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Hydrological model preselection with a filter sequence for the national flood forecasting system in Kenya

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Abstract

The choice of model for operational flood forecasting is not simple because of different process representations, data scarcity issues, and propagation of errors and uncertainty down the modeling chain. An objective decision needs to be made for the choice of the modeling tools. However, this decision is complex because all parts of the process have inherent uncertainty. This paper provides a model selection with a filter sequence for flood forecasting applications in data scarce regions, using Kenya as an example building on the existing literature, concentrating on six aspects: (i) process representation, (ii) model applicability to different climatic and physiographic settings, (iii) data requirements and model resolution, (iv) ability to be downscaled to smaller scales, (v) availability of model code, and (vi) possibility of adoption of the model into an operation flood forecasting system. In addition, we review potential models based on the proposed criteria and apply a decision tree as a filter sequence to provide insights on the possibility of model applicability. We summarize and tabulate an evaluation of the reviewed models based on the proposed criteria and propose the potential model candidates for flood applications in Kenya. This evaluation serves as an objective model preselection criterion to propose a modeling tool that can be adopted in development and operational flood forecasting to the end-users of an early warning system that can help mitigate the effects of floods in data scarce regions such as Kenya.

KEYWORDS

early warning systems, filter sequence, flood forecasting, hydrological model, Kenyan catchments, model preselection, objective model choice, perceptual model

1 | INTRODUCTION

Hydrological models predict the hydrological variables, particularly river flow. In some cases, where little input and output data exist the model can be used to estimate the runoff and river flow in ungauged catchments (Hrachowitz et al., 2013; Sivapalan, Takeuchi, et al., 2003). Therefore, models are useful in applications such as short to extended-range flood forecasting (Alfieri et al., 2013; Emerton et al., 2018), climate assessment (Hattermann et al., 2017; Lu et al., 2018; Tamm et al., 2016), hazard and risk-mapping (Artan et al., 2001; Ward et al., 2015), drought prediction (Van Huijgevoort et al., 2014), and water resource assessment (Dessu et al., 2016; Mutie, 2019; Praskievicz & Chang, 2009; Sood & Smakhtin, 2015). However, the scope of application to extract viable information varies across different classes of models at different spatial and temporal scales and the intended purpose.

The choice of model for operational flood forecasting is not simple because of different process representations, data scarcity issues, and propagation of errors and uncertainty down the modeling chain (e.g., Paul et al., 2019; Paul, Gaur, et al., 2020). For example, the practice of choosing a model for an application may be difficult due to several reasons highlighted in Melsen et al. (2019):—(i) Popular models are not tailored to specific climate or circumstances (unless the west European climate counts, implicitly), which makes exclusion on process presentation alone difficult; (ii) Most popular models share the same main properties and the same weaknesses; (iii) The community has failed to create a generalized benchmarking system to rank models and model set-ups, so that suitability has to be ascertained on a case-by-case basis; and (iv) Model evaluation takes primarily place based on streamflow, which in itself is too little to distinguish between models, especially calibrated models. There is need for a modeler to know the perceptual model (Wagener et al., 2021)—quantitative or qualitative description of the existing knowledge and understanding of the catchments (Beven, 2011; Gupta et al., 2008; Westerberg et al., 2017). For instance, Wagener et al. (2021) illustrate a generic perceptual model included in catchment hydrology functions. The processes herein are dynamic and evolve with time in response to changes in water management or land-use, climate conditions and geomorphological changes, thus need to be integrated into the model development. This implies that if such changes are not taken into consideration during and/or model development and upgrade, then the relevant processes will not be presented adequately, thus limiting of the application of a single model over the entire country.

Models are simplifications of reality and thus cannot completely represent every process and aspect of the catchment. The importance and impact of many processes can evolve with time for example in response to changes in water management. In addition, what is the right approach *now* is not necessarily the right approach in the future. Significant buy-in is required to develop operational forecasting capacity with a specific model, and so in recognition of changes in the importance and impact of many processes as a result of land use change, water management etc., it may mean it is more efficient to choose a modeling approach that can represent a larger range of processes. When there are distinct zones of hydro-climatology within a country it could be necessary to adopt different modeling approaches, but this needs to be balanced against the scaling up of the resources required to have human and technical capacity across several different models.

Moreover, data play an important role in hydrological modeling irrespective of the processes represented in a model (Wahren et al., 2016). Many studies point to challenges in modeling due to data scarcity (e.g. Beck et al., 2017; Fuka et al., 2014; Lavers et al., 2012; Najafi et al., 2012; Quadro et al., 2013; Smith & Kummerow, 2013; Wu et al., 2013) which limits the applications of very detailed and complex models due to inherent unquantified uncertainties. Recognizing that data and model are not independent of the errors, for brevity within this paper we describe the aspects and the models herein considering only those uncertainties related to model structure (Pechlivanidis et al., 2011; Smith et al., 2015).

The choice of model depends on the intended purpose, and the modeler needs to objectively select a model based on the end-user needs for more reliable decisions (Parker, 2020; Boelee et al., 2017; Todini, 2007). Various hydrological models exist at different spatial and temporal scales with diverse levels of complexity and data requirements. Additionally, there exists differences between model codes and implemented modeling systems, which may cause difficulties in the choice and application of a particular model. A Multi Criteria Analysis (MCA Sherlock & Duffy, 2019) is recommended to evaluate and grade models from which, a small number of models would be constructed, calibrated, and tested in a real-world context and at the end, a model(s) is chosen to be used in the operational Flood Forecasting Centre (FFC) experiment. However, the proposed MCA relies heavily on evaluation data, is very time consuming for the number of models available hence for data scarce regions, and/or agencies with limited resources, (or in general) an additional decision tree is helpful to trim down the number of options. There is the need to further evaluate the limited selection with for example an MCA and the FFC experiment. To aid this hypothetical modeler there is a clear need for well-conceived and systematic strategies for selecting model structures and establishing data requirements, which forms the novelty of this research.

A plethora of model reviews exist at global and continental scale applications. For example, (Devia et al., 2015; Emerton et al., 2016; Kauffeldt et al., 2016; Pechlivanidis et al., 2011; Salvadore et al., 2015; Sood & Smakhtin, 2015; Trambauer et al., 2013). Most of these reviews highlight and compare existing modeling concepts and gaps but none have focused on model selection frameworks for final application except for Trambauer et al. (2013) and Kauffeldt et al. (2016). Kauffeldt et al. provide a technical review of large-scale hydrological models for implementation in operational flood forecasting at continental level. Trambauer et al. (2013) review continental scale hydrological models highlighting their suitability for drought forecasting in sub-Saharan Africa. The two cited works look at model review and a selection framework for flood and drought application at continental scales respectively and to the best of my knowledge this is the first model overview and practical objective model selection framework for flood applications at national scale taking into consideration varied catchment characteristics and data scarcity issues.

This paper is to propose a practical approach building on Kauffeldt et al. (2016) and Trambauer et al. (2013) for selecting a model based on a step-by-step filter sequence following objective aspects (such as on the ability to simulate relevant processes to flood applications), as well as considering more practical aspects such as model code availability and ease of use at catchment scale with varied climate characteristics. We follow the filter sequence and develop a Venn diagram to select suitable model candidates. This practical approach is applied to a case study of developing an early warning system that can help mitigate the effects of floods in data scarce regions within Kenya, where there is lack of good observations of climate variables such as precipitation, temperature etc., and this is a limiting factor to properly identify the limitations of model applications at catchment scale.

Our paper is structured as follows. Kenyan hydrology and applications of hydrological models to simulations of flood process is discussed in Section 2. The decision tree is built based on deliberations about Kenyan hydrology and current forecasting experience in Kenya, which outlined in Section 3. The selection of the models based on the decision tree is outlined in Section 4. In Section 5, we focus on specific discussions regarding model selection and how the novelty of the decision tree. The paper then concludes with the key contributions of the suggested preselection along with recommendations for next steps to evaluate the models objectively to improve FF in Kenya.

2 | KENYAN HYDROLOGY AND FORECASTING

2.1 | Applying hydrological forecasting models to the simulations of floods in Kenya

It is important to consider the application of the hydrological model when determining which model to use, due to differences in process generations and representations (Cloke et al., 2011). For example, floods are generated by a range of processes related to extreme rainfall (interception, through-flow), runoff generation process (infiltration, saturation excesses and subsurface storm flow) and runoff routing (Rosbjerg et al., 2013). In addition, floods in snow dominated catchments are regularly caused by snow melt, thus, representation of this process in a hydrological model is crucial, because requires an optimal simulation of the snow related hydrological processes such as snow accumulation and melt (Verzano, 2009).However, this case does not apply to Kenyan catchments.

Moreover, flood formation is a complex combination of extreme precipitation or temperature rise or a combination of both, the retention of the water in different storages and finally the flowing through the river networks. A flood peak caused by extreme rainfall in the upstream part of a catchment, naturally reaches the downstream part of the catchment temporally delayed (Tallaksen & Van Lanen, 2004; Verzano, 2009). Therefore, several effects influence the magnitude of the flood wave in the downstream area, such as tributary contributions and retention in lakes and wetlands. The lateral transport of water through the river network is a particularly important process for the routing of discharge. This applies for average flow conditions as well as for low or high flows. Therefore, it is meaningful to route the water within a hydrological model with a variable flow velocity because the flow velocity varies with the actual river discharge (Verzano, 2009) among other relevant flood generating processes. In many hydrological forecasting systems, the treatment of the rainfall-runoff component (traditionally the core of what is meant by hydrological models) and the routing can be separated. If the routing should be built in, or should be specifically modular, could be another criteria that qualifies the models under consideration. An operational Flood Forecasting System (FFS) aims at producing accurate timely and valuable flood forecast information way in advance to reduce flood-related losses by increasing preparation time. A typical FFS requires a hydrological model, data sources, as well as main processes and fan interactive friendly user interface. For example, Figure 1 shows a simplified conceptual model for a large-scale flood forecasting system, the components required, and the output generated within each component.

