A Brief Review of Flood Forecasting Techniques and Their Applications

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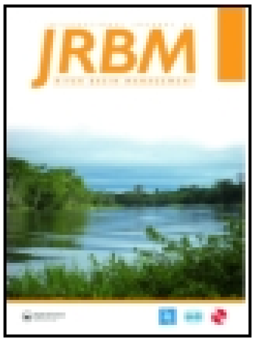

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A Brief review of flood forecasting techniques and their applications

Sharad Kumar Jain[a], Pankaj Mani[b], Sanjay K. Jain[a], Pavithra Prakash[c], Vijay P. Singh[d], Desiree Tullos[e], Sanjay Kumar[a], S. P. Agarwal[f] and A. P. Dimri[g]

[a]National Institute of Hydrology, Roorkee, India; [b]National Institute of Hydrology, Regional Center, Patna, India; [c]Postdoctoral Researcher, University of California, Davis, USA; [d]Texas A and M University, College Station, Texas, USA; [e]Oregon State University, Corvallis, OR, USA; [f]Indian Institute of Remote Sensing, Dehradun, India; [g]Jawaharlal Nehru University, New Delhi, India

ABSTRACT
Flood forecasting (FF) is one the most challenging and difficult problems in hydrology. However, it is also one of the most important problems in hydrology due to its critical contribution in reducing economic and life losses. In many regions of the world, flood forecasting is one among the few feasible options to manage floods. Reliability of forecasts 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. The present paper reviews different aspects of flood forecasting, including the models being used, emerging techniques of collecting inputs and displaying results, uncertainties, and warnings. In the end, future directions for research and development are identified.

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KEYWORDS
Flood forecasting; models; uncertainty; updating; applications

1. Introduction

Among all observed natural hazards, water-related disasters are the most frequent and pose major threats to people and socio-economic development (Noji and Lee 2005, ICHARM 2009). Over the period of 1900-2006, floods accounted for about 30% of the total number of natural disasters, claiming more than 19% of the total fatalities and more than 48% of the total number of people affected (ICHARM 2009). ICHARMv (2009) also reports that water-related disasters account for about 72% of the total economic damages caused by natural disasters, out of which 26% of all the damages are attributed to floods. These losses are expected to escalate in the future due to climate change, land use change, deforestation, rising sea levels, and population growth in flood-prone areas, causing the number of people vulnerable to flood disasters globally to increase to two billion by 2050 (Bogardi 2004, ICHARM 2009, Vogel *et al.* 2011).

Development of optimal flood forecasting and viable flood risk management systems have been advocated as measures of flood preparedness (Arduino *et al.* 2005, WMO 2011a) for a variety of reasons. Due to the uncertainties surrounding the magnitude, timing and place of occurrence, geographical extent, and geophysical interactions of floods, it is often not possible to completely control them. As a result, complete protection from floods is not always considered as a viable alternative (Moore *et al.* 2005). Traditional flood management, primarily composed of structural protection measures (i.e. dams and levees), emphasizes modifying a flood's characteristics to reduce the peak elevations and spatial extents. Although structural measures (e.g. dams and embankments) reduce flood risk, they cannot completely eliminate it. In addition, these measures are not feasible in some areas (i.e. remote mountain areas), are not effective for all flood processes (i.e. glacial lake outburst floods), and generate undesirable environmental impacts (Tullos 2008). Moreover, the cost and consequences of ageing flood management infrastructure are profound, as demonstrated in the United States (ASCE 2013), resulting in flood infrastructure that does not provide the intended level of protection and/or is subject to failure without major and costly maintenance. Furthermore, structural measures are designed for specific flood events (i.e. 1% annual exceedance (country specific)), which is problematic because channel modifications, land use and climate change have resulted in nonstationarity and increasing hydrologic uncertainty, making the likelihood of floods less predictable. As a result, structural measures are always subject to residual risk.

As a result, experts (Gleick 2003, Brooks *et al.* 2009, Opperman 2014) have called for transitioning from structural flood measures to non-structural flood protection measures that reduce exposure to floods, including regulation of land use and flood forecasting, among others, in flood-prone areas that are already occupied. Non-structural measures provide more reversible and less-expensive mechanisms to reduce flood risk than structural actions (DiFrancesco and Tullos 2014). Hence, non-structural measures are equally emphasized, while planning flood risk management systems (WMO 2011b). This paradigm shift is necessarily synchronized with advancements in the instrumentation and remote sensing of the atmosphere and earth surface and in the forecasting of natural hazards.

Floods can be of many different types and scales and this drives differences in the architecture and implementation of flood forecasting systems. For example, flood forecasting systems have been implemented at global (Alfieri *et al.* 2013), continental (Thiemeg *et al.* 2015), basin (Hopson and Webster 2010), and community scales. In addition, flood forecasting systems have been implemented for different types of floods. Plate (2009) distinguished five different types of landscapes with characteristic flooding behaviour: a) high

CONTACT Sharad Kumar Jain s_k_jain@yahoo.com National Institute of Hydrology, Roorkee, India

mountain ranges, which are mainly subject to flash floods and geophysical flows, b) foothill areas where floods are caused by intense rainfalls and snowmelt, and where inundation is widespread, c) large floodplains where velocities are low and floods occur because the landscape is unable to quickly pass all the incoming flows, d) urban areas where flooding is generated by inadequate sewer capacity and numerous barriers to flow, and e) coastal areas where flooding is typically caused by cyclones and storm surges. These different flood types require different architecture and implementation of FF. For example, flash floods are associated with spatially and/or temporally intense precipitation or by a sudden release of water due to dam breach and lake outburst. Flash floods are not common but can have high societal impacts because of their heavy precipitation and rapid onset (within a few hours of rainfall) (Doswell *et al.* 1996). Response time is thus very small; so flash flood forecasts are heavily dependent on real-time assimilation of precipitation data and forecasts, and yet flash flood predictions are still subject to important limitations (Kelsch 2001, Collier 2007, Hapuarachchi *et al.* 2011). Alternately, storm surge flooding, which occurs during a storm, cyclone, or hurricane, produces a massive wave of water that sweeps onto coastal areas. As a result of the unique characteristics of storm surges, flood forecasting systems must be sensitive to wind speeds and pressure fields and be able to represent uncertainties in surge depths and locations associated with deviations in storm tracks (Madsen and Jakobsen

Table 1. Criteria for model classification.

Criteria	Classification		
Spatial distribution	Lumped: black-box model	Semi-distributed model	Fully distributed model
Catchment modelling approach	Deterministic • Empirical • Conceptual ○ Lumped ○ Distributed • Physics based ○ Grid based ○ HRU based ○ Sub-catchment based	Data Driven • Stochastic	Data driven • ANN • Fuzzy
Input data and basin scale	Stream routing models • Hydrological routing • Hydraulic routing	Catchment models	Combined catchment and routing models
Precipitation forecast	No precipitation forecast	Precipitation forecast	Radarnowcast
Updating	No updating	Updating model	Updating model

rapid snow melt, ice jams etc., occur frequently, the catchment lag is very small (i.e. minutes to hours). In such areas, including only the rainfall forecast in FFWS may not always improve the utility of FF to users and thus a customized approach may be required (Doswell *et al.* 1996, Hapuarachchi *et al.* 2011). For larger basins where catchment lag time is long, an effective lead time can vary from hours to days, and inclusion of rainfall forecast is essential to enhancing the lead time.

The factors that impact lead time of forecast in the design of FFWS for a catchment include topographic and hydrometeorological features of the basin, the dynamics of basin response, and the availability of data. Furthermore, limitations on the level of services (how frequently forecasts are issued and updated, reliability, etc.) are largely dictated by the cost of data collection, modelling constraints, trained professionals, FFWS infrastructure, transboundary issues, and institutional factors.

