

# Flood Forecasting and Warning System: A Survey of Models and Their Applications in West Africa

Mohamed Fofana<sup>1\*</sup>, Julien Adoukpe<sup>1,2</sup>, Sam-Quarco Dotse<sup>3</sup>, Hamadoun Bokar<sup>4</sup>,  
Andrew Manoba Limantol<sup>3</sup>, Jean Hounkpe<sup>1,2</sup>, Isaac Larbi<sup>3</sup>, Adama Toure<sup>4</sup>

<sup>1</sup>Graduate Research Program on Climate Change and Water Resources West African Science Service Center on Climate Change and Adapted Land Use (WASCAL), Department of Applied Hydrology, University of Abomey-Calavi, Cotonou, Abomey-Calavi, Benin

<sup>2</sup>National Water Institute, University of Abomey Calavi, Abomey Calavi Atlantic, Benin

<sup>3</sup>School of Sustainable Development, University of Environmental and Sustainable Development, Somanya, Ghana

<sup>4</sup>National Engineer School ENI-ABT, Bamako, Mali

Email: \*momofof21@gmail.com, \*fofana.m@edu.wascal.org

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## Abstract

Flood events occurrences and frequencies in the world are of immense worry for the stability of the economy and life safety. Africa continent is the third continent the most negatively affected by the flood events after Asia and Europe. Eastern Africa is the most hit in Africa. However, Africa continent is at the early stage in term of flood forecasting models development and implementation. Very few hydrological models for flood forecasting are available and implemented in Africa for the flood mitigation. And for the majority of the cases, they need to be improved because of the time evolution. Flash flood in Bamako (Mali) has been putting both human life and the economy in jeopardy. Studying this phenomenon, as to propose applicable solutions for its alleviation in Bamako is a great concern. Therefore, it is of utmost importance to know the existing scientific works related to this situation in Mali and elsewhere. The main aim was to point out the various solutions implemented by various local and international institutions, in order to fight against the flood events. Two types of methods are used for the flood events adaptation: the structural and non-structural methods. The structural methods are essentially based on the implementation of the structures like the dams, dykes, levees, etc. The problem of these methods is that they may reduce the volume of water that will inundate the area but are not efficient for the prediction of the coming floods and cannot alert the population with any lead time in advance. The non-structural methods are the one allowing to perform the prediction with acceptable lead time. They used the hydrological rainfall-runoff

models and are the widely methods used for the flood adaptation. This review is more accentuated on the various types non-structural methods and their application in African countries in general and West African countries in particular with their strengths and weaknesses. Hydrologiska Byråns Vattenbalsavdelning (HBV), Hydrologic Engineer Center Hydrologic Model System (HEC-HMS) and Soil and Water Assessment Tool (SWAT) are the hydrological models that are the most widely used in West Africa for the purpose of flood forecasting. The easily way of calibration and the weak number of input data make these models appropriate for the West Africa region where the data are scarce and often with bad quality. These models when implemented and applied, can predict the coming floods, allow the population to adapt and mitigate the flood events and reduce considerably the impacts of floods especially in terms of loss of life.

### Keywords

Flood Forecasting, Hydrological Models, Climate Change, West

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## 1. Introduction

Floods are one of the important catastrophes with regular occurrences, which affect many regions around the world, damaging properties and economies, harming human health and causing losses of life. Dilley et al. (2005) reported that more than one-third of the world's land area is prone to flooding affecting 82% of the global population. According to EM-DAT (2015), floods are responsible of nearly half of the deaths and one-third of all economic losses. The twentieth century has been hit by more than 5000 major hydrological disasters in the world where 3.5 billion people were affected, 7 million of persons lost life and around \$650 billion USD of economic losses (CRED, 2012). The number of flood-related casualties, affected people, and associated economic losses have significantly increased in Africa since the middle of the 1990s (CRED, 2012), due to an increase of human settlements in flood-prone areas rather than possible climate change issues (Di Baldassare et al., 2010). Thiemig et al. (2011) carried out a study in Africa to determine the flood forecasting mitigation aspects. They find out that there are a significant number of institutional flood forecasting initiatives ongoing in Africa, but information regarding many of these initiatives is not easily accessible. Second, there is a clear need for improved flood forecasting and early warning in Africa. Third, the dissemination of existing flood forecasts and warnings to end-users and the public could be improved. Results of a study done in Africa showed that African Flood Forecasting System (AFFS) detected around 70% of the reported flood events correctly. In particular, the system showed good performance in predicting riverine flood events of long duration (>1 week) and large affected areas (>10,000 km<sup>2</sup>) well in advance, whereas AFFS showed limitations for small-scale and short duration flood events (Thiemig et al., 2014). All