2.2 | Subsequent logic for the need of a decision framework with a filter sequence in Kenya

Both the hydroclimate and the human influences create challenges for hydrological modeling and forecasting (Bai

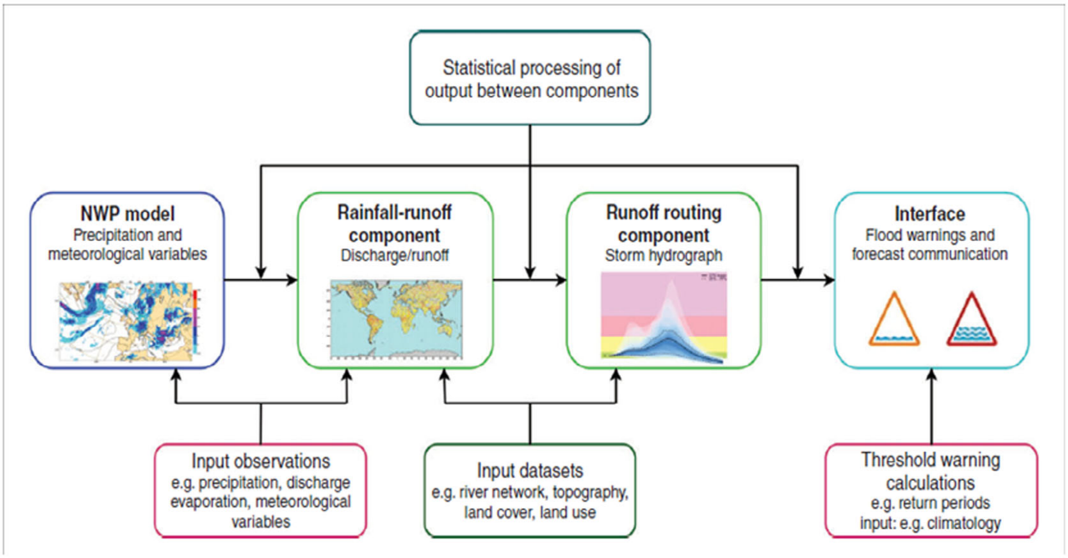

FIGURE 1 Conceptual large-scale hydro-meteorological forecasting system (Emerton et al., 2016)

et al., 2015) because of their massive influence on the catchment processes. For example, Kenya exhibits high variability in physiographic and hydroclimatic conditions (see Figure 2). The highest point is at about 5000 m a.s.l, (mostly areas around central highlands) while the lowest point is about 20 m a.s.l. (mainly around coastal areas). The vegetation cover is mainly a mixed tree cover, grass, and sparse vegetation in most of parts of the country and shrubs and bare land in the arid and semi-arid areas of northern Kenya. As a result, Kenya experiences different climate-related extremes in terms of intensity, magnitude, and timing.

Rainfall pattern follows a bimodal rainfall seasonality (Ongoma & Chen, 2017) with high spatiotemporal variability (Figure 3) (Hession & Moore, 2011). Three seasons are experienced: the “long rains” of March-April-May (MAM), nonrainy months of June-July-August (JJA) and, the “short rains” of October-November-December (OND) (Ogallo, 1988; Ongoma et al., 2015). About 42% of the total annual rainfall is observed during MAM rainfall season (Ongoma & Chen, 2017), with the highest intensity observed near the water bodies of the Indian Ocean, Lake Victoria, and the Kenyan highlands. Freely available packages, proposed models, and inbuilt model functionalities of some of the commonly applied models.

There are five major basins (Marwick et al., 2014) in Kenya (see Figure 4, left panel). These catchments are highly influenced by settlements as well as human activities such as dam constructions and irrigation activities (Figure 4, right panel), which have adverse effects on the catchment response to rainfall runoff processes. At the catchment scale, there is high variability in catchment hydroclimatic characteristics such as surface area and average annual rainfall (Figure 5).

Therefore, it is important to consider the variability in catchment characteristics and the knowledge gaps in the perceptual model (e.g., land cover changes, human activity, data uncertainty and accounting for groundwater fluxes) when selecting a model for application as this may influence the performance of the model. The following section discusses the aspects to consider to objectively preselect a model for application to Kenyan catchments.

3 | MODEL SELECTION FRAMEWORK

Selection framework in this paper follows a selection criterion such as the ability to represent relevant processes, the model structure, flexibility, complexity, availability of the model code and the needs of the user community (Bennett et al., 2013; Kauffeldt et al., 2016), and as such it is more qualitative rather than quantitative. For example, a good model should be able to represent all relevant process such as: gross precipitation (snow, rain), interception storage, evaporation, transpiration, snowpack storage, snowmelt, overland flow, soil storage, recharge to shallow aquifer, capillary rise, intermediate flow, baseflow, leakage to deep aquifer. However, these will require relevant input datasets and more complex models(e.g. fully distributed with numerous parameters) to effectively represent the processes, but worthy to note that increasing the model complexity by incorporating all the above processes does not necessarily increase the model performance (Birkel et al., 2010; Butts et al., 2004). The application and performance of a model may also vary depending on the site (size and characteristics) (Bai