3. Catchment models for flood forecasting

The catchment models used for flood forecasting may be classified according to many criteria (Table 1, Figure 2). Models may be classified depending upon the way catchment processes are represented – deterministic or data driven; or the way the catchment is spatial discretized – lumped or distributed. Deterministic models solve a set of equations representing the different watershed processes that produce a single model output for a given set of parameters. In contrast, data-driven models provide the capability to simulate the random and probabilistic nature of inputs and responses that govern river flows.

The spatial distribution of inputs and parameters is also an important aspect of model selection (Figure 2). In lumped models, the catchment is conceptualized as consisting of various storage tanks representing water storage on the catchment surface, in the root zone, unsaturated zone and in the groundwater zone. Modelling essentially consists of a set of expressions that describe the movement of water through these tanks. The division of precipitation into various compartments is controlled by catchment properties, which are represented in a model by parameters that are tuned during model calibration. In a distributed model, the catchment is divided into a large number of cells or hydrologic response units. While distributed models are generally expected to reproduce the hydrological processes in spatially-varied catchments more accurately, uncertainty in model parameters can lead to substantial errors in distributed models (Carpenter and Georgakakos 2006).

Further classification of catchment models is based on the rainfall estimates for lead time, sometimes called the look back window. A model may be an updating or non-updating model. Forecast updating involves the use of the most recent exogenous inputs, such as observed rainfall and observed flows up to and including the time of forecast, to adjust model-computed flows. Many updating models also update Quantitative Precipitation Forecasts (QPFs) within the lead time as observed precipitation data become available. The catchment models based on updating of QPFs are comparatively more accurate and reliable because they use real-time data observed during the lead time.

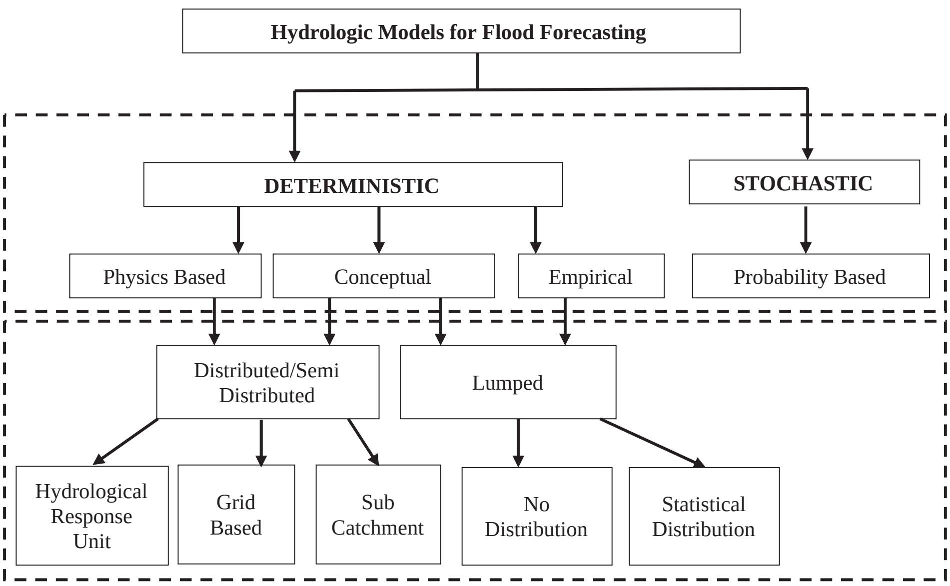

Figure 2. Classification of models used for Flood Forecasting based on model structure and type (Source: WMO, 2011b).

The type of model employed in a particular application depends largely upon the primary processes that produce runoff and their spatial and temporal extent, spatial coverage and resolution of data, and catchment features (see review in Kauffeldt *et al.* 2016). Here we follow the first way to classify the models in greater details.

3.2. Deterministic models

Deterministic models for FF require two key components: 1) flood generating mechanisms, including precipitation formation, snowmelt modeling, catchment runoff within hydrologic models, and 2) flood routing. Deterministic rainfall-runoff (RR) models include components for the various hydrological and related processes, such as precipitation, infiltration and soil moisture dynamics, evapotranspiration, runoff generation and streamflow routing. Precipitation is a critical input to these models and runoff and flow depth are the main outputs.

RR models are used to estimate river flows and depths by integrating hydro-meteorological inputs and the physical description of the catchment. The performance and efficiency of RR models depend not only on the selected model but also on how the catchment is represented (Figure 2), and the extent and quality of available data. The process of transformation of rainfall into runoff is time dependent and is a function of the physical characteristics of catchment and rainfall. For a larger basin, RR models that divide the catchment into sub-basins provide longer lead time for flood forecasting, making them more useful. However, the time of concentration in small basins may not provide sufficient lead time and hence QPFs are generally included in the RR models to enhance the lead time of a forecast (Arduino *et al.* 2005, Goswami and O'Connor 2007). In general, a longer lead time is available in RR models when compared with a FF system that is based solely on flood routing. Further, the RR models should also be able to accommodate the dynamism of the catchment, including changes in landuse/landcover and inclusion/removal of infrastructure, that influence the catchment response to meteorological events.

Flood routing methods may be classified as hydrologic or hydraulic. In hydrologic routing, the time-varying flow is computed at a single specified location downstream. The hydrologic flood routing methods employ the equations of continuity and can be grouped into: (i) level-pool types, which are generally used for reservoir or lakes assuming a horizontal water surface; and (ii) distributed storage types for channel routing assuming a sloping water surface due to the transmission of the flood. In hydraulic flood routing, the hydrograph is simultaneously computed at several cross-sections along the watercourse. Hydraulic routing requires detailed channel bathymetry and roughness data but provides comprehensive flow dynamics for discharge, depth and velocity in space and time domains.

The selection of RR and routing models depends on the forecasting objective, data availability, institutional capabilities, and catchment characteristics. For example, flow in natural channels during floods is typically unsteady, non-uniform, and includes interactions with tributaries and bifurcations with varying cross-sections and roughness. Flood routing in such channels is most commonly accomplished by solving the full or simplified St. Venant equations to obtain flow depth and velocity as a function of space and time throughout the system. Until recently, the modelling approach was limited to one-dimensional(1D) flow simulation (Fread 1993, Ghoneim and Foody 2013), but 2D models are quickly becoming the standard of practice in many places (e.g. Jones *et al.* 2002), while 3D models are becoming increasingly applied in specific scenarios (e.g. Biscarini *et al.* 2010). However, the increased complexity of 2D and 3D models requires high-quality data and modelling expertise to produce accurate results.

3.3. Data-driven fF models

Data-driven models are often referred to as black-box models because they depend upon the statistical or cause–effect relationships between hydrologic variables without considering the physical processes that underlie the relationships (Luchetta and Manetti, 2003). Data-driven models can include stochastic models (e.g. Regression models, Time-Series models, and Bayesian models) and nonlinear time-series models (e.g. Artificial Neural Network models, Fuzzy Systems, and adaptive neural Fuzzy Inference Systems) that require extensive and high-quality time series of hydrologic data.

Stochastic models (Box *et al.* 2016) reflect techniques based on time-series analysis, which have become very popular in hydrology. Stationary stochastic models such as Auto-Regressive 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, say 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.

Nonlinear time-series models such as Artificial Neural Networks (ANNs) are another example of a data-driven FF approach that can be effective at modelling rainfall-runoff processes and floods forecasting (ASCE Task Committee, 2000a, b). ANNs are nonparametric models that adapt to information inputs and are capable of representing complex nonlinear relationships (Antar *et al.* 2006, De Vos and Rientjes 2005). ANNs can learn from input data, generalize behaviour of data, and cope with noise. Comprehensive reviews on applications of ANNs in hydrology can be found in ASCE Task Committee (2000a, b), Abrahart *et al.* (2010), and Maier *et al.* (2010).