major natural disasters combined, flood-related disasters alone are responsible of 22% of total deaths, 24% of total economic losses and 51% of the total people are suffering of flood impact. According to [Alfieri et al. \(2014\)](#), 54 millions of people in the World are exposed to yearly river flood. [ICHARM \(2009\)](#) reported that during the period of 1900-2006, floods accounted for about 30% of the total number of natural disasters, 19% of the total fatalities and more than 48% of the total number of people affected. Out of the 72% of the total economic damages caused by the natural disasters, 26% of the damages were flood related ([ICHARM, 2009](#)). According to the international disaster database, flood occurs more frequently than all other types of natural hazards across the globe and accounts for 39% of all disasters arising from natural hazards since 2000 with 94 million people affected every year in the world. In its 2008 note, [UNESCO \(2008\)](#) stated that half of the deaths and nearly one-third of all economic losses from natural hazards worldwide is due to floods. Africa is the third continent the most affected by flood after Asia and Europe. The climate change along with the urbanization and an increasing African population, make flood risks certain to occur frequently. The reliability to forecasting has increased in the recent years due to the integration of meteorological and hydrological modelling capabilities, improvements in data collection through satellite observations, and advancements in knowledge and algorithms for analysis and communication of uncertainties. Climate change and the steady increase in the population as well as the urbanization, land use change, deforestation, sea level rise, population growth in the flood-prone area will increase the number of vulnerable people to flood disasters up to two billion in 2050 as the flood occurrence is going to increase in the future ([Kundzewicz, 2008](#); [Bogardi, 2004](#); [ICHARM, 2009](#); [Vogel et al., 2011](#)).

Floods happen generally when there is a heavy rain associated with severe thunderstorms, hurricanes, tropical storms enhanced by melted ice, and glaciers water or snow water flowing over ice sheets or snowfields. It appears in geomorphological low-lying areas. The extreme rainfall in addition to the reduced water-holding capacity of the soil are the main origins of more severe floods in Sahelian countries ([Descroix et al., 2018](#); [Mahe et al., 2005](#)). The conversion of the savannah into cereals fields, forest destruction for farming, trees cutting down for firewood in addition to the transformation of flood-prone area to new human settlements due the population growth are the major cause of the occurrence of flood, leading to increase catastrophic flood impacts ([Tiepolo & Tarchiani, 2016](#); [Fiorillo et al., 2017](#)).

West Africa is one of the regions the most negatively impacted by flood events. According to [EM-DAT \(2015\)](#), Africa comes just after Asia and Europe, in terms of human life losses due to flood events. However, due to its weak means of recovery, Africa is severely affected by the flood events. According to [OCHA \(2020\)](#), in West and Central Africa, 465 people lost life because of flood, 1.7 million of people were touched, 94,000 displaced and 152,000 people stayed houseless. The densely populated low-and middle-income countries where exposure

and vulnerability are the highest, are the places where flood victims are located (Dottori et al., 2018; UNISDR, 2014). In Africa, the majority of the countries hit by the flood are located in the Eastern part, Nigeria being the exception (EM-DAT, 2015). Researches showed that the issue of flood will continue to increase both in frequency and magnitude (Nka et al., 2015; Ntajal et al., 2017). These losses are expected to increase in the future due to the climate change, land use change, deforestation, rising sea level and population growth in flood-prone areas leading to two billion by 2050 the number of vulnerable people to flood disasters in the world (Bogardi, 2004; ICHARM, 2009; Vogel et al., 2011).

Many researchers link the causes of floods to climate change attributed to the anthropogenic actions such as urbanization, and land use change. Because of these causes, it is obvious that flood events are expected to occur more frequently in the future as well the damages associated to it.