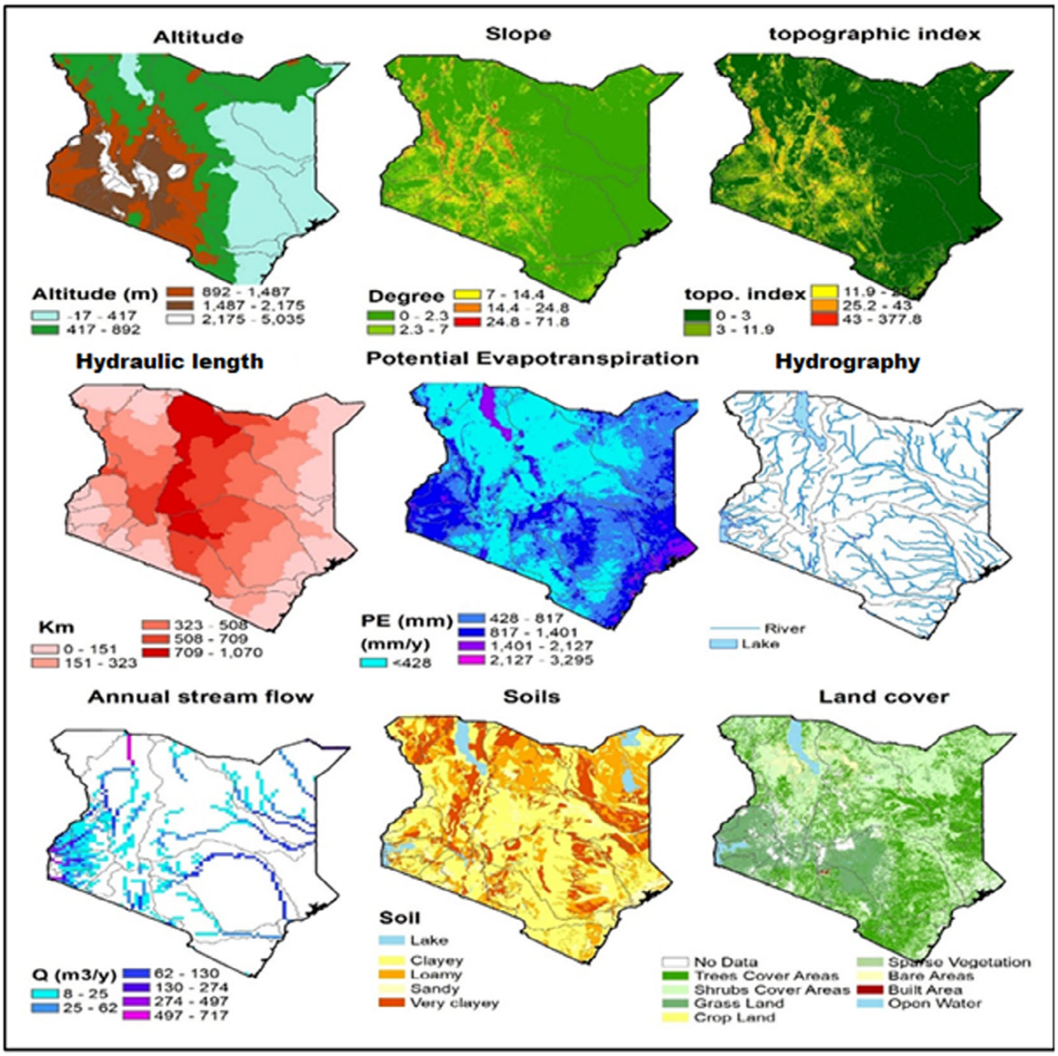

FIGURE 2 Physiographic and hydroclimatic characteristics of Kenya

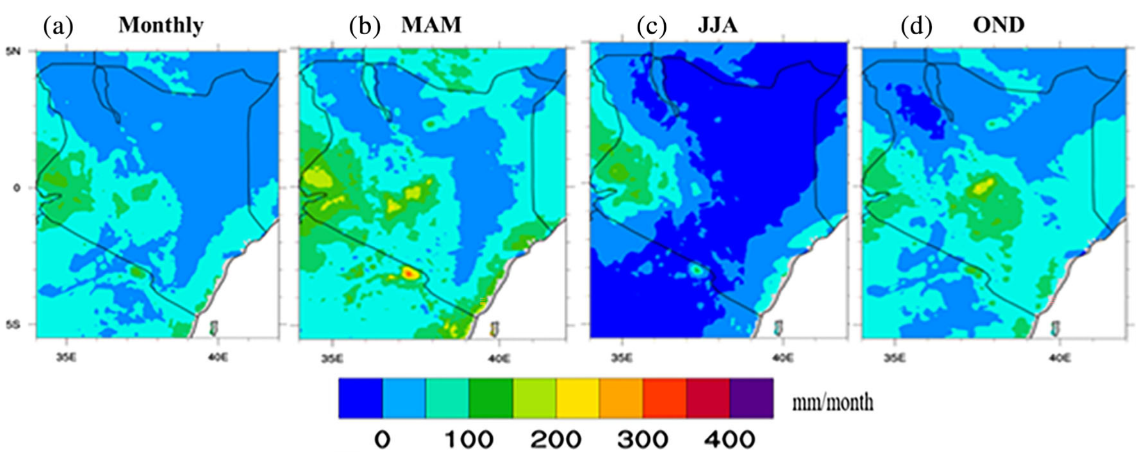

FIGURE 3 Spatial pattern of long-term mean monthly and seasonal rainfall over Kenya (1981–2016) (a) monthly (b) March-April-May (c) June-July-August (d) October-November-December seasons, respectively

et al., 2015; Lanen et al., 2013). Therefore, the following sections summarizes the aspects to aid in objective selection of a hydrological model for flood applications in Kenyan context, considering Kenya's hydrogeology, physiographic and climatic conditions discussed in Section 1. In total six criteria were found to aid in the decision

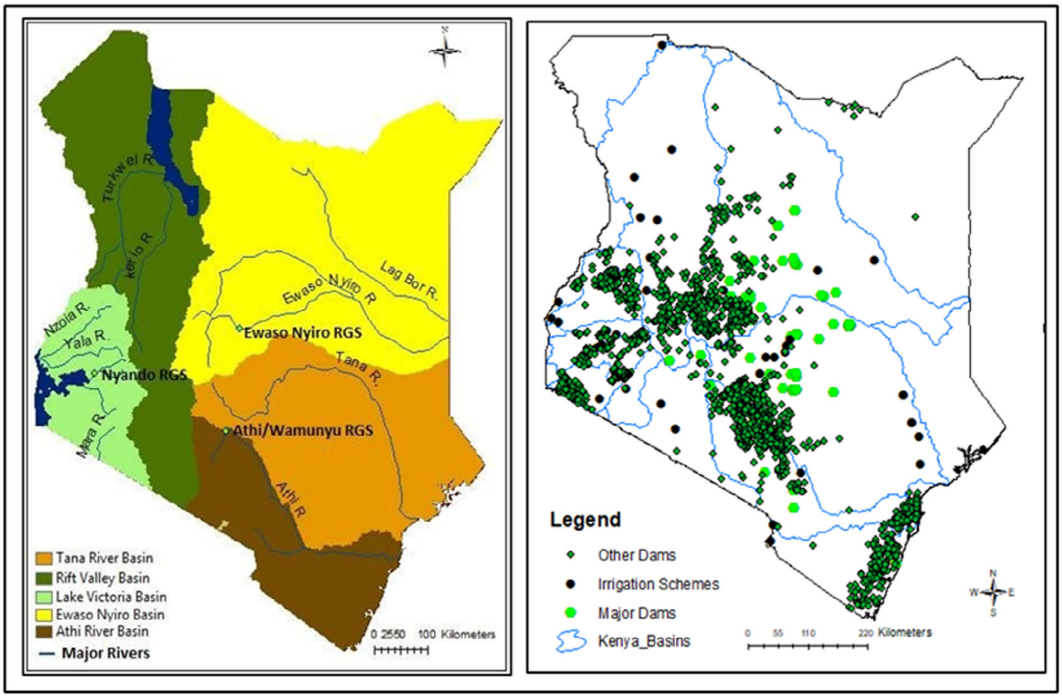

FIGURE 4 Kenya main basins (left panel) and the ongoing human activities (constructed major and small (other) dams and irrigation schemes) in the select catchments (left panel)

making. In the next subsections each of the six criteria is evaluated in relation to Kenya represented processes and fluxes.

A complete hydrological model would represent all the water balance components and fluxes (e.g., as illustrated in Mendoza et al., 2012). The complexity of models often results in many parameters to be determined, which requires more data on hydrogeology (Dobler & Pappenberger, 2013; Muleta & Nicklow, 2005). There needs to be a compromise between model complexity and efficiency for it to work.

More data is needed to make more complex models more accurate. The choice of an appropriate model structure is a crucial step to accurately predict streamflow or other variables, and to understand the dominant physical controls on catchments' responses to climate change (Clark et al., 2008). In Kenya, this requires more data such as groundwater level, which is not readily available.

Some catchments especially those in the arid and semi-arid regions of Kenya have sandy and rocky riverbeds and tend to run dry most of the dry months, for such, the fixed velocity and river channel fields represented in some hydrological models may not apply. This is because of failure to properly represent the roughness index which varies not only with boundary characteristics but also with flow velocity, water depth, and other hydraulic factors (Addy & Wilkinson, 2019; Zhang et al., 2016).

In addition, the more represented process in a model the more the parameterization schemes. For example, a priori estimation requires establishing parameter values from measured physical system properties, presupposing that the model parameters have a sufficiently reliable representation (Beven & Pappenberger, 2003). Therefore, parameter estimation in models of natural systems may require measurements and tests. It then follows that, for effective calibration for such model parameters, it requires more computational power, which may be lacking in the Kenyan operational flood forecasting center.

3.1 | Model applicability to Kenyan hydroclimatic conditions and physiographic settings

Processes that are most relevant for simulating flood conditions in Kenya (see Barasa et al., 2018; Onyando et al., 2003) should be represented in a model. Some extra processes, such as channel losses, evaporation from rivers, wetlands representations, are not considered important in average conditions in some regions due to complexity or lack of interest (Rosbjerg et al., 2013), thus such can be discounted. This is because models incorporating such complex process require more skilled personnel and higher budgets to install and run. This is a challenge in most operational systems in developing

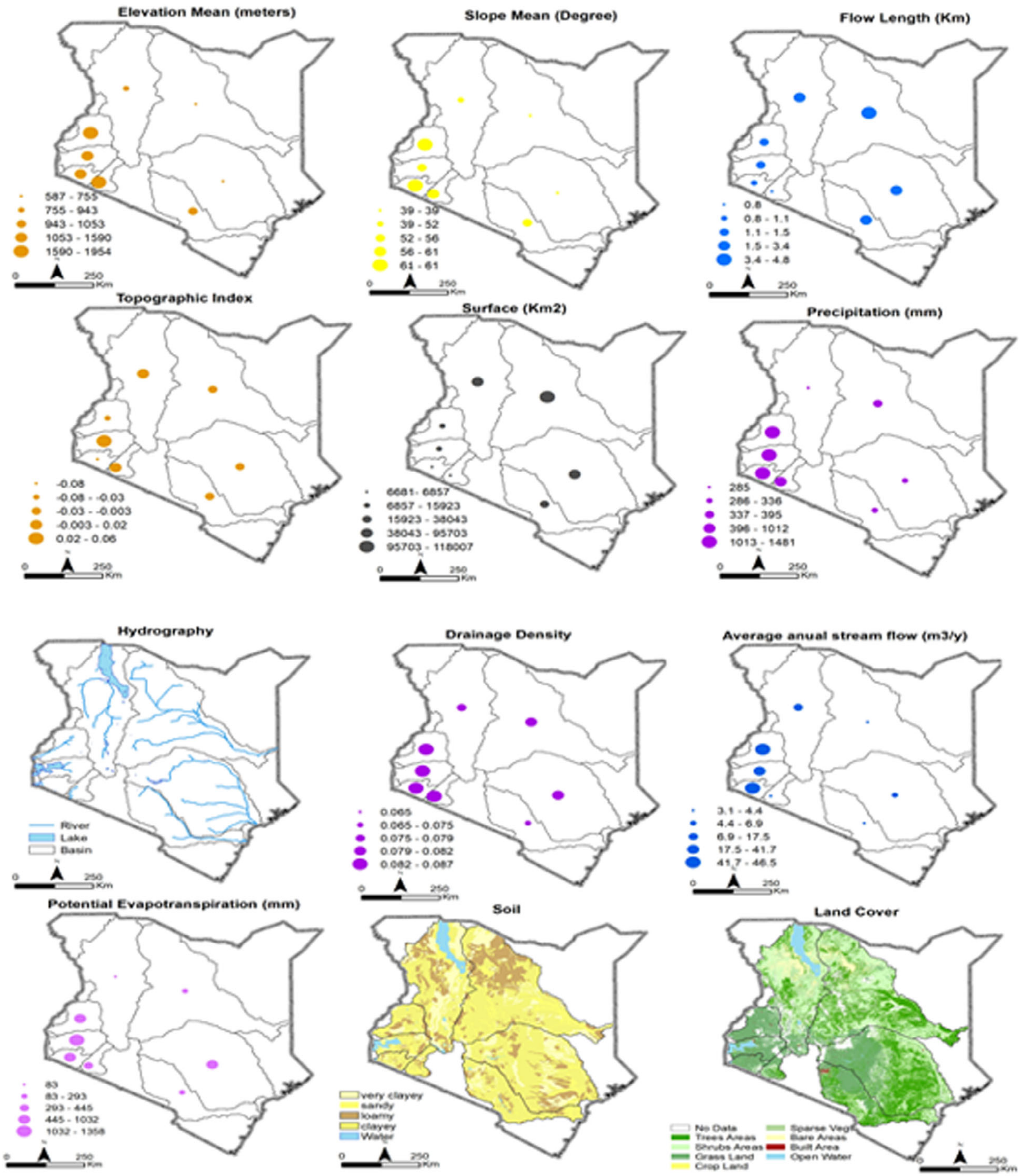

FIGURE 5 -Spatial distribution of the morphological and hydroclimatic characteristics per catchment