An interesting application of data-driven techniques is to improve the real-time forecasts issued by deterministic lumped RR models, in which the catchment response is simulated by a conceptual model and the residuals are simulated by an ARMA model. Brath and Toth (2002) found substantial improvements in discharge forecasts by coupling ARIMA models with data-driven models (i.e. ANNs) for rainfall forecasting and discharge updating.

Despite many successful applications, ANNs have not been deployed in operational flood warning systems, except a few prototype working examples (e.g. Kneale *et al.* 2001). This can be attributed to various practical issues: long training times, the potential to overfit the model to a dataset, phase-shift errors, and a lack of guidance on architecture and parameter selection (Dawson *et al.* 2006). Often, ANN-model-based forecasts are reliable only at small lead times (e.g. one step ahead), which creates uncertainty in their applications for flood management (Prakash *et al.* 2014). In view of the concerns about the performance of ANNs for FF, it will be helpful to deploy these along with other models in a few pilot applications and evaluate their performance.

Another class of data-driven models is based on fuzzy logic and fuzzy set theory (Zadeh 1965). Fuzzy models operate on an IF–THEN principle, where 'IF' is a vector of fuzzy explanatory variables and 'THEN' of fuzzy consequences (Shrestha *et al.* 1996). Several approaches have been used to apply fuzzy set theory to flood forecasting, including fuzzy optimization techniques, fuzzy-rule-based systems, and combinations of the fuzzy approach with other techniques (Dubrovin *et al.* 2002). 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, Bangladesh by using a fuzzy logic model in which the upstream water levels were the inputs. Dubrovin *et al.* (2002) introduced a model called Fuzzy-State Stochastic Dynamic Programming, which can take into account both uncertainties due to random nature of hydrologic variables and imprecision due to variable discretization. Yu and Chen (2005) proposed an error prediction fuzzy-rule-based method as an updating technique to improve real-time flood forecasts with one to four hours of lead time.

The hybrid adaptive neural-based fuzzy inference system (ANFIS) combines ANN and fuzzy theories. Bae *et al.* (2007) developed an ANFIS-based operational forecasting model for monthly reservoir inflow forecasts using rainfall, inflow, temperature, relative humidity and monthly weather forecasts. Firat *et al.* (2007) used ANFIS to forecast daily river flows using antecedent flows on the Great Menderes River in Turkey.

Data-driven models represent the statistical properties of the system and the relationships between cause and effect variables, but do not represent the underlying physics (Abrahart *et al.* 2008). Practical applications of the data-driven models for flood forecasting are still lacking chiefly due to the two reasons: (i) data-driven models do not account for the changing dynamics in the physics of the basin over time (i.e. aggregation/ disaggregation/ changing land pattern); and (ii) the parameters of data-driven models are completely dependent on the range of the data (i.e. maximum and minimum) used for calibration. As a result, process-based hydrological models have traditionally dominated FF.

3.4. Ensemble forecasts

The concept of ensemble forecasting originated in the atmospheric community to overcome the limitations associated with the deterministic models. In ensemble prediction systems (EPS), a set of possible future states of the variable are provided through small changes in the initial conditions, different representations of the physical processes, and changes in parameterization schemes and solution schemes. Rather than providing a single deterministic forecast, the EPS offers an ensemble prediction of hydrological variables, such as streamflow or river level, allowing the identification of the most likely scenario. An EPS, in a way, consists of the propagation of uncertainties through the forecasting system. Notwithstanding the other uncertainties, prediction of rainfall is often the dominant source of uncertainty in FF.

Producing ensemble forecasts at the global scale has become possible in recent years due to the integration of meteorological and hydrological modelling capabilities, improvements in data, satellite observations and land-surface hydrology modelling, and increased computer power. Operational and pre-operational flood forecasting systems now routinely using ensemble weather predictions as inputs (Thiemig *et al.* 2015). These operational flood forecasting systems use ensembles of numerical weather predictions (NWP), known as ensemble prediction systems (EPS) that provide the added value to flood forecast for the issue of early flood alerts with more confidence. The major challenges that EPS witnesses includes (i) improving NWPs, (ii) understanding the total uncertainty in the system, (iii) data assimilation techniques, (iv) inadequate verification through case studies, (v) adequate computational power, (vi) application of EPS in operational settings and (vi) communicating uncertainty and probabilistic forecasts to end users (Cloke and Pappenberger 2009).

Several ensemble forecast systems are now operational (Table 2), for example, the Hydrologic Ensemble Forecast Service (HEFS) in the USA. HEFS generates ensembles of forecast and related products by using: (i) the Meteorological Ensemble Forecast Processor, which produces bias corrected meteorological inputs at hydrological basin scale from multiple NWPs, (ii) hydrological ensemble processor to produce streamflow ensembles, (iii) hydrological ensemble post processor to explicate the hydrologic uncertainty and systematic biases correction and (iv) ensemble verification service to describe the sources of skill and error of forecast (Demargne *et al.* 2014). The streamflow prediction based on coarse space–time resolution numerical ensemble weather predictions are able to identify hazardous events in a large basin, but has limited applicability in smaller basins wherein small size weather system are responsible for flood events (Alfieri, *et al.* 2013, Thiemig *et al.* 2015). Another example of operational ensemble FF systems is the European Flood Awareness System (EFAS) which makes use of multiple meteorological forecasts to produce probabilistic flood forecasts with estimates of uncertainty (Thielen *et al.* 2009).

4. Forecast updating and verification

In flood forecasting, a model with constant parameters may not be able to completely represent the complex processes in a basin. As a result, the simulated hydrograph can differ from the observed hydrograph, mainly due to uncertainties in input data, differences between basin physics and model structure, model calibration, and changes in catchment characteristic over time. Seban and Askew (1991) categorized these errors as (i) volumetric or amplitude errors, (ii) timing or phase errors and (iii) shape errors. The volumetric errors are mainly attributed to inadequate model structure and basin representation, input/output data error or a combination of these errors. Timing errors may be introduced by the routing component of the model or by spatial and temporal discretization, whereas the shape errors are induced mainly in the conversion of rainfall to runoff by the model. These three types of errors can occur in different combinations in hydrologic models. Therefore, an adaptive forecast scheme may be used to update the model parameters, state

Table 2. Operational Flood Forecasting Systems in use by selected agencies in World.