In order to alleviate, mitigate and adapt to these flood events, there are some solutions that have to be put in practice. These solutions, when implemented and applied, can give accurate, timely, precise and understandable forecast information, alerts, and may help to reduce the flood impacts (Perera et al., 2019). Structural and non-structural methods are the widely methods used for the flood adaptation. The structural methods such as Dam, levees and embankments allow sometime to adapt flood events by reducing the water level. However, the main issues will be the maintenance cost of these infrastructures and also their incapacity to stand the coming floods in the future. The structural methods against flood issues can be misleading to users, because it gives hope to population to build in the flood prone area and develop their activities at these places (Haile et al., 2013). In fact, just 25% to 55% of reduction in flood damages are noticed when the structural methods are implemented (Bubeck et al., 2012; Kreibich et al., 2005; Kreibich & Thielen, 2009). The non-structural methods are the ones that are currently used by the hydrologists; it is based on the flood forecasting through hydrological models. Non-structural measures provide more reversible and less-expensive mechanisms to reduce flood risk than structural actions (Di-Francesco & Tullos, 2014). The non-structural methods are not only the most effective in term of flood risk management measures, but also the methods with an important accuracy and increased amount of flood damages reduction (UNISDR, 2004) in addition to more reversible and less-expensive mechanisms to reduce flood damages (Di Francesco & Tullo, 2014). The implementation of flood forecasting and early warning systems, the building of population awareness and preparedness, urban planning, discouraging human settlements in flood-prone areas and the development of local institutional capacities as well as forecasting methods development should be appropriate action to carry out. The flood prediction models are very important due to their ability to provide the forecasted data from short-term to long-term depending on the need. The importance of advanced systems for short-term and long-term prediction for flood and other hydrological events is strongly emphasized to alleviate damages (Pitt, 2008). However, because of the climate condition and nature dynamic, the prediction

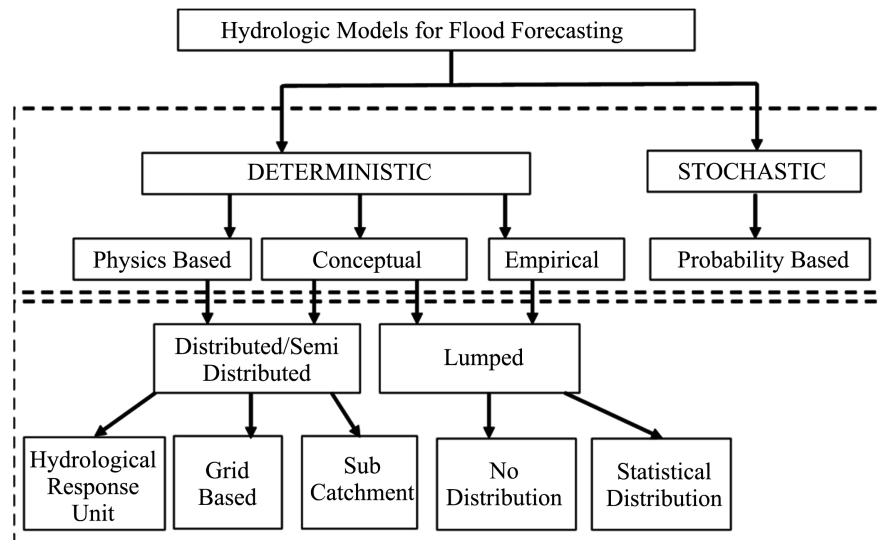
of flood lead time and occurrence location is complex to do. Floods modeling and forecasting are useful to manage and prepare for the extreme flood events. The World Meteorological Organization stated that due to the improved flood forecasting models, there is an important decrease in the number of losses of life, however, economic losses have increased over the past 50 years.

The accuracy of flood forecasting depends on the quality of meteorological forecast and on the performance of the hydrological model. Meteorological models are designed to mimic water and energy cycles in the atmosphere and land. Hydrological models are designed to emulate water and energy cycles that occur over and within the land surface (Roundy et al., 2019). The outputs of the meteorological models are used to force the hydrological models. Various hydrological models are currently used to forecast flooding events. Two main types of models are widely used worldwide: deterministic/stochastic and data driven models. In Africa, several studies have been done using deterministic models for flood forecasting issues. The physical models required lot of input data associated, making its use complicated while data driven models required less data and there is no need for physical equations and parameters, or catchment characteristics leading to the static of the model which cannot evaluate the changes such as land use land changed (Quenum et al., 2022). Despite the impacts and catastrophes induced by flood, West Africa, the central area of this research is unfortunately not well documented that topic. For the best of our ability, the hydrological models used in West Africa are not very important and no one exists in Mali. However, the mostly models used for the purposes of flood forecasting are HEC-HMS, HBV, SWAT, WRH-Hydro. The importance of these models is their ability to predict the floods allowing to reduce the damages of flood events, especially in terms of losses of life.

This review has focused on recent models and techniques applied in flood forecasting and flood warning system in Africa and particularly West Africa. In the present study, the current state-of-the-art technology in flood forecasting and flood warning system in Africa will be deeply reviewed. Various hydrological models currently used in Africa and especially in West Africa for flood forecasting purposes will be analyzed for their strengths and weaknesses.