countries including Kenya. Temperature plays an important role in river channel and catchment evaporation. In Kenyan case, annual means temperatures range from 15 to 35°C which highly correlates with topography, with the lowest temperature experienced in the central highlands and high temperature in lowlands (Mutimba et al., 2010) and a model incorporating such would be best suited for such place.

Model selection, in dry and wet catchments must be more careful due to the large performance difference in dry catchments (Bai et al., 2015). Wet catchments runoff simulation is significantly better than that in dry catchments, (Haddeland et al., 2011), because of high nonlinearity and heterogeneity of rainfall–runoff processes (Atkinson et al., 2002). In addition, high uncertainty is introduced during model parameter estimation resulting in significant differences in simulated runoffs behavior (Andersson et al., 2015). Large river basins are often strongly influenced by human activities (e.g. irrigation, reservoirs, and groundwater use) for which information is rarely available (Döll et al., 2009). The Kenyan case where most basins are ungauged may increase such uncertainty (Hrachowitz & Weiler, 2011; Sivapalan, Takeuchi, et al., 2003).

When there are distinct zones of hydroclimatology within a country it could be necessary to adopt different modeling approaches, but this needs to be balanced against the scaling up of the resources required to have human and technical capacity across a number of different models, which is one of the main challenges in the Kenyan case.

3.2 | Data requirements and spatial and temporal resolution of the model

Kenya suffers from lack of good observations of climate and hydrological data. This is a limiting factor to properly identify the limitations of model applications at catchment scale. For example, a detailed representation of groundwater flows and tables and soil moisture content would be very relevant for flood forecasting. However, there is no reliable data (such as ground water and reservoirs) available for research applications, thus limiting the use of model incorporating such kind of data. As a result, a compromise must be reached regarding model spatial variability due to the ungauged status of most Kenyan catchments (Trambauer et al., 2013), and allow the use alternative freely available remote sensing data. Applying a distributed model would require high spatial and temporal resolution data to represent each of the catchment HRUs whereas a lumped conceptual model would represent an entire river basin (Krysanova et al., 1999), but since there are sparsely or no gauging stations in some of the catchments, then this limits the use of most distributed models across Kenyan catchments. However, limiting the models to the type that can only run when directly calibrated on an outlet would be a mistake. This is because there are plenty of ways to discretize in HRUs without individually calibrating each HRU independently. There are ways to calibrate transfer functions to enable modeling and ungauged HRUs (Samaniego et al., 2010). There are model setups that do not rely on calibration as a first principle (such as wflow-sbm, Imhoff et al., 2020) and based on globally available data. The challenge here is the transferability of the model to suite Kenyan catchment and operations and represents the catchment processes adequately because it needs to be as simple as possible.

Moreover, modeling experiments on Kenyan catchments may yield more plausible results if data at high frequency time steps are used as it contains more information (Ficchì et al., 2016). This is because the better modeling of the rainfall–runoff relationship is highly affected by subhourly dynamics of precipitation (Paschalis et al., 2014) due to nonlinear nature of infiltration process (Blöschl & Sivapalan, 1995), such as the peak discharge value (Gabellani et al., 2007) and runoff volume (Viglione et al., 2010). In Kenya, the temporal resolution of the available reliable data may be limited to a higher time steps (such as monthly and yearly) and this may limit the application of a model on a subdaily/hourly timesteps. Models incorporating higher timesteps data such as daily and monthly are easily applicable in Kenyan case as compared to those limited to hourly or subdaily timesteps.

3.3 | Capability of the model to be downscaled to a river basin scale

The issue of scale problem in hydrological models is highlighted in Beven (1995), where the aggregation approach toward macroscale hydrologic modeling is an inadequate approach to the scale problem. For semi-distributed and distributed models, grid size selection is intricately linked to the spatial scale at which the model will be applied. Also, when lumped approaches are applied to considerably larger basins the integration of the processes will naturally occur over a greater area, and thus any differences in small-scale processes within the basin will not be well considered. Due to lack of locally developed models, the continental models are applied at catchment scale, thus the need to be downscaled to suit the grid size under application. However, for larger grids, processes that are only important at the local scale (such as overland flow) may not be considered in the model structure but only if there is an extensive change in the model grid width and this may at times introduce structural uncertainties. Some models may not be easily downscaled to Kenyan river basins with varying spatial scales (see Table 1) without making significant changes in the structure of the model.

3.4 | Operational model for flood early warning system at large scales with potential adoption to local scale

With the increase in flood events in Africa in the recent past, Thiemig et al. (2015) proposed a FFS for Africa hereafter referred to AFFS. Following the illustration in

TABLE 1 Freely available packages, proposed models, and inbuilt model functionalities of some of the commonly applied models (*Source*: Astagneau et al., 2021)

Package	Repository	Proposed model	Package functionalities						
			Data processing	Criteria	Data transformation	Automatic calibration	Plot function	Graphical user Interface	Independent snow function
airGR		GR models	√	√	√	√	√	√	√
dynatopmodel		Dynamic TOPMODEL	√	√	×	×	√	×	×
HBV. IANIGLA		HBV	√	×	×	×	×	×	√
hydromad		IHACRES AWBM GR4J Sacramento	√	√	√	√	√		√
sacsmar		Sacramento	×	×	×	×	×	×	√
topmodel		TOPMODEL 1995	√	√	×	×	×	×	×
TUWmodel		Modified HBV	×	√×		√×	×	×	×
WALRUS		WALRUS	√	√	√	√×	√	√×	√

Figure 8, LISFLOOD, physical-based hydrological model is selected for AFFS, which relies on historical hydrological observations, historical as well as near real-time meteorological observations, real-time meteorological forecasts, and an African GIS dataset. The four main processes AFFS runs are: the calculation of hydrological thresholds, the computation of the initial hydrological conditions, of the computation of the ensemble hydrological predictions, and the identification of flood events. Figure 8 shows a schematic overview of AFFS with all the components and processes. This was developed as a prototype for Africa but never taken forward to operations and since then no literature or research on the skill or applicability of this system has been documented.

Also, Princeton University has developed African Flood and Monitor (AFDM) tool (Sheffield et al., 2014). The aim is to demonstrate the potential for tracking drought conditions across Africa using available satellite products and modeling in data scarce region. The system provides daily updates in near real-time (2–3 days lag) of surface hydrology, streamflow and vegetation stress, short-term hydrological forecasts for flooding, and seasonal forecasts for drought and agricultural impacts as demonstrated in Figure 9 (https://platform.princetonclimate.com/platform-ng/pca/products).

The system has been installed at regional centers in Africa more notable in West Africa (ACMAD), where it is operational for the Niger basin using the Hype-Niger model and the World-Hype applied to the whole West Africa region. A schematic illustration of the FFS for the Niger Basin in West Africa is shown in Figure 6.

Narrowing down to Kenya, the Kenya Meteorological Department runs an operational flood forecast system in Nzioa basin (Personal communication from Andrew Njogu) with plans underway to upscale to other nine additional flood prone areas spread across the other seven basins (Athi, Galana, Sabaki, Nyando, Tana, Sondu and Ewaso Ngiro etc.). A schematic representation of the FFS in River Nzioa Basin in Kenya and the steps involved is illustrated in Figure 7. The models adopted for this system is the Soil Moisture Accounting and Routing Model (SMAR) incorporated in the Galway Flow Forecasting System (GFFS) (O'Connor, 2005). The GFFS is a suite of models developed at the department of engineering hydrology national university of Ireland, Galway, Ireland. The five models embedded in the software are system theoretic models; simple linear model (SLM), linear perturbation model (LPM), linearly varying gain factor model (LVGF), and artificial neural network (ANN) and one conceptual model which is SMAR model. Ordinary least square solution for (SLM, LPM, and LVGF), conjugate gradient algorithm for ANN and Rosenbrock, simple search and genetic optimization methods for (SMAR) are used for calibration of the model parameters (O'Connor, 2005).