Country	Model	Model Characteristics	Rainfall input	Remarks	Reference
European Flood Awareness System (EFAS)	LISFLOOD-2D	GIS based spatially-distributed hydrological rainfall runoffmodel developed at the Joint Research Centre (JRC, European Commission) for operational flood forecasting	Numerical weather prediction (NWP) forecast	Fully operational since 2012. It provides pan-European overview maps of flood probabilities up to 15 days in advance, and detailed forecasts at stations where the national services are providing real-time data	https://www.efas.eu/ Thielen *et al*. (2009) The European Flood Alert System - Part 1: Concept and development, Hydro. E rth Syst. Sci., 13, 125-140 Bartholmes *et al*. (2009) The European Flood Alert System EFAS – Part 2: Statistical skill assessment of probabilistic and deterministic operational forecasts, Hydrol. Earth Syst. Sci., 13, 141–153
USA	HEFS consists of suits of model; Snow-17, Sacramento Soil Moisture Accounting model (SAC-SMA) and Unit Hydrograph approach	Snow-17 model for snow ablation - distributed energy balance model SAC-SMA - Spatially-lumped continuous soil moisture accounting model UH for flood routing	NWP ensembles	Operational through NWS (NOAA) for all lower USA	Demargne *et al*. 2014
CWC, India	Statistical / correlation techniques for most of the basins MIKE-11 FF models HEC-HMS	Statistical gauge to gauge, gauge & discharge correlations for some sites; multiple coaxial correlations using gauge and rainfall data Semi lumped for rainfall-runoff model and 1D flood routing model Distributed hydrological model	Rain gauge data and Antecedent Precipitation Index (API) datafor some stations. Real-time 3-hourlyhydrometeorological and daily ET data.	For most of basin in India Selected sites in Damodar Basin, Godavari Basin, Mahanadi Basin,and Chambal Basin, India. Godavari basin in India	http://nidm.gov.in/idmc/Proceedings/Flood/B2%20-%2027.pdf CWC 2015. 'Flood Forecasting & Warning System in India', in Regional flood early warning system workshop, 23-27 November 2015, Bangkok.
Flood Warning system in Malaysia	WEHY, HEC RAS & MIKE 11	Physical based watershed Hydrology model (WEHY) and 1D flood routing models	(NWP) from Global Forecast System (GFS)	Rivers of Pahang, Perak and Golok, Malaysian Government web site	http://forecastmuar.water.gov.my/map
BWDB (Bangladesh)	MIKE 11	1-D hydrodynamic model	Radar altimeter measurement of river stage (Satellite-based flood-level observation in upper reach is used to increase lead time)		http://www.ffwc.gov.bd/, 20Workshop%20Proceedings-13Jan2016.pdf Bangladesh Water Development Board An e-service on Flood Forecasting & Warning in *Bangladesh* Flood forecasting & Warning center, WAPDA Building 8th. Floor Motijheel C/A, Dhaka-1000
Nepal	HEC-RAS MIKE NAM, MIKE 11	1 D hydrodynamic model Semi distributed hydrologic model & 1D hydrodynamic model	Web based telemetry system for real-time data acquisition. Rainfall forecast from weather rainfall forecast (WRF) model	West Rapti basin in Nepal. Bagmati Basin, Nepal	http://www.hydrology.gov.np/ new/bull3/index.php/ hydrology/home/main DHM 2015. 'Flood EWS Activities in Nepal', in Regional flood early warning system workshop, 23- 27 November 2015, Bangkok.
Philippines			Satellite-based rainfall estimates in addition to conventional raingauge, WRF		http://www1.pagasa.dost.gov.ph/ index.php/floods/general-flood-advisories
Pakistan	Sacramento model SOBEK model	Distributed hydrological model 1D hydrodynamic routing model	Real-time hydrometeorological data.	Models have been developed by Delft Hydraulic, Netherlands with inputsfrom National Engineering Services Pakistan.	Statistical modelling (http://wci.t.u-tokyo.ac.jp/events/ awcs2016/presen/3-1-7.pdf) IFAS was also developed for Upper, Middle and Lower Indus basin and handed over to FFD/PMD in 2014 http://www.pmd.gov.pk/FFD /index_files/ifashyd.htm
China	Xinanjiangand other models like API, SCLS, Sacramento, Tank, SMAR, Shanbei Xinanjiang, URBSand API, MIKE 11	Distributed basin model Distributed basin model 1D hydrodynamic model	Real-time hydrometeorological data	Used in several basins of China Yangtze and Han Rivers, and Dongting Lake	https://na.unep.net/siouxfalls/ flood/CHINA_FL.pdf Zhiyu LIU Flood Forecasting and Warning in China Bureau of Hydrology, MWR, P. R. of China 2 Lane 2, Baiguang Road 100053 E-mail: liuzy@mwr.gov.cn
Australia	HyFSHydrological Forecasting System: (i) URBS Hydrological model (ii) SWIFT Continuous hydrological model	Rainfall runoff model together with a runoff routing model SWIFT includes 13 conceptual rainfall-runoff models and 2 catchment routing models and 2 channel routing models.	Australian Numerical Weather Prediction (NWP) model	Operational since 2015	https://publications.csiro.au/rpr/download?pid = csiro: EP161184&dsid = DS1
Africa	Hydrological model LISFLOOD,	the African GIS database, the meteorological ensemble predictions by the ECMWF (European Centre for Medium-Ranged Weather Forecasts) and critical hydrological thresholds		For medium- to large-scale African river basins,	Thiemeg *et al*. 2015 Thiemig, B. Bisselink, F. Pappenberger, and J. Thielen, A pan-African medium-range ensemble flood forecast system, Hydrol. Earth Syst. Sci., 19, 3365–3385, 2015

variables and change in basin behaviour that cannot be simulated by the initial model (Young 2002, Mediero *et al.* 2012).

As a result, forecast updating and data assimilation have become major components of FF. A variety of techniques for forecast updating are available with the goals of error prediction, data assimilation, and parameter updating (Sene 2008). Data assimilation involves integrating information coming from a forecast model with available observations to improve the fit between forecasted and observed values. Data assimilation is usually performed in a sequential manner, with a time series of 'assimilation cycles', including a model integration, and a correction due to observations. These days, satellite data are being successfully exploited by new data assimilation schemes. However, these must be verified prior to application in forecast updating.

Updating procedures provide feedback to the hydrological simulation models by estimating errors between model output and observed state variables (Figure 3). A special volume in Journal of Hydrology in 2001 contains several articles on the application of ensemble and data assimilation techniques for updating flood forecasts and estimation of uncertainties in the forecasts. FF updating procedures differ in algorithms and their mode of operation (Xiong *et al.* 2004, Knight and Shamseldin 2006, Cloke and Pappenberger 2008, Mediero *et al.* 2012, Rafieeinsaab *et al.* 2014, Bourgin *et al.* 2014, Li *et al.* 2015, Mure-Ravaud *et al.* 2016). Several authors have reported the use of adaptive techniques for improved flood forecasts, including in the UK (Romanowicz *et al.* 2006), Korea (Shamir *et al.* 2010), and France (Thirel *et al.* 2010).

Simple updating procedures consider addition of the current error to the next new forecast for improving model outputs, compared to the observed hydrograph. More complex procedures involve analyzing the error series δY_1, $\delta Y_{2,\ldots}$, δY_i to identify possible trends or periodicities that can be extrapolated to next time step to estimate the potential new error δY_{i+1}, which are then used to update the new forecast (WMO 2012). The observed values, Y_{o1}, $Y_{o2}, \ldots$, Y_{oi}, can be used to redefine the state variables of the forecast model. This is termed recursive estimation, and if the forecast model can be cast in a sufficiently simple form, it provides a formal strategy for adjusting model output.

Adaptive updating algorithms are used for recursive estimation of parameters as a flood develops and more observations of the rainfall-runoff process become available (Vrugt *et al.* 2006, Abaza *et al.* 2014, Randrianasolo *et al.* 2014, Seo *et al.* 2014). The adaptive filter algorithm updates the model parameters using the previous estimate of the model parameters and a function of the forecast error process. Young (2006) gives a comprehensive description of methods for FF that involve the real-time updating of states (river levels or flows) and parameters in FF models. One example is the Kalman Filter, which is frequently used for updating an FF by employing the general algorithm:

$$\theta_j^{up} = \theta_j^s + Ke_j \tag{1}$$

where θ_j^{up} = the updated state at time j, θ_j^s = the simulated state at time j, K = the Kalman Filter gain, which is a function of noise statistics, and e_j = the error at time j (difference between simulated and observed output). These estimates can be further improved by using an extended Kalman Filter (EKF) that linearizes the error covariance equation and propagates the covariance matrix in the future. However, it fails to represent the error probabilities if nonlinearities are strong, which requires a filter that includes Monte-Carlo simulations (Evensen 2003, 2004). While testing an FF model, Bloschl *et al.* (2008) realized that the performance of the model hinges on the accuracy of the rainfall data. They implemented two updating algorithms that use runoff in a real-time mode. The first adjusts the catchment soil moisture state by an Ensemble Kalman Filter and the second exploits the autocorrelation of the forecast error. Bloschl *et al.* (2008) found that both algorithms improve the fore-

Table 3. A review of applications of various types of models for real-time flood forecasting.

