana Meteorological Agency (GMet), Ghana Hydrological Authority (GHA), and the Water Resources Commission (WRC).

Two agricultural extension officers, a traditional community leader, a district assemblyman, and a unit committee member were included to ensure that grassroots perspectives were captured alongside institutional insights. Participants were recruited through formal institutional contact, local government introductions, and snowball referrals, a common approach in qualitative research where access to key informants is facilitated through trusted intermediaries (Biernacki & Waldorf, 1981).

Inclusion criteria were confirmed by verifying each participant's professional role, organisational mandate, and years of experience related to flood risk or early warning system engagement. Details of the participants' affiliations and expertise are summarised in Tables 3.1 and 3.2 (see Section 3.1). These data confirm that the sample reflects a well-distributed and experienced stakeholder group, with 12 out of 18 participants possessing more than 10 years of relevant experience in flood monitoring, emergency preparedness, or forecasting.

3.2.5 Data Analysis

The qualitative data collected through semi-structured interviews were analysed using thematic analysis (see Braun & Clarke, 2012; Castleberry & Nolen, 2018; Lochmiller, 2021; Sovacool et al., 2023), following the six-phase framework outlined by Braun & Clarke (2006, 2012). This approach was chosen due to its flexibility in identifying patterned meanings across qualitative datasets. The analysis followed an inductive logic, where codes and themes were derived directly from the content of the data without being shaped by predefined categories or theoretical assumptions. Coding was focused on participants' explicit statements, while remaining open to the underlying meanings that emerged through theme refinement.

The process began with familiarisation, where all interview transcripts were read multiple times to ensure deep engagement with the data (Nowell et al., 2017). During the initial coding phase, meaningful segments of text were highlighted and labelled inductively, without reliance on pre-existing categories. Coding was done manually using a constant comparison technique to ensure consistency across transcripts. Next, codes were grouped into preliminary themes based on conceptual similarity and recurrence across stakeholder accounts. The final stage involved defining and naming themes (see Ruslin et al., (2022), leading to the development of four core themes (see Figure 3.3 below).

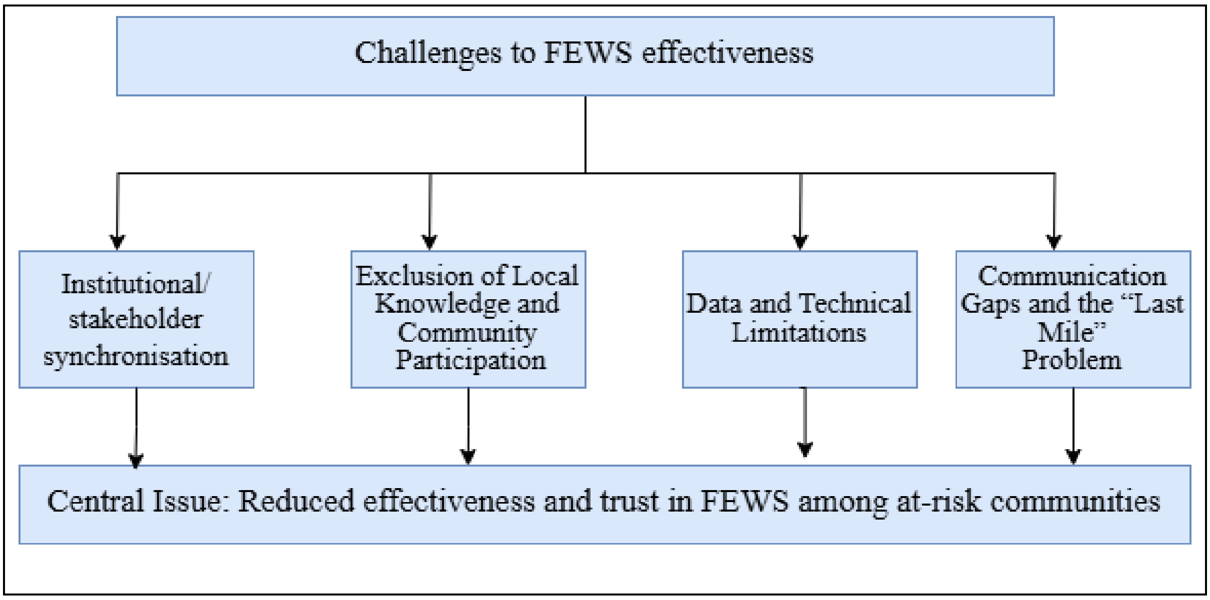

Figure 3.3: Thematic framework developed from stakeholder interviews. Source: Field Data (2024)

3.3 Results and Discussion

This section presents the findings of the study, based on qualitative data gathered through in-depth interviews with stakeholders involved in the design, management, and implementation of FEWS in the White Volta basin. The data were analysed using reflexive thematic analysis (Braun & Clarke, 2006, 2012), which allowed for the identification of patterns across the dataset. Through an inductive and iterative coding process, four key themes emerged that convey stakeholder perspectives on the functionality, strengths, and limitations of the existing

FEWS. A visual summary of these themes is presented in Figure 3.3 above, which highlights their contribution to the broader concern of reduced effectiveness and trust in FEWS among vulnerable communities. We begin this with a pre-theme context.

3.3.1 Demography of Participants

A total of 18 stakeholders were interviewed, representing a cross-section of institutions and community leaders involved in flood management within the White Volta basin. As shown in Table 3.1 below.

Table 3.1: Affiliated organisation of respondents

Affiliated Organisation	Number of Respondents	Role/Level Description
National Disaster Management Organisation (NADMO)	7	Dissemination of FEWS to the communities and serving as an Emergency response unit.
Ghana Meteorological Agency (GMet)	2	Weather forecasting and providing meteorological data.
Ghana Hydrological Authority (GHA)	2	River level monitoring and discharge, flood forecasting.
Water Resources Commission (WRC)	2	Transboundary water management
Agricultural Extension Officers	2	Community outreach and farmer support for climate change adaptations.
District Unit Committee	1	Local governance
Traditional Leader (Titled Man)	1	Community liaison (Nawuni)
Assembly Member	1	Local government representative (Yapei)
Total	18	

At the community level, local leadership was captured through interviews with a district unit committee member, a titled community leader (Nawuni), and an elected assembly member (Yapei), who serve as conduits for risk communication and public mobilisation. As detailed in Table 3.2, participants brought significant institutional knowledge to the study.

Table 3.2: Years of experience by respondents.

Years of experience	Number of Respondents
More than 10 years	12
7-10 years	5
4-6 years	1
Total	18

3.3.2 Monitoring and Observing Floods

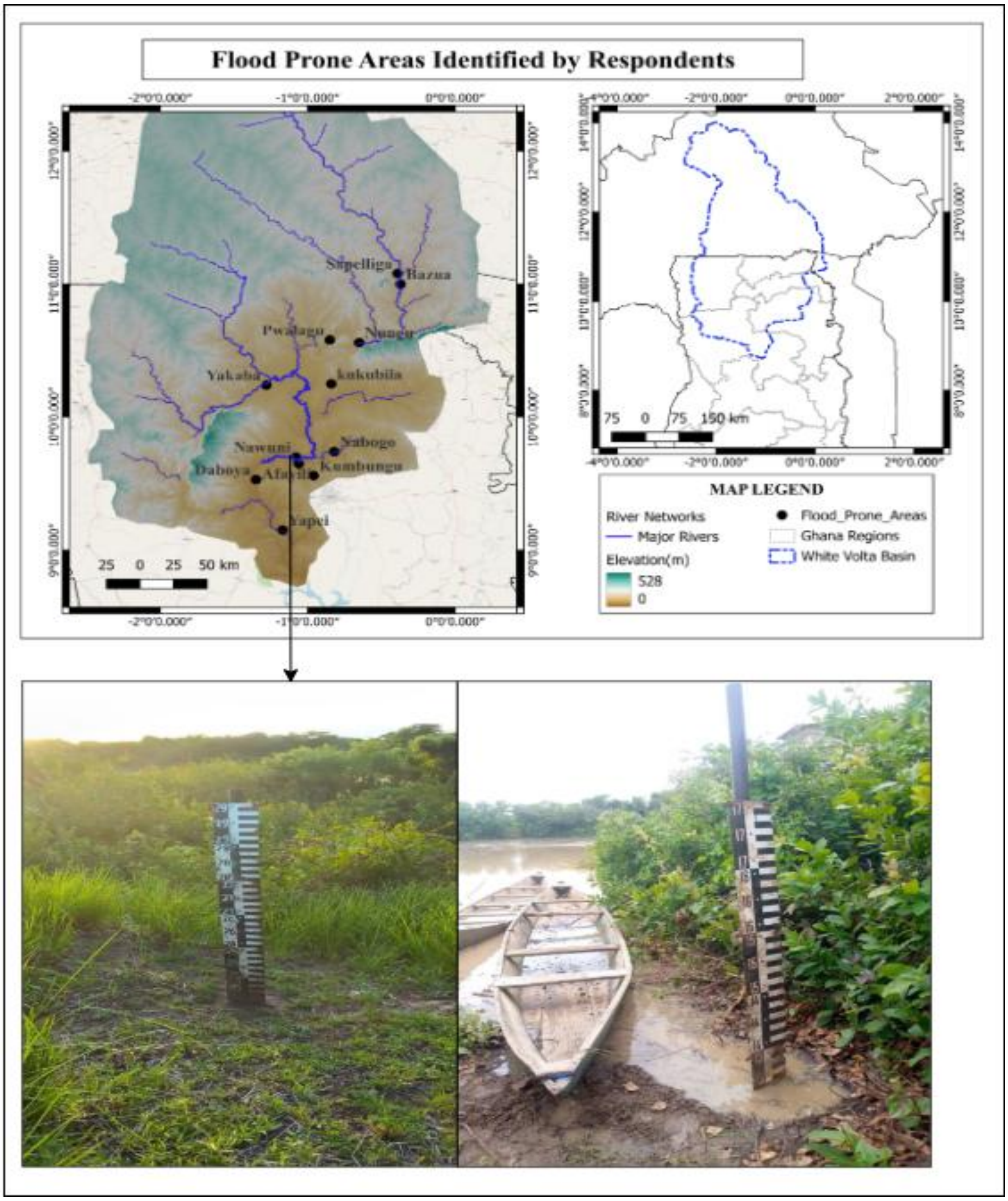

Figure 3.4: Areas liable to flood identified by respondents in the White Volta basin and label sticks used by locals to monitor floods at Nawuni. Source: Field Data (2024).

Figure 3.4 highlights areas within the White Volta basin identified by respondents as flood-prone, mainly settlements near the river. The communities include Nawuni, Daboya, Yapei, Pwalugu, Nungu, Yakaba, Afayili, Nabogo, Kumbungu, Sappelliga, Bazua, and Kukubila. This information is essential for improving FEWS and risk assessment, leading to better preparedness and mitigation strategies. Identifying these areas helps tailor local interventions to protect lives and reduce economic disruptions.

Floods of the White Volta basin are monitored using a framework known as myDEWETRA-VOLTALARM (Mapelli et al., 2024; Reggiani et al., 2022). The myDEWETRA-VOLTALARM platform integrates FANFAR, GloFAS, and GFM to monitor and forecast flood risks across the Volta basin and provide 5-day impact-based forecasts (Mapelli et al., 2024; Reggiani et al., 2022). As elaborated by a GMet official, stating:

> 'We use the myDEWETRA-VOLTALARM platform to monitor floods in the Volta basin, particularly the White Volta. It integrates rainfall and hydrological models like FANFAR, GloFAS, and GFM to provide a 5-day impact-based flood forecast. Risk levels are identified by colour codes: green (no impact), yellow (low impact), orange (medium impact), and red (high impact).'

GloFAS (Global Flood Awareness System) provides medium-range probabilistic flood forecasts at the global scale; GFM (Global Flood Monitoring) delivers near-real-time flood extent mapping using satellite imagery; FANFAR (Flood Forecasting and Alert System for West Africa) supports regional forecasting through a co-designed platform tailored for West African needs; and SWAT (Soil and Water Assessment Tool) is used for long-term watershed modelling and simulating the impact of land use on hydrology (Alfieri et al., 2013; Arnold et al., 1998; Lienert et al., 2022)

Aside from the myDEWETRA-VOLTALARM system, the Ghana Hydrological Authority (GHA) uses discharge and water level simulations to track changes over the years. These simulations are created with the help of Earth Observation (EO) data and validated against global models such as GloFAS and GFM forecasts. Tools like HEC-RAS (Hydrologic Engineering Center-River Analysis System), HEC-HMS (Hydrologic Modelling System), and SWAT are employed in this process.

Local government representatives at the district level, extension officers, and community leaders, apart from the formal system (myDEWETRA-VOLTALARM), employ their methods for monitoring floods. This involves physically checking river levels. Physical examinations include placing labelled sticks in and along rivers shown in Figure 3.4, marking bridges, and observing water levels. As stated by a NADMO official:

> ‘We, the NADMO personnel, have placed marks on the bridges over the river in Yapei, a flood-prone community near Tamale. This process enables us to monitor changes in water levels by reading the labels. We then inform the relevant authorities and community leaders when the water level is rising.’

For these local leaders and extension officers, these are some of the strategies to remain alert for any possible floods.

3.3.3 Theme 1: Institutional/ Stakeholder Synchronisation and Coordination

Effective flood monitoring and early warning in the White Volta basin requires collaboration across multiple institutional levels. Stakeholders emphasised that synchronisation between national and international agencies is crucial to ensure timely forecasting, data exchange, and dissemination. The myDEWETRA-VOLTALARM platform integrates contributions from several key actors, including the Volta Basin Authority (VBA), Global Water Partnership–West Africa (GWP-WA), the CIMA Foundation, the World Meteorological Organization (WMO), and the Adaptation Fund, alongside government agencies from Benin, Burkina Faso, Côte d’Ivoire, Ghana, Mali, and Togo. This collaboration facilitates the exchange of critical data such as rainfall, water levels, and upstream dam operations before flood incidents like the Bagre Dam spillage. National agencies such as the Ghana Meteorological Agency (GMet) and the Ghana Hydrological Authority (GHA) supply vital meteorological and hydrological data used to localise and calibrate global forecasts. As one GMet participant explained:

> ‘We at GMet collaborate with agencies such as VBA, WRC, GHA, and other countries covered by the Volta basin to develop the myDEWETRA-VOLTALARM platform. For instance, we are involved in the development and implementation stages of the FANFAR use on the platform. We also work closely with GHA to provide data such as ground rainfall, temperature, and discharge, which are integral to the flood forecasting models. Furthermore, we issue an impact-based bulletin on extreme rainfall and river floods, particularly for NADMO to inform local authorities.’

A GHA respondent similarly noted their role in integrating discharge data with satellite models:

> ‘We are directly involved when it comes to flood issues. When the myDEWETRA-VOLTALARM platform is being developed, we provide data on water levels and discharge to compare with satellite data for controls and make recommendations.’

Communication Channels

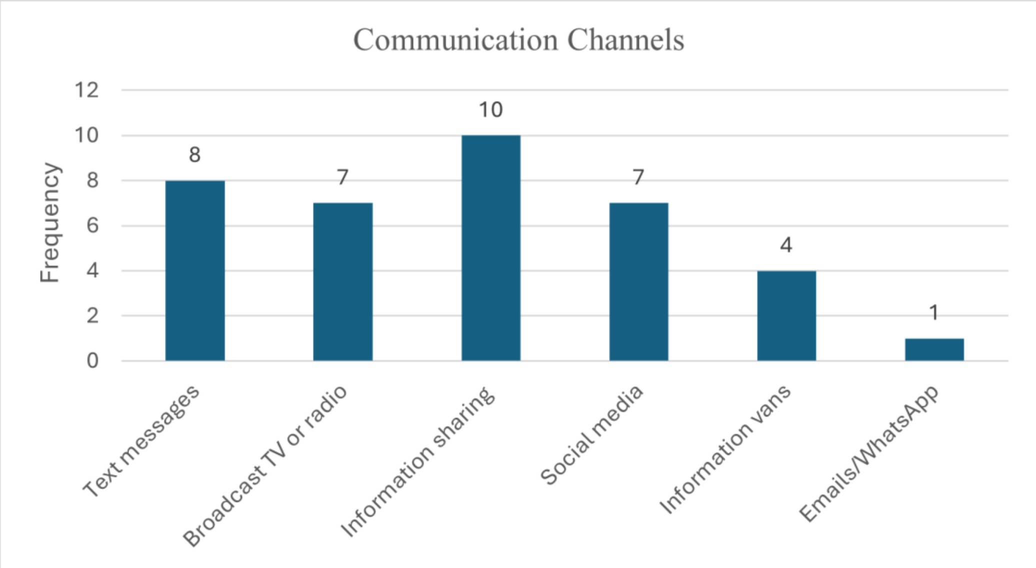

Figure 3.5: Channels used in issuing warnings in the White Volta basin.

Clear communication is critical for tracking FEWS and delivering timely flood warnings (Elkhaled & Mcheick, 2019; Kuller et al., 2021). MyDEWETRA-VOLTALARM uses bulletins as its primary tool for issuing warnings and disseminating risk information. A typical bulletin reads:

> 'Moderate rainfall is expected in most parts of the Volta basin over the next 5 days, with 40-70 mm in the Savannah, Northern, and Eastern regions, associated with low impact. Remaining areas expected to record below 40 mm with no impact.'
>
> (GMet via X, posted at 8:13 pm on 13 June 2025: https://x.com/GhanaMet/status/1933603681217257498)

These 5-day impact-based forecasts are colour-coded by risk level: green (no impact), yellow (low), orange (medium), and red (high). Forecasts issued during the rainy season (June-October) are derived from a combination of global models (e.g., GloFAS) and local observational data from agencies such as GMet and GHA. GloFAS outputs are probabilistic, while local assessments tend to be deterministic or observational. GMet bulletins include daily rainfall estimates by region (e.g., 40–70 mm over 5 days in the Savannah and Northern regions), impact levels (low or none), and specific locations (e.g., Yendi, Akosombo, Sawla). GHA complements this by issuing statements like "no threat of inundation" when water levels remain below risk thresholds. These are integrated into regional impact bulletins produced with the VBA and disseminated as colour-coded maps. The myDEWETRA-VOLTALARM flood and drought bulletin is issued twice weekly (Tuesdays and Fridays). (GMet via Instagram, 25 July 2024: https://www.instagram.com/p/C92fASiItGv/?utm_source=ig_web_copy_link)

While bulletins are designed for national and regional awareness, actionable messages are issued at the district or community level, typically 48-72 hours before the expected impact. These are sent to key agencies, such as NADMO, via email and later shared with the public through WhatsApp, radio, TV, and community vans, as shown in Figure 3.5 above. Other channels include churches and mosques.

Despite these efforts, barriers remain. Stakeholders reported that technical warnings are often not fully understood at the community level due to issues like low literacy, language diversity, and limited understanding of colour scales or rainfall figures. Moreover, participants revealed that institutional silos, unclear mandates, and uneven technical capacity limit the full potential of coordination. These observations support earlier research (Basher, 2006; Cools et al., 2016; Perera et al., 2020), which found that poor institutional cooperation often leads to the failure of FEWS. Some organisations participate only at certain stages of the system lifecycle, while others remain underutilised or overly reliant on external support.

In short, despite promising technical platforms and early collaboration, stakeholders consistently pointed to a range of interconnected challenges that limit the practical effectiveness of FEWS in the White Volta basin. These challenges, spanning community engagement, data infrastructure, and communication breakdowns, are explored further in the next three themes.

3.3.4 Theme 2: Exclusion of Local Knowledge and Community Participation

A key concern raised by stakeholders is the exclusion of local actors, such as traditional leaders, fishermen, and community representatives, from the design and decision-making processes of FEWS. This disconnect erodes both the cultural relevance and local legitimacy of these systems, reducing their effectiveness and undermining public trust. Communities in the White Volta basin play a vital role in environmental monitoring. Relying on traditional knowledge, seasonal cues, and informal techniques, they often detect early signs of flooding well before official alerts are issued. Observations such as changes in water colour, shifts in current, riverbank erosion, or unusual fishing conditions serve as critical warning signals (Khan et al., 2018; P. J. Smith et al., 2017). Despite their value, these insights remain largely unrecognised within formal systems like myDEWETRA-VOLTALARM (Marchezini et al., 2017; Yankson et al., 2017). As a result, local communities often rely more on their observations or informal alerts shared between villages than on official warnings. This gap in recognition contributes to a growing credibility problem for FEWS, weakening its ability to prompt timely protective actions.

In practice, community members use a range of informal yet effective methods to monitor river behaviour. For instance, some farmers and community leaders use marked sticks to track rising water levels, while fishermen pay close attention to changes in current strength or water turbidity. These approaches are critical in areas with limited access to technological forecasting tools. Though rarely documented, these locally grounded strategies complement formal mitigation efforts and merit inclusion in FEWS planning. The lack of integration between community-based knowledge and institutional systems creates a persistent gap between policy frameworks and real-world experiences. One GMet participant highlighted this disconnection and the need for local participation, stating:

> 'Local communities are cut off from the formal framework of FEWS in the White Volta basin. There is a need for a bottom-up approach, where community members are involved in developing the FEWS (respecting the culture of the people). They have the knowledge to identify flood risk areas and provide mitigation procedures (Knowledge is in their hands).'

In addition to advocating for greater involvement of local actors in system development (Sufri et al., 2020), participants emphasised the importance of community education and preparedness. This aligns with Lumbroso (2018) who found that regular evaluations improve the effectiveness of warning systems, especially at the community and local levels. A NADMO official at the district level in Tamale explained:

> 'There is a need for community engagement, sufficient simulation exercises, and drills to prepare people's minds for what will occur during floods and to understand the implications of not evacuating. Regular community engagement is essential to sensitise the people. Also, community drills are necessary to clarify the roles they play when a flood occurs.'

Alongside the issue of local exclusion, stakeholders pointed to fundamental data infrastructure challenges (see Figure 3.6). These include missing or outdated monitoring stations, a lack of real-time telemetry, and poor integration of local and satellite-derived datasets. These themes converge to form a complex landscape of institutional, technical, and social constraints.

3.3.5 Theme 3: Data and Technical Limitations

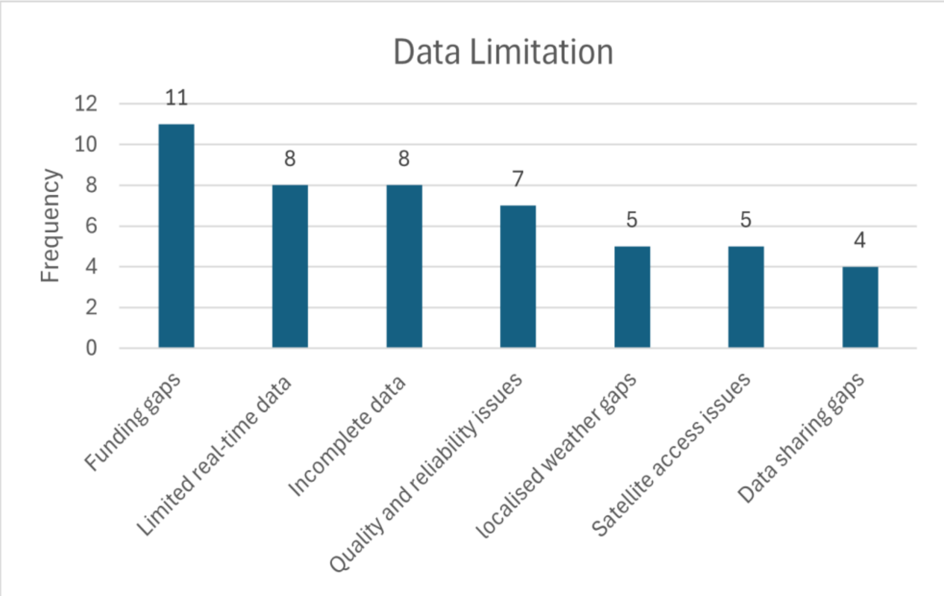

Figure 3.6: Challenges with data in developing FEWS (source: field trip (2024)).

Despite the implementation of regional forecasting platforms like myDEWETRA-VOLTALARM, significant technical and data-related constraints undermine the effectiveness of FEWS in the White Volta basin (Almoradie et al., 2020). The GHA and the GMet rely heavily on gauge station data for hydrological and meteorological monitoring. Figure 3.6 summarises the key data-related challenges raised by participants. These include inadequate funding for data collection and maintenance, limited availability of real-time data, incomplete historical records, and a lack of access to satellite or remote-sensing technologies due to unstable internet connectivity. Outdated sensors and bureaucratic delays in procurement further reduce the system's responsiveness. These findings are consistent with earlier studies on infrastructure and coordination failures in Ghana's disaster response systems (Amoako et al., 2019; Cobbinah & Poku-Boansi, 2018; Poku-Boansi et al., 2020; Revilla-Romero et al., 2015; Smits et al., 2024).

One community leader in Nawuni explained the scarcity of local gauge stations:

> 'There is a limited number of gauge stations in Northern Ghana, especially in communities prone to floods. For instance, there are only a few gauge stations in Nawuni, some of which are owned by the Ghana Water Company. Communities like Yapei and Kumbugu are also prone to flooding; however, they do not have any gauge stations. Moreover, most of the flood-prone communities in the Upper East region of Ghana face similar challenges.'

A GHA official provided further details on the lack of adequate ground data, highlighting the financial constraints that hinder the agency's ability to independently operate or upgrade its monitoring system:

> 'Current in-situ data on discharge and water levels are not adequate. We need sub-gauges on all major water bodies. Automatic water sensors for collecting real-time data. We also need more staff gauges. However, we are unable to secure the necessary funds to obtain this equipment, and even the ones we have installed along the river have been stolen. What is left is very sparse.'

This infrastructure gap leaves regional and global systems like GloFAS and WRF poorly suited for community-level decision-making, as they lack the granularity to capture the White Volta basin's unique hydrological patterns. Although these platforms offer advanced forecasting capabilities, their effectiveness hinges on accurate, real-time local data, something that remains scarce in much of the basin.

As a result, a critical disconnect emerges: forecasts may be technically available, but they often fail to match local realities or respond to the specific needs of affected communities. This undermines trust in the system and limits the practical application of forecasts in decision-making. Bridging this gap requires more than technical upgrades; it demands approaches that are informed by the context, culture, and capacities of those most affected.

Moreover, even when forecasts are available, a persistent challenge lies in how this information is communicated and interpreted by end-users (Chaves-Gonzalez et al., 2022; Reichstein et al., 2025). One reason for this breakdown is that many forecasting systems are not designed with local perspectives in mind.

Evidence from other resource-constrained regions, such as Bangladesh and Uganda, shows that co-developing models with local knowledge and embedding institutional feedback loops can significantly improve how well forecasts align with community needs, ultimately making them more relevant, usable, and trusted in humanitarian contexts (Coughlan de Perez et al., 2016; Hossain et al., 2023; Mitheu et al., 2023).

3.3.6 Theme 4: Communication Gaps and the "Last Mile" Problem

The diversity of channels is critical in the White Volta's rural context, where inconsistent mobile service and infrastructure barriers often hinder communication flow. The use of text messaging has proven effective in reaching remote populations quickly and reinforces the system's potential to reduce disaster risk through timely alerts in other parts of the world (Feldman et al., 2016; Servaes, 2008; Yasmin et al., 2023). Although regional platforms like myDEWETRA-VOLTALARM are designed to provide early warnings for at-risk communities, their effectiveness is significantly constrained by communication gaps in rural and under-resourced areas. Stakeholders identified several factors that disrupt the timely and accessible flow of information: poor internet connectivity, frequent power outages, limited telecommunications infrastructure, and a general lack of capacity among local actors to interpret impact-based bulletins.

These barriers contribute to what is widely recognised as the "last mile" problem, where early warning messages fail to reach or be understood by the very communities most vulnerable to flood hazards (Budimir et al., 2020; Golding, 2022; Shrestha et al., 2021). Technical outputs from forecasting systems often rely on formats and language that are not adapted to local contexts, which limits their usability at the community level. This result supports Lumbroso (2018), Perera et al. (2020) and Shah et al. (2023), who found that warnings not tailored to local communities are often ineffective. A local assemblyman and community leader in Yapei described the consequences of these challenges:

> 'When it comes to floods, we often do not receive timely warnings, due to the poor internet connectivity and power outages. We usually find ourselves caught in the floodwaters.'

He further noted:

> 'Language barriers also pose a significant challenge when warnings are issued. Not everyone understands Twi or English. Additionally, there are times when community members are unwilling to heed the warnings.'

The preceding sections have outlined four core themes that reflect the institutional, technical, and social challenges affecting the operational effectiveness of FEWS in the White Volta basin. Drawing on stakeholder experiences across government agencies, technical experts, and community leaders, these findings reveal a complex web of limitations as summarised in Table 3.3 below.

Table 3.3: Summary of thematic findings

Theme	Summary Description
1. Institutional/Stakeholder Synchronisation and Coordination	Weak coordination among key agencies (e.g., NADMO, GMet, GHA) limits system responsiveness and integration.
2. Exclusion of Local Knowledge and Community Participation	Local actors are not meaningfully included in FEWS design or dissemination; traditional knowledge is underutilised.
3. Data and Technical Limitations	Inadequate real-time data, outdated equipment/gauge stations, and a lack of funding affect forecasting accuracy and reliability.
4. Communication Gaps and the 'Last Mile' Problem	Infrastructure and literacy barriers prevent the timely and accessible dissemination of flood warnings to vulnerable communities.

3.3.7 Local Adaptation Practices and Emergency Response Gaps

Interview participants stressed that flood risk in the White Volta basin must be addressed through a multi-pronged strategy that goes beyond early warnings. While FEWS provides critical lead time, its effectiveness ultimately hinges on the ability of institutions and communities to act. A recurring issue raised by respondents was the lack of emergency response capacity, especially in hard-to-reach or riverine settlements. Several participants cited the absence of motorised rescue boats, life jackets, and safe evacuation shelters as a critical weakness that results in preventable loss of life.

In addition to emergency logistics and mitigation policies, such as redirecting waterways or enforcing the National Riparian Buffer Zone Policy (2011) (Klutse, 2022), stakeholders identified several local adaptation strategies already in use. These include the seasonal relocation of crops to higher ground, informal evacuation drills led by local leaders, and adjusting planting schedules based on observed river behaviours. However, these bottom-up adaptations remain disconnected from formal FEWS processes. Strengthening this interface through sustained funding, decentralised governance, and the formal recognition of community-based knowledge would broaden preparedness outcomes and improve the overall resilience of the FEWS framework in Northern Ghana.

3.4 Summary

The study examines the current state of FEWS in the White Volta basin of Ghana. The effectiveness of this system is shaped by a complex mix of prospects and challenges. The system's structured framework, which integrates multiple predictive models and benefits from collaboration among national and international stakeholders, forms a strong foundation for its operation. Leveraging platforms like myDEWETRA-VOLTALARM to provide flood forecasts that rely on a combination of rainfall, weather, and hydrological data. These predictive capabilities are further enhanced by the involvement of key agencies such as NADMO, GMet, WRC, and GHA, whose expertise in disaster monitoring and management is invaluable. The system's communication strategies, including text messaging, social media, and radio, ensure that warnings reach a wide audience.

Despite these strengths, there are significant challenges that limit the full potential of FEWS. Inadequate funding, technological limitations, outdated equipment, bureaucratic inefficiencies, and a lack of willingness among agencies to coordinate result in limited availability of real-time data, incomplete historical data, and compromised data quality, which hampers the ability to provide precise and localised flood forecasts. The system relies heavily on global models that are not fully tailored to the unique environmental and hydrological conditions of Northern Ghana. This dependence on global forecasting models, combined with gaps in communication infrastructure in rural areas, means that many communities remain vulnerable to floods, even when warnings are issued. There is insufficient integration of local knowledge into the formal framework, which weakens the relationship between the formal system and the communities it is designed to protect.

The findings reinforce that improving FEWS effectiveness in the White Volta basin requires technical upgrades and place-specific interventions. As a transboundary and flood-prone basin marked by infrastructural limitations and rural dispersal, the region faces challenges distinct from more urbanised areas in Southern Ghana. Based on stakeholder input, we recommend: (1) strengthening inter-agency coordination at the regional and district levels; (2) increasing investment in real-time data and community-based logistics such as motorised rescue boats and early warning interpretation training; (3) formally incorporating local knowledge and adaptation strategies into the FEWS model; and (4) enhancing communication tools using local languages and trusted channels.

CHAPTER 4

4 Comparative Analysis of Satellite and Reanalysis Data with Ground-based Observations in Northern Ghana

4.1 Introduction

Chapter four focused on validating satellite and reanalysis datasets in Northern Ghana. It is based on a paper that has been published in the 'Meteorological Applications - https://doi.org/10.1002/met.2226' (Katsekpor et al., 2024a). Apart from the removal of the Introduction section and the conclusion, which have been replaced with a summary, the rest of the text remains unchanged from the published work.

The study systematically assessed the accuracy of rainfall estimates derived from CHIRPS, PERSIANN-CDR, ERA5, ARC2, and TRMM. In addition, mean temperature and soil moisture data from ERA5, CFSR, and MERRA-2 were evaluated. This represents a novel contribution to the literature by validating reanalysis-based soil moisture data in the context of Northern Ghana. An error significance framework, as proposed by Moriasi et al. (2007), was applied to evaluate the datasets. Performance metrics included MAE and MBE, with values falling within half the standard deviation of observed data considered satisfactory, in accordance with the criteria outlined by Yamba, (2016). This methodological approach effectively captures the variability and distinct error patterns across datasets, offering a robust basis for intercomparison and reliability assessment of satellite and reanalysis products.

4.2 Data and Methodology

4.2.1 Study Area

The study focuses on Northern Ghana and the lower White Volta basin, selected for its gauge station network and the basin's geographic features. This transboundary basin, shared by Ghana and Burkina Faso, lies between 8 °N to 15 °N latitudes and 1 °E to 4 °W longitudes (Evers et al., 2024; Mensah et al., 2022). These gauge stations, located within the elevation range of 150 m to 300 m, experience climatic conditions typical of the Sudan and Guinea Savannah zones, with distinct dry and wet seasons (Yamba et al., 2023). The dry season spans from November to March, and the wet season from April to October, with August being the wettest month, except for Tamale, which sometimes peaks in September (Atiah et al., 2020; Yamba et al., 2023). The basin is divided into nine sub-catchments for hydrological study and supports a population reliant on rain-fed agriculture, vulnerable to weather extremes like droughts and floods (Taylor et al., 2006). The population largely depends on rain-fed farming. Figure 4.1 shows a map of Northern Ghana and the catchment of the White Volta.