Speaking to Njongu in an interview, he noted that the choice and use of the SMR model was entirely subjective mainly driven by the project funding following the push to implement a FF system in Nzioa after subsequent destructive flooding events. Additionally, he noted that there is limited documented research on skill assessment inform the choice of the SMAR model adopted for this cause, but rather due to its simplicity and less data requirement. Moreover, model choice is dependent on the project funds available, and the implementers and collaborators are likely to trial out their model of choice based on their interests and advance the application scope, irrespective of the underlying model performance measures. It then follows that the choice and application of the SMAR model in the Kenyan FFS was due to the above reason.

With the current developments, there has been ongoing initiatives spearheaded by the Kenya Water Resources Authority—a parastatal mandated to set and manage the water resources rules and hydrological data. Under the ongoing project—Kenya Water Security and

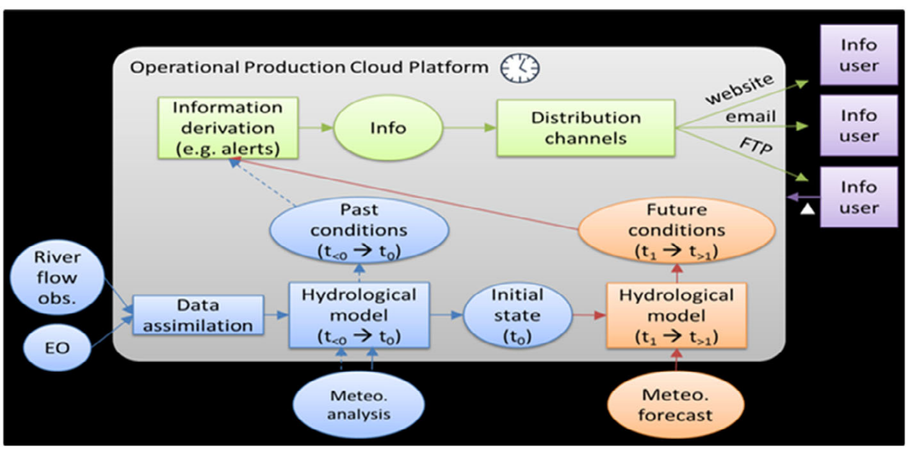

FIGURE 6 Niger HYPE-model for Niger basin and Hype world for the rest of West Africa (https://fanfar.eu/production/)

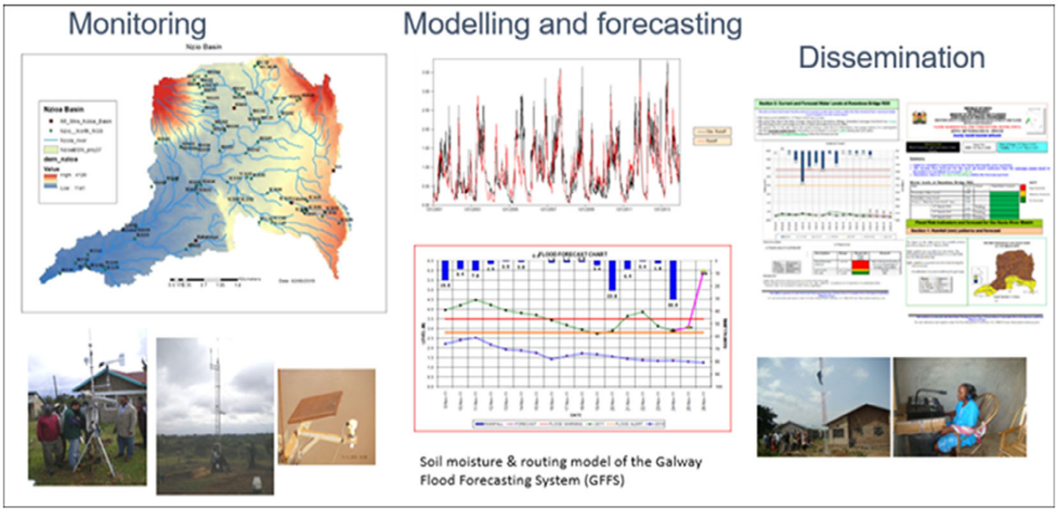

FIGURE 7 Overview of the flood monitoring, modeling, forecasting and dissemination for the operational flood forecasting in Nzioa basin, Kenya (*Source*: Kenya Meteorological Department)

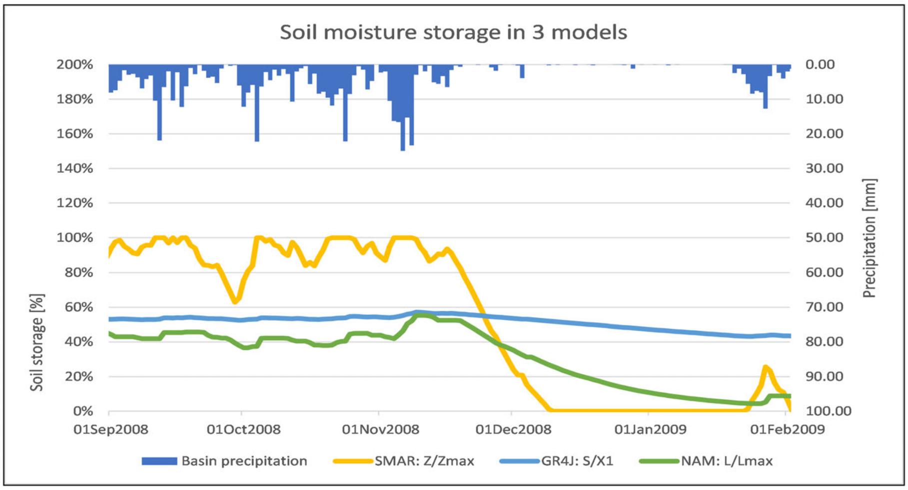

FIGURE 8 A representation of the soil moisture evaluation in soil moisture accounting and routing model (yellow), GR4J (blue) and MIKE NAM (green) over the Nzioa basin in Kenya (*Source*: Kenya Meteorological Department)

Climate Resilient Project, WRA is in the process of trialing out three hydrological models (SMAR, NAM, GR4J) in Nzoia to be incorporated into the FFEWS under development (WRA reports). For example, an initial assessment for model performance in Nzioa basin has been started. Figure 8 shows soil moisture representation in SMAR, GR4J and MIKE NAM over the basin.

The above highlights point to fact that a model needs to be able to be incorporated into an operational (up and running) system, if the main aim of the model selection is to provide a tool for the end-users of an early warning system that can help mitigate the effects of floods. In this respect, a model that can easily be implemented in a forecasting environment is preferred. Hence, the model should be stable, have reliable error and inconsistency checks, be able to flag off missing data (e.g., when input sources fail), be able to fit into an operational environment and should preferably be user friendly.

3.5 | Availability of model code and model run-time

Code must be available for use (open source or through agreements) with possibilities of adaptation to specific purposes (e.g., possibility to change the represented processes, ingested time-step and/or catchment discretization). These adaptions are possible but not existent in most of the freely available model codes. Code must be actively used and developed with core developers identified to ensure that proper support can be given in initial phases. Executable code is not enough, since changes, for instance, reading of input data will be necessary (Paul, Gaur, et al., 2020). Forecast deliveries run the risk of being delayed if bug fixes or updates cannot quickly be incorporated in the model. Key aspects are the service level agreement struck between the model and the forecasting system provider, outlining a clear overview of which parts are maintained locally, and which parts are outsourced. In addition, codes available only through purchases may limit the use of models especially for research and operational purposes, thus model should be open source but then not all open-source licenses are the same.

Some modeling communities have availed accessible packages for some select models with dedicated functions such as input data preparations, data processing and transformation, calibration etc. These packages may have all or limited functionalities for the application under consideration, thus limiting its use. For example, Table 1 shows some of the freely available packages, the proposed models to run and the package functionalities that can be executed.

The model run-time (Central Processing Unit)—computational time to run a simulation from model spin up varies with different models and area of application. For example, Astagneau et al. (2021) show how different models and implementations can differ an order of magnitude in required calculation time for the same set of catchments (Figure 5). The computational power lacks in many of the African National Meteorological and Hydrological Services (NMHS), especially if ensemble simulations, data assimilation methods, and further computational intensive uncertainty estimation methods are to be applied, and Kenya is not an exception.

4 | APPLICATION OF THE SELECTION FRAMEWORK TO KENYA'S CHOSEN CATCHMENTS

The above section outlines the aspects to consider when selecting a suitable model for national flood forecasting and application in Kenya. The application of selection framework to Kenya based on the above proposed selection criteria is outlined in Table 2. There are marked differences from catchment to catchment, which point to the fact that a single model single initialization with all the same parameters cannot be suitably applied at country level but rather at catchment scale, thus the need to objectively select a model based on the user needs and catchment processes.