Authors/ developers	Model(s)	Model type: Rainfall-Runoff (RR)	Model type: Routing	Developed / used by
De Roo *et al.* (2003)	Global numerical weather prediction models, downscaling using regional models, hydrology models: LISFLOOD, HBV, TOPKAPI	TOPKAPI-Distributed hydrological model HBV-conceptual model for runoff simulation	LISFLOOD-2D hydrodynamic model	European Flood Forecasting System
Bartholmes and Todini (2005)	TOPKAPI (TOPographic Kinematic APproximation and Integration)	TOPKAPI distributed hydrological model with	-	-
Thielen *et al.* (2009)	EFAS (European Flood Alert System)	Based on the physically-based distributed hydrological model LISFLOOD	-	Developed and tested at the European Commission, DG Joint Research Centre
CWC andNIDM (2008) CWC (2012)	Statistical / correlation techniques for most of the basins, Rainfall runoff models in selected basins	Antecedent Precipitation Index (API) MIKE RR	Gauge to gauge, gauge & discharge correlations MIKE 11	For river basins in India Selected sites in Damodar Basin, Godavari Basin, Mahanadi Basin,and Chambal Basin, India.
Durga Rao *et al.* (2011)	HEC-HMS hydrological model with SRTM DEM and IRS AWiFS data	HEC-HMS Distributed hydrological model	-	Godavari basin in India
Flood Warning system in Malaysia	Real-time hydrology and meteorology data coupled with hydrodynamic models and GIS tools.	Physical based watershed Hydrology model (WEHY)	HEC-RAS model, MIKE 11, MIKE FLOOD WATCH	Rivers of Pahang, Perak and Golok, Malaysian Government web site (2013)
Rahman (2015)	Rainfall - runoff modelling and hydrodynamic routing modelling	MIKE RR	MIKE 11, MIKE FLOOD WATCH	Used in Bangladesh
DHM (2009) Gautam and Phaiju (2013)	Community Based Flood Early Warning System.	Distributed conceptual model	HECRAS	West Rapti basin in Nepal.
Shahnawaz and Magumdar, 2011	Hydrologic model &, hydrodynamic model	MIKE NAM	MIKE 11	Bagmati Basin, Nepal
Lagmay 2012	Web based FF system	HEC-HMS	Flo2D and ISIS 2D/ISIS FAST	Used in Philippines.
WMO, 2010	FEWS (Flood Early Warning System) Model	Sacramento model	SOBEK model	Used in Pakistan. (Developed by Delft Hydraulic, Netherlands with inputs from National Engineering Services Pakistan)
Zhiyu(2002)	Xinanjiang Model and other models like API, SCLS, Sacramento, Tank, SMAR, Shanbei and Maskingum routing models.	Distributed, basin model	Muskingum routing model	Used in various basins of China
Marker *et al.* (2015)	The Flood Forecasting System (FFS) incorporates three hydrologic models, namely Xinanjiang, URBSand API, and a hydraulic model (Mike 11).	Xinanjiang- a semi-distributed conceptual API - Lumped &conceptual URBS-a distributed rainfall runoff routing model	MIKE 11-hydrodynamic model	Yangtze and Han Rivers, and the Dongting Lake System, China
Elliot *et al.* (1997)	Simple hydrological model including URBS application in Australia	URBS-a distributed rainfall-runoff routing model	-	In part of Australia
IRSTEA, (2015)	Hydrological model 'VIGIE' based on a soil humidity index and rain fall data in real time.	NWP model AROME, Hydrological model VIGIE and AIGA (for ungauged basin)	Ensemble river discharge forecasting system &Hydrodynamic 2D finite-element model (for Gironde Estuary)	Developed by IRSTEA Institute and the French National Hydrometeorological and Flood Forecasting Centre (SCHAPI).
Deltares(2008)	FEWS, an open shell system for managing forecasting processes and/or handling time-series data.	Several external RR model	Several routing model	Implemented in many basins including Po basin (Italy)
De Roo *et al.* (2000)	LISFLOOD	LISFLOOD is a GIS-based 2D hydrodynamic RR routing model.	a two-dimensional hydrodynamic model	The Danube European Flood Alert System (EFAS)
Werner and Dijk (2005)	FewsNL is the operational FF system	Hydrological model HBV	hydrodynamic flow models SOBEK	Dutch Institute for Inland Water Management and Waste Water Treatment (RIZA), to provide operational forecasts for the Rhine and Meuse Rivers (Netherlands).

models, accuracy and resolution of elevations (Alemseged and Rientjes 2005), and scale and details of land use soils. In a study of flood early warning and vulnerability assessment, all the above-mentioned geospatial inputs are integrated. For example, a flood event in August of 2015 caused large damages in parts of Beas River basin near Dharampur in Himachal Pradesh, India. This event was well forecasted three days in advance with a weather forecasting model. The model was run using National Centre for Environmental Prediction (NCEP) Global Forecasting System (GFS) using 0.25 degree data as the initialization state to forecast precipitation over four days (Figure 4). Based on historical and current 0.5 degree gridded daily rainfall data, the validation of a few events that occurred during 2013–2015 monsoon season had been conducted. The simulation accuracy in the prediction of rainfall above 100 mm was found to be 60%. Three hour forecasted precipitation was used in the Hydraulic Engineering Center's Hydrological Modelling System (HEC-HMS) for flood hydrograph generation at various outlets of study area (Figure 5). The 30 m ASTER GDEM was used to delineate the catchments and rivers.