## 2. The State of the Art Flood Forecasting Models and Applications

There are several types of flood forecasting models and criteria for them to be classified. The catchment models used for flood forecasting may be classified according to the components in **Figure 1**. Thus, the models may be classified depending on the way catchment processes are represented either deterministic or data driven; or the way the catchment is spatially discretized such as lumped or distributed (Jain et al., 2018; WMO, 2011). Deterministic models solve a set of equations representing the different watershed processes that produce a single model output for a given set of parameters (Jain et al., 2018). In contrast, data-driven models has the capability to simulate the random and probabilistic nature



**Figure 1.** Classification of models used for flood forecasting based on model structure and type (source: WMO, 2011).

of inputs and responses that govern river flows (Jain et al., 2018). The type of model employed in a particular application depends largely on the primary processes that produce runoff and their spatial and temporal extent, spatial coverage and resolution of data, and catchment features (Kauffeldt et al., 2016). However, the state of the art operational and research on flood forecasting systems around the world are increasingly moving towards using ensemble probabilistic forecasts, known as Ensemble Prediction Systems (EPS), rather than single deterministic forecasts, to drive their flood forecasting systems (Cloke & Pappenberger, 2008; Ramos et al., 2013; Alfieri et al., 2014).

The purpose of a flood forecasting and warning system (FFWS) is to alert in advance, the general public and concerned authorities of an impending flood, and with as much reliability as possible. Many factors can influence the quality of a flood forecasting system. Most of these factors rely on the constituents' quality of the system. The main constituents of the flood forecasting and warning system are: the input data (hydrological and meteorological data), forecasting, modeling, and dissemination of information to the end users.

The input data are the data used to force the hydrological models in the modeling process. They are climatic data obtained through the meteorological models.

The meteorological data, also called climatic data, are used to force the hydrological model. The main climatic data are precipitation and temperature which are frequently used by rainfall-runoff models in flood forecasting processes. Sometimes, the rain gauge data may not be enough in flood forecasting processes, especially when it is about the small catchment where the lead time is short. In that case, it becomes urgent to incorporate the Numerical Weather Precipitation (NWP) data in order to get forecasted rainfall. This data is important when carrying out a flood forecasting and warning system study. The input data of NWP

has improved significantly nowadays, and has consequently improved the forecasting system extending the lead time to more than 15 days.

After the setting up of hydrological rainfall-runoff model, the calibration step begins. For that purpose, the discharge data, also called hydrological data are required. Many rainfall-runoff data used the discharge data in the flood forecasting modeling processes. In fact, the hydrograph resulting from the meteorological data will be compared to the observed discharge data for the calibration processes. Therefore, the quality of such data as well rainfall as discharge, real-time measurement and forecasted is very important for the system.

The choice of the model is very important and depends on the aim of the research. This step is very crucial and need to be treated with major attention. Several types of models exist. The choice of the models is important and will have an impact in the results. Deterministic and data driven models will not provide the same result, also lumped, semi-distribute and physical-based models will not give the same detailed output for the flood forecasting. Their use depends on the type of results that is required. So based on the issue, a specific model that suits better will be used to solve the concerned issue.

The last point of the flood forecasting and warning system is the dissemination of the information, how to disseminate the results among the population in order to alert them about the coming floods and a need to take live saving decisions to avoid the catastrophes. This step is very crucial and everything depends on it. Not only the information has to be communicated on time, allowing the population to evacuate and also the information has to be accurate for the people to trust the future messages. The accuracy of the information is very important for the reliability of the population to the communicated warnings. [Henonin et al. \(2013\)](#) compared the flood forecasting and warning system to a house building processes. While input data corresponds to “the foundation”, the data collection to “the wall”, the modeling processes to the “openings” and the warning is associated to “the roof” of the house. Like for the house architecture, the sustainability of the flood forecasting system relies on the combination of these different components. The quality of the system as well as the warning that will be launched to the people, depends on the quality of these components as well as their interconnection. None of them should be neglected.

### 3. Hydrological Models for Flood Forecasting

According to [Jain et al. \(2018\)](#), catchment models are classified based on several criteria. The two main criteria are based on the way catchment processes are presented and the way catchment is spatially discretized. The models are deterministic or data driven regarding the catchment processes and lumped or distributed according to its spatial discretization. A third type of catchment model is based on the rainfall estimate and lead time.

The type of the models employed in a particular application depends largely upon the primary processes that produce runoff and their spatially and tempo-

rary extent, spatial coverage and resolution of data, and catchment features.