4.1 | Application of decision tree to Kenyan catchments

To assess the suitability of hydrological models with focus to flood applications in Kenya, considering the aspects described, Figure 9 shows a flow diagram of the filter sequence in the selection criteria in defining model suitability to this application which may suffice as a decision tree. At the top of the decision tree are all the processes that are deemed important in a model for effective flood applications in Kenya. Firstly, Kenya has a large distinction in terms climates, some areas are Arid and Semi-Arid (ASALs) for example Eastern and North-eastern parts, whereas others are wetlands (e.g., Western and Central highlands) (see Figure 2). Therefore, a distinction is made in the second step for processes that are important to the different climatic zones. Secondly, Kenya is currently facing data scarcity due to ungauged nature of many catchments. This, however, should not be a setback to hydrological studies and as a result we filter the model based on the input data availability and possibility to use alternative data. In the third step, we explore the availability of the model code to a wider user community. Here the concept of code executability and online updating, accessibility and the computational run time are explored. At the fourth stage the ability of the model to be downscaled to catchment local scale is considered. Fixed grid sizes and limitations of applicability to certain basin sizes are mainly considered here. Finally, we explore the preferences of the model based on their ease to be implemented in the forecasting system environment. However, this piece of work does not involve the actual analysis of the models under consideration, and it is based on the elimination method following previous studies on the performances of the models over the region. As a result, we present a yes/no decision tree which has a potential implicit weighting factors of "0" or "1" based if the model meets a certain criteria or not from the MCA perspective. The above aspects in the selection framework form the basis of this model overview and selection sections. In this study, a combination of conceptual and process-based lumped and distributed hydrological models are considered for further evaluation to establish if they fit in the above aspects. The hydrological model should be suitable to evaluate the spatial and temporal occurrence of floods based on a defined indicator. Therefore, the models considered (and described in Appendix S1) range from the few applied or under consideration for the Kenyan setup as well as the other widely used models in studies across the African continent for FF that in our opinion would be applicable to Kenyan case. A total of 12 rainfall-runoff models were initially listed as potential candidates for small-scale operational flood forecasting (see Table 3 for main references). LISFLOOD and HYPE are included in this review despite being developed for large-scale applications because they were adopted for the prototype in the AFFS and West Africa, respectively. The models were chosen mainly based on the existing literature reviews and application studies particularly to Africa and Kenya. Table 4 provides a summary of the evaluation of all the 12 models based on the explained criteria herein.

TABLE 2 Summary of catchment-by-catchment evaluation based on the proposed framework

Catchment by catchment evaluation based on the proposed framework									
Catchment name	**EWASO NG'IRO**	**TANA RIVER**	**ATHI**	**NZIOA**	**YALA**	**NYANDO**	**TURKWEL**	**GUCHA**	**MARA**
Catchment Area (km^2)	30,000	96,000	46,600	12,800	2777	5110	9, 303	6310	13, 750
Dominant hydrological processes fluxes present									
Precipitation	√(unimodal)	√ (bimodal)	√(bimodal)	√ (bimodal)	√(bimodal)	√(bimodal)	√ (unimodal)	√(bimodal)	√ (bimodal)
Infiltration	√	√×(good upstream, poor in delta)	√×(good upstream, poor in delta)	√×(good upstream, poor in floodplain)	√	√×	√	√	√
Interception	√×	√	√	√	√	√	√×	√	√×
Evapotranspiration	√ (low)	√ (low upstream, high downstream) Hargreaves	√ (low)	√(high)	√(high)	√(high)	√(low)	√(high)	√(low)
Snow	×	×	×	×	×	×	×	×	×
Soil storage	√×	√×	√×	√	√	√	√×	√	√×
Ground water storage	×	√ Shallow and deep	√ Shallow and deep	× ×	×	×	√ Shallow and deep	×	×
Lake and reservoirs	×	√ Linear res.	√ Linear res.	√	√	√	√ Linear res.	√	×
Runoff	√ infiltration excess	√	√	√saturation excess/	√saturation excess	√infiltration excess overland	√infiltration excess	√	√
Ground water recharge	×	√	√	√	√	√	×	√	√
Hydroclimatic and physiographic setting									
Arid	√	×	×	×	×	×	√	×	×
Semi-arid	√	√ (upstream)	√(upstream)	×	×	×	√		√
Wetland	×	√(wet delta)	√(wet delta)	√	√	√	×	√	×
Data availability and resolution									
Observed meteorological data (precipitation, temperature, wind, etc.)	√ ×Daily √monthly	√ ×Daily √monthly	√ ×Daily √monthly	√ ×Daily √monthly	√ ×Daily √monthly	√ ×Daily √monthly	√ ×Daily √monthly	√ ×Daily √monthly	√ ×Daily √monthly
Hydrological data (discharge, ground water reservoir levels	√ × discharge for some stations	× Ground water and reservoir levels √× discharge for some stations	× Ground water and reservoir levels √× discharge for some stations	×Lake reservoir levels √× discharge for Ruambwa and missing years for other stations	√× discharge for some years	√× discharge for some years	× Ground water and reservoir levels √×discharge for some stations	√ ×discharge for some years	√ × discharge for some stations and years
Catchment characteristics									
Size (Sq.km)	30,000	96,000	46,600	12,700	3200	3400	28,000	5100	13,750
Human influence	√Irrigation, dams	√Irrigation, dams	√Irrigation, dams	×√ Irrigation	×√ Irrigation	×√ Irrigation	√Irrigation, dams	×√ Irrigation	×√ Ground water abstraction
Soil type	Sandy/loamy	Sandy/loamy	Sandy/loamy	Loamy/clay	Loamy/Clay	Loamy clay	Sand/loamy	Loamy/clay	Sand/loamy
Vegetation cover	Bare land/ Sparse vegetation	Bare land/Sparse vegetation	Bare land/Sparse vegetation	Grassland/Trees /Croplands	Grassland/ Trees/ croplands	Grassland/ Trees /Croplands	Bare land/Sparse vegetation	Grassland/ Trees /Croplands	Bare land/Sparse vegetation
Some models calibrated over these catchments									
Model applied to the catchment	√×	×	×	√	×	√	√	√	√

Abbreviations: ✓, Present; ×, Not Present; ×✓, Partially Present.

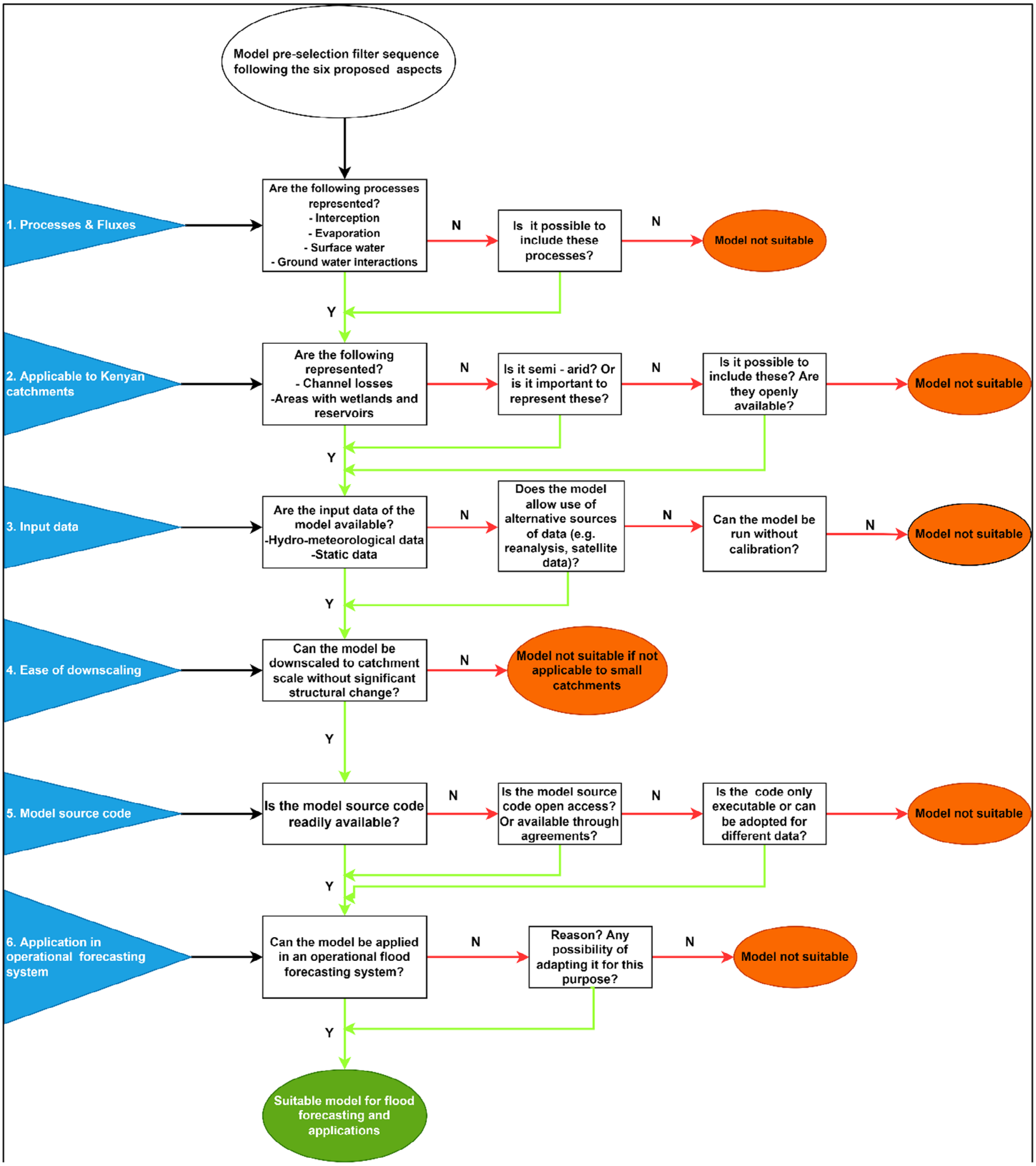

FIGURE 9 Flow sequence to serve as a decision tree for evaluating and selecting a suitable hydrological model for flood forecasting in Kenya, based on the proposed criteria