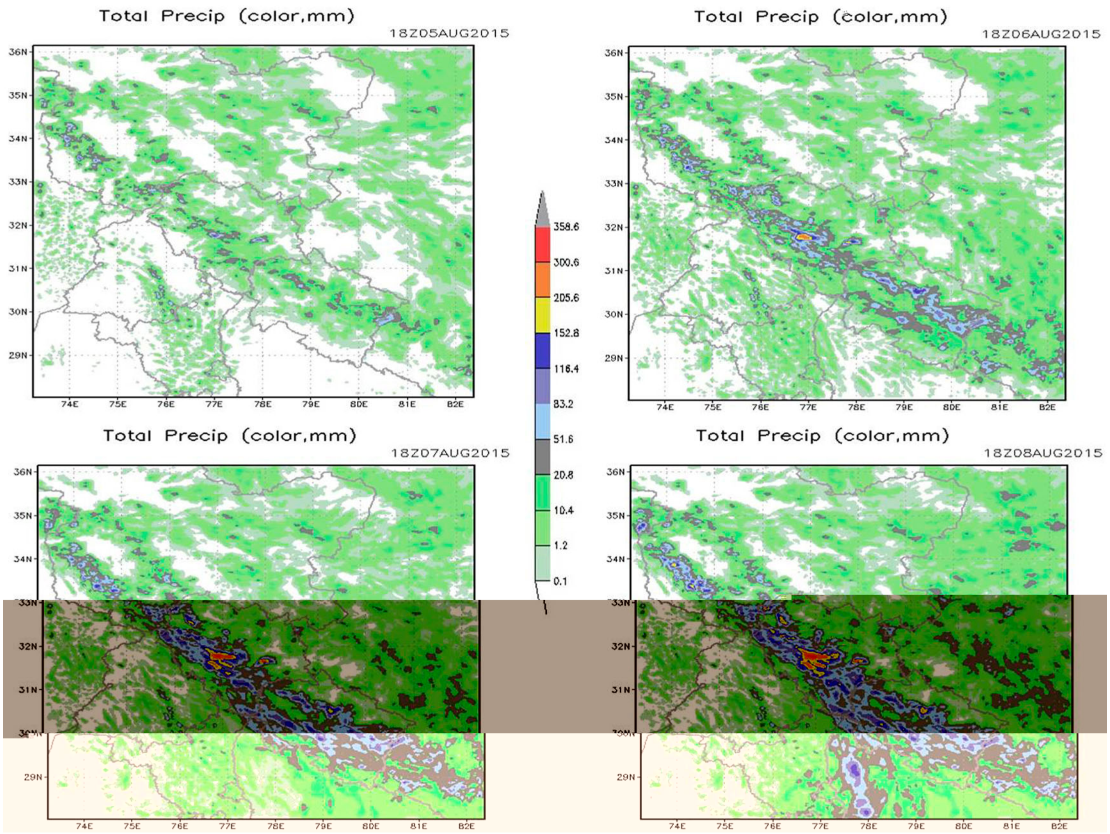

Figure 4. Forecasted rainfall on 05 Aug 2015 for 05 to 08 Aug. 18 Hrs (a, b, c and d) for NWH, showing very heavy rainfall in Mandi district, of Himachal Pradesh, India.

The simulated flood hydrograph was used for flood inundation scenarios mapping along the river reaches using 1-D HydroDynamic (HD) Mike 11 to identify the exposed areas (Figure 5) by overlaying flood inundation scenarios with LULC, roads, settlements, etc. Details on how each of these datasets might be acquired and integrated are described below.

5.1. Remote sensing and gIs for flood modelling and forecasting

The physical characteristics of the basin (such as surface area, topography, geology, and land-surface cover) determine the nature of potential flooding. The hydrological response of a basin is impacted by changes in land use associated with

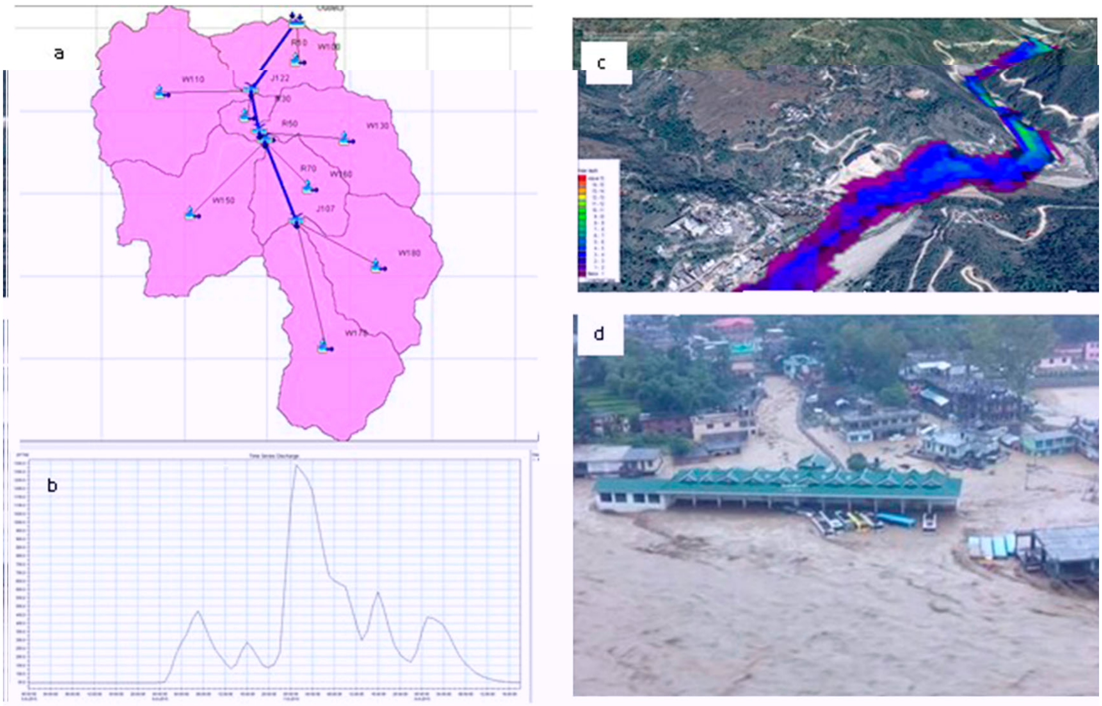

Figure 5. Results of one of the very heavy rainfall events and subsequent simulated and actual floods in Dharampur, Mandi, H.P. **a)** Hydrological model setup for HEC-HMS; **b)** Simulated flood hydrograph from HMS as boundary condition to 1-D hydrodynamic model (Mike-11); **c)** Simulated inundation mapfrom HD model, and **d)** Actual flood inundation in Dharampur, showing 1st floor of bus stand fully under flood waters.

urbanization, forestry, agriculture, drainage, or channel modification (Ma *et al.* 2009). A record of such changes over time is essential to updating FF models.

Remote sensing (RS) generates information, sometimes in real time, on the spatial and temporal characteristics of a storm and a basin. The full potential of RS for applications related to flood forecasting can be harnessed by the integration of data from a variety of sensors operating at different wavelengths (Gangwar, 2013). Geographic Information System (GIS) provides a range of visualization products useful for FFWS, e.g. visualization of areas likely to be submerged and the movement of a flood wave (Figure 5).

Digital Elevation Model (DEM): Accurate topographic data are required for modelling flood flows and to produce correct inundation maps. DEMs provide numerical topographic data and are frequently used to extract the river network and calculate land-surface slopes, flow direction and flow accumulation (Thomas, 2014). Two freely available Digital Surface Models (DSMs) with near-global coverage are the Shuttle Radar Topography Mission (SRTM: Farr *et al.* 2007) and the Advanced Spaceborne Thermal Emission and Reflection Radiometer (ASTER: Tachikawa *et al.* 2011). While these DEMs at ~ 30 m horizontal resolution are available nearly globally, there are some non-trivial limitations with the elevation data due to the presence of vegetation, infrastructure, etc. Since FF models are particularly sensitive to the quality of the elevation data (Bates *et al.* 2015), FF should be based on the best-quality DEM data available. Airborne survey using LIDAR or synthetic aperture radar (SAR) is finding increasing applications in FF since it yields high vertical accuracy, but data acquisition costs make these data resources unaffordable for many local applications.

Land Use/Land Cover: Agriculture, forest management and urbanization alter the physical characteristics of land surface and upper soil as well as evapotranspiration. It is well known that the volume and timing of runoff, soil moisture and groundwater recharge are strongly affected by land use changes (DeFries and Eshleman 2004). RS can be used in analysing land use changes, such as the analysis of multi-spectral data for detection of ground features and land use (Mahapatra *et al.* 2013).

Snow/Ice Melt Data: In many areas around the world, snow and glacier melt may produce floods. Since it is often difficult to collect and transmit snowfall data in mountains, RS remains the primary way of obtaining relevant data. Satellite observations are being commonly used to monitor the areal extent of snow cover and glacier inventories (Wendleder *et al.* 2015). At present, the visible, near infrared (IR) and thermal IR data are being used to map the areal extent of snow cover. Microwave RS is promising because of its ability to acquire data in cloudy or night time conditions.