### 3.1. Physics Based Models

This is a mathematically idealized representation of the real phenomenon. This is also called mechanistic models that include the principles of physical processes. It uses state variables which are measurable and are functions of both time and space. The hydrological processes of water movement are represented by finite difference equations. It does not require extensive hydrological and meteorological data for their calibration but the evaluation of large number of parameters describing the physical characteristics of the catchment are required (Abbott et al., 1986). In this method huge amount of data such as soil moisture content, initial water depth, topography, topology, dimensions of river network etc. are required. Physical model can overcome many defects of the other two models because of the use of parameters having physical interpretation. It can provide large amount of information even outside the boundary and can be applied for a wide range of situations. Hydrological European System (SHE)/MIKE SHE model is an example.

Vischel et al. (2008) carry out a study in South Africa based on the implementation of the TOPographic Kinematic AProximation Integration (TOPKAPI) model for the first time in Africa in the Liebenbergsvlei catchment (4725 km<sup>2</sup>). The TOPKAPI model, a physically-based distributed rainfall-runoff model, has been successfully applied in several countries in the world. The TOPKAPI model, applied in the Liebenbergsvlei catchment, showed good results and ability in modeling the river discharges at a small (6 h) time-step with a limited adjustment of the parameters and low computation times.

A study based on modeling of flood hazard extent in data scarce area has been carried out by Komi et al. (2017) in Togo Republic especially in the Oti River basin. In the study, the hydrological model LISFLOOD was used for the flood modeling. The statistical tools showed a good result of the model (NASH 0.87 and 0.94 respectively for the calibration and validation processes) which means that the LISFLOOD model is a reliable tool for the flood modeling in the region.

Ansah et al. (2020) carried out a study in Ghana investigating the meteorological dynamic for the heavy rainfall that resulted in flood in Kumasi and Accra. The WRF-Hydro model was used to perform this study. It has been concluded that the floods occurring over the study area are non-meteorologically induced. Anthropogenic activities such as buildings on water ways and choked drainage systems were responsible for the floods.

### 3.2. Conceptual Models

This model describes all of the hydrological component processes. It consists of a number of interconnected reservoirs which represent the physical elements in a catchment in which they are recharged by rainfall, infiltration and percolation



and emptied by evaporation, runoff, drainage etc. Semi empirical equations are used in this method and the model parameters are assessed not only from field data but also through calibration. Large number of meteorological and hydrological records is required for calibration. The calibration involves curve fitting which makes the interpretation difficult and hence the effect of land use change cannot be predicted with much confidence.

Many conceptual models have been developed with varying degree of complexity. Stanford Watershed Model IV (SWM) is the first major conceptual model developed by Crawford and Linsley in 1966 with 16 to 20 parameters.

[Tefera \(2015\)](#) has used the hydrological model HEC-HMS in his master thesis in order to be set-up and evaluated for flood forecasting in the Benue basin in Nigeria. The model has been integrated with GIS through HEC-GeoHMS. The model performance was satisfactory with NASH = 0.5 for the calibration period and very good during the validation for some years of validation and poor for other years.

[Hoedjes et al. \(2014\)](#) performed a study in Kenya based on a conceptual flash flood early warning system for Africa. CREST (Coupled Routine and Excess Storage) distributed model is used in combination with the TMPA and rainfall forecast in Kenya for the purpose to generate the flood forecast in Kenya up to 10 days in advance. The results obtained were satisfactory and allowed to considerably reduce the impact of flood events through the implementation of the early warning system.

[Assoumpta and Aja \(2021\)](#) carried out a flood forecasting study in Rwanda using quantitative precipitation forecast and hydrological model in the Sebeya catchment. HBV hydrological model was used to perform the study and gave good results. It has been demonstrated that the number of hits is inversely proportional to the lead time.

HEC—RAS, a physical-based software on the fully De Saint Venant Equation was used to perform the study carried out in the Sirba River river, the Middle Niger River basin ([Massazza et al., 2020](#)). The main goal was to assess the flood hazard in the Sirba river basin, in Niger. At the end of this work, the important output has been the availability of the data for the implementation of the early warning system and to provide the flood hazard map.

[Dessu and Seid \(2016\)](#) in Ethiopia, performed a study based on flood forecasting and stream flow simulation of the Upper Awash River Basin using Geospatial Stream Flow Model (GeoSFM). The GeoSFM gave satisfactory results with NASH values comprised between 0.67 and 0.70 respectively for the calibration and validation while the values of the coefficient of determination range between 0.60 and 0.65 respectively for the calibration and validation.

Probability Distributed Moisture model was used in the lower part of the Nzoia River Basin in Kenya in order to forecast flood events. Satisfactory results were obtained during this study meaning the usefulness of the model for flood issue in the Nzoia River Basin ([Ngaina, 2014](#)).