4.2 | Actual model selection based on decision tree

The Venn diagram (Figure 10) presents model selection following a comprehensive evaluation carried out in Table 4. All the models under consideration are described and summarized in Appendix S1. Following the filter sequence presented in Figure 4, each model is evaluated on step by step then potential models summarized in actual selection presented in Figure 10 shows a Venn diagram following the framework presented in Figure 9 for the models described and summarized (Appendix S1) and the evaluation information presented in Table 4. Table 4 evaluates all the 12 models based on the

TABLE 3 Twelve rainfall-runoff models listed as potential candidates for small-scale flood applications with their main technical references

Model	Main references
GR4J (modele du Genie Rurala 4 parametres au pas de temps Journalier	Technical (Perrin et al., 2003)
NAM (Nedbør-Afstrømnings-Model)	Technical (Nielsen & Hansen, 1973)
SMAR (Soil Moisture Accounting and Routing)	Technical O'Connor, 2005;
PDM (Probability Distribution Model)	Technical (Goswami & O'Connor 2010; Moore, 2007)
SWAT (Soil Water Assessment Tool)	Technical (Arnold et al., 1998; Neitsch et al., 2005)
MIKE SHE (MIKE Système Hydrologique Européen	Technical (Abbott et al., 1986; Ma et al., 2016)
HBV-96 (Hydrologiska Byråns Vattenbalansavdelning)	Technical (Lindström et al., 1997)
TOPMODEL (TOPography based hydrological)	Technical (Beven and Kirby 1979; Beven et al., 1984)
GeoSFM (Geospatial Streamflow Simulation Model)	(Artan et al., 2001, 2004; Asante et al., 2008)
VIC (Variable Infiltration Capacity)	Technical: (Gao et al., 2010; Lohmann et al., 1996)
LISFLOOD	Technical: (Burek, 2013; van der Knijff et al., 2010)
HYPE (European Hydrological Predictions for the Environment	Technical: (Lindström et al., 2010) http://hypecode.smhi.se

framework presented in Section 2. This provides the summary statistics of each of the models based on the process representation, data input requirements, model code availability, ease of downscaling to Kenyan catchments, and application of models to operational flood forecasting. Out of the 12 models, only VIC and TOPMODEL do not represent important processes for flood generation unique to Kenyan catchments. VIC and TOPmodel were eliminated because it could not represent groundwater processes and requires the calibration of all the parameters which in turn means that the calibration data must be available, which is hardly the case in most of the Kenyan catchments. As a result, they were excluded in the final selection presented in the Venn diagram in Figure 10. The figure shows the flow diagram of the filter sequence which is used to filter out the 12 models to those deemed appropriate candidates for flood applications in Kenya (Figure 10).

From the 12 models reviewed, five are considered suitable candidates for flood applications in Kenyan (Figure 8). The outermost circle (A) presents the 10 models under consideration excluding VIC and TOPMODEL. VIC and TOPMODEL were not at this point because lack of representing important process such as ground water (see Table 4). In addition, this category includes all the models which can be applied to the study catchments due to reasonable data input requirements, model code availability, ease of downscaling to Kenyan catchments, both in drylands—semi arid—and wetlands, and application of models to operational flood forecasting.

Circle B represents model selection based on data input requirements and the number of calibrated parameters. At this stage, we eliminate LISFLOOD, HBV-96, PDM, GeoSFM and MIKE SHE. LISFLOOD, MIKE SHE, and HBV 96 and GeoSFM are fully and semi-distributed models, respectively, with very many parameters to be calibrated (Berglöv et al., 2009; Ma et al., 2016; van der Knijff et al., 2010). In addition, they are run on hourly timestep with very many data input requirements. The calibration of many parameters will also require intensive computer run time which may be a challenge in many NMHS (Vema & Sudheer, 2020). The ungauged nature of the most of operational centers in Kenya may not have reliable data at high frequency (e.g., at hourly or even daily timesteps). However, circle B is white area because there is the option of alternative remotely sensed data. These models with high data requirements in data scarce areas, there are alternative sources of satellite and reanalyses datasets that are effectively utilized to force the model with caution. This is because the datasets come with their own uncertainties, including random and systematic errors (Fortin et al., 2015; Sun et al., 2018). Inherent input uncertainties will affect the performance of models for a given catchment, and as a result, we eliminated LISFLOOD, HBV-96 and MIKE SHE at this stage. PDM is also eliminated at this point because model configuration comprises of a probability-distributed soil moisture storage, a surface storage, and a groundwater storage components (Moore, 2007). The latter is hardly available input as there is no data on reservoirs and ground water storage in Kenya's NMHS.

Circle (C) represents models which their code is easily available as free open source. This category is meant to rule out models whose codes are available but only in executable format as changes for instance reading of input data may be necessary and is not provided for in executable model codes. The candidate models filtered through to this step HYPE, SWAT, and SMAR have freely available open-source codes (Paul, Gaur, et al., 2020). GR4J and NAM source codes are available through open

TABLE 4 Evaluation of the 12 models based on the proposed framework

Model evaluation						
Model name/ criteria	**VIC**	**SWAT**	**GeoSFM**	**HBV-96**	**MIKE-SHE**	**TOPMODEL**
Represented processes and fluxes						
Interception	√ f(LAI)	√ f(LAI)	√f(forest/land	×√ (Modified)	√	×√(Modified)
Evaporation	√ Penman-Monteith	√ P-M/P–T/ Hargreaves	√ Penman- Monteith	√	√	√
Snow	√ Energy balance	√Degree day	√ Degree day	√ Degree day	√	√Degree day
Soil	√ 2 or 3 layers	√ ≤ 10 layers	√ 2 layers	√ 2 layers	√ 3 layers	√ 2 layers
Ground water	×	√ Shallow and deep	√ Shallow and deep	×	√ Shallow and deep	√ subsurface and base
Lake, reservoirs	×	√ Linear res.	√ Linear res.	√	√	√
Runoff	√ saturation excess/ function	√ (SCS-CN)	√ (SCS-CN)	√ saturation excess/	√	√ infiltration excess and over land
Routing	√ Linear transfer function	√Muskingum- Cunge	√Muskingum- Cunge/ Diffusion Analogue	√Muskingum- Cunge	√	√
Calibration parameters	×√ Several	√ Several	×	√ Several	√	√ Several
Energy balance	√	×	√	√	√	√
Water use	×	√	√	√	×	√
Data requirement and resolution of the model						
Input Meteorological data	Daily or sub-daily precipitation, air temperature and wind speed	Daily precipitation, minimum and maximum temperature	Daily precipitation, potential evaporation	Daily precipitation, temperature and estimates of potential evaporation	precipitation, air temperature and solar radiation	Precipitation
Model spatial resolution	0.5°	Sub-basins	Semi-distributed	Semi-distributed	Sub-grids	Distributed
Model temporal resolution	Daily	Daily	Daily	Daily	Daily	Hourly/daily
Model code availability						
Open source	×	√	×	√ Executable	×	√ (as an R code called top model
Only Executable			√		√	
Model applicability to Kenyan catchments						
Geographically	√	√	√	√	√	×√ sensitive to grid size (≤50 recommended
Climatic conditions	× in semi-arid catchments √ in humid catchments	√	× in semi-arid catchments √ in humid catchments	× in semi-arid catchments √ in humid catchments	× in semi-arid catchments √ in humid catchments	√in semi-arid catchments √ in humid catchments
The ease of model to be downscaled to river basin scale						
Ease of downscaling without model structure modification	√	√	√	√	√	×√
Models have been calibrated over some Kenyan catchments and applied to operational FF						
Model applied to Kenyan catchment	×	× √	× √	×	× √	×

TABLE 4 (Continued)

PDM	Soil moisture accounting and routing model	NAM	HYPE	GR4J	LISFLOOD
PDM	Soil moisture accounting and routing model	NAM	HYPE	GR4J	LISFLOOD
Represented processes and fluxes					
√ f(canopy)	√ f(LAI)	√ f(LAI)	√ f(LAI)	√ f(LAI)	√ f(LAI)
√	√	√	√	√	√input
√Degree day	√ Degree day	√ Degree day	√ Degree day	√Degree day	√Degree day
√ 2 layers	√ 2 layers	√ 2 layers	√ 2 layers	√ 2 layers	√ 2 layers
√ subsurface and base	√	√Shallow and deep	√ subsurface and base	√	√ 2 parallel surface
√ Linear res.	√	√	√ Linear res	√	√linear reservoir
√	√	√	√	√	√ infiltration excess
√ cubic nonlinear	√	√	√	√	√Kinematic Wave Appr
√ Several	√9 parameters	×√9 parameters	√ Several	√4 parameters	×
×			×	×	×
√		×	√	×	×
Data requirement and resolution of the model					
Daily rainfall and potential evapotranspiration	Daily rainfall and Temperature	Daily rainfall, potential evapotranspiration and temperature	Daily precipitation, estimates of potential evaporative	Daily precipitation, estimates of potential evaporative	Daily rainfall, potential evaporative and daily mean air temperature
0.5°	Lumped	Lumped	Sub-basins	Lumped	100 m and larger
Hourly/Daily	Daily	Daily	Daily	Daily	Hourly/Daily
Model code availability					
√	√	√	√open source	√ R-package called airGR	×
					√
Model applicability to Kenyan catchments					
√	√	√	√	√	√
× in semi-arid catchments √ in humid catchments	√in semi-arid catchments √ in humid catchments	√in semi-arid catchments √ in humid catchments	√in semi-arid catchments √ in humid catchments	√in semi-arid catchments √ in humid catchments	√in semi-arid catchments √ in humid catchments
The ease of model to be downscaled to river basin scale					
√	√	√	√ can be run on subgrid	√	× √
Models have been calibrated over some Kenyan catchments and applied to operational FF					
×	√	× √	× √	× √	×