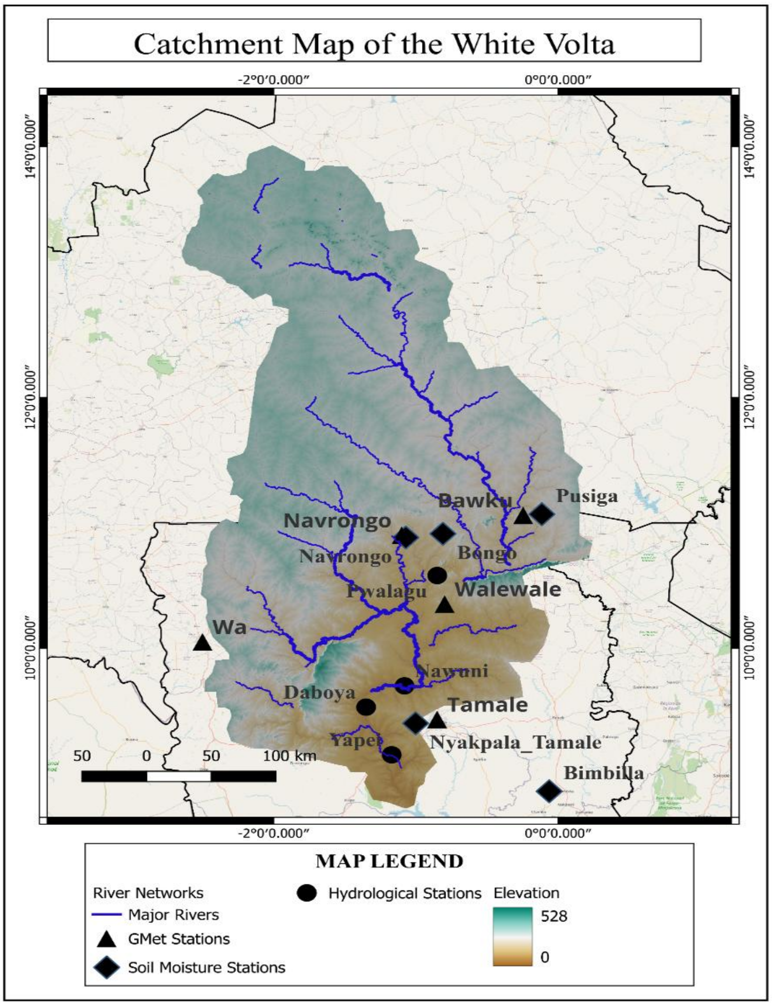

Figure 4.1: Catchment map of the White Volta enabled by Shuttle Radar Topography Mission (SRTM) with available gauge stations.

4.2.2 Datasets

In-situ Data

This research utilised rainfall, mean temperature, and soil moisture gauged data obtained from GMet (https://www.meteo.gov.gh/gmet/what-types-of-data-are-available/) and the International Soil Moisture Network (ISMN- https://ismn.bafg.de/en/dataviewer/# - last access: 20 September 2023 (Dorigo et al., 2021)). Rainfall and mean temperature cover the period of 1998 to 2019 while soil moisture covers from 2019 to 2022. GMet provides daily rainfall and mean temperature (point source) records for various locations in Ghana including Wa, Bawku, Tamale, Navrongo, and Walewale. Daily surface soil moisture (0-10cm) measurements (point source) were also sourced from ISMN for Bimbilla, Pusiga, Bongo, Navrongo, and Tamale gauge stations. The locations were chosen for their proximity to hydrological stations, as shown in Figure 4.1. The surface layer (0-10 cm) was selected for validation due to its sensitivity to atmospheric conditions and quick response to rainfall and temperature changes. This depth is crucial for soil moisture studies and agricultural applications, directly affecting seed germination and root development. While soil temperatures can be measured up to 1 meter, the 0-10 cm range balances capture essential surface interactions. The study did identify certain limitations within the ISMN datasets, such as gaps in data and inadequate temporal resolution. To address these issues, the study employed a linear interpolation to fill in the missing values. This method was adopted because it is straightforward and works well for datasets where the values change gradually and predictably. After interpolation, the cleaned dataset was saved to a new Excel file, ensuring the original dataset remained unaltered. This is crucial for maintaining previous data and ensuring there are no outliers.

Satellite and Reanalysis Data

CHIRPS

The CHIRPS dataset was developed by experts at the USGS Earth Resources Observation and Science (EROS) Centre and is an amalgamation of the Climate Hazards group Precipitation Climatology (CHPclim) and CHIRP, enriched with station data (Funk et al., 2015). This dataset is specifically designed to support EWS for natural disasters, including floods and droughts. CHIRPS offers a detailed high-resolution (0.05-degree) precipitation dataset that covers data from 1981 to the current period, leveraging the technological progress in satellite observations from agencies like the National Aeronautics and Space Administration (NASA) and the National Oceanic and Atmospheric Administration (NOAA). The dataset undergoes regular updates with a nominal three-week lag. It provides data at varying time intervals, regions, and formats. CHIRPS features a fine spatial resolution of 0.05 by 0.05 degrees. However, for certain applications like land surface modelling in Africa, the daily data's resolution is adjusted to 0.25 by 0.25 degrees (Funk et al., 2015). Rainfall data spanning from 1998 to 2019 was retrieved from https://data.chc.ucsb.edu/products/CHIRPS-2.0/ (last accessed on September 28, 2023).

PERSIANN-CDR

The PERSIANN-CDR system is an enhanced iteration of the original PERSIANN model, utilizing a mix of high-frequency data from geostationary (GEO) and low Earth orbit (LEO) satellites (Ashouri et al., 2015; Baig et al., 2023). Initially relying on longwave infrared data from GEO satellites, the system has evolved to incorporate visible imagery during daylight. The model's parameters are refined through passive microwave imagery from LEO satellites. The PERSIANN algorithm processes GridSat-B1 infrared satellite data, and Artificial Neural Networks (ANN) classifiers are honed using NCEP stage IV hourly precipitation data at a resolution of 0.25° by 0.25° (Baig et al., 2023). The dataset is further calibrated with the GPCP monthly product version 2.2 and spans daily data from 1983 to nearly the present (Ashouri et al., 2015). The precipitation data covering 1998 to 2019 was retrieved from https://climatedataguide.ucar.edu/search?search_api_fulltext=persiann-cdr (last accessed on September 28, 2023).

TRMM

TRMM was Launched in 1997; the TRMM mission was a collaborative endeavour between NASA and Japan to capture comprehensive rainfall patterns and latent heat release in the tropics and subtropics, areas that previously lacked extensive monitoring (Liu et al., 2012). The mission's instruments, including the Visible and Infrared Scanner (VIRS), TRMM Microwave Imager (TMI), Precipitation Radar (PR), and Lightning Imaging Sensor (LIS), facilitated this (Chen et al., 2020; Liu et al., 2012). The TRMM provided rainfall data from 1998 and officially ended in 2019 (https://gpm.nasa.gov/missions/trmm, last accessed on September 28, 2023) (Caloiero et al., 2020). Subsequently, the Multi-satellite Retrievals for GPM (Global Precipitation Measurement-GPM (IMERG)) took over, with records starting from June 2000. Both datasets are synchronized monthly with GPCC rain gauges (Caloiero et al., 2020).

ARC2

ARC2 was developed to address the limitations of its predecessor, ARC1, particularly the latter's shorter data span and reprocessing inconsistencies. Drawing on recalibrated historical infrared imagery and daily summary gauge data, ARC2 delivers daily, gridded rainfall estimates with a resolution of 0.1° by 0.1°. Its spatial domain stretches from 40 °S to 40 °N in latitude and 20 °W to 55 °E in longitude, covering the African continent (Novella & Thiaw, 2013). The timeline for this dataset extends from 1 January 1983 to the present and into the future. Daily rainfall data was available for download in netCDF4 format and retrieved from 1998 to 2019 (https://www.icpac.net/data-center/arc2/, last accessed on September 28, 2023) for further processing.

ERA5

ERA5, developed by the European Centre for Medium-Range Weather Forecasts (ECMWF) through the Copernicus Climate Change Service (C3S), is the latest reanalysis dataset, succeeding ERA-Interim (Hersbach et al., 2019). Its primary goal is to furnish data for understanding past, present, and projected climate conditions to aid water management and policy decisions (Hersbach et al., 2019). ERA5 assimilates various data, including in-situ and satellite observations, to refine land surface variables such as soil moisture and temperature, snow cover, and more (https://cds.climate.copernicus.eu/#!/search?text=ERA5&type=dataset last accessed on September 28, 2023). ERA5 covers the globe with a 0.25° latitude resolution and details the Earth's atmosphere across multiple levels, from the surface to upper-level layers (Hunt et al., 2022). It also offers uncertainty assessments for all variables, which enhances the data's reliability for various resolutions (Hersbach et al., 2019). Hourly rainfall, mean temperature and soil moisture (volumetric soil water layer 1 (0-7cm)) were retrieved from 1998 to 2019 for the former two and 2019 to 2022 for the latter in netCDF4 format.

MERRA-2

MERRA-2, an upgrade from the original MERRA dataset, is generated using the Goddard Earth Observing System (GEOS) atmospheric assimilation system (Gelaro et al., 2017). It integrates modern observations like hyperspectral radiance and microwave data, along with GPS-Radio Occultation and NASA ozone profiles, enhancing the original dataset (Gelaro et al., 2017). This comprehensive reanalysis provides daily data starting from 1980 and is retrievable from https://climatedataguide.ucar.edu/climate-data/nasas-merra2-reanalysis (last accessed on September 28, 2023). It maintains a spatial resolution comparable to its predecessor, around 50 km in latitude (Gelaro et al., 2017). Mean temperature from 1998 to 2019 and soil moisture (surface soil wetness (0-5cm)) from 2019 to 2022 were used for the validation.

CFSR

The Climate Forecast System Reanalysis (CFSR) employs advanced data assimilation techniques that merge conventional meteorological observations with satellite data. It uses models that simulate the interplay between the Earth's atmosphere, oceans, land, and sea ice (Lu et al., 2019; Mok et al., 2018; Saha et al., 2010). The data from 1979 to 2011 is available in hourly intervals with a spatial resolution of approximately 0.312°. Its successor, CFS Version 2 (CFSV2), extends the data record post-March 2011, offering a finer resolution (Mok et al., 2018). When combined, these datasets provide a comprehensive set of variables, referred to collectively as CFSR. Retrieved from https://climatedataguide.ucar.edu/climate-data/climate-forecast-system-reanalysis-cfsr (last accessed on September 28, 2023 - (Schneider et al., 2013)). In this research, CFSR and CFSV2 are collectively called CFSR. Mean temperature from 1998 to 2019 and soil moisture (0-5cm) from 2019 to 2022 were used for the validation.

4.2.3 Data analysis

The study examined rainfall and mean temperature data covering the period from 1998 to 2019, along with soil moisture data from 2019 to 2022. These datasets were obtained for Tamale, Walewale, Navrongo, Wa, Bongo, Pusiga, Bimbilla and Bawku gauge stations in Northern Ghana. Longitudes and latitudes of the available ground-based stations (GMet and ISMN) were used in retrieving the satellite and reanalysis data (ERA5, PERSIANN-CDR, CHIRPS, ARC2, TRMM, MERRA-2, and CFSR) in grid formats. Thus a point-to-pixel method was employed to evaluate satellite and reanalysis data against ground-based measurements. A method adopted by Benítez et al., (2024); Hosseini-Moghari & Tang, (2020); Wei et al., (2018) in validating reanalysis data. This method involves comparing the rain gauges closest to the center of the grid pixel, which includes precipitation, temperature, and soil moisture data, with the corresponding satellite and reanalysis data (Benítez et al., 2024). The point-to-pixel approach allows for validating satellite and reanalysis estimates by directly comparing them to ground-based observations, ensuring spatial and temporal alignment. The time frame chosen in retrieving both satellite and reanalysis data was influenced by the availability of TRMM (1998-2019) and ISMN (2019-2022) databases. Hourly data for temperature and soil moisture were converted to daily values by averaging the hourly measurements for each day. These daily datasets were then aggregated and averaged to obtain monthly mean values. In contrast, hourly rainfall data were aggregated by summing the hourly totals to obtain daily rainfall amounts. These daily totals were then summed to calculate the monthly rainfall amounts. To assess the accuracy of the satellite and reanalysis data against the ground-based observations, statistical metrics such as Mean Absolute Error (MAE), Mean Bias Error (MBE), and Standard Deviation (SD) of the observed data were utilised. These metrics are instrumental in quantifying the accuracy and reliability of the models being evaluated. MAE measures the average size of the errors between predicted values (e.g., ERA5) and observed values (e.g., GMet), without accounting for whether the errors are positive or negative, offering a simple assessment of prediction accuracy. Unlike MAE, MBE accounts for the direction of the errors, indicating whether the model's predictions are consistently higher or lower than the actual observations, giving either a negative or positive value. This can be particularly useful for identifying systematic biases in the model outputs. MAE values approaching 0 indicate that the average prediction error is minimal, suggesting that the predicted values closely match the actual values, on average. Similarly, an MBE value approaching 0 signifies that the average prediction is unbiased, indicating that the model tends neither to consistently overestimate nor underestimate the actual values. The study adopted the principle of error significance as proposed by (Singh et al., 2005) and subsequently used by Moriasi et al. (2007) and Yamba, (2016). According to this principle, MAE and MBE values that are less than or equal to half of the standard deviation of the observed data are deemed acceptable for model performance assessment. This threshold is chosen because the standard deviation represents the variability within the observed data, and maintaining errors within half of this value ensures that the model predictions are well within the natural variability of the data. The formulae for the MAE, MBE, and SD are below:

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|O_i - P_i|$$

$$MBE = \frac{1}{n}\sum_{i=1}^{n}(O_i - P_i)$$

$$SD = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(O_i - \overline{O}\right)^2}$$

$Where\ n\ indicate\ the\ sample, O_i\ indicate\ the\ observed,\ P_i\ indicate\ the\ predicted.$ $\overline{O}\ represent\ the\ mean\ observed.$

4.3 Result

This section presents the findings (presented in figures) of the satellite and reanalysis data against half SD of the ground-based data on a daily and monthly (seasonal) basis.

4.3.1 Seasonal Rainfall Distribution

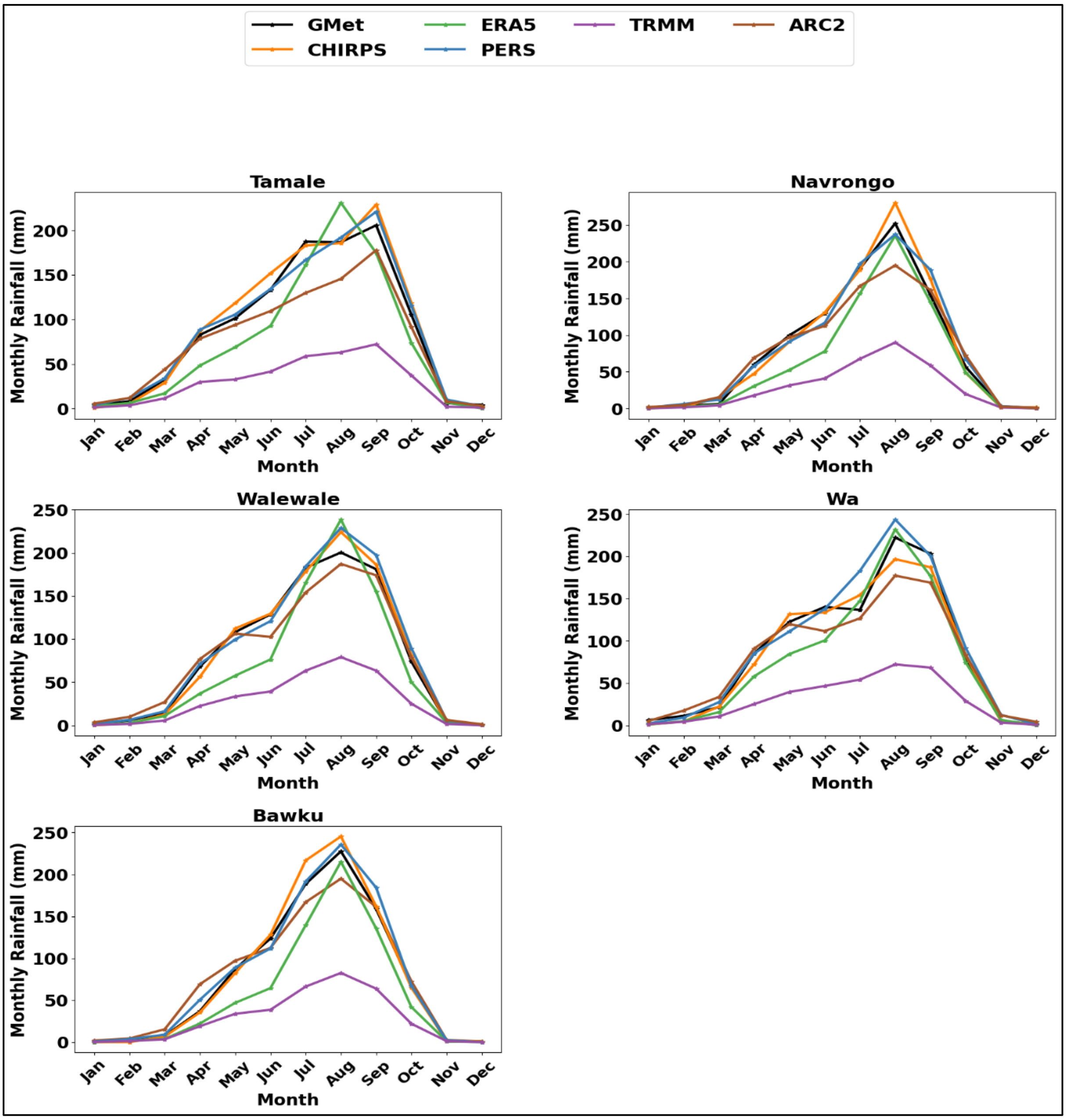

Figure 4.2: Monthly rainfall recorded by GMet, CHIRPS, PERSIANN-CDR, ERA5 ARC2, and TRMM at Wa, Tamale, Walewale, Bawku, and Navrongo gauge stations.

Figure 4.2 shows the seasonal distribution of rainfall from satellite and reanalysis data compared to ground-based measurements from GMet for Wa, Tamale, Bawku, Walewale and

Navrongo. CHIRPS and PERSIANN-CDR closely match GMet data, outperforming TRMM, ARC2, and ERA5. TRMM, however, diverges significantly from GMet. August is typically the peak rainfall month across datasets, except for Tamale, which peaks around August to September, indicating variation in climatic zones. The data reveals CHIRPS and PERSIANN-CDR's accuracy and the variable performance of ERA5, ARC2, and TRMM.

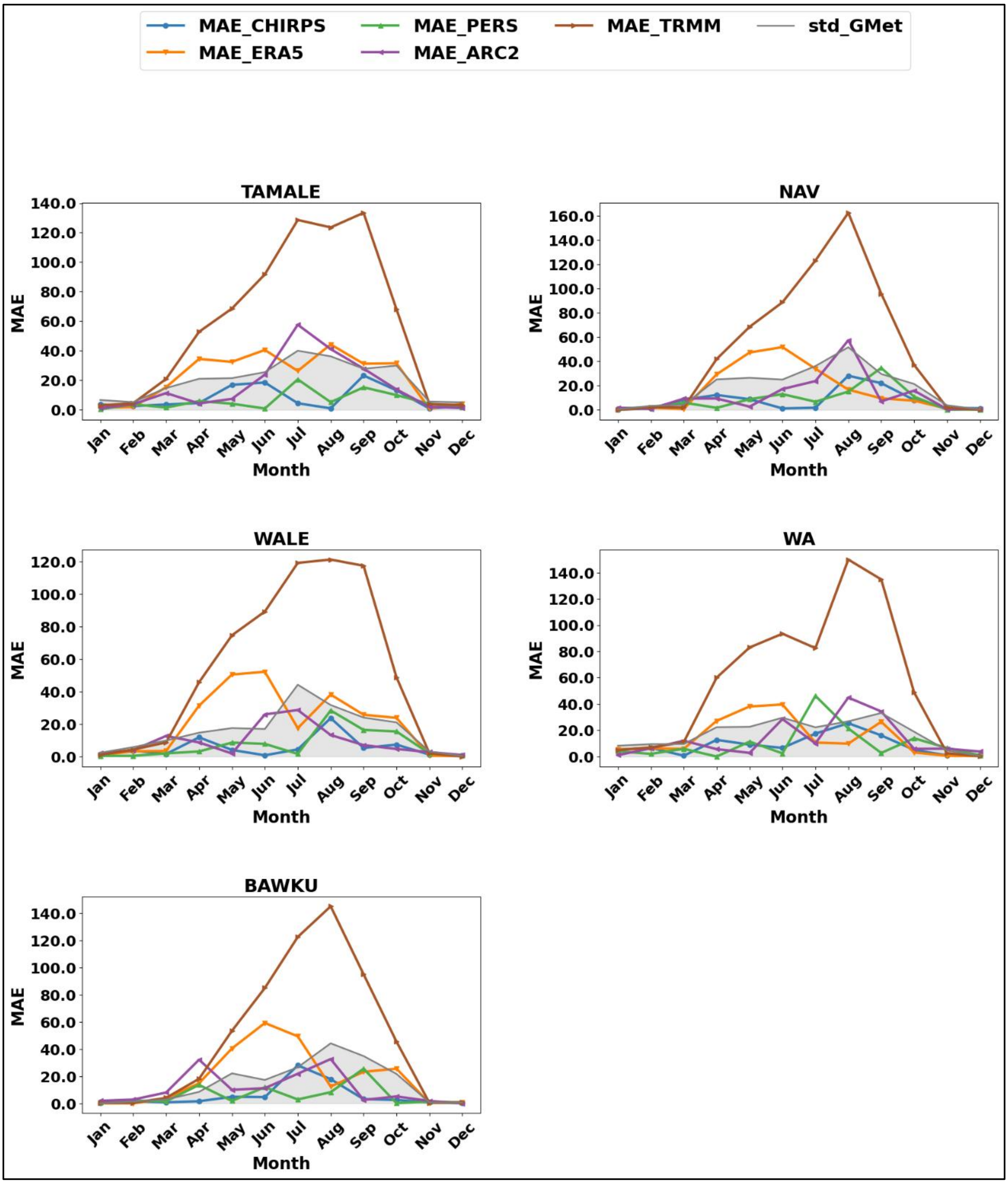

Figure 4.3: Monthly MAE against half SD of the observed rainfall recorded at the five stations.

From Figure 4.3 above, the study used Mean Absolute Error (MAE) to quantify prediction errors. CHIRPS showed the lowest errors, such as 43.2 mm for Wa in August, outperforming PERSIANN-CDR, ERA5, ARC2, and TRMM, which had higher errors for the same period and location. CHIRPS excelled, particularly in Bawku, with a 26.3 mm error in August. Across all stations, CHIRPS errors remained within the observed data's Standard Deviation (SD), indicating its reliability for climate studies. PERSIANN-CDR also fared well, especially in Tamale, Walewale, and Bawku. Errors from ARC2 and ERA5 commonly exceeded the SD, while TRMM had the most significant errors, often surpassing half the SD from March to November at all five stations.

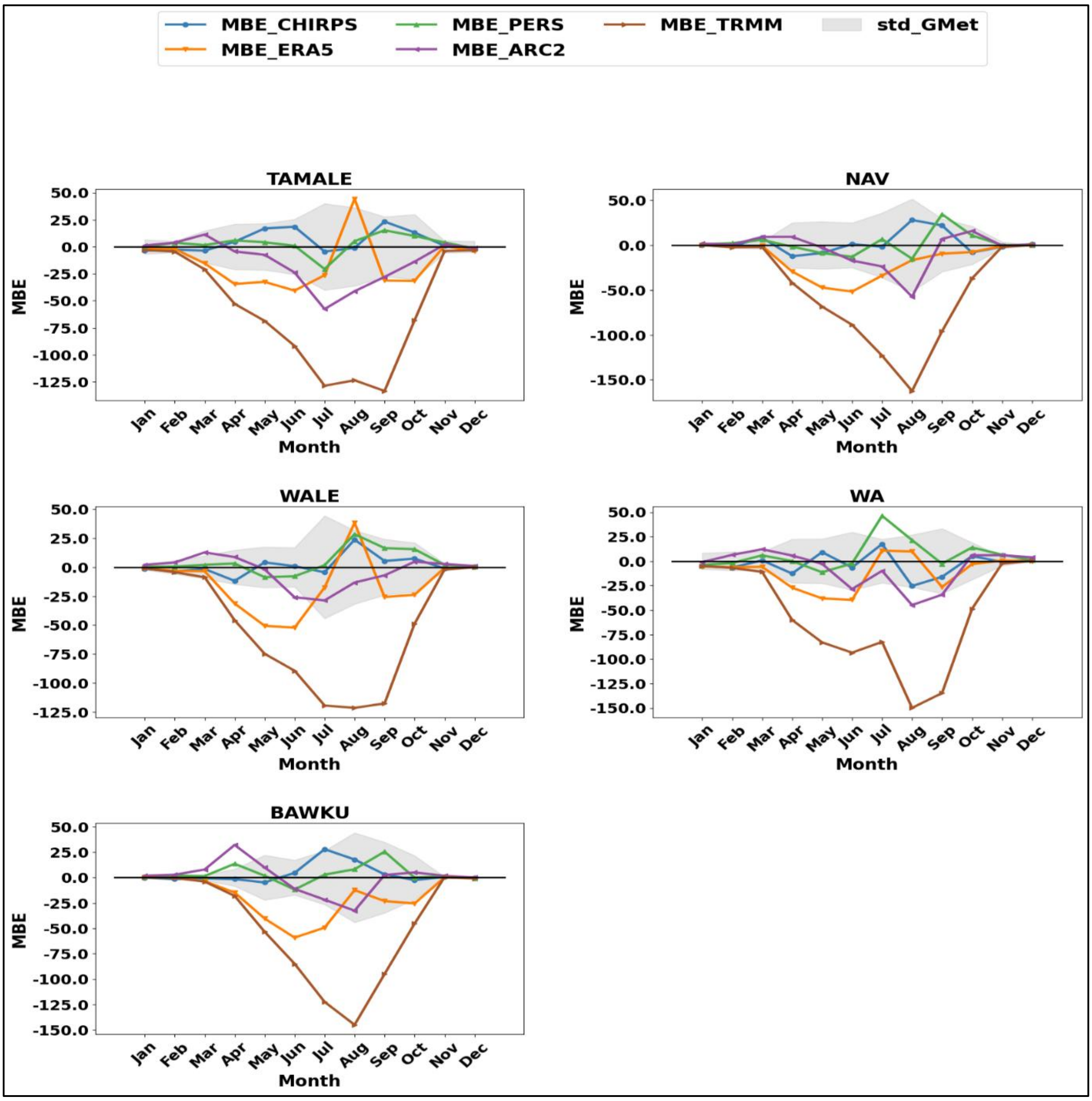

Figure 4.4: Monthly MBE against half SD of the observed rainfall recorded at the five stations.

Figure 4.4 compares the MBE of CHIRPS, ERA5, ARC2, PERSIANN-CDR, and TRMM against the observed data's half SD. Despite some over- and underestimations, CHIRPS remained within the observed SD, whereas PERSIANN-CDR aligned well except for overestimating at Wa and Navrongo during peak rainfall. CHIRPS outperformed PERSIANN-CDR, ARC2, ERA5, and TRMM across all stations. Both ARC2 and ERA5 varied in estimations, with ERA5 consistently underestimating at Bawku and Navrongo. TRMM's significant underestimations at all stations suggest a need for more scrutiny.

4.3.2 Temperature

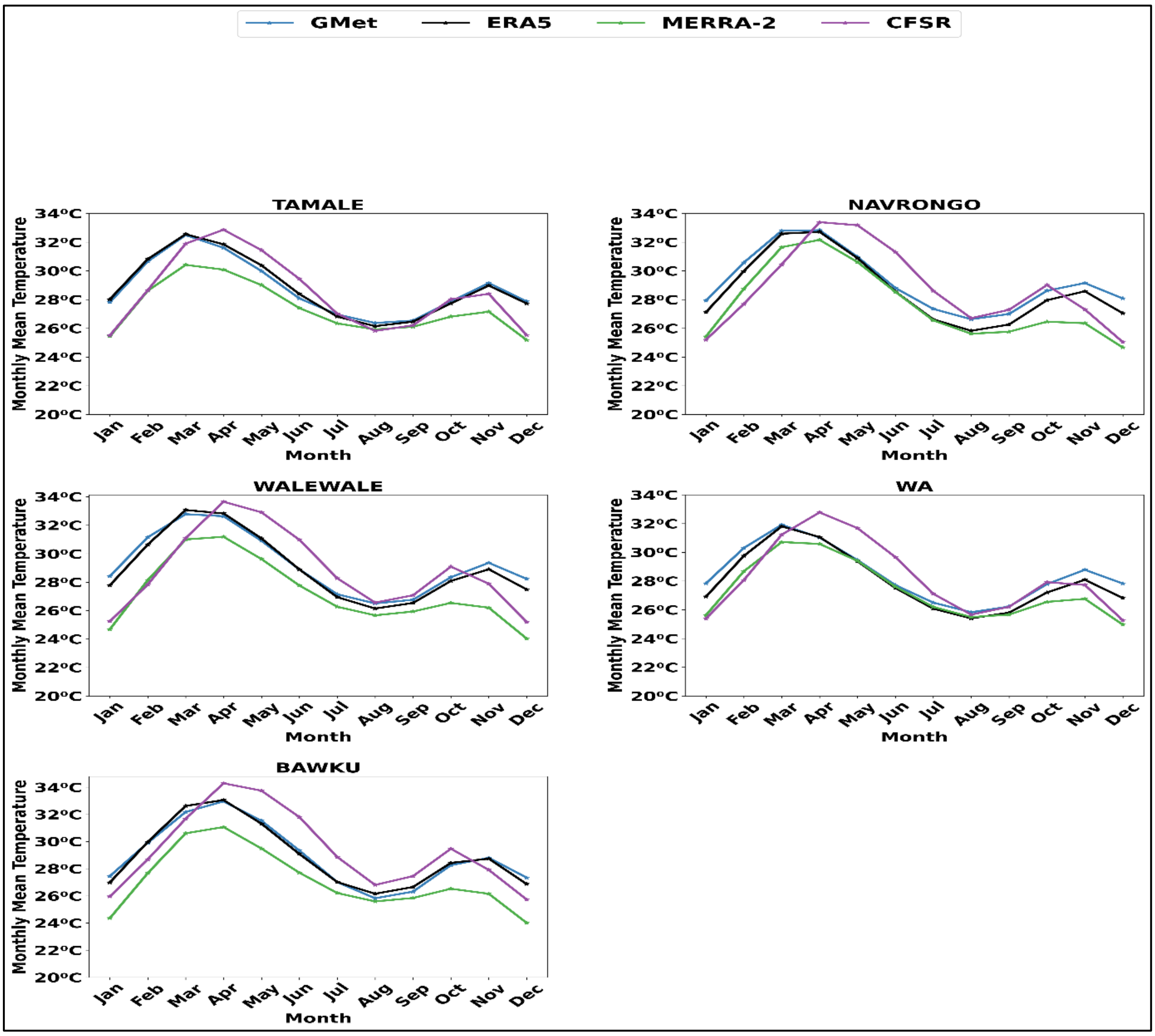

Figure 4.5: Monthly mean temperature recorded by GMet, ERA5, MERRA-2, and CFSR at Wa, Tamale, Walewale, Bawku, and Navrongo gauge stations.

Temperature analysis is vital for climate research. Validating temperature data from ERA5, MERRA-2, and CFSR against GMet data across five Northern Ghana stations, Figure 4.5

illustrates monthly temperature trends. ERA5 mostly aligns with GMet, except for some late-month deviations at Navrongo and Wa. MERRA-2, while underestimating mean temperatures, follows GMet's pattern consistently across all stations. CFSR's temperature trajectory, however, markedly differs from GMet's observed data.

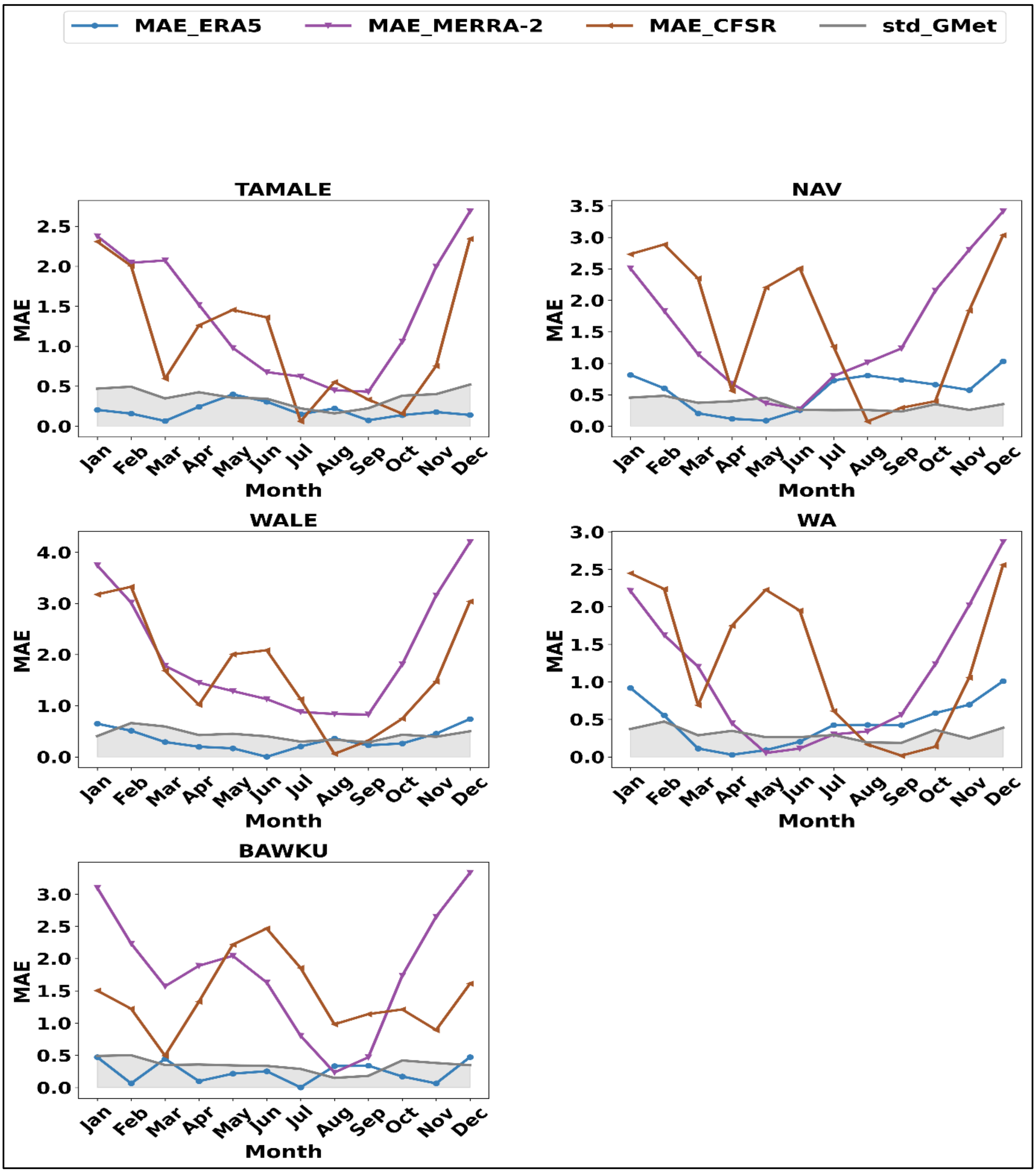

Figure 4.6: Monthly MAE against half SD of the observed mean temperature recorded at the five stations.