The flood impacts were very important in Mozambique with any flood control

mitigation response. The Stream Flow Model (SFM), semi-distributed hydrological model was used as a flood forecasting tool to reduce flood impacts in the region (Artan et al., 2002).

The Centre for Ecology and Hydrology (IHE) developed a flow forecast model for the Somalian part of the Juba Shabelle River Basin, called Somalia FFM. The system uses upstream measurements and simple regression equations to predict river levels and flows at the key gauging stations. Fry et al. (2002) stated the reliability of the system for flow forecasts with a lead time of up to 1 week.

### 3.3. Empirical Models

These models are observation-oriented models that take only the information from the existing data without considering the features and processes of hydrological system and hence these models are also called data driven models. It involves mathematical equations derived from concurrent input and output time series and not from the physical processes of the catchment. These models are valid only within the boundaries. Unit hydrograph is an example of this method. Statistically based methods use regression and correlation models and are used to find the functional relationship between inputs and outputs. Artificial neural network and fuzzy regression are some of the machine learning techniques used in hydro informatics methods.

Al-Zu'bi et al. (2010) developed the Takagi-Sugeno fuzzy model to estimate the Nile river flow at the Dongola station in Sudan. The performance of the model was assessed using observed discharge records of almost two decades. The results of the training and testing phase had a high VAF (variance-accounted-for) value indicating good modeling capacities. Within the study, it is demonstrated that the fuzzy model is able to represent the river flow at Dongola better than traditional modeling approaches and outlined the potential of their approach to provide accurate forecasts, in time and quantity.

### 3.4. Stochastic/Probabilistic Models

Stochastic models reflect techniques based on time-series analysis, which have become very popular in hydrology (Box et al., 2016). Stationary stochastic models such as Autoregressive Moving Average (ARMA) and non-stationary models such as Auto-Regressive Integrated Moving Average (ARIMA) can provide adequate representation of the dynamics of the RR process at large timescales, monthly or seasonal; parameters of these models have some physical interpretation in those cases. The success of these models can be attributed mainly to their simple mathematics, small computational requirements and their ability to reliably reproduce hydrographs. In the context of operational flood forecasting, ARMA models are mainly used for error correction.

Sadek (2006) carried out a study in Egypt in the Nile river basin based on flood forecasting. He used the statistical forecasting approaches (ARIMA models) for flood prediction with analysis of the historical inflow data. All the ana-

lyses of results proved the model suitability in forecasting the incoming floods to the lake Nasser upstream the high dam. Consequently, the statistical model could be used to predict the incoming flood during the period from year 2005 until the expected national project implemented at year 2017.

### 3.5. Ensemble Forecasts

This type of flood forecast takes into account different aspects leading to an accurate early warning system. For the system to be accurate and reliable, the prerequisites are: accurate and high-resolution weather forecasts, availability of accurate ground observations for data assimilations, due consideration to the hydrological and meteorological aspect of the flooding, skilled personnel to interpret and issue timely warnings, effective communication of warnings signals to the most vulnerable sections of the population. The first points to be considered are the precipitation forecast data which have to be in an accurate range of acceptable resolution. Thanks to the NWP, precipitation forecast data can be downloaded with precision and used as an input data to force hydrological models. The main source of uncertainties that may disrupt the result of the flood forecasting comes from the inaccuracies of the precipitation forecast (Hapuarachchi et al., 2011; Seo et al., 2014). The bias correction is needed to overcome this concern. The hydrological models, rainfall-runoff models are used to compute and to run the discharge output. The final point is to issue the flood information to the vulnerable and other type of population that are in the flood-prone area. Most of the African countries are at the earlier stage of the flood forecasting system development. This type of ensemble forecasting is not well developed and implemented in several African countries.

## 4. Data Driven Model/Machine Learning

They provide the capability to simulate the random and probabilistic nature of inputs and responses that govern the river flows (Jain et al., 2018). Data driven models are often referred to as black-box models because they depend on the statistical or cause-effect relationship between hydrologic variables without considering the physical processes that underlies the relationship (Luchetta & Manetti, 2003). Data driven models can include stochastic models and non-linear time series models. An interesting application of data-driven techniques is to improve the real-time forecasts issued by deterministic lumped rainfall-runoff models, in which the catchment response is simulated by a conceptual model and the residuals are simulated by an ARMA model.