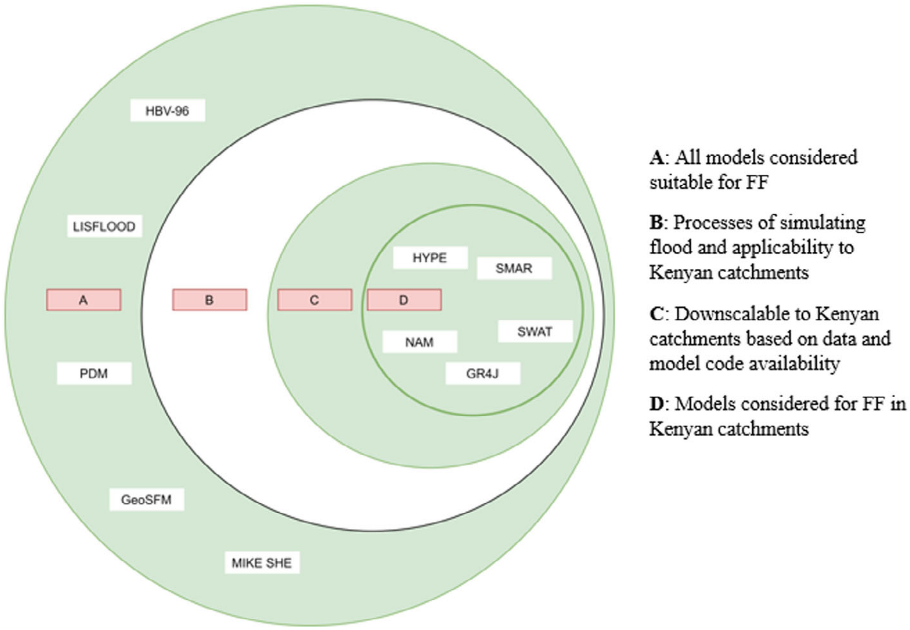

FIGURE 10 Venn diagram following the model selection procedure, starting with all the all models under consideration in circle A resulting with the selected models in innermost circle D.

collaborations (Humphrey et al., 2016). The innermost green circle represents models that can be applied easily to Kenyan catchments through simplistic downscaling and suitable for flood forecasting in different Kenyan catchments. Regarding the last criterion as to whether the model is suited for operational purposes, all models reviewed are continuous simulation models and no model is rejected at this step because we assume that, if necessary, they can be modified to be suitable for use in an operational environment.

5 | DISCUSSION

We provide an insight into the need to understanding of the quantitative or qualitative description of the existing knowledge and understanding of the catchments and how this would influence the choice of the modeling tools at catchment scale, acknowledging the gaps and challenges. Models used for different applications in different parts of the world are reviewed based on the six aspects, which builds on the previous works of Kauffeldt et al. (2016) and Trambauer et al. (2013), with the aim of assessing their suitability for flood applications in Kenya. The two foundational works provide a technical review of large-scale hydrological models for implementation in operational flood forecasting highlighting their suitability for drought forecasting at continental level, specifically in sub-Saharan Africa. They are important and provide a comprehensive model review and a selection framework for flood and drought application at continental scales, respectively. However, these studies are applied at a larger scale (continental), yet models simulate process differently in different hydroclimatic conditions thus, the need to link the process at catchment scale to model specifications and applications.

It can be noted that not all models are good at capturing and or representing the important processes relevant to flood generations (e.g., as transmission losses along the river channel, re-infiltration, and subsequent evaporation of surface) both in wetland and ASALs of Kenya as summarized in Table 2. It should be noted that, with the current data scarcity, most modeling frameworks incorporate satellite and reanalyses data. These products have a coarse resolution and high uncertainty in their estimations at catchment scale, which in turn impacts the model performance. Thus, the way forward for objective choice of modeling tools should ensure that the models are stable, have reliable error and inconsistency checks, be able to flag missing data errors (e.g., when input sources fail), be able to fit into an operational environment and should preferably be user friendly. Considering the data scarcity issues, most models can be implemented as the redundancy related to missing data can be incorporated in the preprocessing. Therefore, if a model can run with missing data, it is a requirement that the run is clearly flagged as having missing data. Model stability can be tested by looking at the distributions of parameters where they became remarkably well-behaved and near-elliptic when numerical error control is implemented in the model (Kavetski et al., 2006). However, since the properties of parameter distributions are dependent on (i) the data, (ii) the model, and (iii) the objective function, testing model stability before application may not be achieved. A sensitivity and uncertainty analysis of model parameters is run to establish model errors, which should be reliable (Song et al., 2015), but this requires more computational power, which is missing in Kenya.

The practical proposed and presented model preselection with a filter sequence for flood applications was used to filter out models to a subset considered suitable for Kenyan catchment types. Through the filter sequence presented, possible adaptation assumptions are considered in some cases. The filter sequence criteria to assess model suitability including the representation of important processes, availability of the model code, existing user community, input data requirements, possibility of calibration, model resolution and data assimilation and operational implementation into a flood forecasting system. Out of the 12 models, only 5: SWAT, SMAR, GR4J, NAM, HYPE were considered suitable candidates for catchment scale flood forecasting by local authorities in Kenya. The above preselection process forms initial steps and criterion in the choice of a modeling tool to the end-users of to effectively be used both at catchment scale modeling and potentially adopted in an operational early warning system to help mitigate the effects of floods in data scarce regions such as Kenya.

This work does not look at direct analysis of each of the proposed model to evaluate its performance based on some past events. As a starting point, this work provides background of hydrological models and the Kenyan set up to inform a criteria of model preselection for flood applications at national level. The modelers and users of the models can then use the information and arrive at models to apply for some select events. A MCA (Sherlock & Duffy, 2019) forms the basis of these initial steps. The whole process of an MCA is to assess multiple alternatives based on a mix of quantitative and mostly qualitative information from multiple sources. However, the proposed MCA relies heavily on evaluation data, is very time consuming for the number of models available hence for data scarce regions, and/or agencies with limited resources, (or in general) an additional decision tree is helpful to trim down the number of options. There is the need to further evaluate the limited selection with for example an MCA and the FFC experiment. This is mainly because within the same catchment, inhomogeneities of the physical and hydroclimatic properties is a complex issue that is essential in deciding which model to use, thus the importance of the selection criteria.

6 | CONCLUDING REMARKS

There are some challenges that are inherent when applying the above decision framework not only to data scarce regions but also to a wider global scale. For example, with the advancement in research, there is an increasing number of models and none of them is error free, mainly due to a compromise reached when considering model complexity and computational run time, which is a major challenge (McMillan et al., 2011). Also, it is difficult to balance complexity of model structure, the parameterization and input data requirements, because complex models do not guarantee reliable results (Paul, Gaur, et al., 2020; Trambauer et al., 2013). The use of certain models depends on the computational capabilities (skills) of the individuals as well as the NMHS in general. As a result, model selection may be biased based on the easy of applications depending on the skills of the modeler. In addition, there is no documented research outlining the pros and cons of each of models in a single platform in which a potential model user may easily use to identify which model is suitable (Mannschatz et al., 2016).

To address the highlighted challenges modeling communities in developing countries, Paul, Zhang, et al. (2020) and Souffront Alcantara et al. (2019) suggest some of the way forward. For example, developing countries should consider working on developing their own models. The current models tailored to catchment scale or geographical locations, developed with nicely all year round flowing rivers in relatively wet catchments and the inclusion of a variety of hydrologists and model developers with different needs and perspectives is most welcome and needed to produce hydrological models for a wider range of environments. This may take a long time due to inadequate technological capacities but will suffice as a milestone to addressing some of the challenges associated with model selection. A well-prepared and comprehensive database platform with useful information pooled together, such as:—different input information, advantages and disadvantages of different models is important in providing initial information to judge by eye on which model would work best. This is also likely to facilitate easy model selection alongside frequent webinars by model developers to enhance the skill of modelers in developing countries.

This research provides initial steps to inform the choice of modeling tools in data-scarce region. There is need for further analysis of the proposed model to Kenyan catchments, to assess their skills in simulating the past events. This will provide additional and useful information in the choice and application of these models at catchment scale with varied hydroclimatic characteristics. We acknowledge that it has not proven that the criteria "suffice" as the selection procedure leads because it leads to multiple models and no follow-up strategy is presented here as these forms the basis of future work. Additionally, the filter steps are not operationalized to the level where it can be said to be objective. For example, a model may be excluded on "many parameters" and that the preselection criteria presented here follows a flow chart which may be subjective. First, we make a preselection based on expert judgment and link to models that have been applied to diversified environments that deem suitable candidates to Kenyan setup.

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CONFLICT OF INTEREST

The authors declare that they have no conflict of interest.

DATA AVAILABILITY STATEMENT

The data availability statement is not applicable for this study.

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SUPPORTING INFORMATION

Additional supporting information can be found online in the Supporting Information section at the end of this article.

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