Figure 4.6 shows the MAE for mean temperature from ERA5, MERRA-2, and CFSR against GMet's half SD. ERA5 performs best, with the lowest errors (e.g., 0.21 ºC for Bawku in July), while MERRA-2 (0.82 ºC for Bawku in July) and CFSR (1.86 ºC for Bawku in July) are higher. ERA5's errors generally stay within GMet's half SD, unlike MERRA-2 and CFSR, which often exceed this margin, indicating their limited reliability across the studied stations and months.

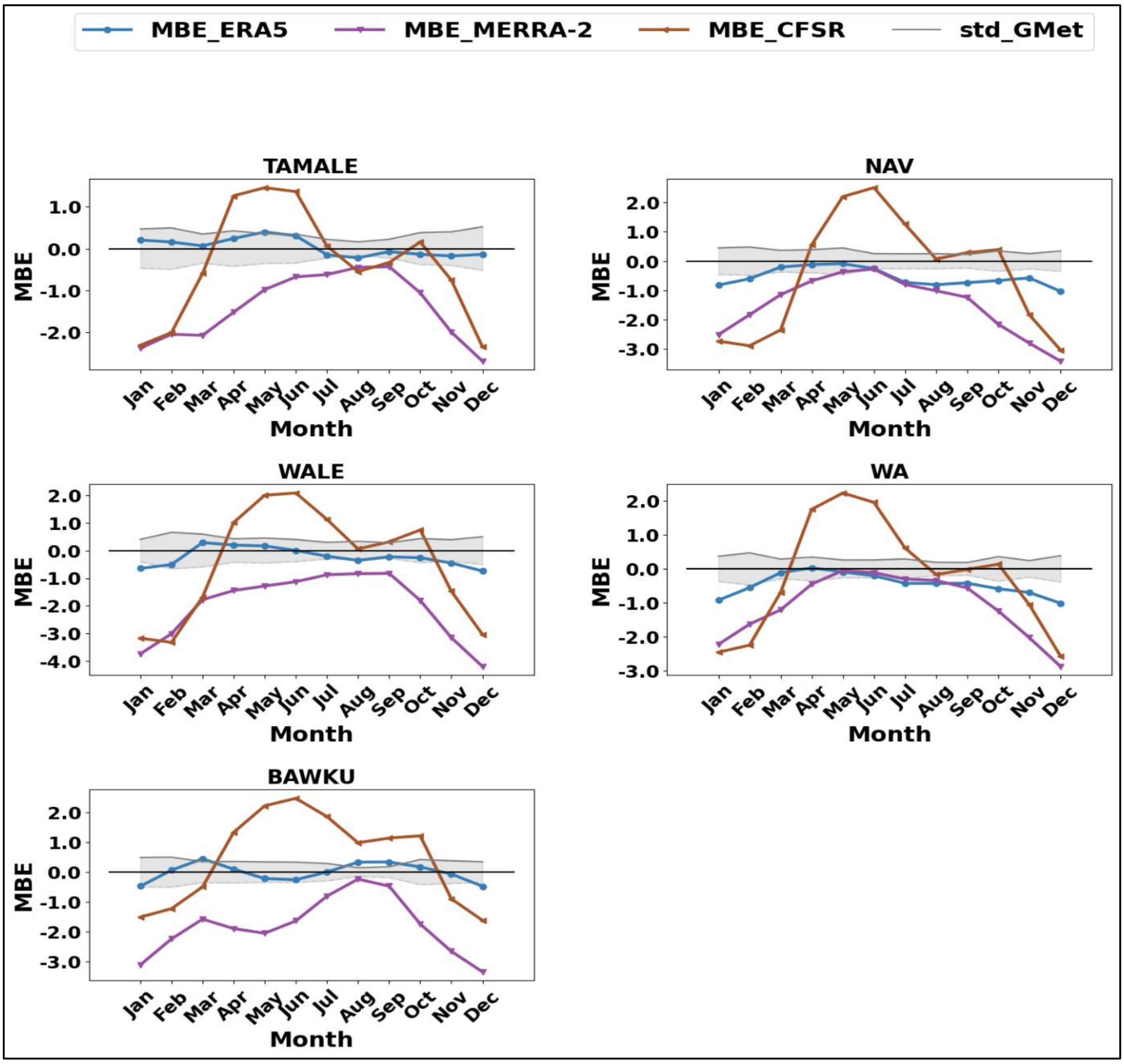

Figure 4.7: Monthly MBE against half SD of the observed mean temperature recorded at the five stations.

Figure 4.7 presents the MBE for temperature predictions. MERRA-2 consistently shows cooler biases across all stations. CFSR's estimates are cooler in early and late months but warmer from April to October, except in Tamale and Wa, where it overestimates from August to October. ERA5's bias (0.002 ºC for Bawku in July) is minimal compared to MERRA-2 (-0.80 ºC for Bawku in July) and CFSR (1.86 ºC for Bawku in July). Despite ERA5’s cooler estimates for Navrongo and Wa, its overall accuracy deems it a viable choice for simulating mean temperature, especially when considering the broader inaccuracies of MERRA-2 and CFSR.

4.3.3 Soil Moisture

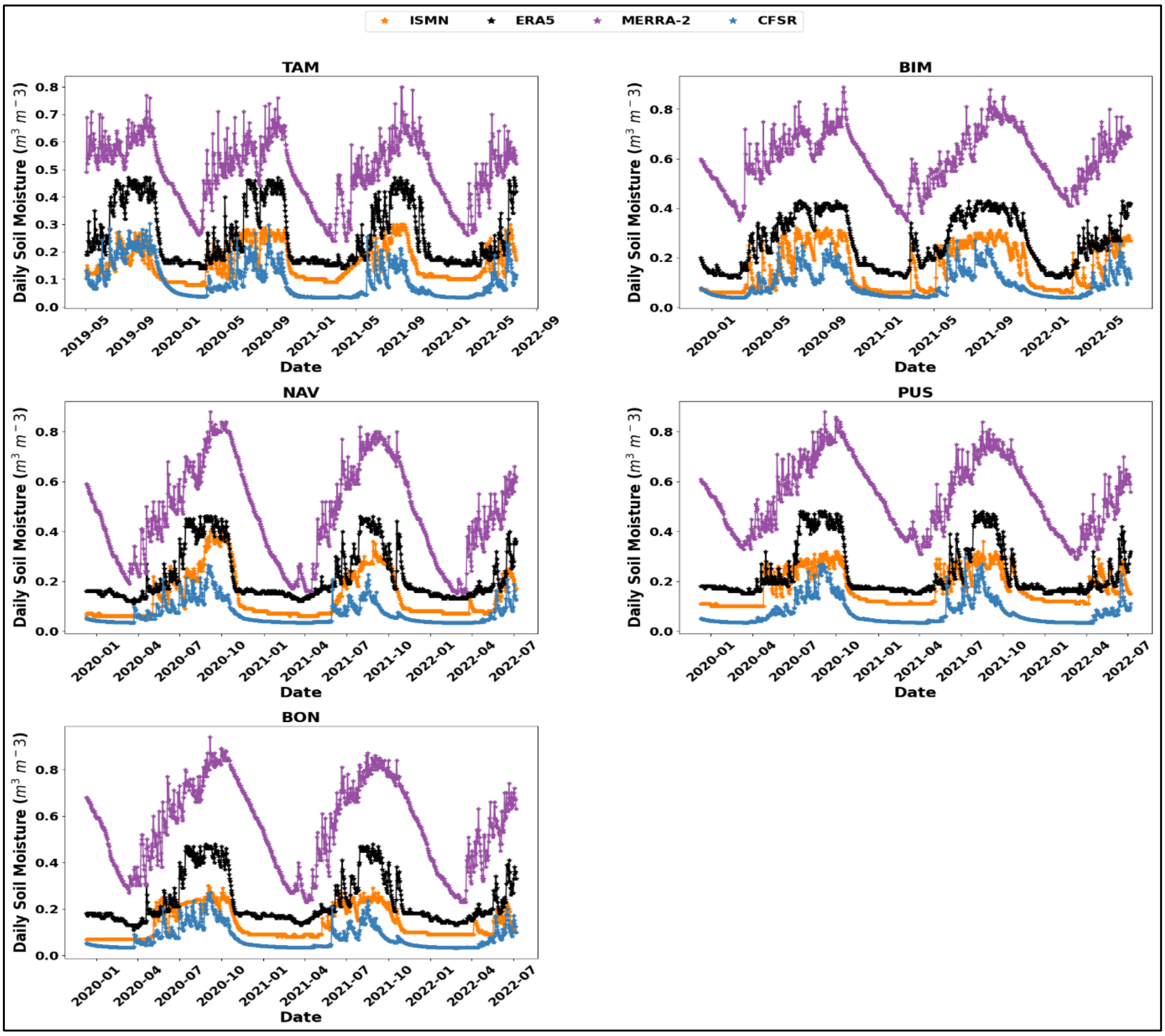

Figure 4.8: Daily soil moisture recorded by ISMN, ERA5, MERRA-2, and CFSR at Tamale, Navrongo, Bongo, Bimbilla, and Pusiga gauge stations.

Figure 4.8 depicts daily soil moisture trends from ISMN, ERA5, MERRA-2, and CFSR between 2019 and 2022. All datasets show similar patterns, with CFSR aligning closest to ISMN across the five stations. ERA5 is notably accurate in Bimbilla and Navrongo, while MERRA-2 displays slight divergence from the observed data. Seasonal monthly data analysis will provide further insights into the performance of the reanalysis datasets.

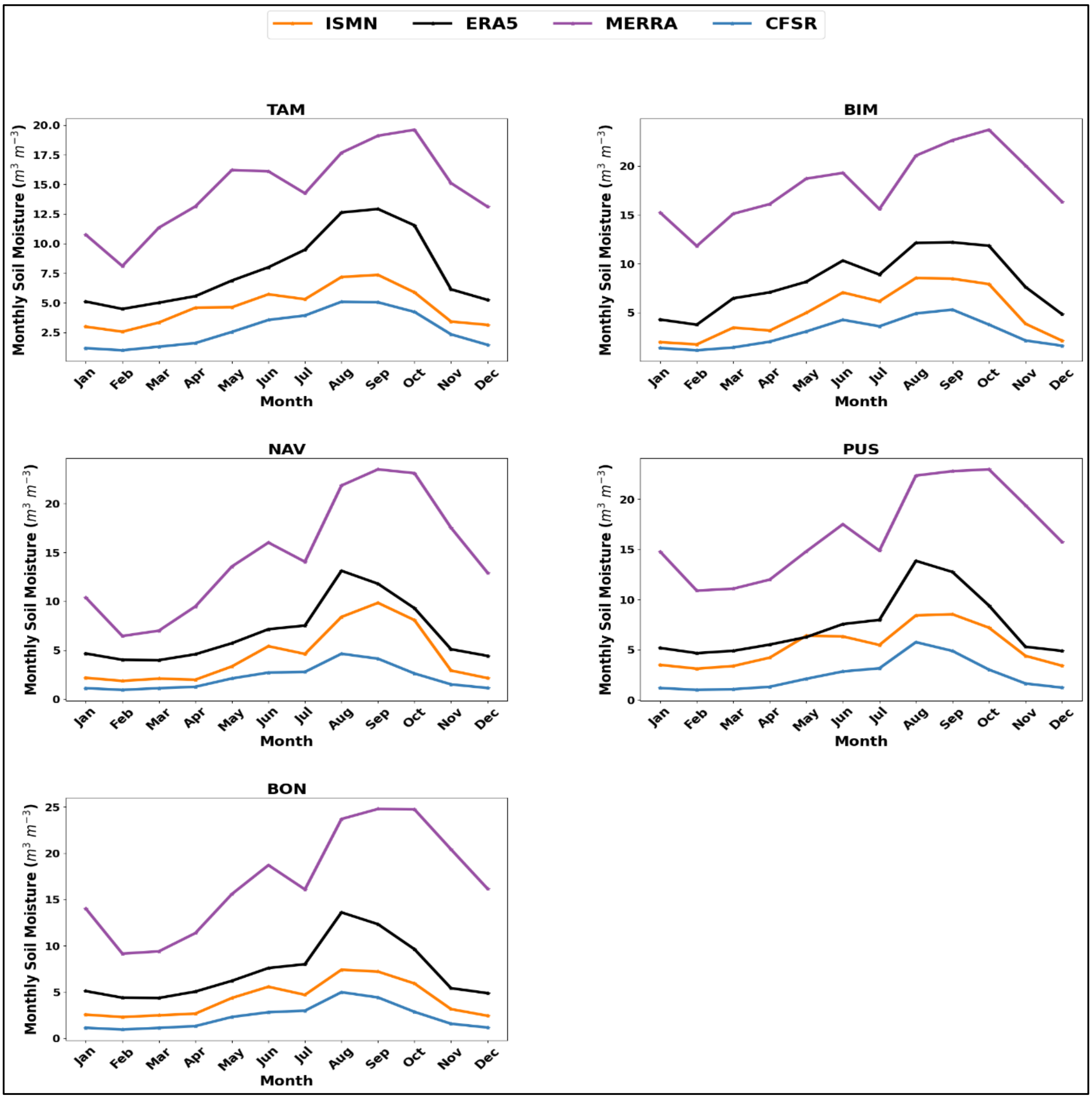

Figure 4.9: Monthly soil moisture recorded by ISMN, ERA5, MERRA-2, and CFSR at Tamale, Navrongo, Bongo, Bimbilla, and Pusiga gauge stations.

Figure 4.9 illustrates the monthly soil moisture records from the four datasets. Just like rainfall data, the peak period of soil moisture was recorded between August and October. While ERA5 (5.73 m^3m^{-3} in May for Navrongo) and CFSR (2.14 m^3m^{-3} in May for Navrongo) show a close alignment with the observed data (3.36 m^3m^{-3} in May for Navrongo), MERRA-2 (13.57 m^3m^{-3} in May for Navrongo) stands out by consistently deviating across all five stations.

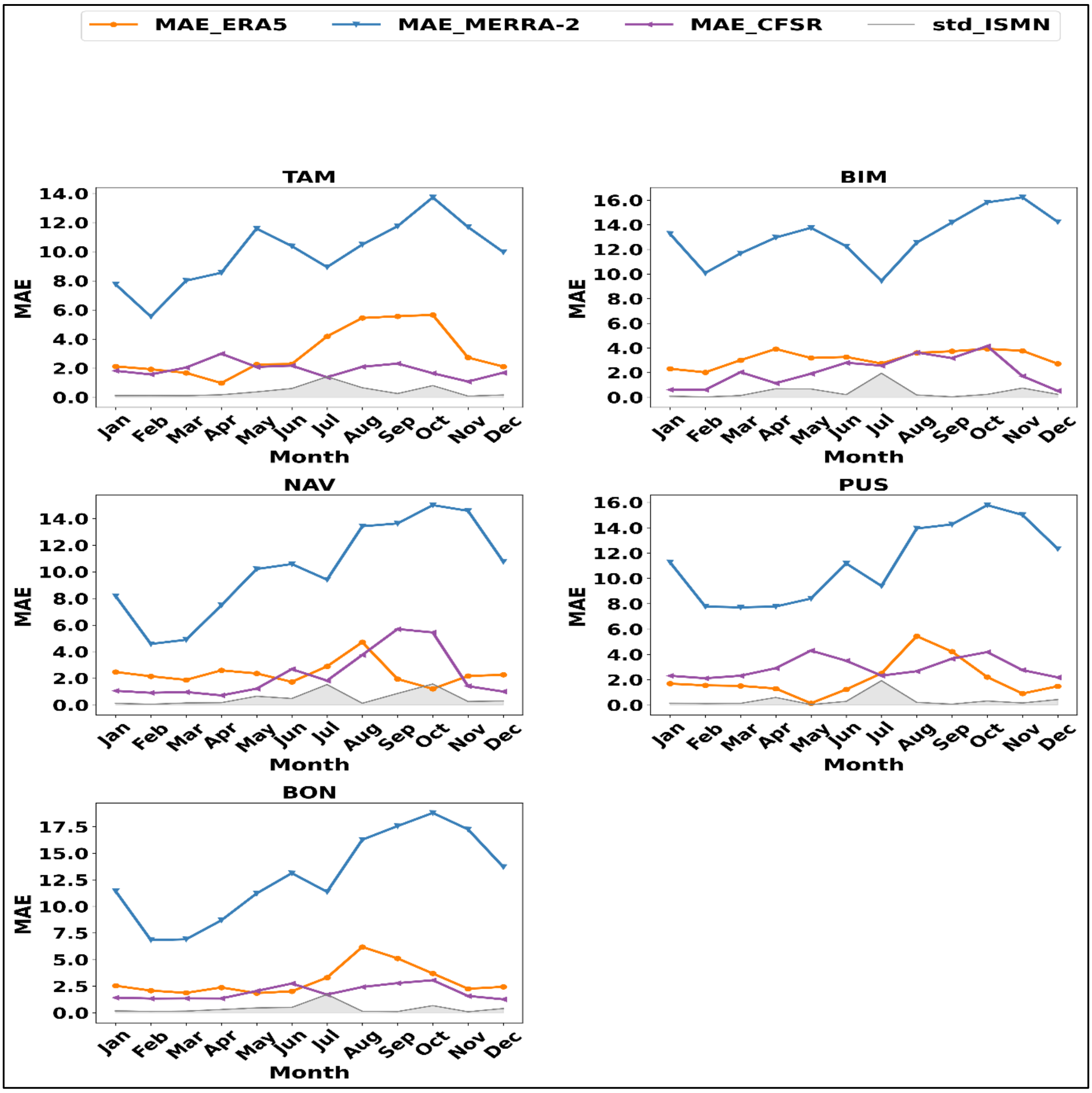

Figure 4.10: Monthly MAE against half SD of the observed soil moisture at the five stations.

Figure 4.10 displays the MAE for the reanalysis of soil moisture data relative to the observed half SD. Data gaps recorded in the observed data could affect consistency. CFSR shows the lowest MAE (2.31 m^3m^{-3} in August for Tamale), outperforming ERA5 (5.56 m^3m^{-3} in August for Tamale) and MERRA-2 (11.75 m^3m^{-3} in August) at Tamale, Bongo, and Bimbilla. However, errors often exceed the observed data's half SD. At Navrongo and Pusiga, ERA5 (2.5 m^3m^{-3} in July for Pusiga) and CFSR (2.3 m^3m^{-3} in July for Pusiga) errors are alike, while MERRA-2's errors (9.4 m^3m^{-3} in July for Pusiga) routinely exceed half SD across all stations, highlighting its limitations.

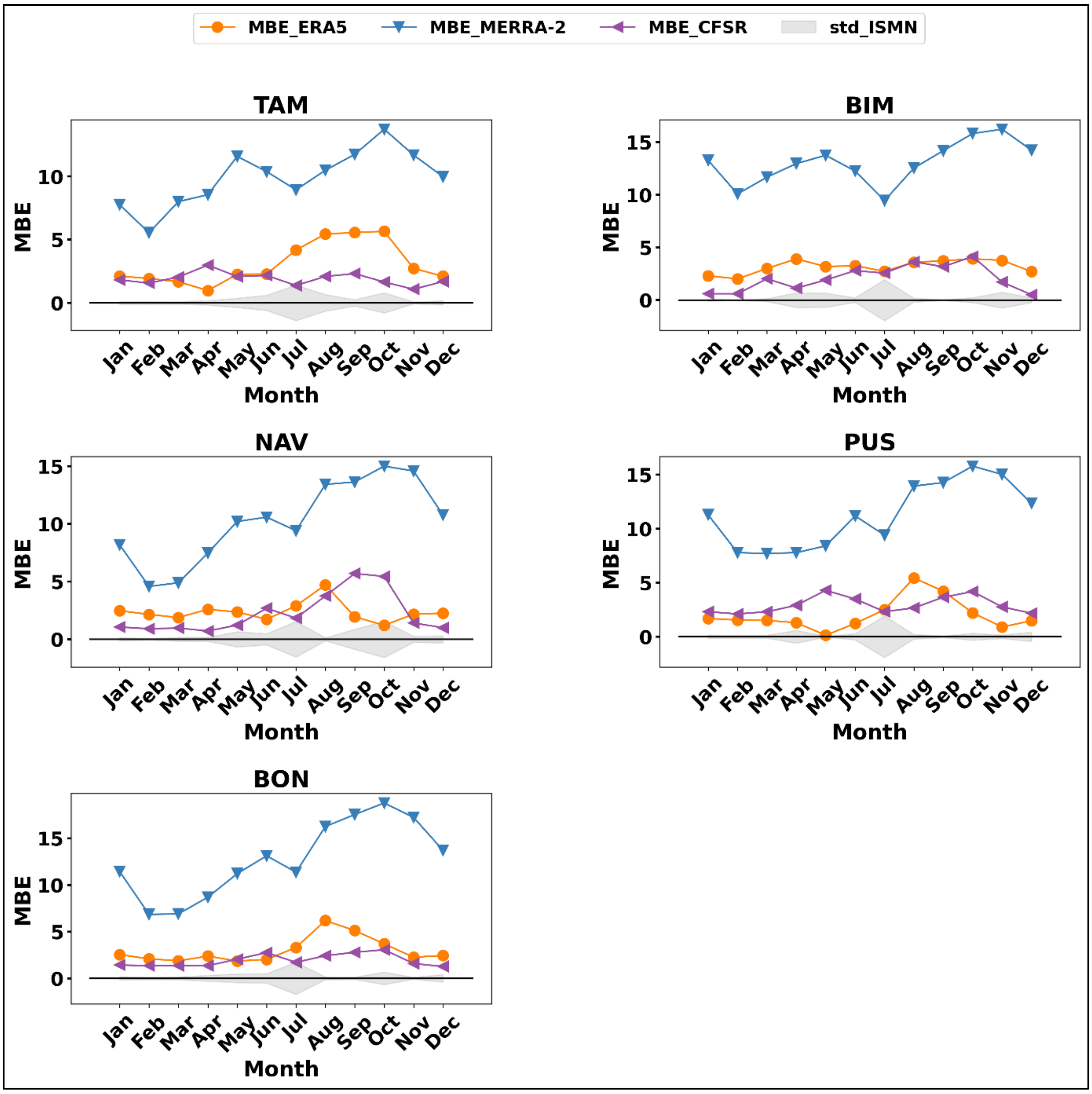

Figure 4.11: Monthly MBE against half SD of the observed soil moisture recorded at the five stations.

Figure 4.11 illustrates the monthly MBE for the reanalysis of soil moisture data against observations at five stations. Each dataset consistently overestimates moisture levels, with MERRA-2 showing the greatest overestimation, casting doubt on its precision. CFSR's overestimation is notably less at Tamale (1.37 m^3m^{-3} in July), Bimbila (2.57 m^3m^{-3} in July), and Bongo (0.32 m^3m^{-3} in July), suggesting its performance varies by location. Across all stations, no reanalysis dataset underestimates soil moisture.

4.4 Discussion

CHIRPS emerged as the frontrunner in accurately simulating rainfall, a finding that mirrors the research of Welde et al. (2021); López-Bermeo et al. (2022), particularly in topographical regions like plains. PERSIANN-CDR stands out for its commendable accuracy, albeit with some deviations from the half-standard deviation benchmark at certain stations (Zubieta et al., 2019). The high-resolution capabilities of CHIRPS and the sophisticated data amalgamation methods used in PERSIANN-CDR, which include ongoing recalibrations with the Global Precipitation Climatology Project's monthly product (GPCPv2.2), contribute to their efficacy. ARC2 and ERA5, while they demonstrate certain inaccuracies, could serve as proxies for ground-based measurements if they are properly downscaled to account for local conditions. In contrast, TRMM's performance was poorer, suggesting that it may not be suitable for application across the studied stations, contradicting Atiah et al. (2020), who suggested a reasonable alignment with gauge data. The MBE analysis for CHIRPS revealed both underestimations and overestimations, but these remained largely within the accepted thresholds, signifying its robustness for climate studies. PERSIANN-CDR's performance, despite being generally satisfactory, exhibited some challenges at the Navrongo and Wa stations. ARC2's underperformance during the rainy season and ERA5's in the dry season point to their limitations, and the necessity for downscaling becomes evident to enhance their utility. TRMM's suitability remains questionable, as its error margins exceeded the half SD benchmark, indicating significant discrepancies compared to the gauge data. These insights are crucial, as they inform the selection of appropriate datasets for specific research needs and highlight the importance of continual data verification and validation in the dynamic field of climate science.

Excluding CFSR, ERA5, and MERRA-2 datasets are closely aligned with GMet data in simulating mean temperature on a monthly basis. However, MERRA-2 and CFSR have high Mean Absolute Error (MAE) values at all stations. Although ERA5's errors do not always fall within half the standard deviation of the observed data, it outperforms MERRA-2 and CFSR (Zheng et al., 2023). The commendation of ERA5 extends beyond this study, with multiple researchers, including Choudhury et al. (2023); Graham et al. (2019); Lan et al. (2023); Tetzner et al. (2019); Welde et al. (2021), validating its effectiveness in simulating mean temperatures in various geographic regions. MERRA-2's systematic underestimation and CFSR's overestimation of temperatures, particularly noticeable in April through June, highlight the challenges in achieving precise temperature data assimilation.

Soil moisture significantly impacts Earth's atmospheric and hydrological cycles, affecting weather, climate, and evaporation. It is vital for predicting runoff, streamflow, and refining temperature and precipitation models (Liu et al., 2022). In this context, the study's validation of soil moisture data from the ISMN, ERA5, MERRA-2, and CFSR across daily and monthly intervals is particularly salient. Despite identifying sporadic data omissions, especially in the dry season months of February and March, likely due to the harmattan's effect on soil conditions, the study found a substantial alignment in the daily soil moisture patterns among the datasets. CFSR notably showed the closest correlation to ISMN observed data, suggesting its utility for soil moisture analysis. In periods of peak soil moisture, ERA5's data closely reflected the observed values, particularly in the Navrongo region. This observation aligns with Li et al. (2021), who reported that ERA5's soil moisture data are a marked improvement over the preceding ERA-Interim data, offering enhanced resolution and accuracy. This improvement underscores ERA5's increasingly reliable performance in simulating soil moisture observations, reinforcing its value as a tool for environmental modelling and forecasting.

Upon monthly evaluation, the datasets from CFSR and ERA5 have demonstrated a stronger correlation and pattern resemblance to the ISMN soil moisture data, outperforming MERRA-2. This is evident in their ability to replicate the observed data's temporal patterns. The use of precise analytical metrics, including MAE, MBE, and the half SD of the observed dataset, was instrumental in quantifying the performance levels of the reanalysis data. The findings indicate that CFSR and ERA5 data not only exhibit a higher degree of accuracy but also maintain a robust consistency in humid climate settings, a conclusion that is similar in scope to the work of Zheng et al. (2023), who identified ERA5-Land and CFSv2 as notably reliable in such environmental conditions. In localities such as Tamale, Bimbilla, and Bongo, CFSR's error margins closely approached the half-standard deviation threshold of the observed data, suggesting an impressive alignment with the actual soil moisture conditions in these areas. Despite this precision, it is essential to acknowledge a general trend across all reanalysis datasets to overestimate soil moisture levels, with MERRA-2 presenting the most significant deviation.

The comprehensive nature of this assessment must be considered, as it provides a valuable perspective on the dependability and exactitude of soil moisture data derived from various reanalysis sources. The implications of these insights extend to many practical applications, facilitating more informed decision-making processes in fields such as climate modelling and hydrological sciences, where accurate environmental data is paramount. ERA5's competence in capturing the essence of temperature and soil moisture profiles surpasses its representation of precipitation patterns. This differential in performance may be attributable to the inherent characteristics of the land surface models and data assimilation techniques employed within the ERA5 framework (Hersbach et al., 2020). These models are inherently more receptive to variables such as temperature and soil moisture, which are directly influenced by land conditions, as opposed to rainfall, which is subject to more complex atmospheric processes and variability. The advancements in ERA5's land surface model, HTESSEL (Hydrology Tiled ECMWF Scheme for Surface Exchange over Land), significantly contribute to the improvements in soil moisture accuracy (Hersbach et al., 2020). These enhancements encompass the integration of a comprehensive soil texture map, refined methodologies for simulating bare soil evaporation, and the incorporation of dynamic vegetation maps that reflect seasonal variations. The evolution of the Land Data Assimilation System (LDAS) and the refinement of the Simplified Extended Kalman Filter (SEKF) have been instrumental in refining the process of integrating satellite and ground-based observations into the model, as detailed by Hersbach et al. (2020). These advancements collectively amplify the capacity of ERA5 to provide a more accurate representation of the Earth's soil moisture dynamics.

4.5 Summary

The study provided a validation of satellite and reanalysis products with ground-based data in Northern Ghana, covering the period from 1998 to 2022. Utilising statistical tools such as MAE, MBE, and half the SD of observed data, the study assessed the reliability of rainfall, mean temperature, and soil moisture data from various sources. The CHIRPS data emerged as the most accurate dataset for rainfall in Northern Ghana. Its high-resolution capabilities and ongoing recalibration with ground data make it particularly effective for climatic studies. CHIRPS consistently outperformed other datasets, including PERSIANN-CDR, ARC2, ERA5, and TRMM, accurately capturing rainfall patterns. On the other hand, TRMM displayed significant discrepancies, especially during peak rainfall periods, raising questions about its suitability for detailed hydrological studies in this region.

The ERA5 dataset emerged as the most reliable source for mean temperature data, consistently aligning closely with ground-based observations. In contrast, MERRA-2, although demonstrating consistent patterns, generally underestimated temperatures, suggesting potential limitations in its data assimilation methods. Meanwhile, CFSR exhibited significant variability in its temperature estimates, indicating limited reliability for temperature analysis in this region. In contrast, the CFSR dataset demonstrated the closest alignment with the ISMN data for soil moisture analysis. The study revealed that CFSR's performance was notably robust during the peak soil moisture months from August to October, highlighting its suitability for hydrological and agricultural applications during critical growing periods. ERA5 also exhibited strong performance, particularly in regions such as Navrongo and Pusiga, underscoring its potential utility in localised agricultural planning and ecosystem service management. MERRA-2 displayed significant overestimations in soil moisture levels, indicating a need for further refinement of its algorithms or the development of bias-correction techniques.

CHAPTER 5

5 Streamflow Forecasting using Machine Learning for Flood Management and Mitigation in the White Volta Basin of Ghana

5.1 Introduction

Chapter five presents a manuscript on streamflow forecasting using ML as part of the FEWS in the White Volta basin of Ghana. The manuscript has been published in the journal 'Environmental Challenges - https://doi.org/10.1016/j.envc.2025.101181' (Katsekpor et al., 2025). The introduction and conclusion sections have been removed and replaced with a summary. Aside from this modification, the content remains identical to the published version. The study highlights the increasing applicability and reliability of ML models in hydrological forecasting and water resource management. Following an extensive literature review, this study is identified as the first to apply RF and LSTM models for streamflow forecasting in the basin, specifically to support flood mitigation efforts. The research is structured around two core objectives: (i) to forecast streamflow at 1-, 5-, and 10-day lead times using historical data on rainfall, mean temperature, soil moisture, and evapotranspiration from 1985 to 2019; and (ii) to project future streamflow from 2020 to 2050 based on rainfall and temperature projections from the CMIP6 dataset under the SSP5-8.5 scenario. By employing RF and LSTM models, the study improves the accuracy and lead time of streamflow predictions, contributing directly to enhanced flood risk management, drought response, and irrigation planning in a region that faces recurrent hydrological extremes. The proposed ML-based forecasting approach is both adaptable and scalable, offering a replicable framework for similar water-scarce and climate-vulnerable regions.

5.2 Data and Methods

5.2.1 Study Area

This research focuses on the White Volta basin in Northern Ghana. The area has ground-based hydrological stations that provide streamflow records with Nawuni, Pwalugu, and Yarugu having drainage areas of 92,950, 63,350, and 41,550 km^2 respectively. These are the three gauge stations in the basin with sufficient open-source data for streamflow forecasting (Darko et al., 2021; GRDC, 2020; Mensah et al., 2022).

The basin stretches from Burkina Faso (Upstream) to Ghana (downstream), 8°50'N to 11°05'N latitudes and 0°06'E to 2°50'W longitudes (Mensah et al., 2022). The region is predominantly low-lying, with an elevation range of 150m to 300m. Climatic conditions typical in this region include the Sudan and the Guinea Savannah zones, characterised by distinct dry and wet seasons (Katsekpor et al., 2024b). The dry season spans November to March, and the wet season runs from April to October (Katsekpor et al., 2024a; Yamba et al., 2023). The basin sustains a population primarily engaged in rain-fed agriculture, susceptible to weather extremes such as droughts and floods (Taylor et al., 2006).