Practical applications of the data-driven models for flood forecasting are still lacking chiefly due to two reasons: data-driven models do not account for the changing dynamics in the physics of the basin over the time (land use change pattern, aggregation/disaggregation), the parameters of data-driven models are completely dependent on the range of the data (maximum, minimum) used for the calibration. The machine learning methods are an example of data-driven

models tools that are becoming popular and quicker to develop with minimal inputs. Contrary to the physical and numerical models that are unsuitable for the short-term prediction, the machine learning models are able to simulate both the short-term and the long-term prediction forecasts. Moreover, the easiest way to implement the model, associated to the low computation cost, as well as the fast training, validation, testing and evaluation with high performance compared to the physical models make it more accessible to the users. Several authors mentioned the accuracy of the machine learning models in comparison to the physical models (Mohammadi, 2021). Also according to Agudelo-Otalora et al. (2018); Kratzert et al. (2019) data driven models (such as machine learning) have proven to be even better than the physical, conceptual models in flood forecasting studies. Artificial Neural Network (ANN), Neuro-fuzzy, Support Vector Machine (SVM), Support Vector Regression (SVR), were reported to be the most machine learning algorithms widely used with ANN at their head. They were reported to be suitable for the prediction of both the short-term and long-term flood forecasting. New techniques such as hybridization with other methods (soft computing techniques, numerical methods, physical methods) when applied to the machine learning methods, could allow a better improvement of the results (Mosavi & Rabczuk, 2017).

Luchetta and Manetti (2003) compared a fuzzy-logic-based algorithm for hydrologic forecasting to an ANN model and showed that the fuzzy approach outperformed the ANNs. Liong et al. (2000) predicted daily river water levels in the Buriganga River, in Bangladesh by using a fuzzy logic model in which the upstream water levels were the inputs.

**Table 1** represents a summary of different countries with the hydrological models implemented for flood issues with their characteristics.

In Africa, it is very difficult to obtain information related to flood forecasting system implemented for the most of the flood institutions in the region. According to Thiemig et al. (2010) most of the flood forecasting already implemented in Africa are obsolete and need to be improved. Moreover, it is well to recognize that the flood forecasting has improved nowadays because of the improvement of the rainfall forecast. The lead time, which can go beyond 15 days, has also improved with the rainfall forecast improvement. However, in Africa, lot of have to be done especially in West Africa where the data resources are scarce.

## 5. Discussion

Hydrological modeling for flood forecasting is of utmost importance for early warning system and to decision makers. This review of literature reveals that Africans started to be interested into the mitigation of flood events by the implementation of flood forecasting models. Africa is the third continent after Asia and Europe the most negatively affected by flood events causing important damages such as losses of life and enormous economic damages.

**Table 1.** Summary of some hydrological models used in Africa for flood forecasting.

Countries	Models name	Models characteristics	Inputs	Remarks	References
Nigeria	HEC-HMS	Conceptual semi-distributed model	Temperature, Rainfall, Discharge	Gave satisfactory results were obtained	Tefera, 2015
Ghana	WRF-Hydro	Conceptual Physical model	Rainfall, Temperature, Evapotranspiration, Land use	satisfactory results were obtained	Ansah et al., 2020
Benin	HBV	Conceptual lumped model	Rainfall, Evapotranspiration, Discharge	satisfactory results were obtained	Hounkpe & Diekkruger, 2018
Morocco	HEC-HMS	Conceptual semi-distributed	Rainfall, Evapotranspiration, Discharge	satisfactory results were obtained	Aqnouy et al., 2018
Mali	MIKE-BASIN	Conceptual Physical model	Rainfall, Evapotranspiration	satisfactory results were obtained	Danish Hydraulic Institute, 2003
Senegal	SWAT	Conceptual semi-distributed	Rainfall, Evapotranspiration, Land use	satisfactory results were obtained	Neitsch et al., 2005
Rwanda	HBV	Conceptual Lumped	Rainfall, Evapotranspiration, Discharge	satisfactory results were obtained	Assoumpta & Aja, 2021
Togo	LISFLOOD	Coconceptual physical	Rainfall, Evapotranspiration, Discharge, Land use	satisfactory results were obtained	Komi et al., 2017
Kenya	CREST	Conceptual physical	Rainfall, Evapotranspiration, discharge, land use	satisfactory results were obtained	Hoedjes et al., 2014
Egypt	ARIMA	Machine learning	Rainfall, evapotranspiration,	satisfactory results were obtained	Sadek, 2006
South Africa	TOPKAPI	Conceptual Physical	Rainfall, Evapotranspiration, discharge, land use	Satisfactory results were obtained	Vischel et al., 2008