Soil Moisture and Water Storage: In addition to storm characteristics, the magnitude of floods also depends on soil moisture (Bloschl *et al.* 2008). Soil moisture estimates are critical for accurate prediction of floods, because soil moisture determines the partitioning of rainwater between infiltration and runoff. In addition, soil moisture can help correct for errors produced using satellite precipitation products such as false detections and missed events (García *et al.* 2006). Recent advances in RS techniques by using microwave satellite observations have enabled the estimation of surface soil moisture (~10 cm depth) (Hirschi *et al.* 2014), thus generating global soil moisture data (NASA 2015).

Basin-scale estimates of water storage derived from satellite observations of time-variable gravity can be used to characterize regional flood potential and may ultimately result in longer lead times in flood warnings. Using the data of the 2011 Missouri River floods, Reager *et al.* (2014) demonstrated how to establish a relationship between measured river discharge and basin-wide water storage, as measured by the Gravity Recovery and Climate Experiment (GRACE) mission. Applying a time-lagged auto-regressive model of river discharge, they showed that the inclusion of GRACE-based total water storage information allowed for assessing the predisposition of a river basin to flooding by as much as 5–11 months in advance.

Precipitation Measurement: Due to practical limitations in measuring spatially averaged rainfall over large and inaccessible areas, RS-based rainfall estimation is a useful tool for FF. Many satellites have been launched to provide an assessment of rainfall. The National Oceanographic and Atmospheric Administration (NOAA) series, Global Precipitation Measurement, Defense Meteorological Satellite Program (DMSP), Global Operational Environmental Satellite (GOES), Geosynchronous Meteorological Satellite (GMS), Meteosat, and Indian INSAT series of satellites are frequently used for rainfall estimation. Optical and thermal remote sensing provides an indirect assessment of rainfall by assessing cloud cover, type, cloud top temperature, etc.

Flood Inundation Mapping: Detailed mapping of floods and standing water is required to plan relief and rehabilitation, and for damage claims (Sun *et al.* 2011). Satellite-derived near-real-time flood maps are required by stakeholders and policy-makers for disaster monitoring and response. In case of floods, the most common data used during pre- and post-flood is Synthetic Aperture Radar (SAR) and cloud free optical datasets for flood damage assessment and flood inundation model calibration/validation activities (Thakur *et al.* 2011, Sarkar and Vaidya 2014). For hazard planning, model evaluation, and loss and risk analysis, time series of historical flood inundation images are used to create flood hazards maps at various scales (NRSC, 2014).

6. Uncertainties in flood forecasting

A FFWS may have two types of prediction failures: a) the system may fail to issue a warning for a flood event (error of omission), and b) it may issue a warning for an event that does not materialize (error of commission). In the first case, there may be loss of life, infrastructure, and property due to a flood. In the second case, people may lose trust in the forecast and may not respond to the next warning. Thus, analysis and communication of FF errors and uncertainties are critical to minimize the possibilities of either type of failure.

6.1. Sources of errors and uncertainties

Uncertainties arise in FF due to a number of sources: input data uncertainty, model uncertainty, and model parameter uncertainty. Leahy *et al.* (2007) have characterized the uncertainties in the flood warning process and identified the various sources of errors (Figure 6), and Sene (2008) has outlined the general approaches for evaluating uncertainties.

The critical meteorological input in FF is observed and/or forecasted precipitation (Krzysztofowicz 1999, Marty *et al.* 2013). Forecasted precipitation is typically derived from

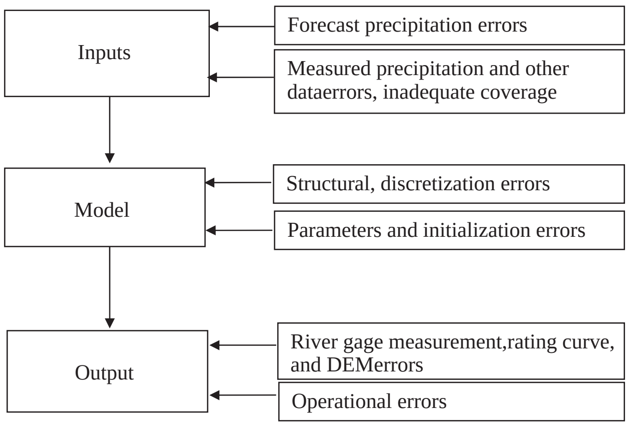

Figure 6. Error framework for rainfall-runoff models used in flood forecasting.

quantitative precipitation forecasts (QPF) by numerical weather prediction (NWP). The grid size of NWP can be a major source of error in rainfall forecast, which is further aggravated by the positional error of these grids. Even observed precipitation can have significant uncertainties. Rain gauges sample a very small area and there can be large gaps between them, which can translate into large precipitation errors, particularly in mountainous areas (Stanton *et al.* 2016). Weather radars can sample large areas but do not directly measure rainfall and there are issues with conversion from reflectivity to rainfall (Catchlove *et al.* 2005). Flood producing storm events typically occur at highly localized scales (<10 km^2) and may not be captured by gridded remotely sensed products, such as TRMM (Stanton *et al.* 2016).

In addition to precipitation, a number of other errors and uncertainties can be substantial. For example, errors associated with the initial conditions (e.g. soil moisture) are particularly important when the models are applied to isolated storm events. In addition, any model updating or downscaling can create errors and uncertainties, as can infrastructure operations (Cloke and Pappenberger 2009). Errors can be introduced with the use of rating curves. Flood forecasts are generally given in the form of level (gauge data), while the hydrological models typically compute discharge. A rating curve is used to transform calculated flows to water levels. Generally, rating curves are developed with a limited number of discharge observations that may not cover extreme flood events, giving sufficient room for uncertainty. In addition, there can also be uncertainties in the gauge observations. Furthermore, operational uncertainty of a FFWS can be caused by erroneous or missing data, human processing errors, or unpredictable interventions (Krzysztofowicz 1999).

Finally, important errors can arise from issues with the structure of RR models misrepresenting hydrologic processes, characterized by: model structure errors, parameter errors, and spatial discretization errors. Model structure results from the decomposition of complex physics of catchments into models of physical processes. These structure errors are not resolved with more data. There may also be significant uncertainty relating to model parameters, which tends to decrease with time as more recorded runoff data become available and is used to tune the model parameters. Parameter uncertainties tend to vary with the size of study area, variabilities in its properties, the number of sub-divisions of the area, and resolution of data. A third primary error associated with RR models is the spatial representation of the catchment, of which there are three common approaches: rectangular grids (e.g. the SHE model), sub-catchments, and response units (e.g. the SWAT model).

6.2. Quantifying uncertainty

Quantifying predictive uncertainty of FF is important in communicating flood risk and in reducing the uncertainties (Arduino *et al.* 2005). However, a full characterization of the cascade of uncertainties from the input data to warning is a complex and computer-intensive process, resulting in uncertainty analysis as one of the key challenges of FFWS (Cloke and Pappenberger 2009).

Several approaches are available for uncertainty quantification of individual FF components. One approach is to evaluate the sensitivity of model to a plausible range of inputs by varying the forecasted rainfall and model parameters. In the initial phases of forecast, the uncertainty is high, as model parameters may be based on past calibration and experience. As the event continues and more observed data become available, improved model calibration increases the confidence in parameters and uncertainty is reduced. The importance of observed data is highlighted by the results of Hunter *et al.* (2005), who reported a greater utility of more stage data over parameterization of inundation models in reducing uncertainty of inundation depths and extents.

A second approach is based on predictive uncertainty (PU) paradigm, which represents the probability of occurrence of a future value of a prediction (water level, discharge, etc.). This probability is conditioned on all of the information that can be obtained on the future value, usually provided by forecast modelling (Krzysztofowicz 1999, Coccia and Todini 2011). The advantage of the PU approach is that uncertainty is quantified in terms of a probability distribution.