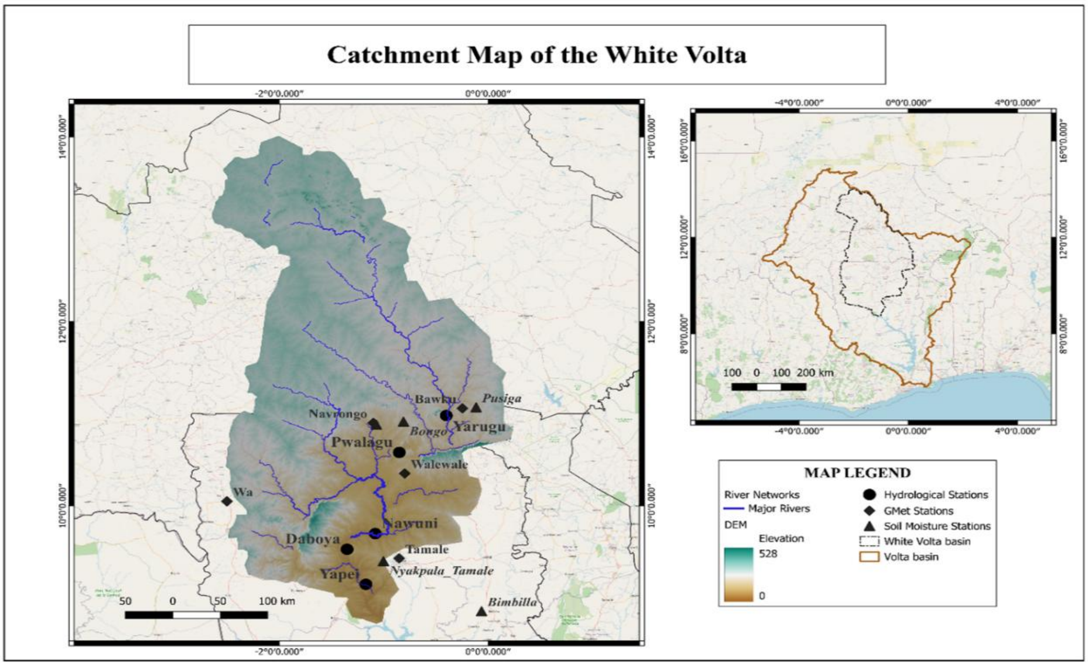

Figure 5.1: Study area outlook enabled by SRTM with available gauge stations (Source: adapted from Katsekpor et al. (2024a)).

5.2.2 Data

Discharge

Daily discharge data were obtained from the Global Runoff Data Centre (GRDC), which operates under the supervision of the World Meteorological Organisation (WMO) (GRDC, 2020). The GRDC's primary role is to collect, archive, and provide access to historical runoff data from river basins around the world. Its database contains daily and monthly river discharge from more than 10,000 stations globally (Burek & Smilovic, 2023; GRDC, 2020). These datasets are critical for hydrological research, climate modelling, and water resource management, particularly in the calibration of models (Burek & Smilovic, 2023). For this study, daily discharge data from 1985 to 2007 were obtained for the Nawuni, Pwalugu, and Yarugu gauge stations in Northern Ghana (https://portal.grdc.bafg.de/applications/public.html?publicuser=PublicUser#dataDownload/Home, last accessed on July 20, 2024).

GloFAS is a river discharge reanalysis dataset from the Copernicus Emergency Management Service (CEMS). It aims to provide consistent hydrological data for flood monitoring and forecasting globally. The system primarily uses the LISFLOOD-OS hydrological model forced with ERA5 rainfall data (called GloFAS-ERA5 from here on), enabling river discharge calculations at catchment scales (Harrigan et al., 2020, 2023; Hersbach et al., 2020). The horizontal resolution of the data for version 4.0 is 0.05^0. Daily discharge was downloaded from 1985 to 2019 using the link https://ewds.climate.copernicus.eu/datasets/cems-glofas-historical?tab=overview (last accessed on September 25, 2024).

Rainfall

Daily rainfall data were obtained from the CHIRPS and the GCMs CMIP6. The CHIRPS dataset, created by experts at the USGS, EROS Centre, combines the CHPclim and CHIRP, supplemented with station data (Funk et al., 2015). Designed to support early warning systems for disasters like floods and droughts, CHIRPS provides a high-resolution precipitation dataset (0.05°) covering 1981 to the present. The data is offered in various time intervals and formats with a resolution of 0.05° x 0.05° (Funk et al., 2015). CHIRPS mimics well with the observed data in the White Volta basin (Katsekpor et al., 2024a), influencing its selection. Rainfall data spanning from 1985 to 2019 were retrieved from https://data.chc.ucsb.edu/products/CHIRPS-2.0/ (last accessed on July 20, 2024).

The GCMs developed under the CMIP6, in collaboration with the IPCC, provide projections of future climate change scenarios under various SSPs (Nguyen et al., 2024; Siabi et al., 2023). In this study, historical data (1985 – 2014) and future projections under the SSP5-8.5 (2020 - 2050), which include five rainfall models, were sourced from the Earth System Grid Federation (ESGF) data portal (https://esgf-node.llnl.gov/projects/esgf-llnl/). These experiments include ACCESS-CM2, BCC-CSM2-MR, INM-CM5-0, MIROC6 and MRI-ESM2-0. These datasets were selected because they provide daily historical simulations and future projections under the SSP5-8.5 scenario, which assumes the highest radiative forcing of 8.5 W/m² by 2100. Moreover, the findings of Singh et al. (2023) and Siabi et al. (2023) have shown the ability of ACCESS-CM2, BCC-CSM2-MR, INM-CM5-0, and MRI-ESM2-0 in simulating observed rainfall. This scenario was chosen due to the limited progress on climate change policy implementation in Ghana (Awuni et al., 2023).

Mean Temperature

Temperature data were obtained from ERA5 and GCMs-CMIP6. The CMIP6 data include the ACCESS-CM2 and ACCESS-ESM1-5 spanning from 1985 to 2014 for the historical period and 2020 to 2050 for the future period under the SSP5-8.5 scenario. This data combination was informed by the findings of Siabi et al. (2023), Singh et al. (2023) and Liu et al. (2024), who have shown their ability in simulating observed temperature. Daily mean temperatures were sourced for further preprocessing and analysis.

ERA5, developed by ECMWF under the C3S, is the latest reanalysis dataset following ERA-Interim. It provides comprehensive data for analysing past, present, and future climate conditions, supporting water management and policy decisions (Hersbach et al., 2019). ERA5 combines in situ and satellite observations to improve land surface variables such as soil moisture, temperature, and snow cover (Hersbach et al., 2020). It offers global coverage at a 0.25° latitude resolution and includes uncertainty assessments to enhance reliability (Hersbach et al., 2020). ERA5 has shown a strong agreement with observed data in the White Volta basin (Katsekpor et al., 2024a) influencing its selection. Hourly temperature data spanning from 1985 to 2019 were processed into daily timesteps.

Soil Moisture

Soil moisture data (0–5 cm) from 1985 to 2019 were collected from the CFSR. The CFSR datasets integrate conventional meteorological observations with satellite data using advanced data assimilation techniques. It models interactions between the atmosphere, oceans, land, and sea ice (Lu et al., 2019; Mok et al., 2018; Saha et al., 2010). Data from 1979 to 2011 are available at hourly intervals with a spatial resolution of 0.312°. The follow-up version, CFSV2, continues the data record after March 2011 with improved resolution (Mok et al., 2018). These datasets, known as CFSR, offer a comprehensive collection of climate variables.

Evapotranspiration

Daily evapotranspiration (et), evaporation from open waters (e0), and evaporation from bare soil (es) were obtained from the LISVAP model spanning from 1985 to 2019 (Appendix: Figure A.3.6 - A.3.8). LISVAP uses either the Penman-Monteith or Hargreaves equations, implemented in a Python using the PCRaster modelling framework (Burek et al., 2013; Knijff et al., 2010).

5.2.3 Models

Random forest

RF is a widely adopted machine learning model for both classification and regression tasks. It functions by generating an ensemble of decision trees through a bagging technique, which helps to reduce variance and improve predictive performance (Adnan et al., 2023; Blandini et al., 2023). Each tree is built on a random feature subset, ensuring the model's diversity and robustness. Final predictions are made by averaging (regression) or majority voting (classification). RF is highly effective for large, complex datasets and is used in fields such as flood frequencies and land cover classification (Desai & Ouarda, 2021; Park et al., 2020; Tyralis et al., 2021). Key parameters of the model include the number of trees, max features per node, and bootstrapping (Kim & Han, 2020). Despite the possibility of tuning, RF is generally not overly sensitive to hyperparameters (Cutler et al., 2011; Janitza & Hornung, 2018).

LSTM - Long Short-Term Memory

The LSTM model, introduced in 1997, improves upon traditional RNNs by addressing vanishing and exploding gradient problems (Staudemeyer & Morris, 2019; Van Houdt et al., 2020). The architecture features a memory block regulated by three primary gates: the input gate, output gate, and forget gate (Fathi et al., 2025). These gates primarily control the information across the memory of the LSTM model.

5.2.4 Data Preprocessing and Analysis

Data Processing

Since the ML models were run daily to generate forecasts, it was important to ensure that all input data were in daily formats. Rainfall and observed streamflow were already available in daily formats. However, mean temperature and soil moisture were originally retrieved hourly. Therefore, they were converted to daily formats by averaging.

Streamflow data obtained from GRDC had gaps, especially at the Pwalugu and Yarugu gauge stations, as detailed in Table 5.1. To construct a complete time series, these gaps were filled using discharge data from GloFAS, which has demonstrated strong performance in simulating discharge globally (Harrigan et al., 2020; Prudhomme et al., 2024). Due to limited observed data in the White Volta basin, GloFAS data were further used to replace missing records from 2008 to 2019. This data augmentation was essential to improve the performance of the ML models.

Table 5.1: Percentage gaps in data.

Station	Missing data (%)
Nawuni (1985 – 2007)	3.63%
Pwalugu (1985 – 2007)	44.69%
Yarugu (1990 – 2007)	56.72%

Running LSTM and RF

The RF model was trained using multiple configurations of decision trees ranging from 50 to 200 trees. This configuration is important to choose the number of trees that yields the highest performance of the model. Consequently, 100 trees were selected based on the performance metrics as detailed in Appendix Figure A.3.12. The RF model code was adapted from Pham et al. (2021).

Similarly, the LSTM is configured with 50 units to capture the complex nature of hydrological patterns. Hunt et al. (2022) also used 50 neurons when training their LSTM model, achieving high accuracy in model performance. The input shapes used were 1 and 2, as training was conducted daily. In the LSTM architecture, the tanh function helps control gradient flow, while the sigmoid function regulates the flow of information through the cell state (Van Houdt et al., 2020). The linear activation function enables scaling of the LSTM output. The study also employed the Adam optimiser to accelerate training. This optimiser is known to be stable for time series data and requires minimal tuning (Hunt et al., 2022). To determine the optimal batch size and number of epochs for improving LSTM performance, an experimental tuning process was used to strike a balance between effective learning and computational efficiency. Batch sizes of 16, 32, and 64, and epochs of 20, 50, and 100 were tested. Consequently, the model was trained for 50 epochs (see Appendix Figure A.3.11) with a batch size of 32, as shown in Appendix A.3.11 The LSTM code was adapted from Hunt et al. (2022).

Table 5.2: Characteristics of the LSTM model.

Layer	Input Shape	Activation	Output Shape
LSTM layer 1	(1, number of features)	Tanh	(1, 50)
Dense layer	(50,)	Linear	(1,)

The LSTM and RF models were trained using CHIRPS rainfall, ERA5 temperature, CFSR soil moisture, evapotranspiration, and evaporation from soil and open water. CHIRPS, ERA5, and CFSR were chosen based on the findings of Katsekpor et al. (2024a), who found them accurate for simulating rainfall, temperature, and soil moisture, respectively, in the region. The LSTM and the RF models were trained to simulate streamflow spanning from 1985 to 2019 for both Nawuni and Pwalugu and from 1990 to 2019 for Yarugu. Datasets were split into 70% for training, 20% for testing, and 10% for operational use. Operational data were used in forecasting streamflow at 1-day, 5-day, and 10-day intervals.

GCMs-CMIP6 data were also used to run the RF and LSTM models to forecast streamflow from 2020 to 2050. Models were trained using GCMs-CMIP6 rainfall and mean temperature data from 1985 to 2014 for Nawuni and Pwalugu, and from 1990 to 2014 for the Yarugu gauge station. The data were split into 80% for training and 20% for testing.

Trends in Climate Variables

Annual trends in rainfall and mean temperature from the GCMs-CMIP6 were analysed using Kendall's Tau and the p-value. Kendall's Tau (τ) measures the monotonic (increasing or decreasing) relationship in ordinal data. Kendall's Tau (τ) ranges from -1 to 1: a positive value means the trend is rising, while a negative one means it is falling (Brossart et al., 2018). A trend is considered statistically significant if the p-value is below 0.05; if the p-value exceeds 0.05, the trend is not statistically significant (Wood et al., 2014).

Low and High Flows Analysis

High flows indicate flows that are likely to occur or exceed 10% of the time (Q10). Low flows, on the other hand, are those that happen or are exceeded 90% of the time (Q90). Moreover, a rise in Q10 suggests higher peak flows and greater flood risk, while a drop in Q90 indicates lower base flows and increased vulnerability to river drought (Aich et al., 2014; Dembélé et al., 2022). Q01 indicates a rise in flood risk, which is useful for identifying more extreme events (Pechlivanidis et al., 2017).

Performance Metrics

To evaluate the accuracy of the simulated data against observations, CMIP6 data were validated using CHIRPS rainfall and ERA5 temperature. These datasets (CHIRPS rainfall and ERA5 temperature) were identified by Katsekpor et al. (2024a) as the best alternatives to observed data in the data-scarce White Volta basin. Statistical metrics such as MAE, MBE, and SD were used for the evaluation. These metrics are essential for quantifying the tested model's precision and reliability. MAE quantifies the average size of errors between simulated and observed values, providing a straightforward measure of prediction accuracy regardless of error direction. Unlike MAE, MBE considers the direction of the errors, indicating whether model predictions are consistently higher or lower than the actual observations, resulting in a positive or negative value. This helps identify systematic biases in the model outputs. An MAE value close to 0 suggests minimal average prediction error, meaning the predicted values closely align with the actual values (Katsekpor et al., 2024a). Similarly, an MBE value near 0 indicates an unbiased prediction with no consistent overestimation or underestimation. The study followed the error significance principle proposed by Singh et al. (2005), later adopted by Moriasi et al. (2007) and Yamba (2016), where MAE and MBE values less than or equal to half of the observed data's standard deviation (SD) are considered acceptable, as stated in the work of Katsekpor et al. (2024a). The Kling-Gupta Efficiency (KGE) was also adopted to measure the model's performance of the simulated data compared to that of the observed data. The Kling-Gupta Efficiency is one of the standard metrics adopted in hydrological studies for measuring the accuracy of models (Cinkus et al., 2023; Harrigan et al., 2020; Hunt et al., 2022). Similar to the KGE, the R^2, which is the coefficient of determination, measures the variance of the predicted from the observed data (Singh et al., 2023). A perfect forecast using both the KGE and the R^2 indicates a value of 1. The formulas are shown below:

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|O_i - P_i|$$

$$MBE = \frac{1}{n}\sum_{i=1}^{n}(O_i - P_i)$$

$$SD = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(O_i - \overline{O}\right)^2}$$

$$\text{KGE} = 1 - \sqrt{(r-1)^2 + (\beta - 1)^2 + (\gamma - 1)^2}$$

$$\beta = \frac{\mu_{sim}}{\mu_{obs}}$$

$$\gamma = \frac{\sigma_{sim}}{\sigma_{obs}}$$

$$R^2 = \left(\frac{\sum_{i=1}^{n}\left(O_i - \overline{O}\right)(P_i - \bar{P})}{\sqrt{\sum_{i=1}^{n}\left(O_i - \overline{O}\right)^2} x \sqrt{(P_i - \bar{P})^2}}\right)$$

In this context, n denotes the sample size, O_i represents the observed values, P_i the predicted values, and $\overline{O}$ is the mean of the observed values (Katsekpor et al., 2024a). In the KGE metric, r represents Pearson's correlation coefficient, γ signifies the variability ratio, and β denotes the bias ratio. Here, μ_{sim} and σ_{sim} refer to the mean and SD of the simulated discharge, while μ_{obs} and σ_{obs} are the corresponding statistics for the observed discharge (Hunt et al., 2022). R^2 is the coefficient of determination.

5.3 Results

5.3.1 Historical Streamflow Prediction at 1, 5, and 10 days using RF and LSTM models

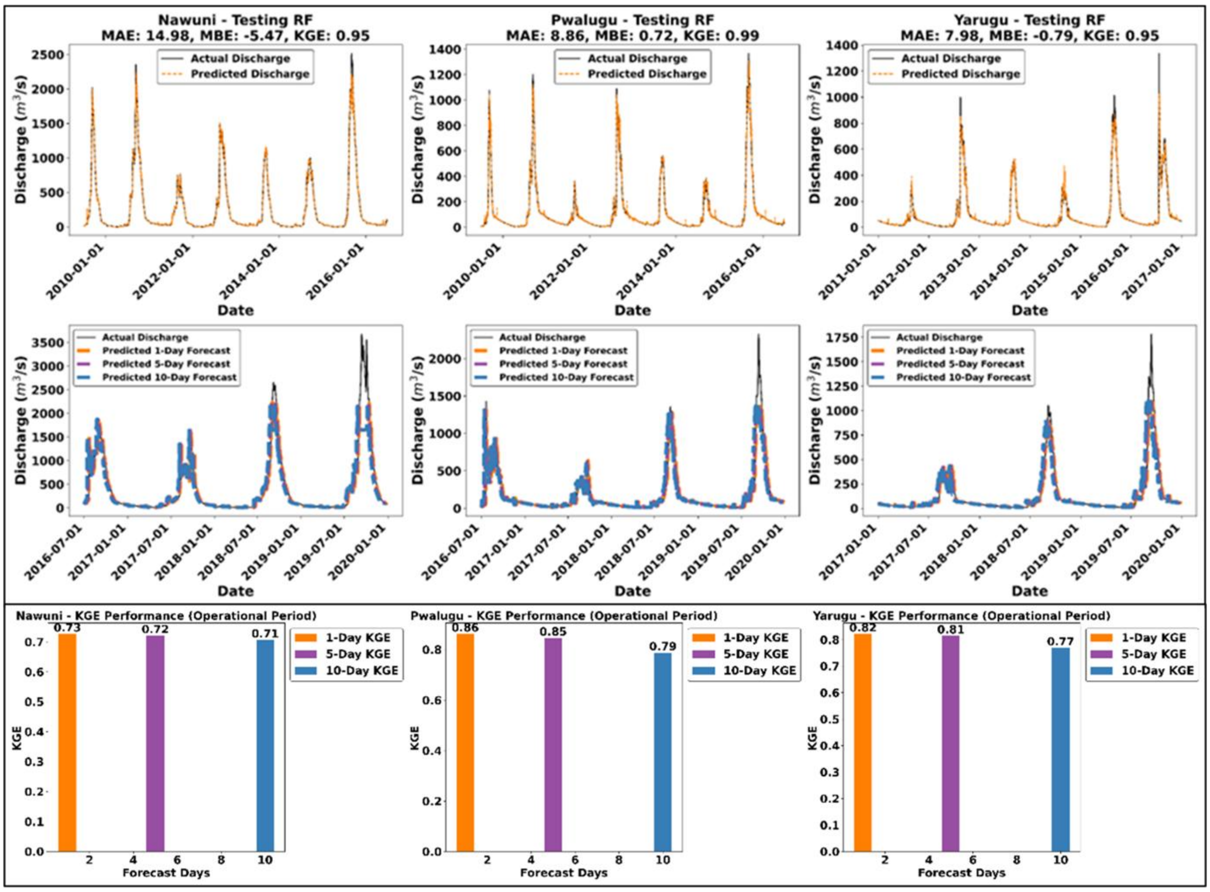

Figure 5.2: RF model in forecasting streamflow at 1, 5, and 10 days.

Figure 5.2 shows the ability of the RF to mimic the observed data at 1-day, 5-day, and 10-day forecasts. Both the testing and the operational period recorded a high KGE, ranging from 0.86 for a 1-day forecast to 0.71 for a 10-day forecast. During the testing phase, MAE was higher in larger basins like Nawuni (14.98 m^3/s) compared to smaller ones like Yarugu (7.98 m^3/s). Similarly, the magnitude of negative biases recorded in Yarugu (-0.79 m^3/s) are much lower than the magnitude of biases recorded in the Nawuni (-5.47 m^3/s) gauge station. The outstanding performance of the model in mimicking the discharge data can be attributed to the large amount of validated data used in training the models.

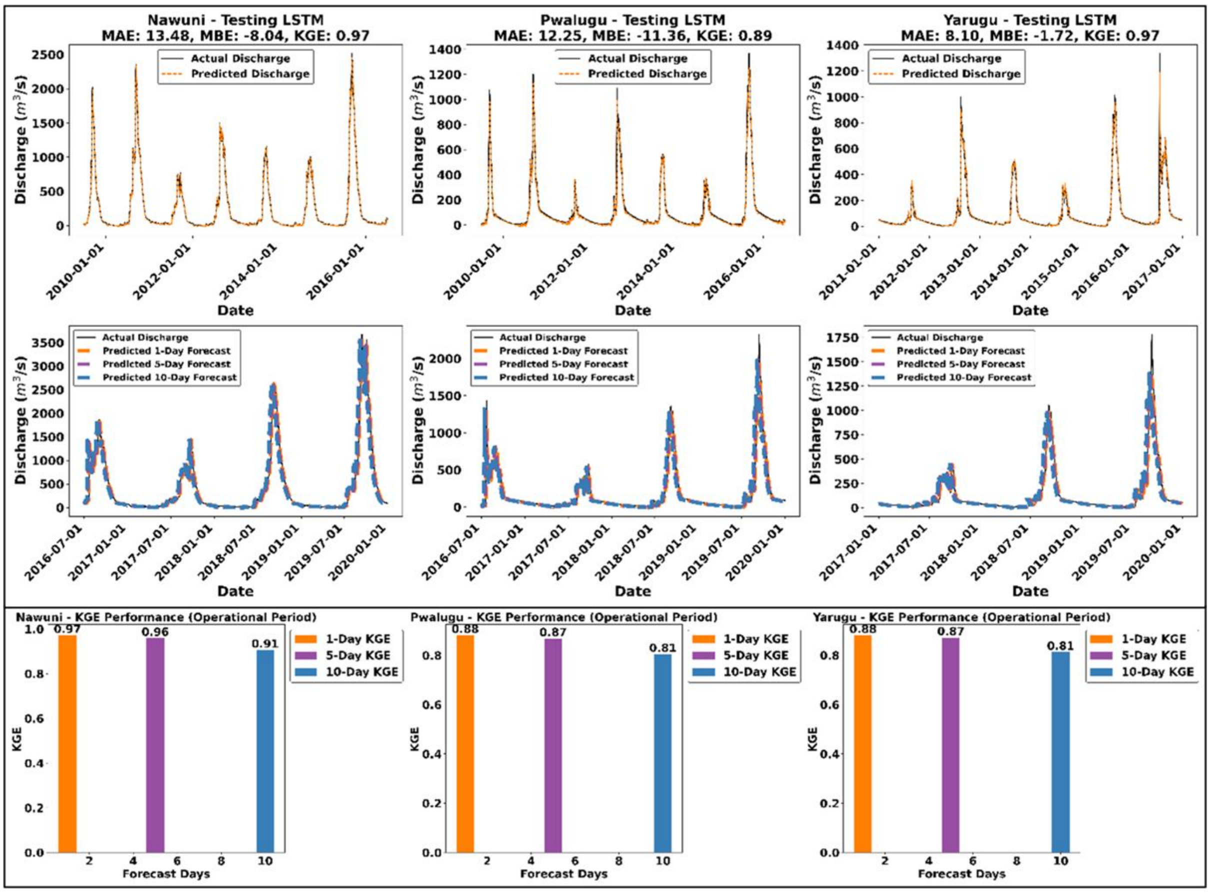

Figure 5.3: LSTM model in forecasting streamflow at 1, 5, and 10 days.

Figure 5.3 shows the ability of the LSTM model to mimic the observed data at 1-day, 5-day, and 10-day forecasts across the three gauge stations. Similar to Figure 5.2, the KGE recorded by the model is generally high, between 0.97 and 0.89. During the testing period, the predicted data underestimated the actual flow at all three gauge stations. Pwalugu recorded the highest magnitude (-11.36 m^3/s), followed by Nawuni (-8.04 m^3/s) and Yarugu (-1.72 m^3/s). Again, the MAE recorded by the simulated data is higher in larger basins (Nawuni: 13.48 m^3/s) compared to smaller basins (Yarugu: 8.10 m^3/s). In the operational period, the KGE drops slightly as the lead time is extended from 1 to 5 days and 10 days. For instance, the KGE recorded at Nawuni is 0.97 for 1 day, 0.96 for 5 days, and 0.91 for 10 days. The model's outstanding performance in mimicking the discharge data, even at a 10-day forecast, can be attributed to the large amount of validated data used in training the models.

5.3.2 Validation of Rainfall Data from GCMs-CMIP6

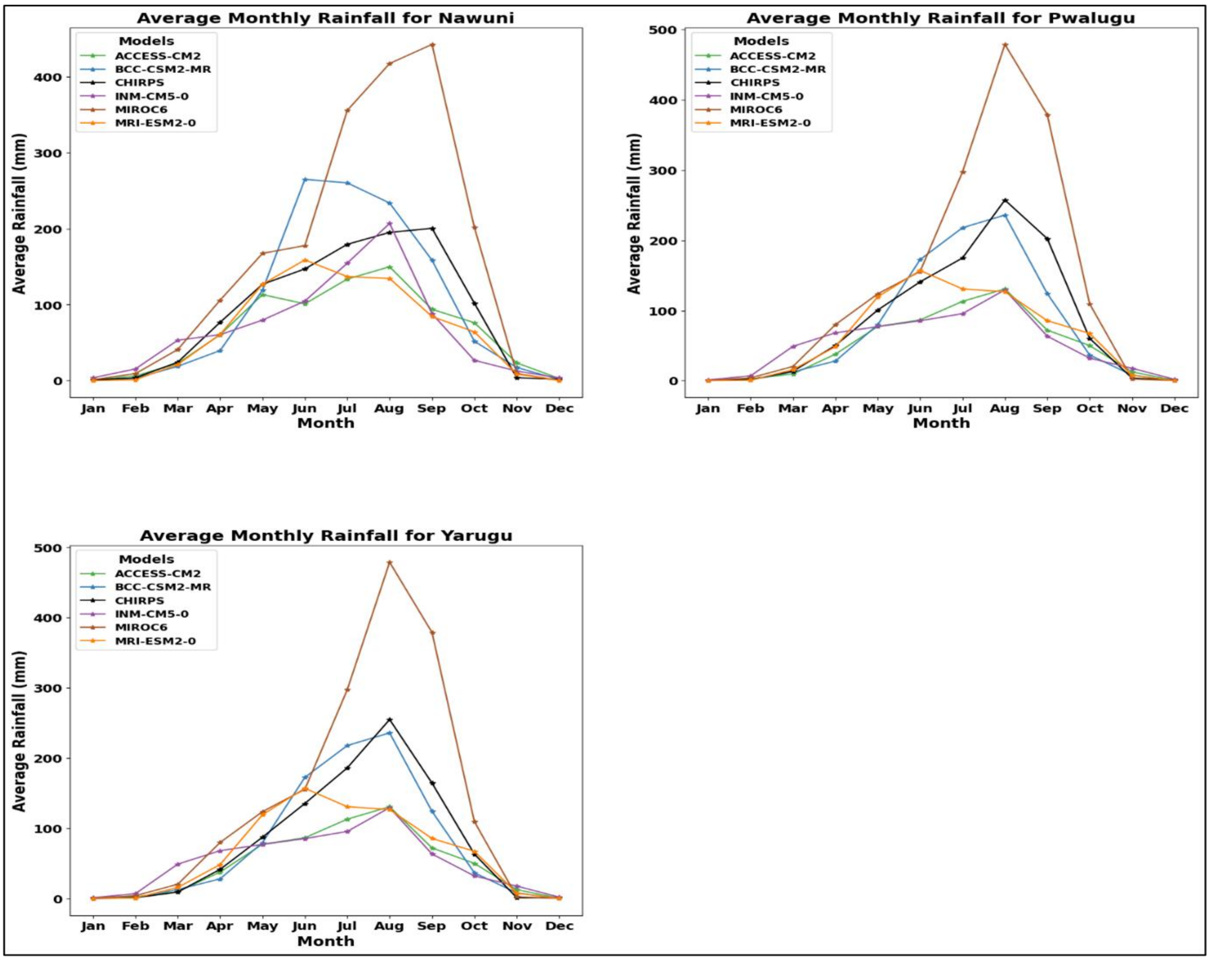

Figure 5.4: Monthly rainfall recorded by the CHIRPS observed and the CMIP6 data.

Figure 5.4 shows the monthly rainfall pattern recorded by the CMIP6 data, including ACCESS-CM2, BCC-CSM2-MR, INM-CM5-0, MIROC6, and MRI-ESM2-0 against the observed CHIRPS data. The BCC-CSM2-MR shows a consistent alignment with the observed data, at the Pwalugu (for example, 235.87mm and 257.29mm for the BCC-CSM2-MR and CHIRPS, respectively) and Yarugu (for example, 235.87mm and 254.88mm for the BCC-CSM2-MR and CHIRPS, respectively) gauge stations. At the Nawuni gauge station, MRI-ESM2-0 closely matches the observed data from January to June, INM-CM5-0 aligns closely in July and August, and BCC-CSM2-MR matches well from September to December. MIROC6 consistently records a larger gap from the observed data, especially in the wet season between July and October across all three stations (for example, 417.31mm and 195.1mm for MIROC6 and CHIRPS, respectively, at Nawuni).

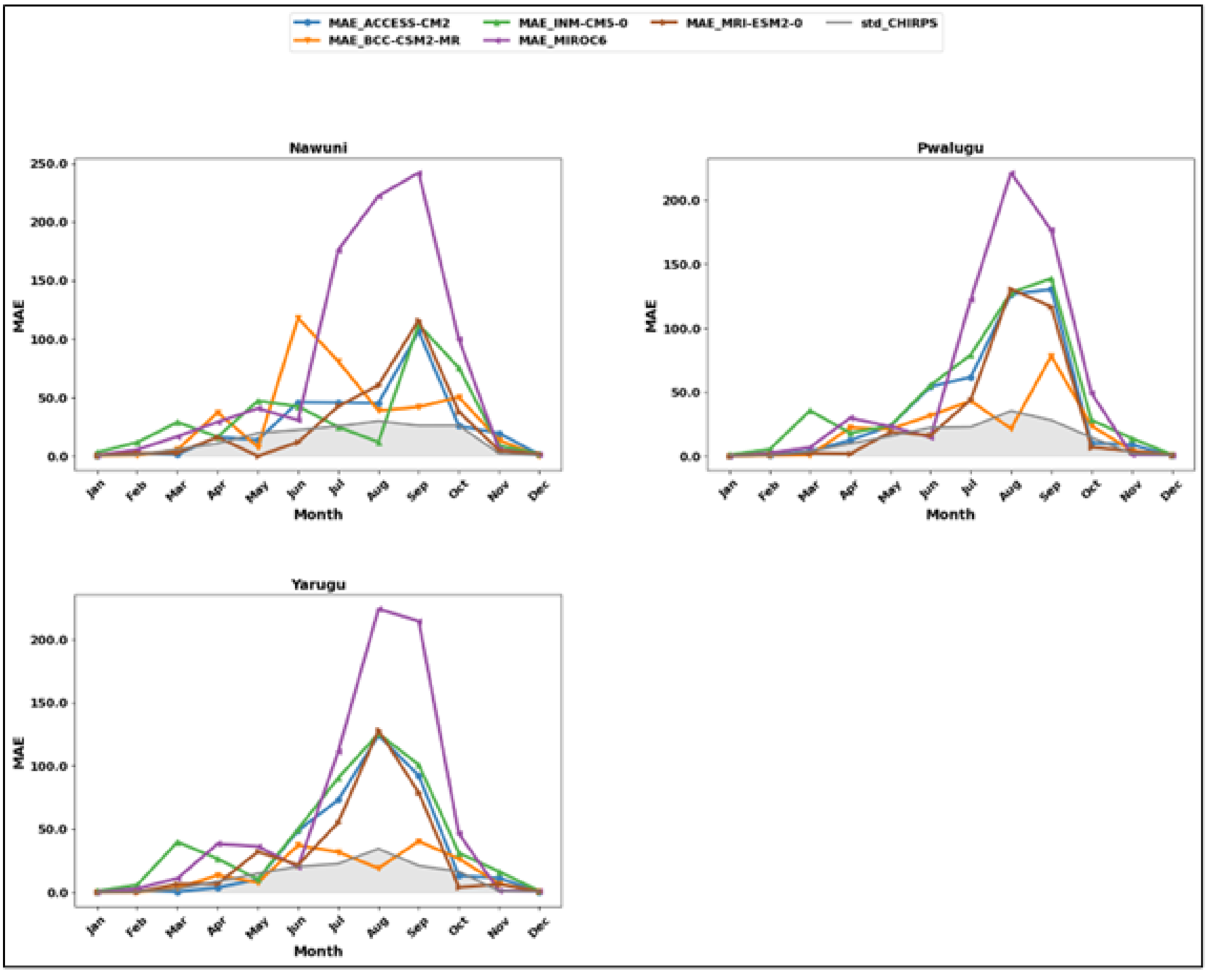

Figure 5.5: Monthly MAE recorded by the CMIP6 at the three gauge stations.