Despite the recognized importance, the flood topic has not received enough attention it deserves especially in Africa (Haile et al., 2016). HEC-HMS (Hydrological Engineering Center, 2009), HBV (Hydrologiska Byråns Vattenbalansavdelning, Lindström et al. (1997)), MIKE BASIN (Danish Hydraulic Institute, 2003), GeoFSM (Artan et al., 2007), SWAT (Neitsch et al., 2005) are the widely models that are used by many African institutions for the flood forecasting issues (Thiemig et al., 2011). SWAT was used in Senegal, Egypt and Tanzania respectively by the University of Cheick Anta DIOP, the Water resources institution and the Dar es Salam University. The HEC-HMS is applied in Burundi, Egypt, Ethiopia with a lead-time varying from 12 h for small catchments to 3 days, it has been used in Nigeria (Tefera, 2015). HBV was used in Zou basin in Benin to evaluate water resources and flood hazard (Hounkpe & Diekkruger,

2018).

Africa is at an early stage of flood adaptation through hydrological modelling. This is why there are not so many hydrological models implemented and applied in West Africa region. In West Africa, to the best of authors ability, the models widely used for flood forecasting issues are HEC-HMS, HBV and SWAT. They have the ability to easily simulate the observe discharge. Also, the required input data are not too much for the model calibration. The computation time of the model is not very important. The fact that these models have been used in Africa can let us hope that their usefulness in every West Africa catchment. One of the main problem scientists are facing is the data collection issue. The weaknesses of HBV as well HEC-HMS can be the incapacity to model the physical aspect of the catchment. Because of that, the model cannot reproduce exactly certain reality aspects of the basin.

One of the challenges in flood forecasting domain in Africa is the difficulty to have access to the information. The majority of the implemented early warning system are already obsolete and need to be revised (Thiemig et al., 2011).

Urgent solution has to be found and implemented for the welfare of Population. Nowadays, there have been numerous methods and models developed and used for flood forecasting around the world; however, it should be noted that flood forecasting requires a good understanding of both meteorological and hydrological conditions of the particular country or region (WMO, 2011). As numerical weather prediction models continue to improve, operational centers are increasingly using their meteorological output to drive hydrological models, creating hydro meteorological systems capable of forecasting river flow and flood events at much longer lead times than has previously been possible. Furthermore, developments in, for example, modelling capabilities, data, and resources in recent years have made it possible to produce global scale of flood forecasting systems. The main challenges African People are facing, are the financing for such kind of researches as well as the motivation and ambitious of the decision makers to take this issue seriously into account. The data required to carry out such kind of works are scarce in the region, making the study difficult to be undertaken. With the climate change, it will be more logic to go for flood prediction and implement hydrological models for the flood mitigation in advance rather than waiting for the catastrophe to happen and try to mitigate it.

Several flood forecasting models are available and some already implemented in some countries. There are different from their structures, their required data, their outputs. If the physical models provide reliable results with a high accuracy, however, it required an important quantity of data with a high computation cost. That aspect makes its use difficult and restricted by just a few quantity of researchers. However, the conceptual models are more suitable in West Africa regions because of the weak number of input data.

## 6. Conclusion

Flood events not only are occurring frequently and with a high intensity causing

important losses of life as well as economic damages. In Africa particularly, the increasing occurrences and intensity of flood events in several countries and with very weak means of mitigation and adaptation is noticed. The focus should be put on the flood forecasting models in Africa, in order to reduce considerably the damages. Also, the various flood-prone areas, occupied by the population for settlements should be evacuated. Structural methods against flood (such as construction of levees, flood control reservoirs and river training work) have showed their limits, they have failed in the majority of the cases in preventing floods leading to enormous damages. Therefore, the researches should be oriented in the flood forecasting. Data collection, scarcity and inaccuracy are issues that need to be solved. Decisions makers have to be conscious of these facts and find solutions to data collection difficulties.

The data collected from EM-DAT website showed that the economic powerful countries (China, United States) which are the most contributed to the greenhouse gases, and then to the climate destruction, are also the one that is the most affected. African countries are affected by the impact also, but in comparison with the developed countries, the impact is low as well as the occurrences, economic damages issues. Asian continent comes first followed by the Europe and then Africa. However, this has not misled Africans because even one death is too much. Due to the weak means to fight against flood, a lot of damages in terms of losses of life and economic damages are noticed in Africa during flood events. The developed countries are in advance upon Africa because of their various means of protection against flood events, one of the important and useful solution is the flood forecasting systems implemented in several European and Asian countries, whereas in Africa, so much have to be done in that aspect.

### Conflicts of Interest

The authors declare no conflicts of interest regarding the publication of this paper.

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