The ensemble prediction systems (EPSs) previously discussed allow for the incorporation of effects of a wide range of forecast uncertainties (Kavetski *et al.* 2002), resulting in a probabilistic forecast with uncertainty directly represented (Ebert 2001). Individual models within the ensemble may vary in their assumptions about initial conditions, boundary conditions, model parameterization, model structure, or some combination thereof so as to reflect the uncertainty about them (Buizza *et al.* 2005). Ensembles can be generated in many ways. A popular way is the use of NWP forecasts from an EPS, which are then input to hydrological models to produce HEPS-based forecasts. This approach was the basis for the development of the European Flood Awareness System (EFAS) (Thielen *et al.* 2009). Some ensembles use more than one model within the ensemble (multi-model HEPS) or the same model but with different combinations of physical parameterization schemes (multi-physics EPS) (WMO 2012). Examples of other approaches to ensemble forecasting include consideration of model parameter uncertainty and multi-model approaches, using climatology and initial conditions to generate an ensemble, using error distributions computed from past hydrological forecasts to improve current predictions, or considering spatial uncertainty in rainfall forecast. Generating a suite of forecasts, rather than a single deterministic forecast, provides a way to quantify and thereby communicate the uncertainty about the flood event.

While in broad use, the use of HEPSs is not without challenges. HEPSs need to process large amounts of data generated by ensemble models that may not be available or computationally feasible in many situations. There are difficulties in understanding how best to base flood warning decisions on probabilistic forecasts (Demeritt *et al.* 2010, Nobert *et al.* 2010, Ramos *et al.* 2010). For example, emergency service agencies may be confused by probabilistic forecasts and react either with panic or indifference (Demeritt *et al.* 2010). Furthermore, efforts are needed to characterize and communicate the factors affecting the accuracy of HEPS-based forecasts. Liguori and Rico- Ramirez (2013) assessed the performance of hydrological predictions driven by probabilistic hybrid rainfall forecasts. They provided a hydrological focus on forecast performance by determining the bias affecting ensemble and deterministic hydrological forecasts based on the probability of exceeding predefined thresholds of discharge at the catchment outlet. Zappa *et al.* (2013) provide a 'peak-box' approach to evaluate ensemble forecasts. This approach focuses on the magnitude and time of peak discharges.

In addition, decision making based on probabilistic forecasts issued by an HEPS requires tools to visualize such forecasts and provide user-focused evaluation of ensemble forecasts. Despite the importance of forecast visualization and communication techniques, only a few studies (e.g. Pappenberger *et al.* 2013) have investigated how forecasts are perceived, understood and acted upon by those who receive them. Developing visualization tools and forecast products for communicating uncertainty is a very important task if forecasts are to be useful for flood management. Demeritt *et al.* (2013) discussed communication, perception, and use of EFAS alerts in operational flood management across Europe. Although EFAS alerts are useful and are welcomed, there is hesitance in responding to EFAS medium-term probabilistic alerts, and some institutional obstacles need to be overcome if alerts are to fulfil their potential.

Building on the established success of ensemble weather forecasting, there are now several initiatives to promote the application of meteorological techniques to hydrological modelling, and in particular to real-time FF. One example is the Hydrologic Ensemble Prediction EXperiment (HEPEX) (www.hepex.org) is an ambitious international effort for the reliable quantification of hydrologic forecast uncertainty. By investigating the algorithms and approaches for reliable quantification of hydrologic forecast uncertainty (Schaake 2007), this project is expected to advance both the science and response to flood forecasts. The project has produced a number of special issues in journals, including a 2013 special issue on 'Hydrologic Ensemble Prediction Systems' in Hydrologic Processes and a 2014 special issue on 'Ensemble prediction and data assimilation for operational hydrology. Such large-scale and collaborative projects are essential to advancing the quality and application of FFWS.

7. Warnings and dissemination

The flood warning and dissemination process is a complex and critical component of the FFWS system that involves two distinct stages: (1) creation and transmission of forecasts and warnings to end users, and (2) response. A prompt and wide coverage of flood warning is the key to a successful FFWS, but an accurate forecast without adequate planning and communication will fail to achieve the intended responses by the exposed community, including the evacuation of vulnerable groups (e.g. very young or old and mobility-limited) who are unable to respond quickly to warnings, movement of assets (food, livestock, moveable goods, etc.; Wood *et al.* 2015) to safer locations, efficient and timely operation of flood regulation infrastructure, and initiation of flood fighting measures. Key factors in dissemination include packaging information into forms that are understandable and usable by end users, and the rapidity with which information is communicated to them.

Information must be targeted to the range of end users of the FFs, which include disaster managers, municipalities and local government officers, affected population, and infrastructure managers. Forecasts are also sent to decision-makers to help visualize how an event is likely to develop, how significant it will be upon arrival, and what sections of the population will likely be at risk. Emergency services and media agencies need clear information that defines the hazard. Establishing a user group association or an inventory of users is important for a well-functioning and effective FFWS.

Dissemination of forecasts and warnings may be achieved through a variety of communication methods, such as internet, flood bulletins to disaster management authorities (including police and fire departments), television, radio, telephone, bulk SMS, sirens, flags, and social media (i.e. Facebook, Twitter). In remote locations, local radio, if present, may be the most reliable means for disseminating information in local language. Other locally available alert systems, such as community/ temple bells and loudspeakers, can be an effective means and have shown success in Nepal and Bangladesh.

8. Future directions

Although a number of models have been developed and applied for operational FF in various countries, there is still a need for computationally efficient models that can adequately take into account catchment properties and their variations, and where forecasts can be quickly updated. Pagano *et al.* (2014) describe four key challenges in operational forecast, namely: (i) best use of available data, (ii) modelling for accurate prediction, (iii) translating forecasts to effective warnings-disseminating timely information to affected community and concerned authority for taking right decision, and (iv) administering the operational forecast - conservative approach of forecasting institutions due to perceived liability, capacity building of personals and retention of talented employee. Further, hydrologic forecasting in ungauged basins continues to be a challenging problem, though the reliability of global flood models is rapidly increasing (Bates *et al.* 2015).

It is also important to compute uncertainties in the forecasts and incorporate these as an integral part of warnings. Significant advances are being made in remote-sensing techniques, and hydrologic modelling tools for FF need to be continuously updated to make full use of these techniques. Measurement of river flow by satellite-based sensors has the potential of overcoming problems, where such data are not available. Insufficient implementation and maintenance of ground-based, real-time hydrologic observation still remains a challenge, because it is necessary to determine the lag time between data observation and availability to flood forecasters. Administrative barriers to data availability, across geopolitical boundaries and within the same boundary but across different agencies, also hamper FF. The consequences are that lead time is compromised and unreliable forecasts may be issued.

The design of a FFWS is technical but its implementation is non-technical. The non-technical aspects are primarily logistics and administrative and include preparation, accumulation of needed amenities, plans for evacuation, facilities for transportation of people, issuance of warning, communication systems, electrical systems, shelter for people, food and clothing, medical supplies, manpower for help, counselling, among others. The effectiveness of an FFWS greatly depends on these nontechnical aspects. It is important that technical and non-technical aspects are seamlessly integrated. Often, a simple FFWS may work well, provided non-technical issues are properly addressed.

Communication systems, especially in developing countries, are often vulnerable in times of severe flooding and are rendered inoperative when they are needed most. In these areas, back-up communication systems and educational campaigns are needed to help the general public understand the various facets of floods so that they follow warnings and protect themselves even in the absence of any warning. During and after flooding, adequate relief measures must be provided at short notice, which requires that administrators have the technical, financial, and political resources to prepare in advance and respond quickly and effectively. Likewise, post-flood disaster, people should be helped so that they can become more resilient to future potential floods.

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No potential conflict of interest was reported by the authors.

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