The study used the MAE to quantify prediction errors as shown in Figure 5.5. BCC-CSM2-MR recorded the lowest errors at both Pwalugu and Yarugu gauge stations, particularly in the peak rain season in September (78.2 mm and 40.3mm for Pwalugu and Yarugu, respectively), outperforming ACCESS-CM2, INM-CM5-0, MIROC6, and MRI-ESM2-0, which had greater errors for the same period and location. Across Pwalugu and Yarugu gauge stations, the BCC-CSM2-MR errors remained closer to half the SD of the observed, indicating the reliability of the data for climate studies. At the Nawuni gauge station, the lowest MAE from January to June was recorded by MRI-ESM2-0 (0.05 mm in May and 11.8 mm in June). For July and August, INM-CM5-0 recorded the lowest MAE (24.8 mm in July and 11.9 mm in August), while from September to December, BCC-CSM2-MR showed the lowest values (41.9 mm in September). MIROC6 recorded the highest MAE across all gauge stations, particularly between July and October.

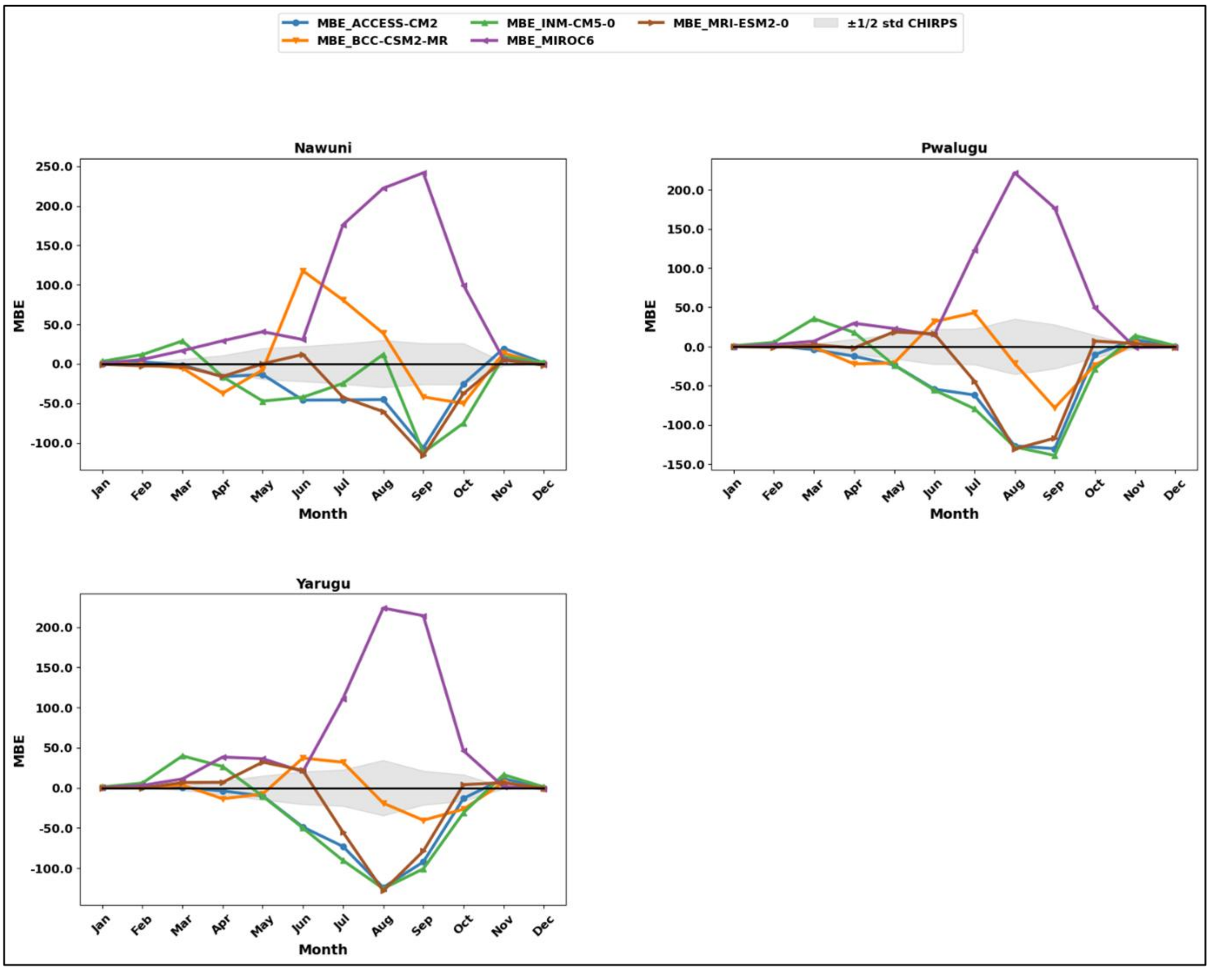

Figure 5.6: Monthly MBE recorded by the CMIP6 at the three gauge stations.

The study used the MBE to quantify prediction biases recorded by the CMIP6 data, as shown in Figure 5.6. All CMIP6 data, except MIROC6, underestimated the monthly rainfall between August and October. Similar to Figure 5.5, BCC-CSM2-MR recorded the lowest magnitude of biases at Pwalugu and Yarugu gauge stations (for example, -21.4mm in August at Pwalugu) outperforming INM-CM5-0 (for instance, -127.9mm in August at Pwalugu), ACCESS-CM2 (for instance -126.6mm in August at Pwalugu), MRI-ESM2-0 (for instance -130.6mm in August at Pwalugu) and MIROC6 (for instance 221.5mm in August at Pwalugu). MIROC6 consistently overestimated the monthly rainfall in all 12 months. At the Nawuni gauge station, MRI-ESM2-0, INM-CM5-0, and BCC-CSM2-MR each show close agreement with the half SD of the observed data from January to June, July and August, and September to December, respectively. All simulated data recorded higher biases in the wet season between May and October.

As shown in Appendix Figure A.3.1, the study also performed a monthly coefficient of determination (R^2) of the observed data with BCC-CSM2-MR at Pwalugu and Yarugu and the ensemble MRI-ESM2-0 (January to June), INM-CM5-0 (July and August), and BCC-CSM2-MR (September to December) at Nawuni gauge station. The observed data show a strong agreement with the simulated data across all gauge stations, with Yarugu recording the highest of 0.94, followed by Nawuni (0.93) and Pwalugu (0.88).

5.3.3 Validation of Mean Temperature Data from GCMs-CMIP6

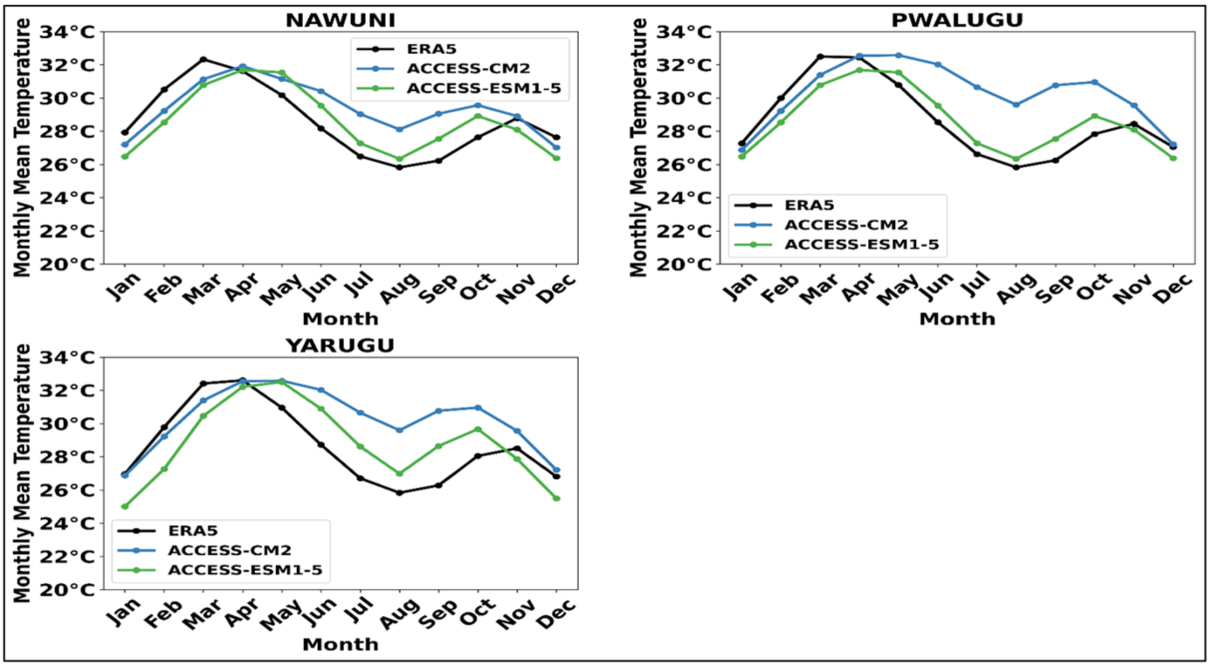

Figure 5.7: Monthly mean temperature recorded by the ERA5 observed and the CMIP6 data.

Figure 5.7 shows the monthly temperature patterns from ERA5 observations, ACCESS-CM2, and ACCESS-ESM1-5 models at the three gauge stations. Although ACCESS-CM2 and ACCESS-ESM1-5 closely match the observed data, particularly at the beginning of the month, slight deviations are noted in March and April. Both simulated data peaks much quicker starting from March, showing a slight distortion in the pattern compared to the observed.

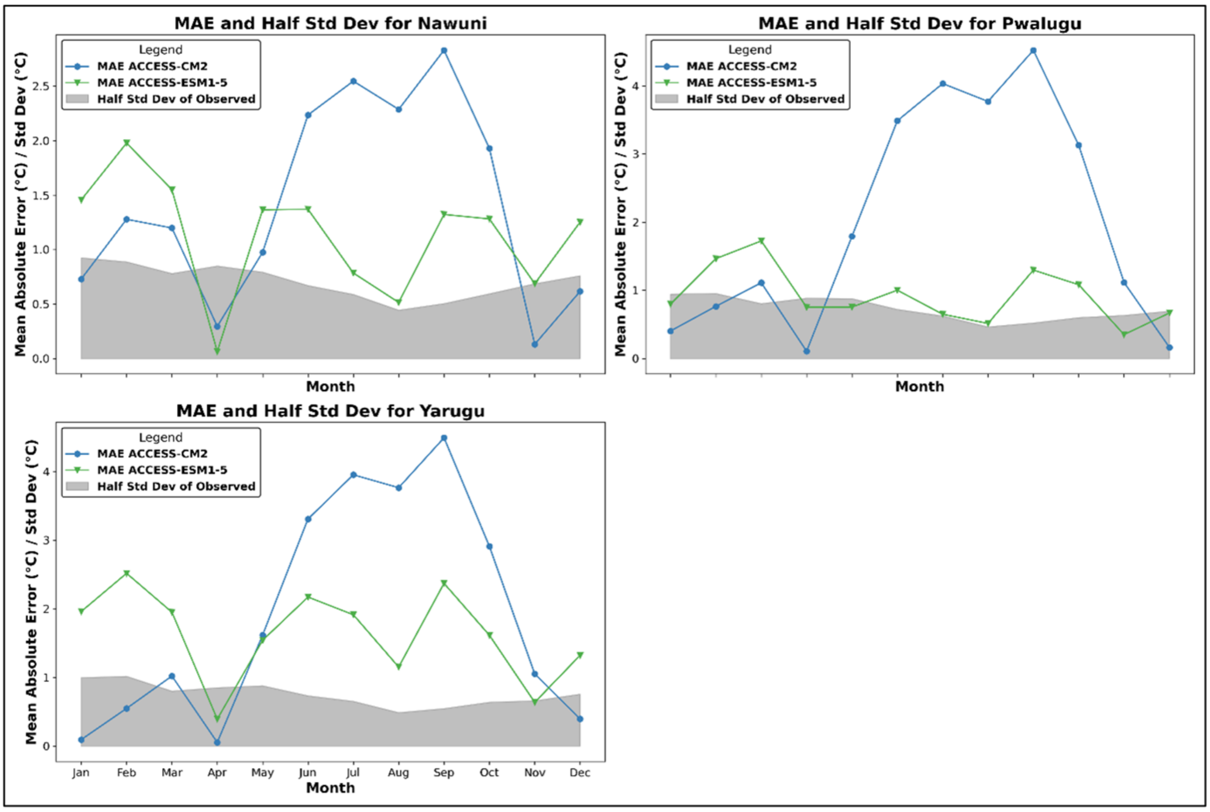

Figure 5.8: Monthly MAE recorded by the CMIP6 for the three gauge stations.

Figure 5.8 compares the MAE values from ACCESS-CM2 and ACCESS-ESM1-5 with half the SD of the observed ERA5 data. Although all simulated data (CMIP6) do not cover the SD of the observed data, ACCESS-ESM1-5 records the lowest error in the wet season between June and October (for example 1.0°C, 0.65°C, 0.51°C, 1.3°C and 1.08°C in June, July, August, September, and October respectively at Pwalugu) outperforming the ACCESS-CM2 (for example, 3.49°C, 4.03°C, 3.77°C, 4.52°C and 3.13°C in June, July, August, September and October respectively at Pwalugu) across all three gauge stations. In contrast, the ACCESS-CM2 (for example 0.16°C, 0.40°C, 0.77°C, and 1.11°C in December, January, February, March respectively at Pwalugu) outperforms ACCESS-ESM1-5 (for example 0.67°C, 0.8°C, 1.46°C, and 1.72°C in December, January, February, March respectively at Pwalugu) in the dry season between December and March. The MAE recorded by the ACCESS-CM2 between May and October for all three gauge stations is very high, highlighting its limitations and reliability.

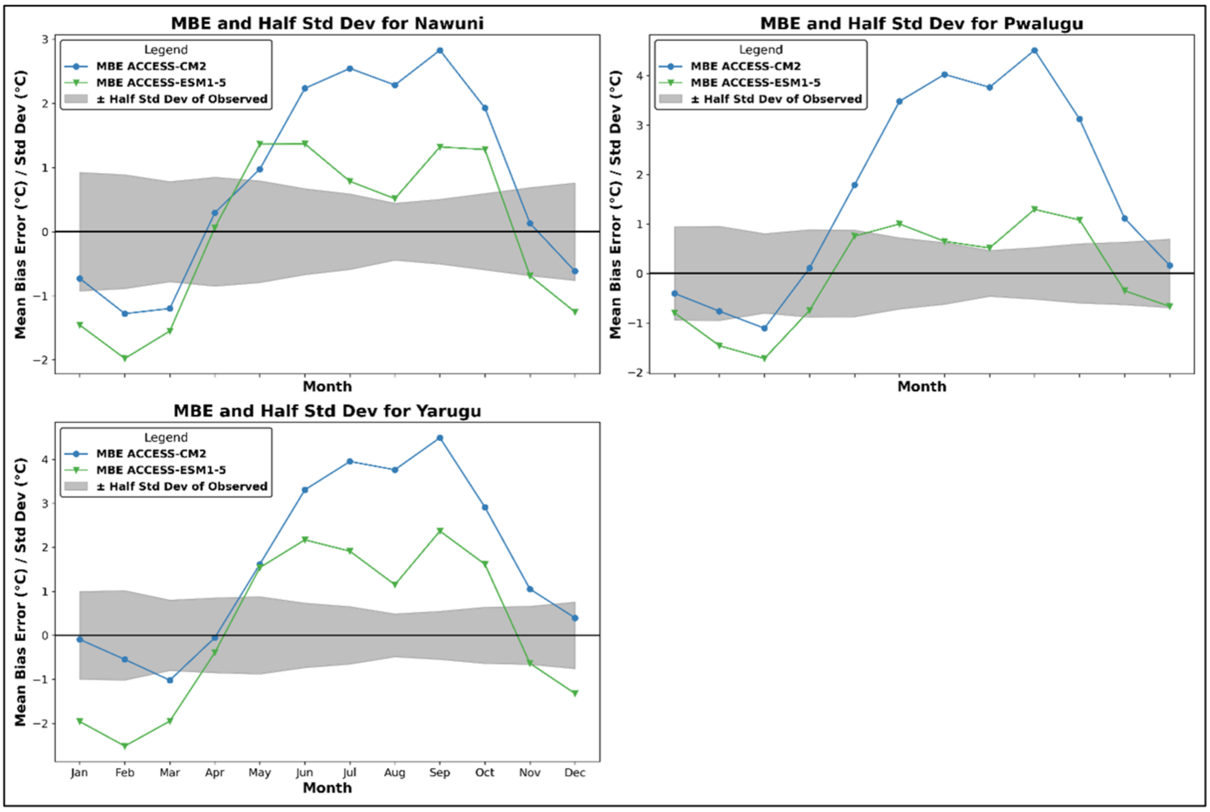

Figure 5.9: Monthly MBE recorded by the CMIP6 data at the three gauge stations.

From Figure 5.9, ACCESS-CM2 and ACCESS-ESM1-5 estimates are cooler in the dry season from November to March, but warmer from April to October. Similar to Figure 5.8, ACCESS-CM2 exhibits higher positive biases during the peak rainfall months (June to October) compared to ACCESS-ESM1-5. In contrast, ACCESS-ESM1-5 shows greater negative biases in the dry season (December to March). For example, at Pwalugu, ACCESS-ESM1-5 recorded -0.8°C, -1.46°C, and -1.72°C in January, February, and March, respectively, while ACCESS-CM2 recorded -0.4°C, -0.77°C, and -1.11°C for the same months.

The R^2 was used to estimate the relationship between the observed data (ERA5) and the simulated data (Ensemble of ACCESS-CM2 and ACCESS-ESM1-5) as shown in Appendix Figure A.3.2. All values show a good performance between the observed and the predicted for all three gauge stations, with Pwalugu showing the highest value of 0.89, followed by Nawuni (0.76) and Yarugu (0.73).

5.3.4 Trends in Annual Rainfall for the Historical and Future Periods

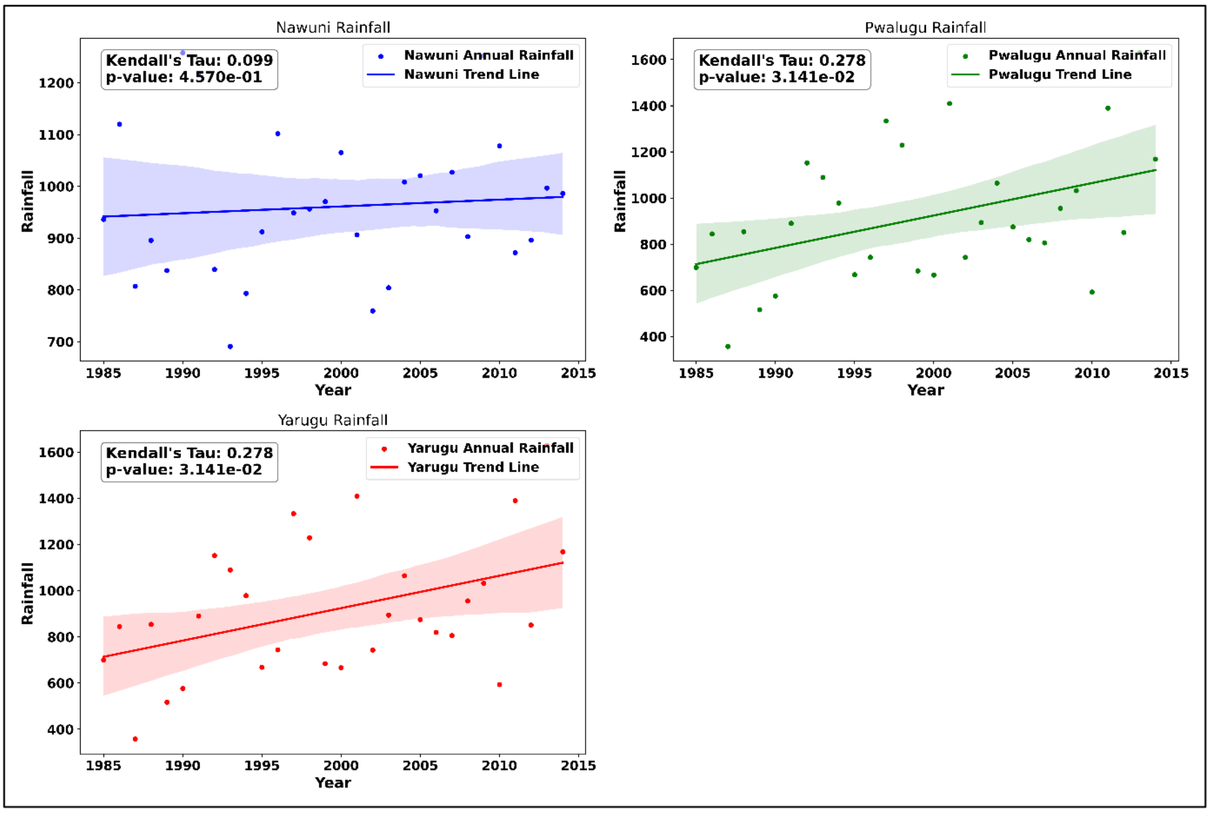

Figure 5.10: Trends in annual rainfall from 1985 to 2014 at the three gauge stations.

Figure 5.10 shows the trend in the annual rainfall from 1985 to 2014 at Nawuni, Pwalugu, and Yarugu gauge stations. Annual rainfall across all gauge stations shows an increasing trend ranging from 0.099 (Nawuni) to 0.278 (both Pwalugu and Yarugu). The p-values for both Pwalugu and Yarugu (0.03) are less than 0.05, which provides evidence of an increasing annual rainfall pattern between 1985 and 2014. In contrast, the p-value for Nawuni (0.4) is greater than 0.05, showing that the increasing trend is not statistically significant and that there is no clear evidence of an increase in rainfall at this gauge station.

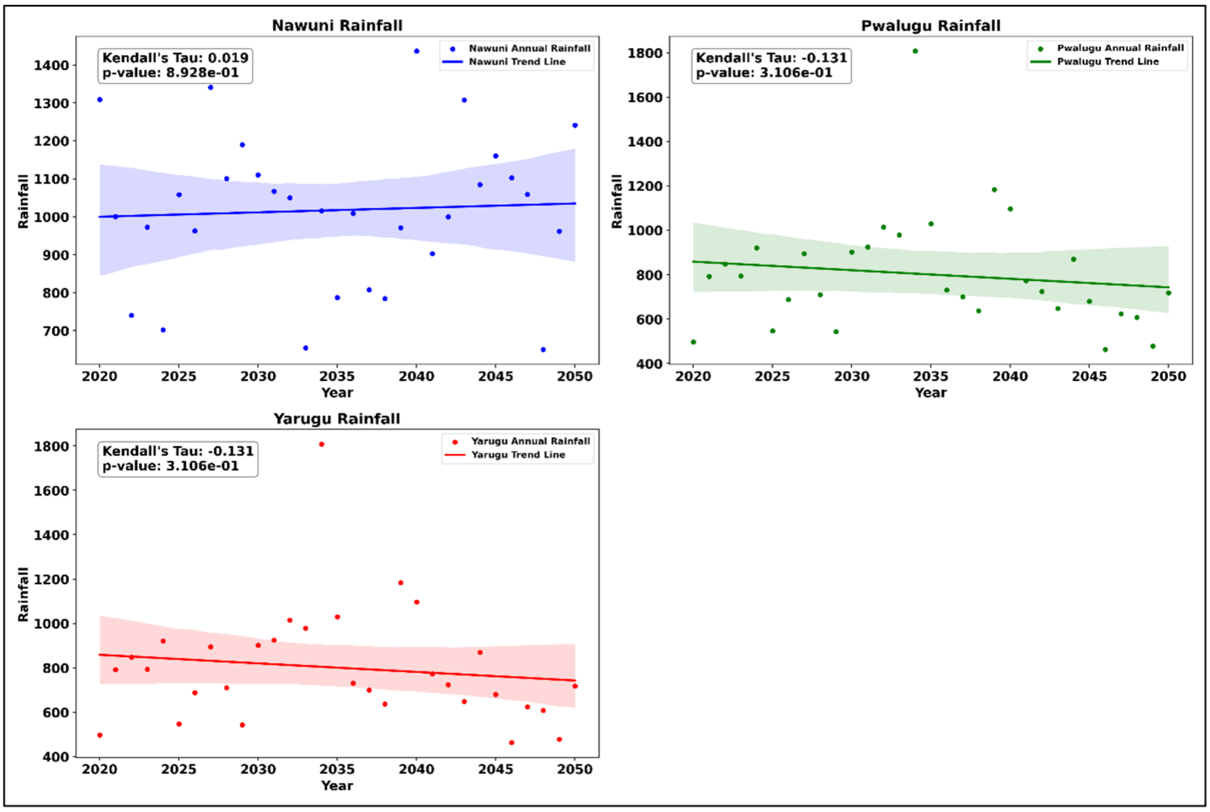

Figure 5.11: Trends in annual rainfall from 2020 to 2050 at the three gauge stations.

Figure 5.11 shows the trend in annual rainfall for Nawuni, Pwalugu, and Yarugu gauge stations from 2020 to 2050. In contrast to Figure 5.10, the annual rainfall trends at the Pwalugu and Yarugu gauge stations show a decrease, while the trend at the Nawuni gauge station shows a slight annual increase. The p-values recorded at Nawuni (0.9), Pwalugu (0.3), and Yarugu (0.3) are all greater than 0.05, indicating that the observed trends in annual rainfall, whether increasing or decreasing, are not statistically significant. This does not provide any clear evidence of an annual rainfall increase or decrease between 2020 and 2050.

5.3.5 Trends in annual mean temperature for the historical and future periods

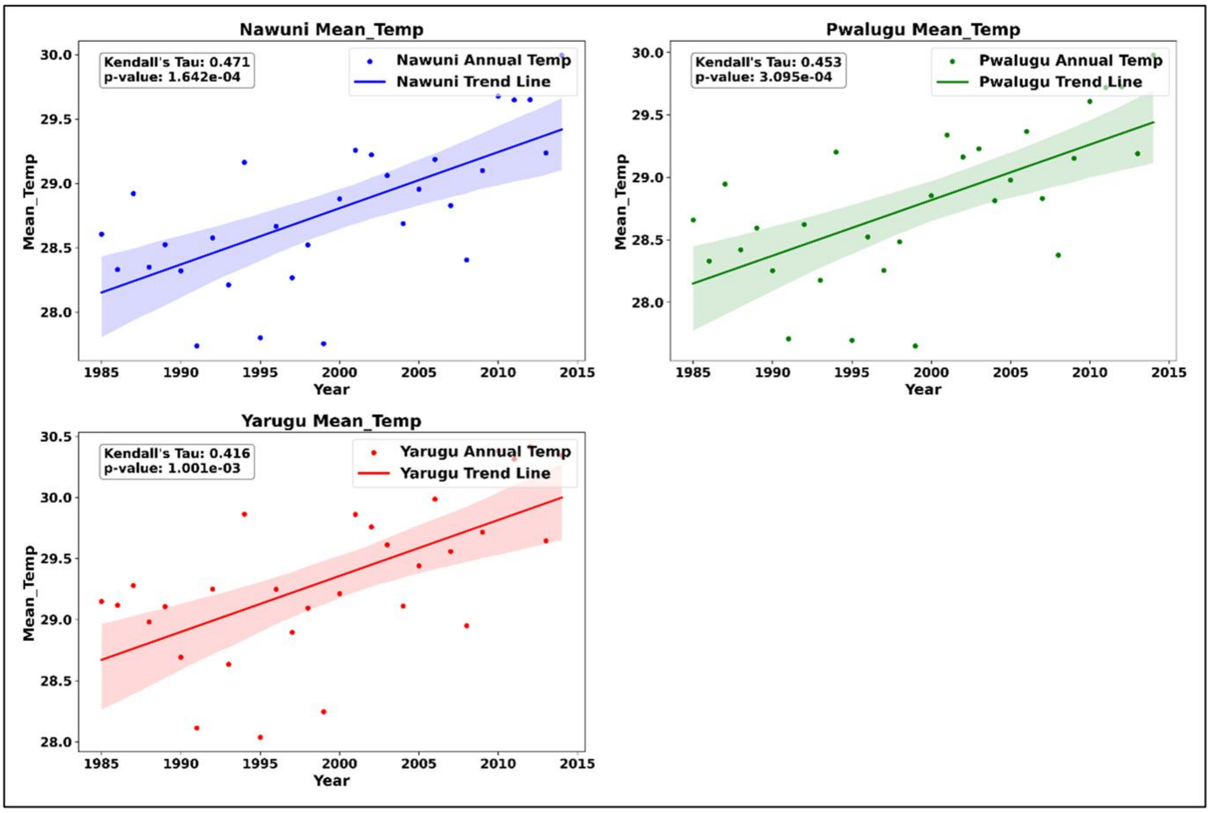

Figure 5.12: Trends in annual mean temperature from 1985 to 2014 across the three gauge stations.

Figure 5.12 shows the annual mean temperature trend from 1985 to 2014 at the Nawuni, Pwalugu, and Yarugu gauge stations, based on data from the ACCESS-CM2 and ACCESS-ESM1-5 ensemble. The trends show an increase in annual mean temperature of 0.471, 0.453, and 0.416 at Nawuni, Pwalugu, and Yarugu, respectively. Moreover, the p-values for all three gauge stations are less than 0.05, indicating a statistically significant trend. This provides evidence of an increasing trend in annual mean temperature.

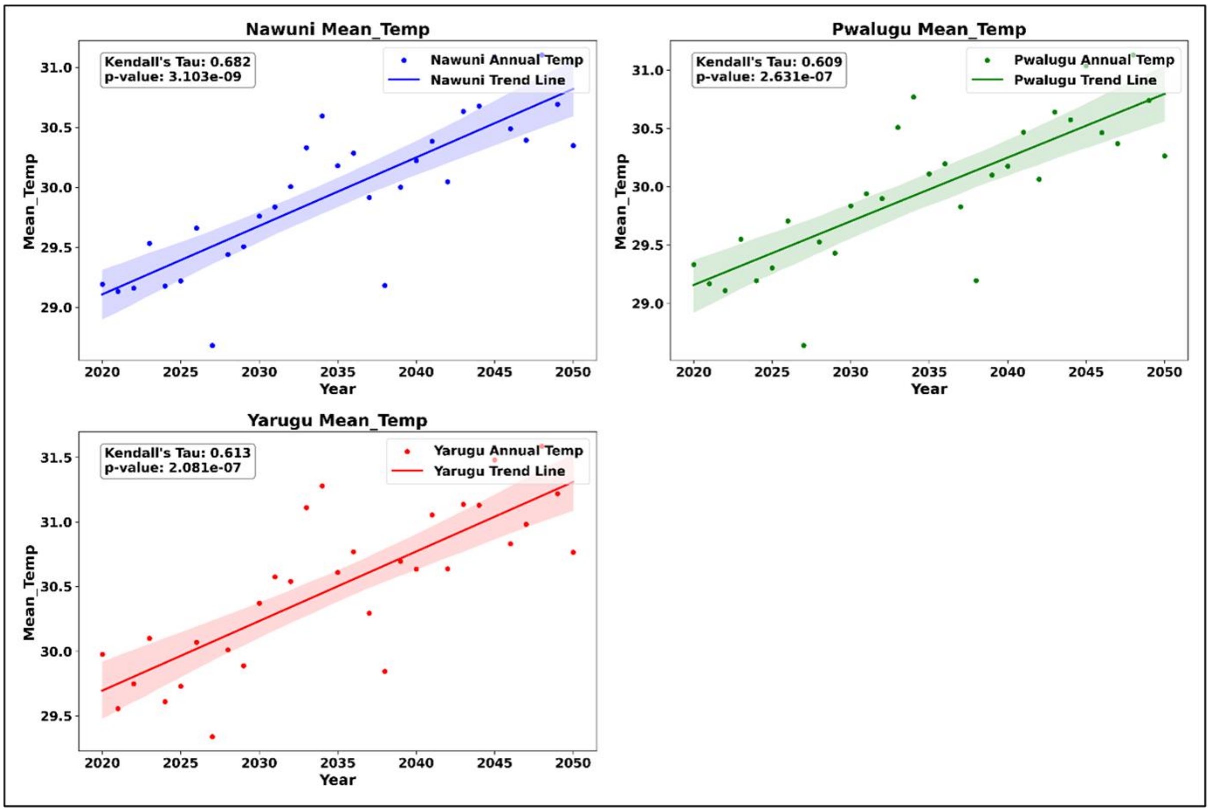

Figure 5.13: Trends in annual mean temperature from 2020 to 2050 across the three gauge stations.

Figure 5.13 shows the trend in the annual mean temperature from 2020 to 2050 at all three gauge stations. Similar to Figure 5.12, there is an increase in annual trends of mean temperature with a value ranging from 0.682 (Yarugu) and 0.609 (Pwalugu). The p-values for all three gauge stations are less than 0.05, indicating that the increasing trend in annual mean temperature is statistically significant. This provides evidence of an annual temperature increase between 2020 and 2050.

5.3.6 Monthly and Decadal Changes in Rainfall and Temperature

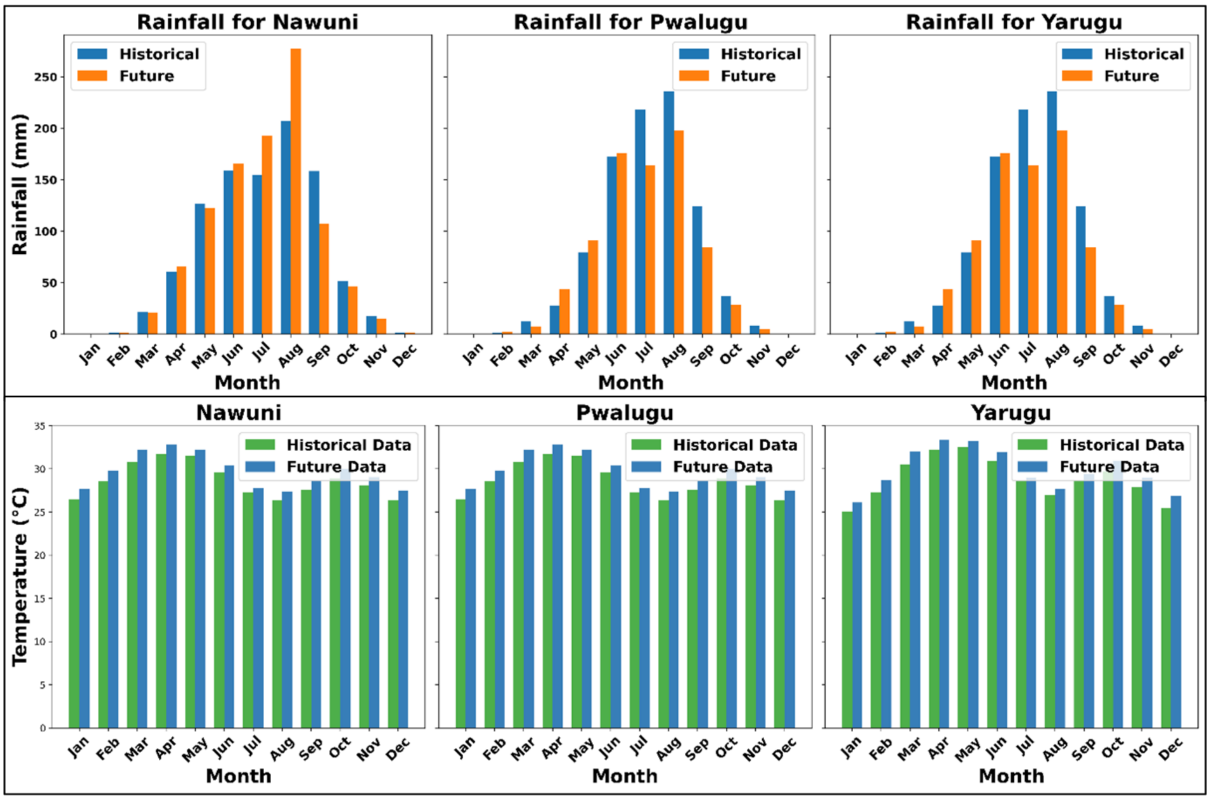

Figure 5.14: Monthly rainfall and temperature for the historical period (1985-2014) and the future period (2020-2050).

Figure 5.14 shows monthly rainfall and mean temperature data for the historical period (1985-2014) and projections for 2020-2050 under the SSP5-8.5 scenario using CMIP6 data. The projections indicate an expected increase in rainfall during the early wet season (April-June). However, a significant decrease is projected for the peak wet season (July-October) at the Pwalugu and Yarugu gauge stations, for example, both recorded a -54 mm change in July. Rainfall is also expected to decline during the dry season (November-March) at these stations. In contrast, Nawuni is projected to experience increased rainfall from June to August, followed by a sharp drop in September and October. The dry season here also shows a slight decline in rainfall. Overall, this pattern points to a dual risk of drought and increased surface runoff (flooding).

Furthermore, temperatures are expected to rise under the SSP5-8.5 scenario, with most months showing an increase of more than 1°C at all three gauge stations. Notably, December shows the highest increase compared to historical values, reaching up to 2°C at the Yarugu gauge station. Conversely, July records the smallest temperature increase, up to 0.4°C, also at the

Yarugu gauge station. The overall rise in monthly temperatures suggests increased evaporation rates continuing into the 2050s under the SSP5-8.5 scenario.

Table 5.3 shows the average changes in rainfall per decade for the historical (1990s, 2000s, 2010s) and near future (2030s, 2040s, and 2050s). Throughout the decades, each station has exhibited fluctuating rainfall trends. In the 1990s, rainfall increased for all three gauge stations. Nawuni recorded an increase of 0.13 mm/decade, while Pwalugu and Yarugu each saw larger increases of 0.77 mm/decade. In the 2000s, rainfall slightly increased at Nawuni (0.002 mm/decade), while both Pwalugu and Yarugu experienced declines of -0.02 mm/decade. In the 2010s, rainfall trends reversed at Pwalugu and Yarugu, with both stations recording increases of 0.55 mm/decade, whereas Nawuni showed a slight decline of -0.01 mm/decade. This upward trend continued into the 2030s at Pwalugu and Yarugu (0.73 mm/decade), while Nawuni experienced a sharper decrease of -0.31 mm/decade. In the 2040s, rainfall again declined at Pwalugu and Yarugu (-0.81 mm/decade), while Nawuni recorded an increase of 0.39 mm/decade. By the 2050s, rainfall increased at all three stations, 0.48 mm/decade at Nawuni and 0.06 mm/decade at both Pwalugu and Yarugu.

Table 5.3: Decadal rainfall changes at Nawuni, Pwalugu, and Yarugu gauge stations.

Decade	Nawuni (mm/decade)	Pwalugu (mm/decade)	Yarugu (mm/decade)
1990s	0.13	0.77	0.77
2000s	0.002	-0.02	-0.02
2010s	-0.01	0.55	0.55
2030s	-0.31	0.73	0.73
2040s	0.39	-0.81	-0.81
2050s	0.48	0.06	0.06

Table 5.4 presents the average decadal changes in mean temperature for historical periods (1990s, 2000s, 2010s) and the near future (2030s, 2040s, 2050s). The historical trend shows fluctuations, with both increases and decreases in mean temperature. Temperatures start by showing declining trends of -0.24 °C/decade, -0.33 °C/decade, and -0.32 °C/decade at Nawuni, Pwalugu, and Yarugu, respectively. Temperature then increased significantly in the 2000s, with Pwalugu recording the highest increase (0.75 °C/decade), followed by Yarugu (0.71 °C/decade) and Nawuni (0.66 °C/decade). The warming trend continued in the 2010s but at a slower rate,

with Pwalugu recording the lowest (0.63 °C/decade). Similarly, future projections indicate an expected increase in mean temperature in the 2030s, with Yarugu expected to show the highest warming rate of 0.81°C/decade. By the 2040s, a moderate increase in the rate of warming is projected across all gauging stations. Projected warming rates indicate an increase of 0.56 °C per decade at Nawuni, 0.53 °C at Pwalugu, and 0.46 °C at Yarugu. By the 2050s, mirroring the 1990s, temperatures are projected to decline with negative values of -0.22 °C/decade at Nawuni and -0.3 °C/decade at both Pwalugu and Yarugu gauge stations.

Table 5.4: Decadal mean temperature changes at Nawuni, Pwalugu, and Yarugu gauge stations.

Decade	Nawuni (°C/decade)	Pwalugu (°C/decade)	Yarugu (°C/decade)
1990s	-0.24	-0.33	-0.32
2000s	0.66	0.75	0.71
2010s	0.68	0.63	0.70
2030s	0.74	0.74	0.81
2040s	0.56	0.53	0.46
2050s	-0.22	-0.3	-0.3

5.3.7 Streamflow Forecasting using the CMIP6-GCMs Rainfall and Mean Temperature

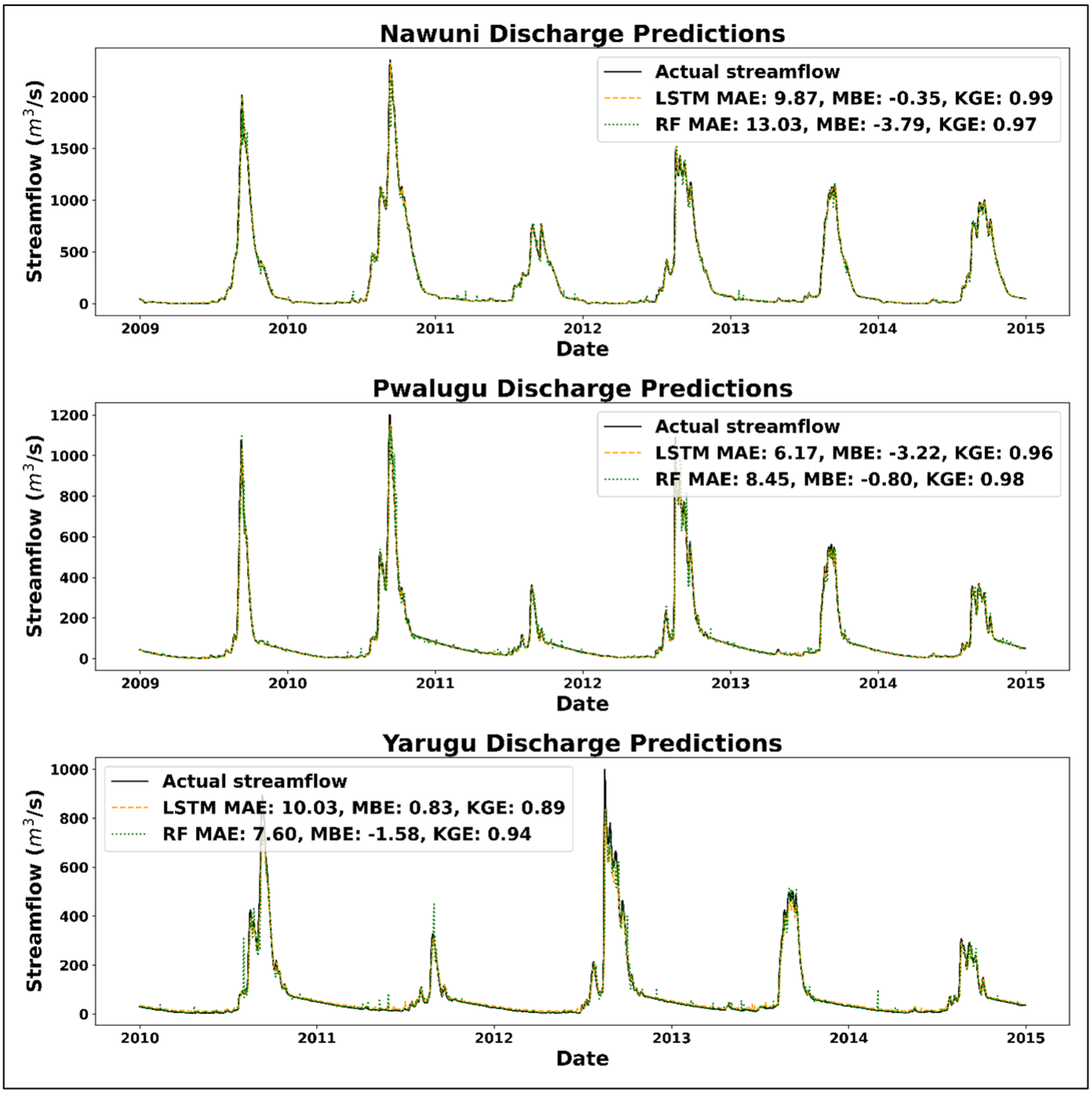

Figure 5.15: Comparison of the actual streamflow with the simulated streamflow by the RF and the LSTM during the testing period.

Figure 5.15 illustrates the predictive accuracy of the RF and LSTM models using ensemble MRI-ESM2-0, BCC-CSM2-MR, and INM-CM5-0 (Nawuni), BCC-CSM2-MR rainfall data (both Pwaluu and Yarugu), and the ensemble mean temperature from ACCESS-CM2 and ACCESS-ESM1-5 (for all three gauge stations). Both models capture the patterns of lower and higher flow at the Nawuni, Pwalugu, and Yarugu gauge stations. The RF model performed slightly better than the LSTM in predicting daily streamflow, achieving KGE values of 0.98 at Pwalugu and 0.94 at Yarugu during the testing period. Both models underestimated streamflow at Nawuni and Pwalugu, while the LSTM slightly overestimated it at Yarugu (with an MBE of 0.83 m^3/s).

Appendix Figure A.3.10 shows a close fit of the predicted RF and LSTM to that of the observed streamflow. In using the R^2, the LSTM slightly outperforms the RF at the Pwalugu and Yarugu gauge stations by 0.02 and 0.03, respectively (Appendix A).

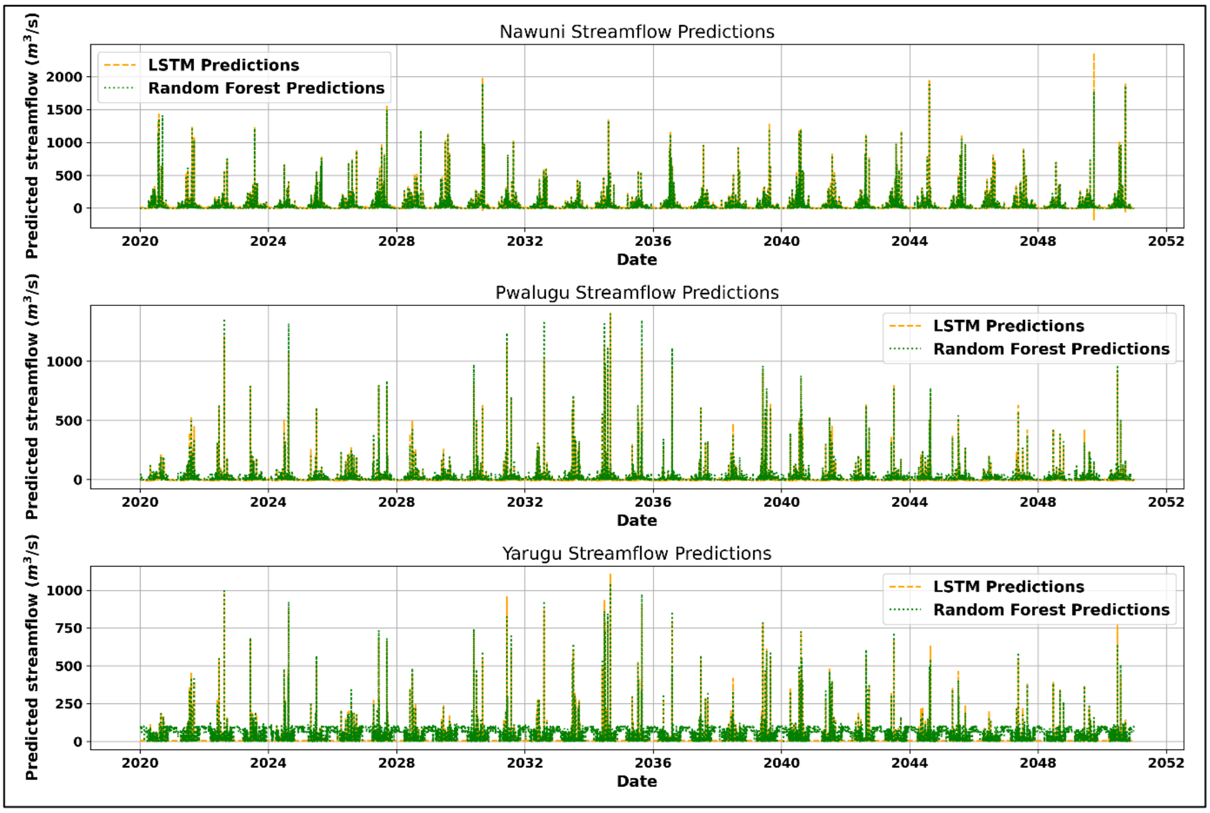

Figure 5.16: Daily streamflow prediction by the RF and LSTM model under the SSP5-8.5.

The diagram in Figure 5.16 demonstrates a consistent pattern of low and high flow events by the RF and LSTM models across the three stations. Similar to Figure 5.15, the Nawuni gauge station is expected to record the highest streamflow by the 2050s, exceeding 2000 m^3/s. The predominantly lower flows recorded by the RF model could indicate potential drought conditions. Conversely, the high peak flows estimated by both models, particularly around the 2040s and 2050s, suggest an increased risk of flooding, although both models underestimated (except the LSTM at Yarugu gauge station – see Figure 5.15) the actual flow. Overall, the flows captured by the RF and LSTM until the 2050s reflect a mix of both drought and flood conditions.

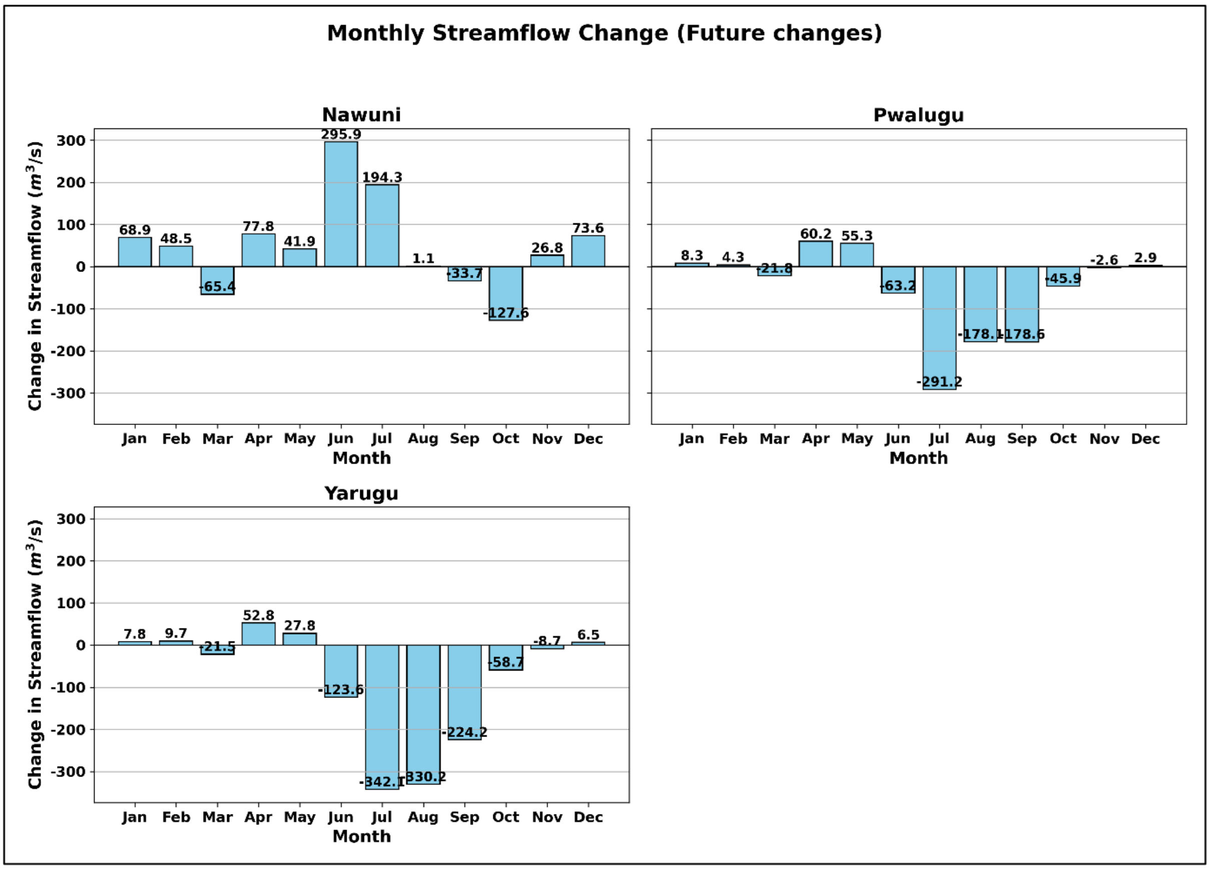

Figure 5.17: Predicted change in monthly streamflow (2020 – 2050) relative to the historical record (1985 – 2014) by the LSTM model.

Figure 5.17 shows the projected change in monthly streamflow from 2020 to 2050 relative to the 1985 - 2014 baseline. Similar to Figure 5.14, Pwalugu and Yarugu are expected to be drier than the Nawuni gauge station. During the peak rainfall months (August and September), streamflow will drop by up to 300 m^3/s evidence at Pwalugu and Yarugu gauge stations. In contrast, streamflow is projected to increase from April to July at the Nawuni gauge station.

Table 5.5 presents the expected frequency of droughts, floods, and extreme floods in the basin, based on historical Q90, Q10, and Q01 thresholds, respectively. Under the SSP5-8.5 scenario, the basin is projected to experience an increase in drought days (defined as days with streamflow below the Q90 threshold) at all three gauge stations. Pwalugu and Yarugu, located further North and influenced by the Sudan Savanna climate, are expected to be the most affected, with 9,605 and 7,592 drought days respectively. The risk of flood events (days exceeding the Q10 threshold) is also higher at Yarugu (111 days) and Pwalugu (90 days), compared to Nawuni (46 days). For extreme floods (days exceeding the Q01 threshold), Yarugu and Pwalugu recorded 13 days, while Nawuni recorded 4 days. These figures indicate that while Nawuni sees fewer extremes, both Yarugu and Pwalugu face significantly higher frequencies of drought, flood, and extreme flood events.

Table 5.5: Frequency of future flow relative to the historical thresholds (Q01, Q10, Q90).

Gauge stations	Q01 (m^3/s)	Q10 (m^3/s)	Q90 (m^3/s)	Days > Q01	Days > Q10	Days < Q90
Nawuni	1760.32	761.89	3.44	4	46	3651
Pwalugu	877.32	281.4	7	13	90	9605
Yarugu	745.42	220.88	7.06	13	111	7592

5.4 Discussion

5.4.1 Evaluation of Historical Streamflow Predictions using the LSTM and RF Model

Despite data scarcity and gaps in existing observed discharge data, the performance of LSTM and RF models were evaluated by comparing model forecasts with historical streamflow at three gauge stations in the White Volta basin. The model was tested on forecasting streamflow at 1, 5, and 10 days, ingested with rainfall, mean temperature, soil moisture, and evapotranspiration. Both RF and LSTM exhibited high predictive capacity, capturing complex, nonlinear relationships between input variables, which is crucial for accurate hydrological forecasting. Models like RF utilise an ensemble of decision trees to enhance predictions and reduce overfitting risks (Prasad et al., 2006; Schoppa et al., 2020). The LSTM is more effective at capturing peak and high flows up to 10 days in advance, which is crucial for detecting extreme events and ensuring adequate preparedness. These findings are similar to those of Breiman (2001), Hunt et al. (2022), Nevo et al. (2022), Sabzipour et al. (2023), and Xiang et al. (2020). The LSTM effectively captured temporal dependencies essential for modelling dynamic streamflow (Sarker, 2021; Surucu et al., 2023). Additionally, the exceedance probability (Appendix Figure A.3.4 and A.3.5), which indicates the likelihood that streamflow will meet or exceed a certain threshold within a given period (Piechota et al., 2001), provides water managers with a concrete measure of risk, helping them better prepare for extreme events and improve water management systems.

The integration of GloFAS with the observed data and making predictions with 34 years of data (1985 - 2019) enhances the prediction accuracy of the model with a high KGE of 0.94. However, the performance of the model decreases as the lead time is extended (Sabzipour et al., 2023). These findings highlight the need for ongoing model training and the potential integration of more real-time data inputs to enhance the predictive reliability of streamflow and flood early warning systems over extended periods, addressing challenges typical of extended-range forecasts in hydrology, especially in data-scarce regions like the White Volta basin (Gupta, 2024; Li et al., 2024; Muñoz et al., 2021; Tang et al., 2023).

5.4.2 Rainfall and Mean Temperature Validation under the SSP5-8.5 Scenario

All CMIP6 data align closely with the SD of the observed data in the dry season. However, BCC-CSM2-MR outperformed ACCESS-CM2, INM-CM5-0, MRI-ESM2-0, and MIROC6 in simulating monthly rainfall during the wet season, as evidenced by its close alignment with the half SD of the observed data at both Pwalugu and Yarugu gauge stations. At the Nawuni gauge station, MRI-ESM2-0 closely matches the observed data from January to June, INM-CM5-0 aligns well in July and August, and BCC-CSM2-MR corresponds closely from September to December. MIROC6 consistently overestimated the observed data, especially in the wet season, highlighting its limitations in forecasting rainfall and floods. ACCESS-ESM1-5 performs better in simulating the monthly mean temperature in the wet season, outperforming ACCESS-CM2. ACCESS-CM2 consistently overestimated the actual temperature in the wet season. However, the ACCESS-CM2 outperformed ACCESS-ESM1-5 in simulating the actual temperature in the dry season, especially between December and February. The strength of these models is significant in understanding the impact of climate change and reducing biases. Moreover, researchers have most of the time used the strength of multiple GCMs-CMIP data, known as the ensemble, in simulating the impact of climate change on hydrological cycles (Dembélé et al., 2022; Mensah et al., 2022; Siabi et al., 2023; Singh et al., 2023; Smits et al., 2024).

5.4.3 Trends in Annual and Monthly Rainfall and Mean Temperature for the Historical and Future Periods

Analysis of historical rainfall data using MRI-ESM2-MR, INM-CM5-0, and BCC-CSM2-MR models indicates an increase in annual rainfall from 1985 to 2014. However, projections under the SSP5-8.5 scenario suggest a decline in annual rainfall at both Pwalugu and Yarugu and a slight increase at Nawuni until 2050, though this is not statistically significant, highlighting uncertainty in the trend. Monthly rainfall is projected to increase from June to August at the Nawuni gauge station. This aligns with the findings of Siabi et al. (2023), who anticipate increased rainfall in July and August in southern Ghana. In contrast, rainfall is expected to decrease in most months, including the typically wet months of July, August, and September, at both the Pwalugu and Yarugu gauge stations, consistent with the findings of Yeboah et al. (2022). The dry season, particularly from November to January (2020 - 2050), is projected to be much drier, potentially increasing the risk of drought at both stations. While increased rainfall from April to June may not offset the prolonged dry periods, the intensity of the rain could cause surface runoff and flooding, especially due to hardened soil that absorbs water slowly at these two locations.

Additionally, historical temperature from the ACCESS-CM2 and ACCESS-ESM1-5 ensembles showed an annual rise in temperatures at the three gauge stations from 1985 to 2014. This confirms the findings of Kranjac-Berisavljevic (1999), cited in Klutse et al. (2020), who noted a rising temperature trend between 1931 and 1990 in Northern Ghana. Similarly, Frimpong et al. (2014) observed that the Bawku East district in the Northern region of Ghana experienced a yearly temperature increase of 0.075°C from 1961 to 2012, exceeding the southern average increase of 0.021°C per year, aligning with our findings. Higher temperatures (both annually and monthly) are expected to increase further up to the 2050s under the SSP5-8.5 scenario. Monthly temperatures are expected to rise as high as 2°C in December at Yarugu. These findings align with those of Klutse et al. (2020), who projected an increase in temperature in Northern Ghana under the RCP8.5 scenario. This could lead to higher evaporation rates, drier conditions, and reduced water availability, aligning with findings from Siabi et al. (2023) and Singh et al. (2023) in Asia. However, a warmer atmosphere capable of holding more moisture may result in more intense rainfall events and an increased risk of flooding.

5.4.4 RF and LSTM Evaluation and Forecasting Future Streamflow under the SSP5-8.5 Scenario

The RF and LSTM models successfully simulated daily streamflow at three gauge stations, with RF showing slightly better performance at Pwalugu and Yarugu based on KGE scores. Monthly and daily streamflow analysis shows significantly drier conditions at the Yarugu and Pwalugu stations compared to Nawuni, partly due to differences in climatic zones. Streamflow is expected to increase during the early rainy season in April and May, and further from June to July at the Nawuni gauge station. This finding aligns with Dembélé et al. (2022), who projected an increase in flow in the Volta basin under the RCP8.5 scenario. The frequency of both floods and extreme floods is also projected to rise at all three gauge stations. These projections are also consistent with the findings of Dembélé et al. (2022). However, the frequency of dry days (drought) will increase significantly compared to wet days. Lower flows may stem from heightened evaporation due to warming, consistent with observations by Adib

& Harun (2022) and Singh et al. (2023) in Asia. Similarly, Awuni et al. (2023) and McCartney et al. (2012) projected a 24% drop in streamflow by 2050 and up to 45% by 2100 in Ghana, attributing this decline to reduced precipitation and rising heat. Floods and droughts during this period could have a significant impact on farmlands, groundwater, and irrigational facilities. These emphasize the need for water managers, including the Ghana Hydrological Authority (GHA) and the Water Resource Commission (WRC), to implement policies tailored to sustainable water management strategies, such as protecting groundwater reserves and upgrading irrigation infrastructure. It is also important to prevent overgrazing and promote cover cropping in the basin to protect the soil and reduce surface runoff. Moreover, the findings of this study are instrumental in advancing sustainable water management and strengthening climate resilience, particularly regarding droughts, floods, and extreme weather events. By facilitating timely early warning systems, the study contributes to mitigating the adverse impacts on agriculture, water resources, and climate adaptation efforts. It also contributes to reducing risks related to food security, water supply, public health, and economic stability, supporting progress toward key Sustainable Development Goals (SDGs) such as Zero Hunger, Clean Water and Sanitation, Sustainable Cities and Communities, Life on Land, and No Poverty.

While climate change adds uncertainty to flood timing, model limitations may also affect the results. The use of GloFAS discharge data instead of direct observations, along with reliance on ensemble MRI-ESM2-0, INM-CM5-0, BCC-ESM2-MR, ACCESS-CM2, and ACCESS-ESM1-5, could miss certain flood occurrences, affecting the broader applicability of findings. Despite these constraints, the study highlights the urgency of improving ground-based streamflow monitoring in the White Volta basin. Upgrades in irrigation systems, investment in water harvesting, and construction of sustainable dams are crucial. Pre-season waterway clearance and enhanced early warning systems will also be key to mitigating future flood and drought impacts.

5.5 Summary

This study employed RF and LSTM models to forecast streamflow at 1-, 5-, and 10-day lead times using a combination of CHIRPS rainfall, ERA5 temperature, CFSR soil moisture, evapotranspiration, and evaporation from bare soil and open water surfaces. Additionally, the models were used to predict streamflow from 2020 to 2050 under the SSP5-8.5 scenario. Future projections incorporated rainfall data from MRI-ESM2-MR, INM-CM5-0, and BCC-CSM2-MR, and mean temperature data from ACCESS-CM2 and ACCESS-ESM1-5.

The results demonstrate the effectiveness of both RF and LSTM models in capturing the complex, nonlinear dynamics of streamflow in the White Volta basin. While the LSTM model showed superior performance in predicting peak and extreme flows, RF provided more stable long-term forecasts. Projections based on CMIP6 data under the SSP5-8.5 scenario indicate a warming trend through the 2050s, accompanied by shifting rainfall patterns. An increase in the onset of rainfall (April–June) is projected, followed by declines during the core rainy season (July–September) at the Pwalugu and Yarugu gauge stations, signalling increased drought risk. Conversely, an increase in rainfall during July and August at the Nawuni gauge station raises concerns about potential flood events. Forecasted streamflow patterns reflect the region's climatic variability, underscoring its growing hydrological uncertainty. Moreover, the analysis suggests that Pwalugu and Yarugu are likely to experience a higher frequency of both droughts and high-flow events compared to Nawuni, highlighting the need for localised and adaptive water resource strategies.

CHAPTER 6

6 Conclusion and Recommendations

6.1 Conclusion

6.1.1 Flood Early Warning System: Opportunities and Challenges

The study offers a comprehensive perspective on flood early warning systems (FEWS) by examining their opportunities and challenges in the White Volta basin of Ghana. The study draws on interviews with 18 respondents, including representatives from the Ghana Meteorological Agency (GMet), the Ghana Hydrological Authority (GHA), the National Disaster Management Organisation (NADMO), the Water Resources Commission (WRC), Extension officers, Assemblymen, and Community leaders. Using a qualitative case study approach and specifically thematic analysis, the study revealed a structured framework for FEWS in the basin, which shows promising strengths for flood risk management. Built around the myDEWETRA-VOLTALARM platform, it integrates various meteorological models to enhance real-time flood prediction. A notable strength is the collaborative framework involving national and international stakeholders such as NADMO, GMet, GHA, WRC, VBA, GWP-WAF, and the CIMA Foundation, who share data, technical expertise, and resources. This cooperation boosts the system's effectiveness. FEWS also excels in its multi-channel communication strategy, using social media, community radio, mobile vans, messengers, and SMS to distribute flood alerts. This approach ensures warnings reach diverse communities across.

However, the system faces several challenges that hinder its full potential. One major issue is the lack of integration of local knowledge. Communities in rural areas possess traditional ecological knowledge and can help in the management and mitigation of floods in the basin. Yet, this informal insight is often not incorporated into the formal system, weakening trust in official forecasts. Some residents rely on physical observations or information from neighbouring villages about rising levels of rivers and possible flood risk, which might not always be sustainable. FEWS also struggles with data limitations: frequent theft, inadequate funds, and poor maintenance of gauge stations have led to a shortage of in situ monitoring stations, and ground data crucial for accurate flood forecasting. The system further suffers from outdated technology, funding shortages, and weak inter-agency coordination. As a result, it often relies on global models like FANFAR and WRF, which, while useful for broader weather patterns, fail to capture the local flood dynamics of the basin due to a lack of high-resolution data and up-to-date ground streamflow measurements. To improve flood management, a multi-pronged strategy is needed. This includes enforcing existing policies like the White Volta Flood Hazard Assessment and the National Riparian Buffer Zone Policy (2011) to restrict settlement in high-risk flood zones. Regular river dredging, especially before the rainy season, is essential to improve water flow. Additionally, relocating vulnerable communities to higher ground and strengthening the capacities of response agencies through better logistics, motorboats, life jackets, and shelters are crucial. Long-term improvements require consistent funding and strong government support to build resilience and implement sustainable flood mitigation efforts and early warning systems. This effort should include expanding gauge stations and maintaining existing ones to ensure the adequate collection of ground streamflow data, which is important for developing early warning models and calibrating existing platforms like GloFAS, FANFAR, and others. These findings address the first specific objective of the study, which seeks to evaluate the current state of the FEWS in the White Volta basin. Through a qualitative stakeholder involvement, the study presents the positionality, highlighting key strengths and weaknesses of the existing FEWS and critical insights for improvement.

6.1.2 Satellite and Reanalysis Data Validation

Faced with limited ground-based data in the White Volta basin and, specifically, the lack of observed meteorological data in hydrological gauge stations, this study validated the effectiveness of satellite and reanalysis data for predicting streamflow and floods. Precipitation and mean temperature data span from 1998 to 2019, and soil moisture data from 2019 to 2022. Data were obtained from a combination of sources, including the GMet, ISMN, and various satellite and reanalysis datasets such as CHIRPS, PERSIANN-CDR, ERA5, ARC2, MERRA-2, TRMM, and CFSR. Gauge stations included Tamale, Wa, Walewale, Bawku, and Navrongo for both rainfall and temperature analysis. Gauge stations for soil moisture analysis included Bongo, Tamale, Pusiga, Navrongo, and Bimbilla. The accuracy of these datasets was assessed using statistical metrics, including SD, MAE, and MBE.

CHIRPS emerged as the most accurate rainfall dataset, mimicking closely the observed data. Its high spatial resolution and regular calibration with station data allowed it to reliably capture rainfall patterns, particularly during the peak rainy season in August and September. This accuracy makes CHIRPS highly valuable for agricultural, hydrological planning, and water resource management in Northern Ghana. PERSIANN-CDR also performed well but showed some inconsistencies at the Tamale gauge station, indicating the importance of localised validation. TRMM, however, displayed significant errors during periods of intense rainfall, limiting its usefulness for detailed flood forecasting and water resource planning in the region.

For temperature, ERA5 proved to be the most reliable dataset, closely matching ground-based measurements at all five stations. Its advanced data assimilation techniques, which incorporate a wide range of observational inputs, contribute to its superior performance. In comparison, MERRA-2 consistently underestimated temperatures, suggesting limitations in its processing methods. The CFSR dataset showed high variability, reducing its suitability for accurate climate analysis.

Regarding soil moisture, CFSR aligned most closely with ground-based ISMN data, particularly during the rainfall months from August to October. This makes it a strong candidate for streamflow simulations, flood forecasting, and agricultural applications. ERA5 also performed well in specific areas such as Navrongo, Bimbilla, and Pusiga, supporting its use in localised water resource and ecosystem planning. MERRA-2, however, significantly overestimated soil moisture, highlighting the need for bias correction or improved algorithms. The study offers practical recommendations for choosing appropriate datasets for streamflow and flood forecasting, climate change analysis, and water resource planning research in Northern Ghana. CHIRPS and PERSIANN-CDR are suitable for rainfall analysis, ERA5 is preferred for temperature studies, and both CFSR and ERA5 are reliable for soil moisture monitoring. These validated datasets can improve the accuracy of streamflow forecasts and flood risk assessments, which are essential for disaster preparedness, water resource management, and agricultural planning. Beyond immediate applications, the findings support the development of climate-responsive policies and infrastructure, especially in areas vulnerable to climate impacts. This study also establishes a benchmark for dataset validation in climate research and provides a framework that can be adapted to other geographic regions. Its insights are critical for strengthening climate resilience, guiding policy decisions, and ensuring sustainable management of water and agricultural resources in data-limited settings. As climate change continues to reshape weather and hydrological patterns, the use of accurate, context-specific data becomes increasingly vital for effective adaptation and long-term planning.

These findings address the second objective of the study, seeking to validate satellite and reanalysis products with ground-based observations in the White Volta basin. Through robust statistical comparison, the study identified reliable datasets for training and building models in monitoring and forecasting floods.

6.1.3 Streamflow Forecasting Using Machine Learning for Flood Management and Mitigation

This study focused on forecasting streamflow using ML models to manage and mitigate floods in the basin. Validated data, including CHIRPS rainfall, ERA5 temperature, and CFSR soil moisture, were used as input to train the RF and the LSTM, and forecast streamflow at 1, 5, and 10 days. Aside from these input data, models were also trained on evapotranspiration, evaporation from bare soil, and open waters obtained from the LISVAP model. Forecasts covered the period from 1985 to 2019 at the Nawuni and Pwalugu gauge stations, and from 1990 to 2019 at the Yarugu gauge station.

Both RF and LSTM models showed strong predictive performance, effectively capturing the complex, nonlinear interactions among hydrological variables, key to accurate forecasting. The RF model, with its ensemble of decision trees, reduced overfitting and improved prediction accuracy. Meanwhile, the LSTM model excelled at predicting peak and extreme flow events, even with a 10-day lead time, making it useful for early warning systems and emergency planning. The study also used streamflow exceedance probabilities, providing water managers with a practical tool to estimate flood risks and improve planning. By combining GloFAS reanalysis with observed streamflow data over 34 years (1985-2019), the model's accuracy improved. However, forecast reliability declined with longer lead times, highlighting the need for continuous updates and integration of real-time data. This is especially important for long-range forecasting in data-scarce regions like the White Volta basin.

The LSTM and RF models were also trained using CMIP6 GCM projections under the SSP5-8.5 scenario to forecast streamflow from 2020 to 2050. Rainfall data were sourced from BCC-CSM2-MR, INM-CM5-0, and MRI-ESM2-0, while temperature data were from the ensemble of ACCESS-ESM1-5 and ACCESS-CM2. These CMIP6 datasets aligned well with historical CHIRPS and ERA5 observations. Future streamflow simulations showed both models accurately captured daily discharge patterns at the three gauge stations, with RF slightly outperforming LSTM at Nawuni and Pwalugu. The models projected drier conditions at Yarugu and Pwalugu, especially between July and October, but increased streamflow in April and May, likely due to earlier seasonal rains. The frequency of dry days is expected to rise, outpacing floods and extreme flood events. These findings point to an urgent need for climate-responsive water policies and infrastructure investments. These measures are critical for adapting to the projected impacts under the SSP5-8.5 scenario, as outlined in the research hypothesis. Effective adaptation strategies should also include groundwater protection, expanded irrigation, erosion control through cover cropping, and construction of water retention structures. Strengthening early warning systems and maintaining river channels seasonally are also key to minimising flood impacts.

Overall, this research confirms the effectiveness of both shallow (RF) and deep learning (LSTM) models in forecasting streamflow in the basin. Their compatibility with open-source data makes them scalable for other data-limited regions. The model's high short- and long-term accuracy supports better flood preparedness and drought planning. As climate change drives rising temperatures and shifts in rainfall patterns, proactive water management, resilient infrastructure, and climate-smart agriculture are essential. While surrogate data introduced some uncertainty, future research should aim to reduce this and expand inputs, such as satellite-derived vegetation data, to further improve predictions.

These findings address the third specific objective of the study: to predict and evaluate streamflow using a shallow model (RF) and a deep learning model (LSTM) for flood mitigation and management in the White Volta basin. The study provides robust, data-driven models for monitoring streamflow and managing floods as well as droughts in data-scarce regions.

6.2 Significance of the Study

The study highlights the importance of providing a comprehensive outlook on flooding in the White Volta basin of Ghana by examining the state of FEWS, alternative satellite and reanalysis data, and the potential of incorporating machine learning models to forecast streamflow for improved flood management and mitigation in the basin.

The state of FEWS in the basin unravels why it continues to face persistent floods yearly. Fundamental issues such as a lack of real-time data, limited public trust in warnings, insufficient monitoring infrastructure, outdated technology, and poor inter-agency coordination offer critical insights into why existing flood warning mechanisms have failed to protect vulnerable communities sufficiently. Moreover, the disconnection between formal monitoring tools built around the myDEWETRA-VOLTALARM and the absence of community involvement in these frameworks undermines the effectiveness of early warnings in the basin. Consequently, the study proposes solutions that are important for an active FEWS in the basin, capable of reducing the impact of floods and enhancing preparedness and mitigation efforts. Centred around improved real-time and ground-based data collection, enhanced community engagement, stronger institutional collaboration, and sustainable financing models. It provides policymakers and disaster management agencies with evidence-based directions for reforming FEWS systems, ultimately aiming to reduce flood impacts, improve livelihoods, and enhance climate resilience across Ghana and comparable contexts. As such, the study fills a vital knowledge gap in understanding the socio-technical dimensions of disaster risk reduction in Africa.

This study validates open-source data, rainfall, temperature, and soil moisture. It also uses RF and LSTM models to forecast streamflow at 1, 5, and 10-day intervals, as well as from 2020 to 2050 under the SSP5-8.5 climate scenario. The results of this study will help researchers, hydrologists, and policymakers identify reliable datasets that improve the accuracy of hydrological models and EWS, particularly in areas with limited ground-based observations. The study offers a data-driven framework for predicting floods, extreme floods, and droughts. For water managers in the basin, this presents scalable alternatives for building EWS vital for flood and drought response. Because the framework relies on open-source data, it is valuable in data-scarce regions like the White Volta. The forecasts also highlight how climate change may alter rainfall and streamflow patterns, insights that are crucial for agricultural extension officers and farmers seeking to plan, adopt cover crops or drought-resistant varieties, and invest in irrigation to manage climate risks. More broadly, the findings of this study play a crucial role in promoting sustainable water resource management and enhancing climate resilience, especially in the face of droughts, floods, and other extreme weather events. By enabling more effective EWS, the study helps reduce negative impacts on agriculture, water supply, and climate adaptation strategies. It also contributes to lowering risks related to food security, water access, public health, and economic stability, thereby supporting progress toward key Sustainable Development Goals (SDGs) such as Zero Hunger, Clean Water and Sanitation, Sustainable Cities and Communities, Life on Land, and No Poverty.

6.3 Study Limitation

Local weather and gauge station observations typically provide the most reliable meteorological and hydrological time series for such studies. However, in this case, the available observation stations were inadequately distributed and had incomplete records. As a result, the study relied on alternative meteorological and hydrological datasets, including CHIRPS, ERA5, CFSR, and GloFAS discharge data. The use of these surrogate datasets, however, introduces the risk of overestimating or underestimating actual rainfall, temperature, soil moisture, and discharge levels. Such inaccuracies could significantly affect the final streamflow predictions generated by ML models like RF and LSTM networks.

6.4 Recommendation for Further Research

Future research could further examine the potential for enhancing local community engagement in flood monitoring and response efforts. While local knowledge plays an important role in flood risk identification, there is a need to understand how this knowledge can be systematically integrated into formal FEWS frameworks.

The importance of vegetation and land cover data in hydrological studies, particularly streamflow and flood predictions, must be considered. Vegetation provides significant resistance to water flow through processes like interception in the hydrological cycle. The absence of land use/land cover data in this study is a limitation that should be addressed in future research to enhance the accuracy of hydrometeorological models.

This study did not fully address the uncertainty associated with surrogate data. Future work should incorporate models that explicitly account for both forecast uncertainty and the limitations of surrogate inputs. Ongoing research should focus on sensitivity analysis and feature importance methods that consider time-lagged variables, aiming to improve model interpretability in data-scarce regions. Furthermore, integrating satellite-derived vegetation indices can enhance model accuracy by providing valuable information on land cover dynamics and plant transpiration. Further research could also account for anthropogenic impacts, including dam operations, irrigation, land use changes, and sediment transport, which were not explicitly addressed in this study. These provide insights in regions where human activity and geomorphic processes significantly affect streamflow, particularly in urban areas.

6.5 Recommendation for Policy Directions

A key area to ensure that future forecasts are accurate is to invest in real-time data infrastructure. Outdated models and the limited availability of automatic weather stations and telemetric systems undermine the accuracy of flood predictions. Expanding the monitoring network with modern data collection technologies would enable more localised and timely data, significantly improving the predictive capability of FEWS. This should be coupled with integrating advanced technologies such as artificial intelligence and machine learning, which enhance data processing and forecasting accuracy.

Community engagement must also be strengthened through an inclusive, bottom-up approach. Local communities possess valuable ecological knowledge that, when incorporated into formal predictive models, can improve the relevance and trustworthiness of flood warnings. Training and capacity-building programs should empower these communities to actively participate in monitoring and preparedness efforts.

Improving communication infrastructure in rural areas is critical, as many vulnerable communities lack access to timely flood warnings due to unreliable networks. Investments in satellite-based communication systems and low-cost, localised warning mechanisms would ensure that even remote areas receive alerts promptly. Additionally, addressing bureaucratic inefficiencies and improving coordination among agencies such as NADMO, GMet, and GHA are essential. Establishing clear protocols for data sharing and decision-making can reduce delays in flood response and ensure agencies have access to real-time information.

Given the increasing threat of climate change and the rising frequency and intensity of floods, FEWS must adapt to a rapidly evolving environment. This will require sustained investment in ground data collection and EWS, stronger inter-agency cooperation, and dedicated efforts to build local capacity for flood risk management.

The White Volta basin is a predominantly agricultural region, which makes it highly vulnerable to the impacts of intensified droughts and floods. These conditions pose a significant threat to food security. Given that farming is the main economic activity in the basin, the increasing frequency and severity of droughts and floods heighten the risk of food shortages. It is therefore crucial to implement policies that focus on expanding irrigation infrastructure, promoting afforestation, planting drought-resistant vegetation, and curbing deforestation. Policies should particularly support domestic and local rainwater harvesting to reduce flood risks and improve drought resilience.

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Appendix

Appendix A.1

Evaluating the effectiveness of frameworks for flood early warning (FEW) in the White Volta basin, Northern Ghana.

Demographic Information:

1. Which organization are you affiliated with?

a. National Disaster Management Organization (NADMO)
b. Ghana Hydrological Authority (GHA)
c. Ghana Meteorological Agency (GMet)
d. Volta River Authority (VRA)
e. Water Resources Commission (WRC)
f. Water Research Institute (WRI)
g. West African Science Service Center on Climate Change and Adapted Land Use (WASCAL)
h. Others: Please, specify other affiliation?

2. What is your role or affiliation related to flood management in the White Volta basin, Northern Ghana?

a. Government official responsible for flood management policies or implementation.
b. Local or regional administrator overseeing flood mitigation efforts.
c. Environmental or water resource management agency staff.
d. Community leader or representative from a flood-prone area.
e. Civil engineer or infrastructure planner involved in flood protection projects.
f. Emergency response or disaster management personnel.
g. Others, please specify?

3. How many years of experience do you have in flood monitoring and management?

a. Less than 1 year
b. 1-3 years
c. 4-6 years
d. 7-10 years
e. More than 10 years

Flood risk assessment:

4. Can you identify specific regions or communities prone to flooding within the White Volta basin?

5. What are the typical characteristics of these Communities?

a. Urban areas near rivers or streams

b. Low-lying agricultural plains

c. Communities located downstream from dams or reservoirs

e. Others, Please specify other characteristics of these communities?

6. What is the typical amount of rainfall required to trigger flooding in the identified vulnerable areas?

a. Less than 20 mm in 24 hours

b. 20-100 mm in 24 hours

c. More than 100 mm in 24 hours

d. Others, can you specify others?

7. What critical infrastructure exists within flood-prone zones?

a. Schools

b. Hospitals

c. Roads and bridges

d. Agricultural fields

e. Others, can you specify other critical infrastructures?

8. What are the gaps or limitations in the availability of relevant data for flood risk assessment?

a. Limited availability of real-time data.

b. Incomplete historical data records.

c. Lack of access to satellite or remote sensing data.

d. Insufficient data on localized weather patterns.

e. Issues with data quality and reliability.

f. Lack of data sharing among relevant agencies.

g. Inadequate funding for data collection and maintenance.

h. Others, Please specify other gaps.

Monitoring and Forecasting:

9. Are you into monitoring floods and streams (rivers) in the White Volta basin?

a. Yes

b. No

If yes, could you answer question 10-14

10a. Do you monitor rainfall pattern to issue flood early warning in the White Volta basin?

a. Yes

b. No

If yes, please specify the sources of this data?

10b. Do you monitor storms pattern to issue flood early warning in the White Volta basin? a. Yes

b. No

If yes, please specify the sources of this data.

10c. Do you monitor soil moisture pattern to issue flood early warning in the White Volta basin?

a. Yes

b. No

If yes, please specify the sources of data.

10d. Do you monitor Water levels/discharge/runoff of streams/rivers/dams to issue flood early warning in the White Volta basin?

a. Yes

b. No

If yes, please specify the sources of this data.

10e. Do you monitor Wind speed and direction to issue flood early warning in the White Volta basin?

a. Yes

b. No

If yes, please specify the sources of data.

10f. If there are other data used, can you specify these data and their sources?

11. Are you monitoring and forecasting floods based on model(s)?

a. Yes

b. No

12. If yes, could you specify this model(s)/system?

a. Global Flood Awareness System (GloFAS)

b. Global Flood Monitoring (GFM)

c. Soil & Water Assessment Tool (SWATS) models

d. Hydrologic Modeling System (HEC-HMS)

e. Others, Please specify other models?

12a. If No, how you monitor and forecast floods?

13. Are your monitoring and forecasting models supported by Artificial Intelligence (AI)?

a. Yes

b. No

14. If Yes, please specify.

Communication of Hazards:

15. Who are the primary stakeholders or agencies you communicate with before, during, and after flood events?

a. Local government agencies (Assembly)

b. National Disaster Management Organization (NADMO)

c. Water Resources Commission (WRC)

d. Chiefs

e. Ghana Hydrological Authority (GHA)

f. Media

g. Ghana Meteorological Agency (GMet)

h. Others

Please specify other stakeholders and agencies you communicate with?

16. How much lead time is used in warning individuals and communities about impending floods?

a. Less than 6 hours

b. 6-12 hours

c. More than 12 hours

d. Others

Please specify other lead time?

17. Do you see flood damage reduction as a function of lead time?

a. Yes

b. No

c. Not sure

18. If Yes, can you give an example?

19 a.What communication channels do you use to disseminate flood warnings to the public?

a. Cellular alerts

b. Broadcast TV or radio/telephone

c. Information sharing by person

d. Sirens

e. Social media

f. Information vans

g. Others

Please specify if there are other channels of communication.

19 b. How effective are these channels in reaching vulnerable populations?

a. Very Effective

b. Effective

c. Somewhat effective

d. Not very effective

e. Not effective at all

20. What are the designated evacuation routes for communities at risk of flooding?

a. Main highways

b. Local roads

c. Footpaths or trails

d. River embankments

e. Others, Please specify other designated evacuation routes for communities at risk of flooding?

21. What are the established emergency response plans specifically tailored to flood events?

22. How regular are these plans updated and tested?
a. Updated and tested monthly
b. Updated and tested quarterly
c. Updated and tested annually
d. Updated and tested every 2 or more years
e. Rarely or never updated and tested
23. How do different stakeholders (government agencies, NGOs, local communities) collaborate in flood risk assessment and management?
a. Interagency task forces
b. Local government forums
c. NGO-led workshops
d. Community meetings
e. Others, Please specify other means of collaborations.

24/25. What are the platform(s) for sharing information and coordinating flood response efforts among various actors?

26. To what extent are local communities involved in identifying flood risks and developing mitigation strategies?
a. High involvement
b. Moderate involvement
c. Limited involvement
d. No involvement
e. others, Please specify others.

27. Are there community-based initiatives aimed at enhancing flood resilience and preparedness?
a. Participatory mapping exercises
b. Community awareness campaigns
c. Volunteer flood response teams
d. Community-based flood monitoring networks

e. Others, Please specify other community-based initiatives aimed at enhancing flood resilience and preparedness?

28. How do you ensure that the general public receives timely and accurate flood warnings?
a. Public education campaigns
b. Community outreach programs
c. Integration with existing emergency alert systems
d. Others, Please specify other means of ensuring that the general public receives timely and accurate flood warnings?

29. What are the challenges faced in communicating flood hazards?
a. Limited resources
b. Language barriers
c. Technological limitations
d. Community engagement
e. Others, Please specify other challenges faced in communicating flood hazards?

Response to Flood Hazards:
30. What pre-planned actions or protocols are in place for responding to different flood scenarios?
a. Evacuation procedures
b. Shelter locations
c. Emergency service deployment
d. Road closures
e. Others, Please specify other pre-planned actions or protocols in place for responding to different flood scenarios?

31. How do you coordinate emergency response efforts with various agencies and organizations?
a. Interagency agreements
b. Emergency operation centers
c. Mutual aid agreements
d. Joint training exercises

e. Others, Please specify other means you coordinate emergency response efforts with various agencies and organizations?

32. What are the specific resources or infrastructure dedicated to flood response in your organisation?

a. Flood barriers
b. Rescue equipment
c. Emergency shelters
d. Medical facilities
e. Others

33. Please specify other resources or infrastructure dedicated to flood response in your organisation.

34. How do you ensure the safety and well-being of residents during flood events?

a. Public awareness campaigns
b. Evacuation shelters
c. Search and rescue operations
d. Emergency medical services
e. Others

Please specify other means you ensure the safety and well-being of residents during flood events?

Evaluation and Improvement:

35. Following a flood event, what process do you follow to evaluate the effectiveness of your flood warning system? a. Post-event debriefings

b. Data analysis
c. Stakeholder (eg. affected community) feedback
d. After-action reports
e. Others, Please specify other process you follow to evaluate the effectiveness of your flood warning system?

36. Have any changes or improvements been made to the system based on past flood events?

a. Yes

b. No

c. Not sure

37. If yes, could you mention these improvements?

38. How do you gather feedback from stakeholders and the community regarding the performance of the flood warning system?

a. Surveys

b. Public meetings

c. Focus group discussions

d. Online feedback forms

e. Others, Please specify other means you gather feedback from stakeholders and the community regarding the performance of the flood warning system?

39. What measures are in place to ensure continuous improvement and adaptation of the flood warning system over time?

a. Regular system audits

b. Technology upgrades

c. Training and capacity building

d. Collaboration with research institutions

e. Others, Please specify other measures in place to ensure continuous improvement and adaptation of the flood warning system over time?

Open-ended Questions on the state of existing framework for managing floods.

1. What strategies does your organization use to monitor floods in the White Volta basin, Northern Ghana?

2. How directly are you or your organization involved in developing and implementing these strategies?

3. Who are the main stakeholders involved in the implementation and management of these frameworks/strategies?

4. Can you mention specific tools or technologies utilized for flood monitoring and management within these frameworks/strategies?

5. How adequate are the existing facilities and resources for flood monitoring and management in the White Volta basin?

6. In your opinion, what strategic initiatives should be prioritized to strengthen the overall effectiveness of the flood management framework in the White Volta?

7. Can you mention emerging technologies or approaches that could strengthen flood monitoring and management efforts in the White Volta basin, Northern Ghana?

8. How do varying lead times impact your ability to manage resources, protect infrastructure, communicate with the public, and minimize economic losses during flood events? Please share detailed experiences and any innovative solutions your agency has implemented to address these challenges."

Summary of the State of Flood Management

1. How do you perceive the current effectiveness of flood warning systems within the White Volta basin, considering the variables monitored and the communication channels utilized?

2. Could you elaborate on any specific challenges or limitations encountered in obtaining and utilizing data for flood risk assessment and early warning systems?

3. In what ways do you see local communities actively contributing to flood risk identification, mitigation strategies, and emergency response efforts within the region?

4. Can you provide insights into the collaboration dynamics among various stakeholders, including government agencies, NGOs, and local communities, in addressing flood risks and managing responses?

5. Following past flood events, what key lessons have been learned, and how have these lessons influenced the ongoing improvement and adaptation of flood warning systems and emergency response protocols?

Appendix A.2

Table A.2.1: Summary of the GMet (observed) and satellite/reanalysis rainfall data from 1998 to 2019.

Variable	Min	Max	Mean	Std Dev
GMet-Bawku (observed)	0	81	2.48	6.33
ARC2-Bawku	0	157.41	2.47	6.24
CHIRPS-Bawku	0	81.42	2.59	6.3
ERA5-Bawku	0	108.76	1.85	4.97
PERS-Bawku	0	59.23	2.6	5.43
TRMM-Bawku	0	44.12	0.91	2.84
GMet-Navrongo (observed)	0	116	2.62	8.6
CHIRPS-Navrongo	0	76.63	2.7	6.6
ERA5-Navrongo	0	104.3	2.08	5.33
PERS-Navrongo	0	58.38	2.69	5.58
TRMM-Navrongo	0	45.01	0.91	2.91
ARC2-Navrongo	0	157.41	2.47	6.23
GMet-Tamale (observed)	0	120.3	2.9	8.88
CHIRPS-Tamale	0	67.49	3.07	6.41
ERA5-Tamale	0	166.31	2.43	6.1
PERS-Tamale	0	58.2	2.98	5.53
TRMM-Tamale	0	40.56	0.98	2.9
ARC2-Tamale	0	144.76	2.47	6.3
GMet-Wa (observed)	0	142.4	2.83	8.34
CHIRPS-Wa	0	49.07	2.72	5.8
ERA5-Wa	0	116.94	2.47	5.5
PERS-Wa	0	55.98	3.03	5.73
TRMM-Wa	0	35.57	0.97	2.84
ARC2-Wa	0	127.42	2.61	6.47
GMet-Walewale (observed)	0	164.9	2.66	8.07
CHIRPS-Walewale	0	54.04	2.71	6.07
ERA5-Walewale	0	102.38	2.19	5.22
PERS-Walewale	0	48.82	2.81	5.54
TRMM-Walewale	0	38.07	0.92	2.77

ARC2-Walewale	0	99.22	2.55	6.16

Table A.2.2: Summary of the GMet (observed) and the reanalysis mean temperature data from 1998 to 2019.

Variable	Min	Max	Mean	Std Dev
GMet-Bawku (observed)	21.23	36.94	28.9	2.67
ERA5-Bawku	20.89	36.68	28.89	2.74
MERRA-Bawku	17.53	35.28	27.09	2.65
CFSR-Bawku	19.89	37.79	29.36	3.38
GMet-Navrongo (observed)	21.8	36.95	29.22	2.6
ERA5-Navrongo	21.37	36.45	28.67	2.72
MERRA-Navrongo	19.18	36.67	27.7	2.93
CFSR-Navrongo	19.53	37.67	28.76	3.32
GMet-Tamale (observed)	22.25	36.05	28.77	2.5
ERA5-Tamale	23.29	35.56	28.81	2.46
MERRA-Tamale	18.67	34.74	27.36	2.3
CFSR-Tamale	20.65	36.1	28.39	3.11
GMet-Wa (observed)	21.75	35.1	28.42	2.36
ERA5-Wa	21.61	34.88	27.97	2.43
MERRA-Wa	19.26	34.96	27.34	2.48
CFSR-Wa	20.36	36.31	28.22	3.15
GMet-Walewale (observed)	22.65	36.44	29.25	2.61
ERA5-Walewale	22.39	36.56	29.02	2.69
MERRA-Walewale	17.83	35.36	27.24	2.72
CFSR-Walewale	20.37	37.83	28.81	3.33

Table A.2.3: Summary of the ISMN (observed) and the reanalysis soil moisture from 2019 to 2022.

Variable	Min	Max	Mean	Std Dev
ISMN-Bimbilla (observed)	0.06	0.32	0.16	0.09
ERA5-Bimbilla	0.12	0.43	0.26	0.1
MERRA-Bimbilla	0.35	0.89	0.59	0.12
CFSR-Bimbilla	0.04	0.27	0.09	0.06
ISMN-Bongo (observed)	0.07	0.3	0.14	0.07
ERA5-Bongo	0.11	0.48	0.23	0.1
MERRA-Bongo	0.23	0.94	0.55	0.18
CFSR-Bongo	0.03	0.27	0.07	0.05
ISMN-Navrongo (observed)	0.06	0.41	0.14	0.09
ERA5-Navrongo	0.11	0.46	0.22	0.1
MERRA-Navrongo	0.15	0.88	0.47	0.19
CFSR-Navrongo	0.03	0.26	0.07	0.05
ISMN-Tamale (observed)	0.08	0.3	0.16	0.06
ERA5-Tamale	0.14	0.47	0.26	0.11
MERRA-Tamale	0.24	0.8	0.49	0.12
CFSR-Tamale	0.03	0.3	0.09	0.06
ISMN-Pusiga (observed)	0.1	0.36	0.17	0.07
ERA5-Pusiga	0.15	0.48	0.24	0.1
MERRA-Pusiga	0.29	0.88	0.54	0.14
CFSR-Pusiga	0.03	0.3	0.08	0.05

Appendix A.3

Table A.3.1: Summary of data used in training the LSTM and the RF model for forecasting streamflow at 1, 5, and 10 day ahead.

Variable	Min	Max	Mean	Std Dev
Rainfall-Nawuni	0	87.85	2.91	6.46
Mean_Temp-Nawuni	22.5	35.87	28.69	2.5
Soil Moisture- Nawuni	0.03	0.33	0.1	0.06
eo-Nawuni	0.34	8.47	5.51	1.21
es-Nawuni	0.27	8.17	5.12	1.17
et-Nawuni	0.22	8.16	4.85	1.17
Target_observed-Nawuni	0	3677.12	267.59	464.37

Rainfall-Pwalugu	0	67.03	2.77	6.39
Mean_Temp-Pwalugu	21.35	36.48	28.71	2.68
Soil_moisture-Pwalugu	0.03	0.32	0.1	0.07
e0-Pwalugu	0.22	8.97	5.66	1.23
es-Pwalugu	0.19	8.64	5.26	1.21
et-Pwalugu	0.17	8.51	5	1.23
Target_observed-Pwalugu	0	2326.48	109.18	195.74
Mean_Temp-Yarugu	20.95	36.66	28.75	2.7
Rainfall-Yarugu	0	80.67	2.61	6.21
Soil_Moisture-Yarugu	0.03	0.31	0.09	0.06
e0-Yarugu	0.46	9.17	5.75	1.22
es-Yarugu	0.42	8.84	5.36	1.2
et-Yarugu	0.34	8.69	5.1	1.21
Target_observed-Yarugu	0	1781.7	87.12	147.2

Table A.3.2: Summary of the CHIRPS (observed) and the GCMs-CMIP6 rainfall data.

Variable	Min	Max	Mean	Std Dev
CHIRPS-Nawuni (observed)	0	87.85	2.91	6.44
ACCESS-CM2-Nawuni	0	61.73	2.15	4.74
BCC-CSM2-MR-Nawuni	0	377.98	3.2	15.16
INM-CM5-0-Nawuni	0	111.47	2.22	6.01
MIROC6-Nawuni	0	295.14	5.28	14.73
MRI-ESM2-0-Nawuni	0	50.19	2.19	4.31
CHIRPS-Pwalugu (observed)	0	67.03	2.76	6.39
ACCESS-CM2-Pwalugu	0	59.9	1.62	4
BCC-CSM2-MR-Pwalugu	0	268.24	2.51	12.89
INM-CM5-0-Pwalugu	0	146.24	1.72	5.38
MIROC6-Pwalugu	0	296	4.52	15.13
MRI-ESM2-0-Pwalugu	0	70.9	2.08	4.25
CHIRPS-Yarugu (observed)	0	80.67	2.59	6.22
ACCESS-CM2-Yarugu	0	59.9	1.62	4
BCC-CSM2-MR-Yarugu	0	268.24	2.51	12.89
INM-CM5-0-Yarugu	0	146.24	1.72	5.38

MIROC6-Yarugu	0	296	4.52	15.13
MRI-ESM2-0-Yarugu	0	70.9	2.08	4.25

Table A.3.3: Summary of the ERA5 (observed) and the GCMs-CMIP6 mean temperature data.

Variable	Min	Max	Mean	Std Dev
ERA5-Nawuni (observed)	22.5	35.87	28.59	2.49
ACCESS-CM2-Nawuni	18.01	36.78	29.39	2.16
ACCESS-ESM1-5-Nawuni	19.08	37.04	28.58	2.56
ERA5-Pwalugu (observed)	21.35	36.44	28.62	2.67
ACCESS-CM2-Pwalugu	16.04	38.8	30.28	2.51
ACCESS-ESM1-5-Pwalugu	19.08	37.04	28.58	2.56
ERA5-Yarugu (observed)	20.95	36.5	28.62	2.72
ACCESS-CM2-Yarugu	16.04	38.8	30.28	2.51
ACCESS-ESM1-5-Yarugu	17.14	38.03	28.8	3.1

Table A.3.4: Summary of data used in training the LSTM and the RF model for forecasting future streamflow.

Variable	Min	Max	Mean	Std Dev
Rainfall-Nawuni	0	304.41	2.63	7.95
Mean_Temp-Nawuni	18.01	37.04	28.78	2.47
Target_observed-Nawuni	0	2354.98	250.21	422.78
Rainfall-Pwalugu	0	268.24	2.51	12.89
Mean_Temp-Pwalugu	16.04	37.04	28.79	2.57
Target_observed-Pwalugu	0	1474.73	98.7	167.23
Rainfall-Yarugu	0	268.24	2.66	13.65
Mean_Temp-Yarugu	16.04	38.03	29.38	2.75
Target_observed-Yarugu	0	1326.68	78.71	120.66

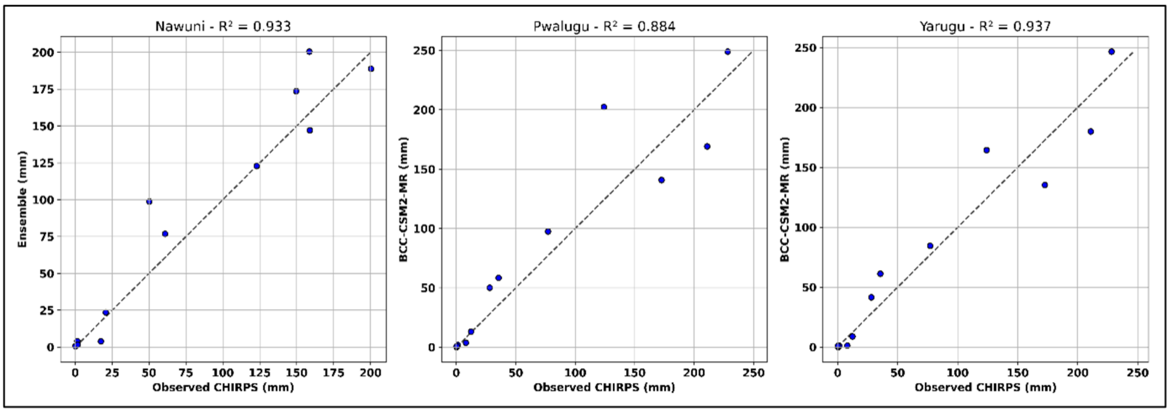

Figure A.3.1: R^2 of observed data with rainfall ensemble at Nawuni and BCC-CSM2-MR at Pwalugu and Yarugu gauge stations.

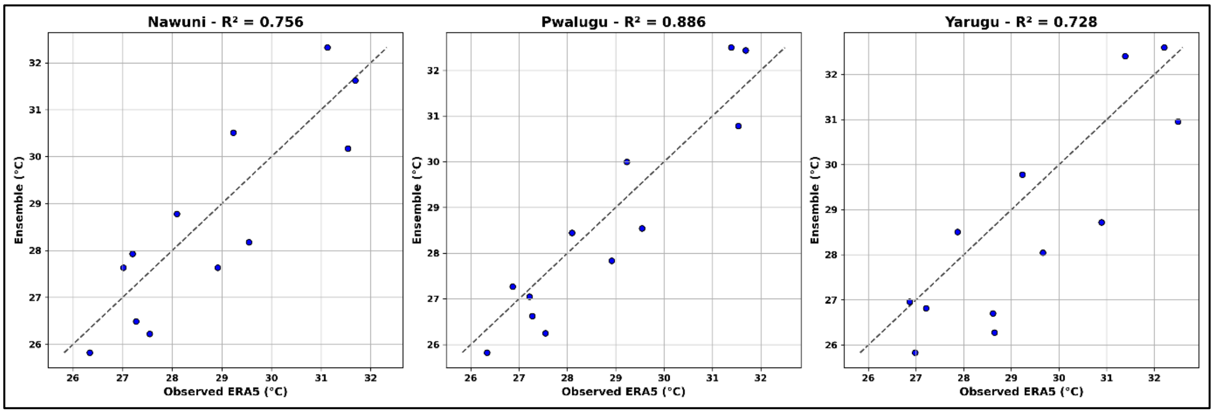

Figure A.3.2: R^2 between the observed data and the ensemble temperature data at the three gauge stations.

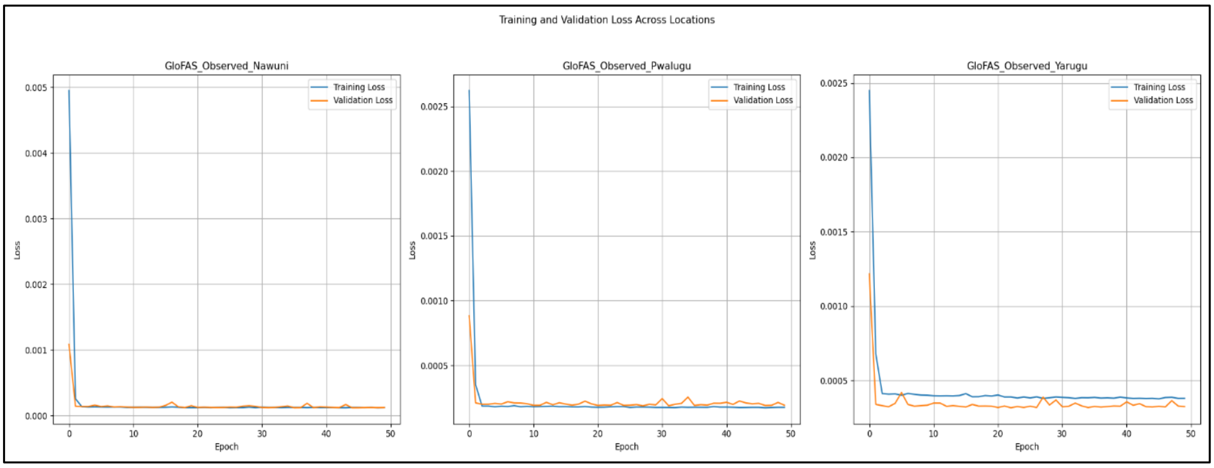

Figure A.3.3: The loss functions recorded by the LSTM for the three gauge stations during the training and testing.

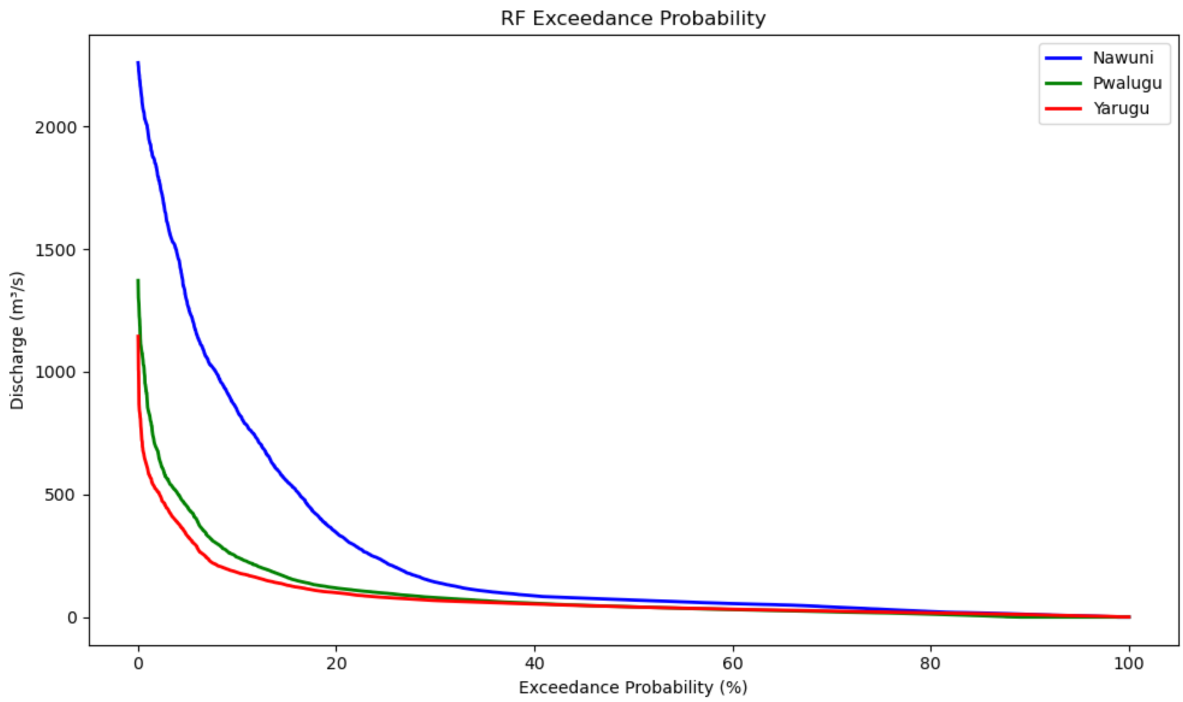

Figure A.3.4: Exceedance probability recorded by the predicted streamflow using the random forest model for the three gauge stations in the testing phase.

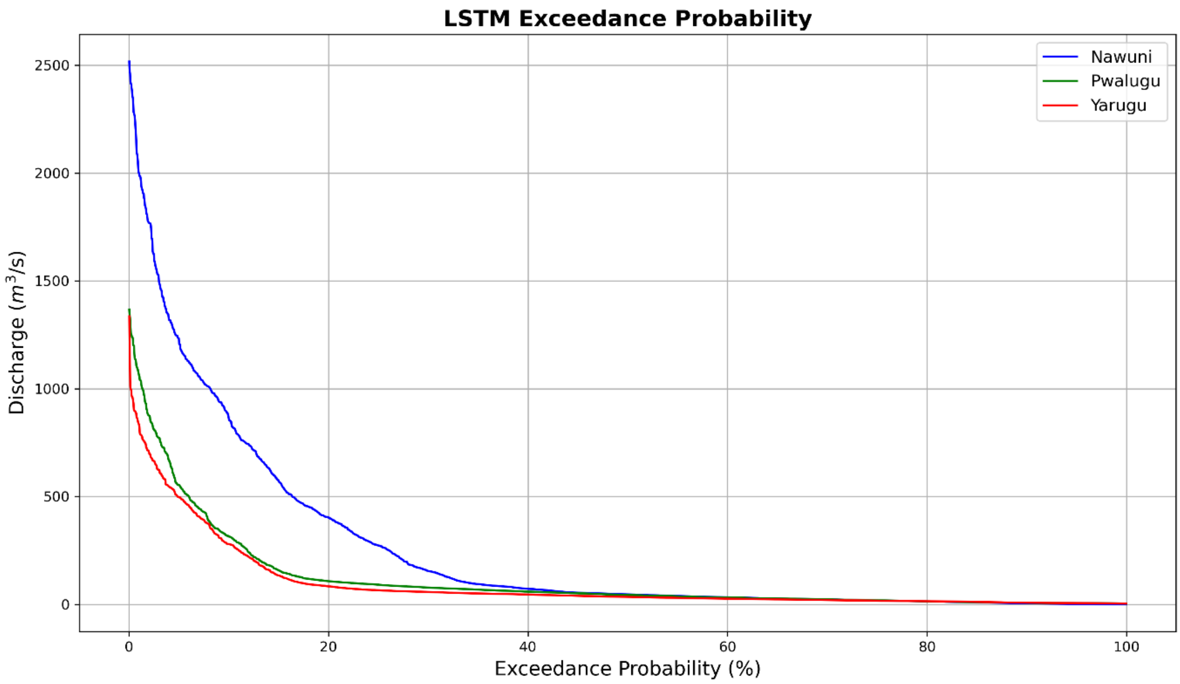

Figure A.3.5: Exceedance probability recorded by the predicted streamflow using the LSTM model for the three gauge stations in the testing phase.

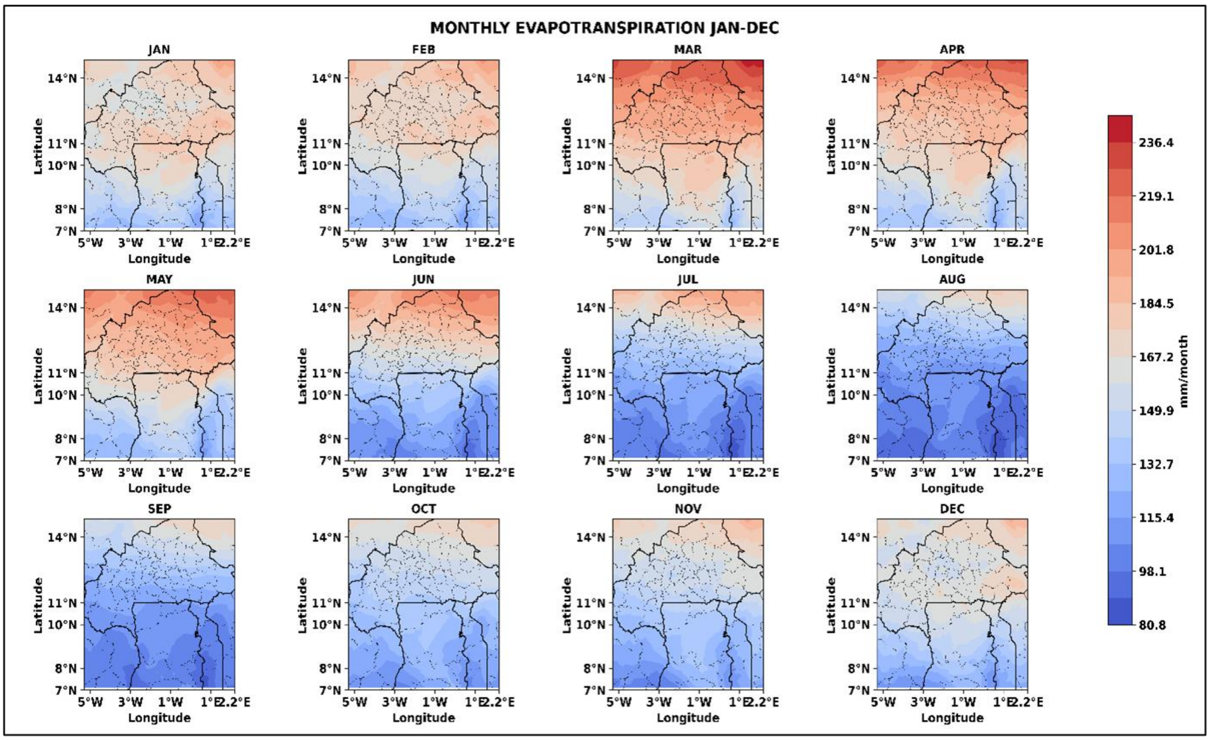

Figure A.3.6: Monthly average evapotranspiration recorded from 1979 - 2019.

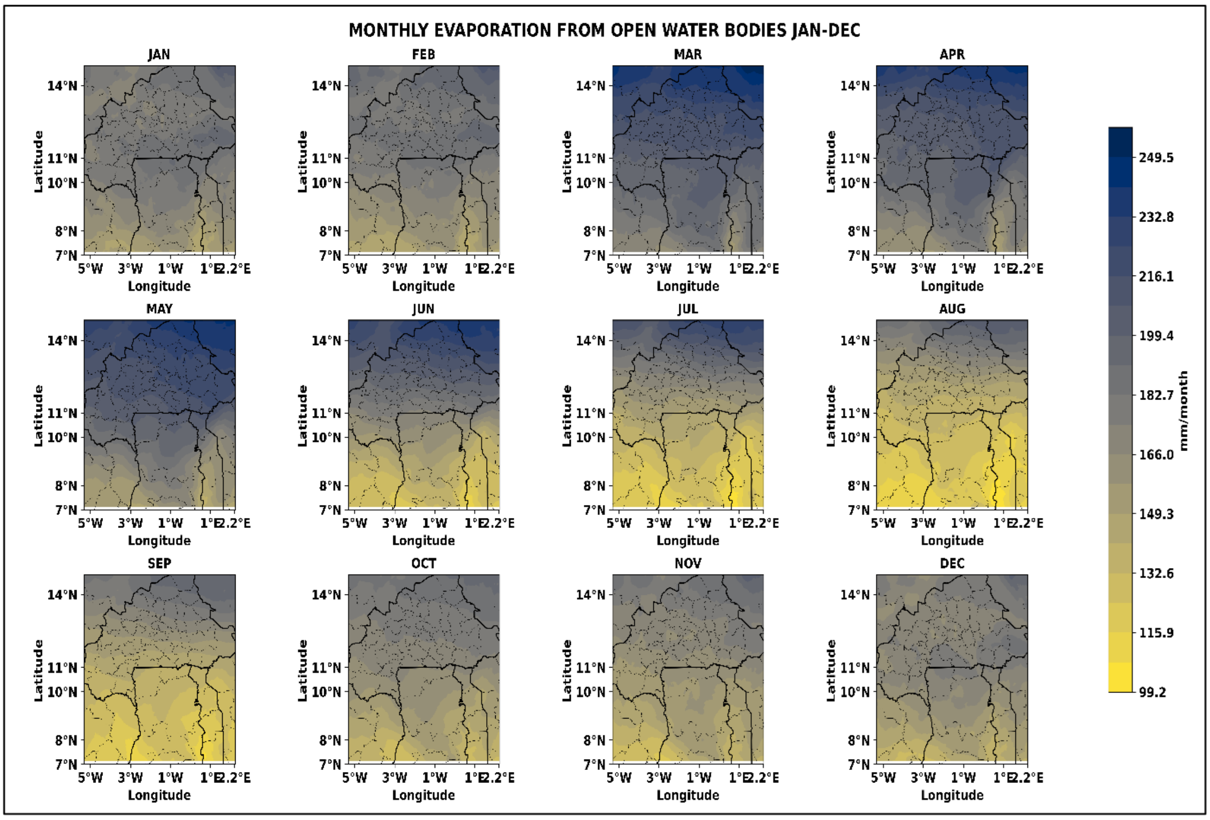

Figure A.3.7: Monthly average evaporation from open waters recorded from 1979 - 2019.

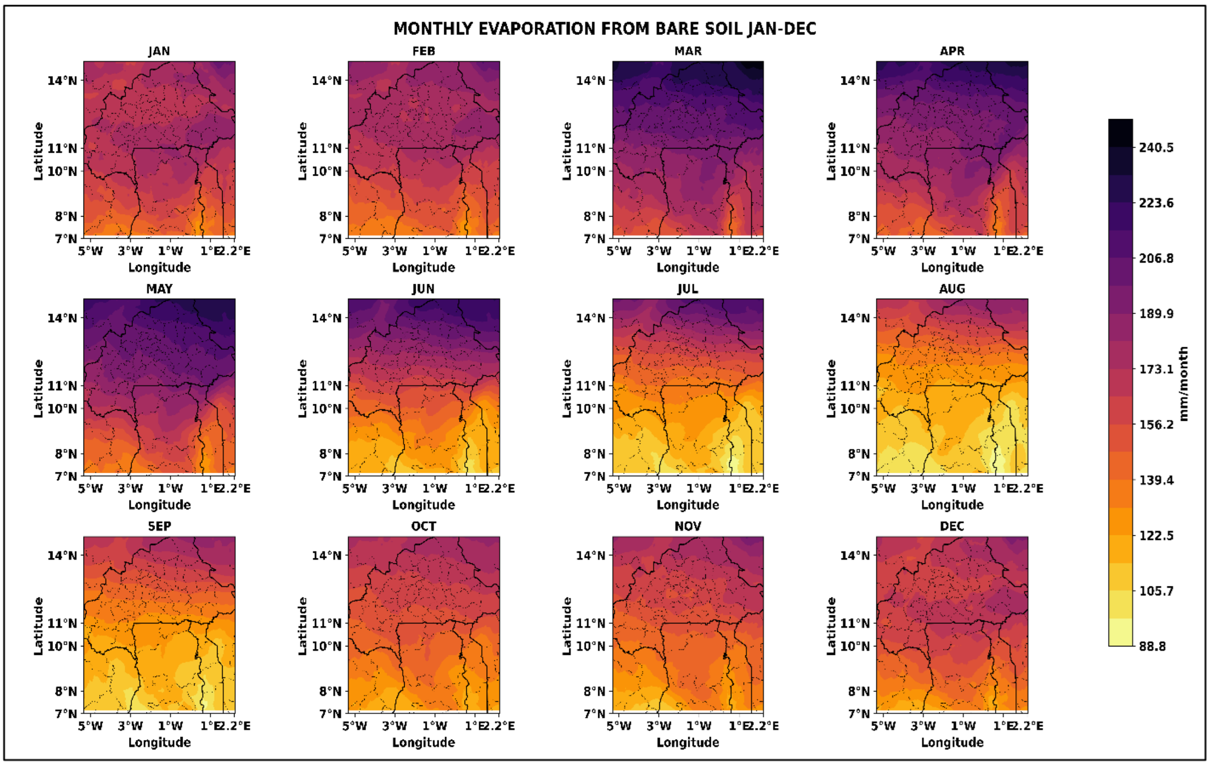

Figure A.3.8: Monthly average evaporation from bare soil recorded from 1979 - 2019.

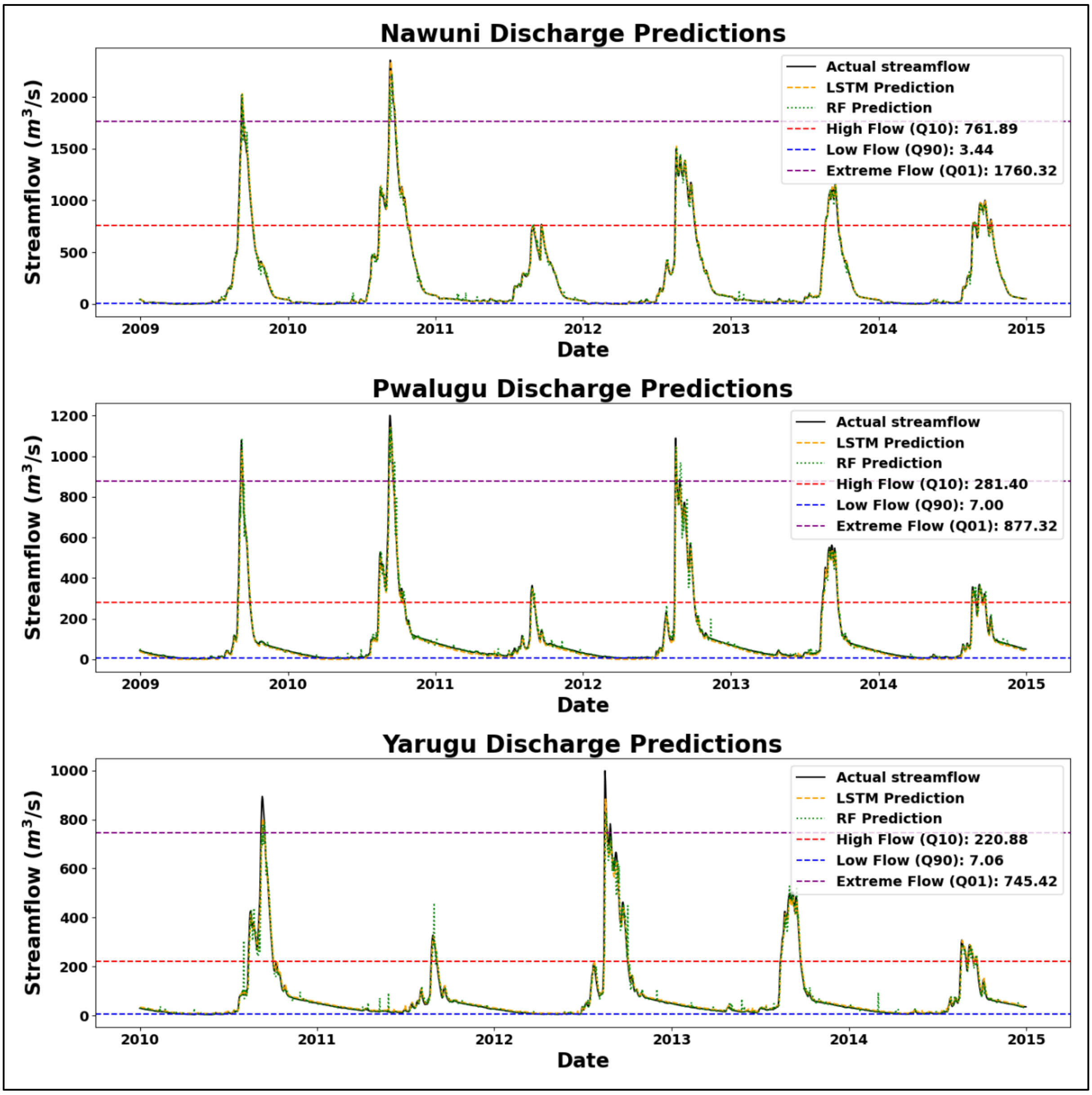

Figure A.3.9: Q90, Q10, and Q01 recorded by simulated and actual streamflow in the testing period.

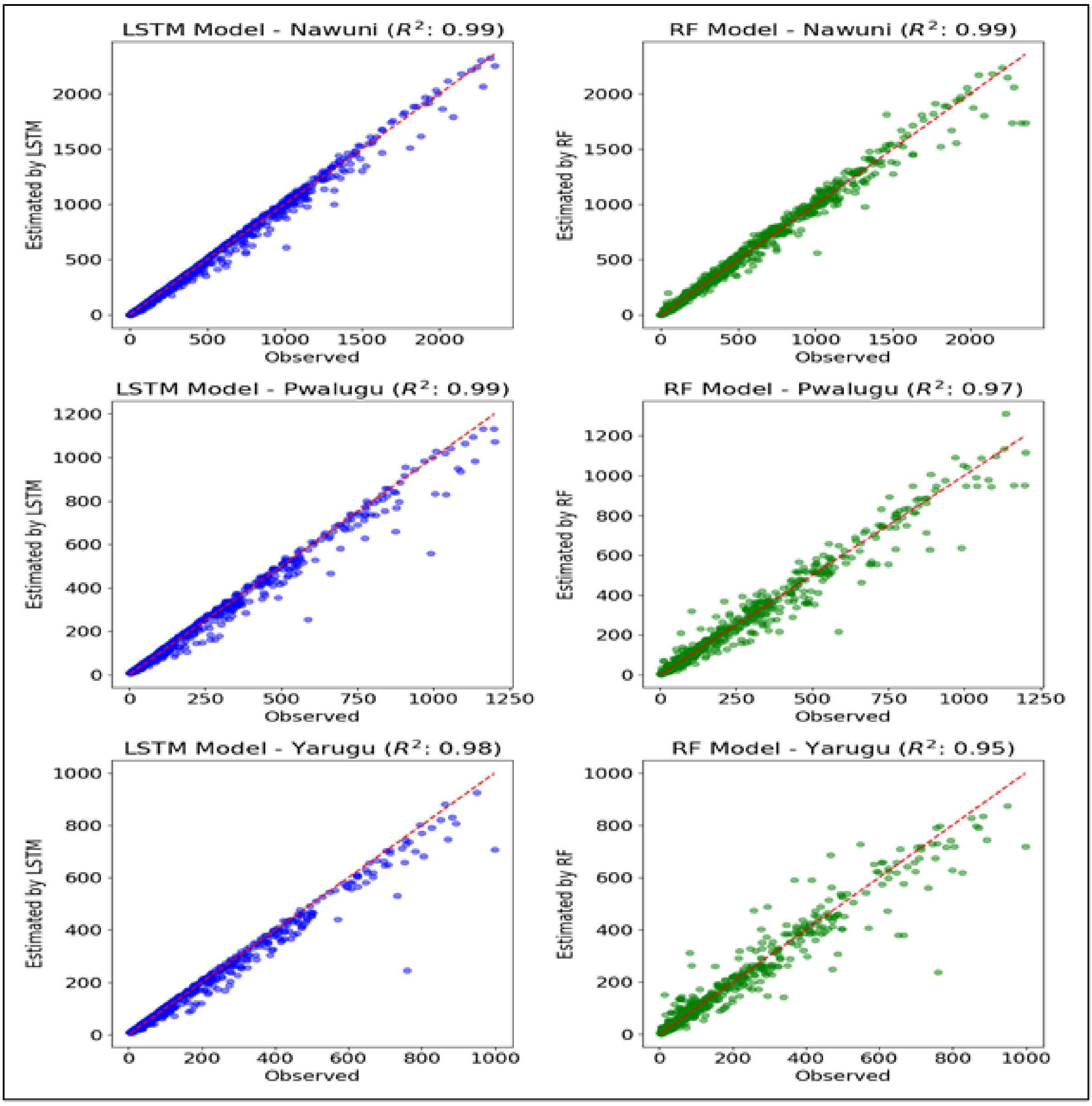

Figure A.3.10: R^2 between the observed streamflow and the predicted Random Forest (RF) and Long Short-Term Memory (LSTM) from 1985 to 2014.

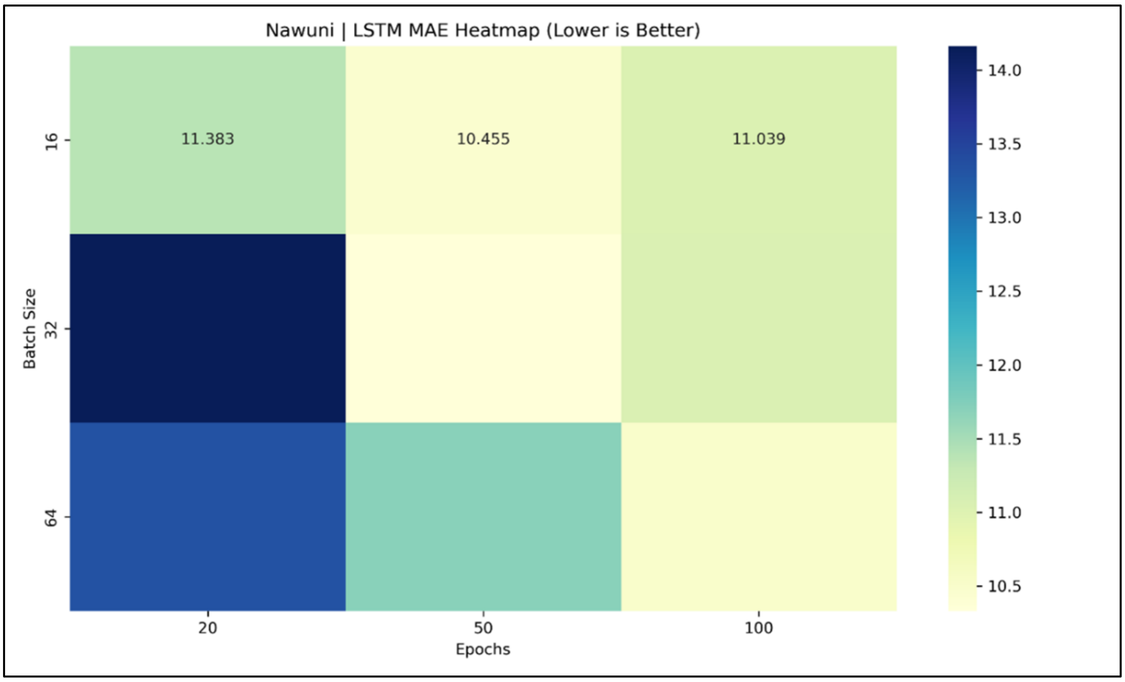

Figure A.3.11: MAE of the simulated streamflow from the LSTM model under different epoch and batch size configurations at the Nawuni gauge station.

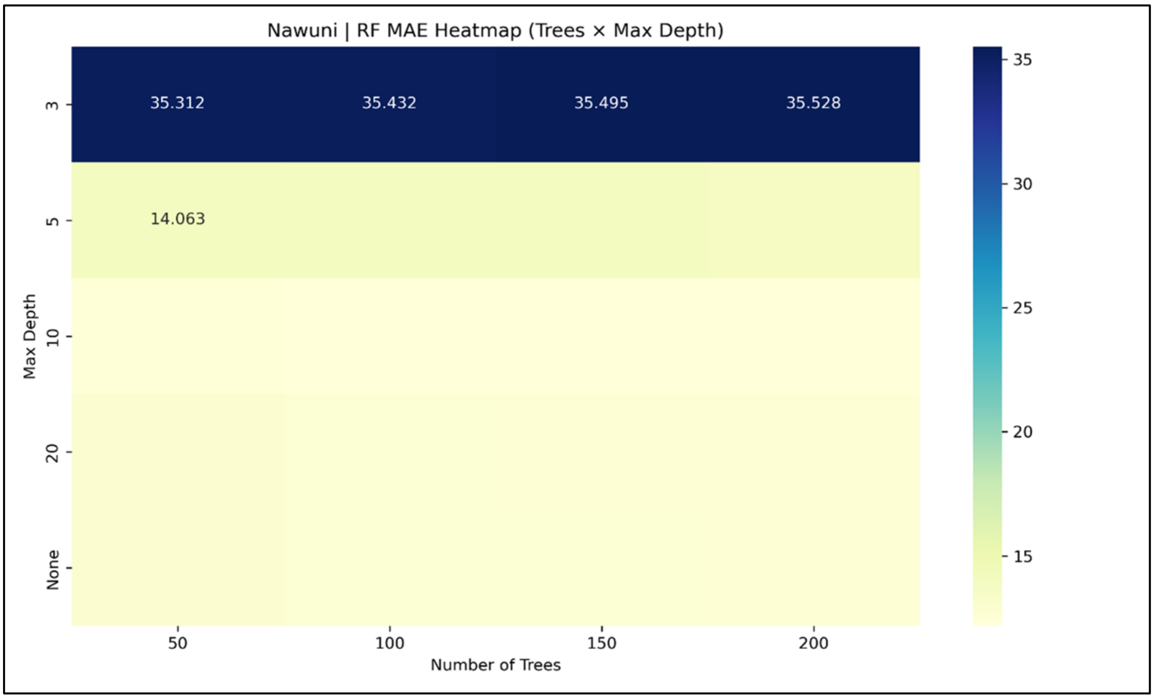

Figure A.3.12: MAE of the simulated streamflow from the RF model under different tree configurations at the Nawuni gauge station.

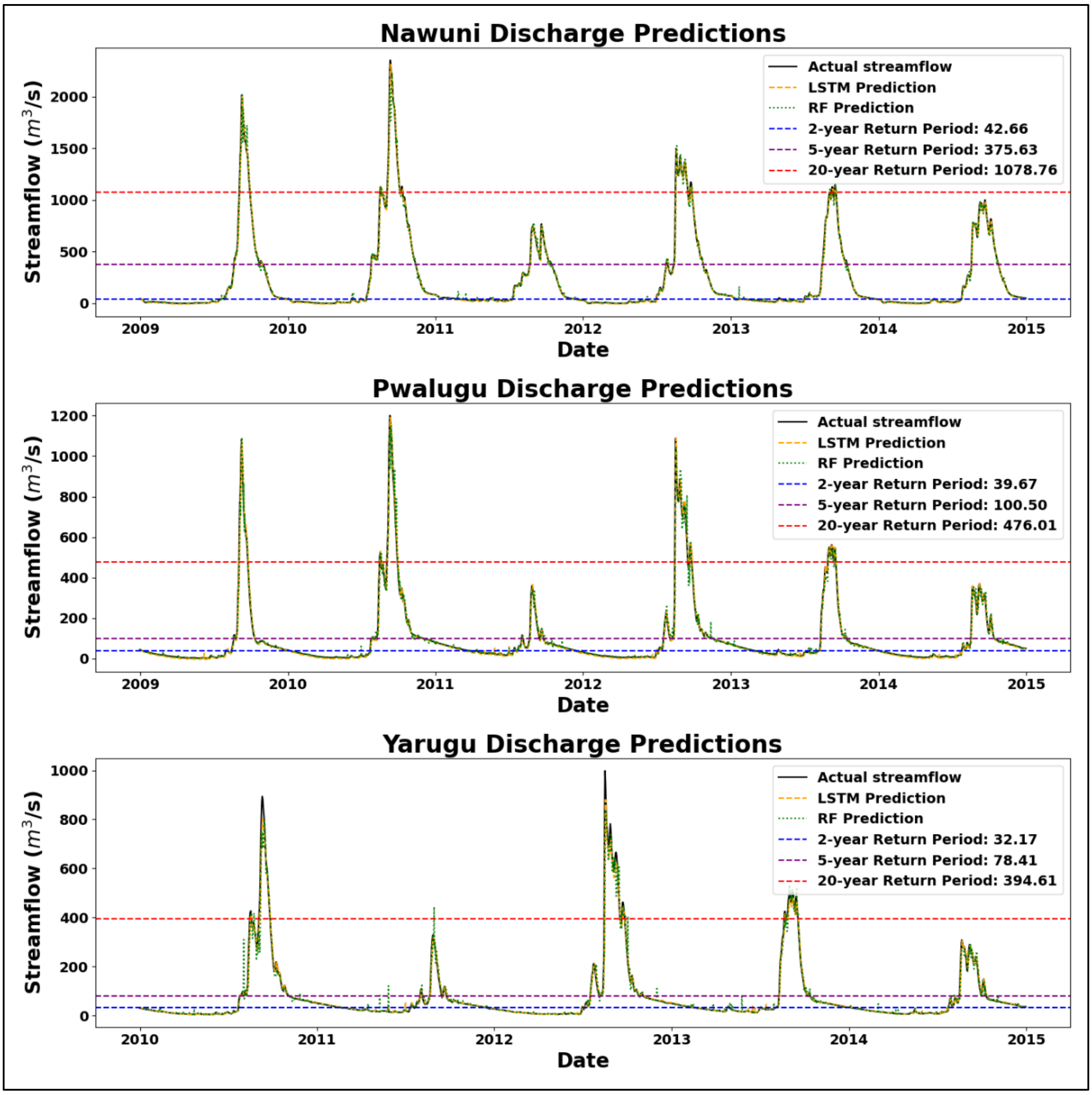

Figure A.3.13: Return period estimated across the three gauge stations.

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