A review of the understanding of uncertainty in a flood forecasting system and the available methods of dealing with it

Leonore Boelee[1], Darren Lumbroso[1], Paul Samuels[1], Elisabeth Stephens[2] & Hannah Cloke[2]

[1,] HR Wallingford Wallingford, Oxfordshire OX10 8BA, UK
(Email:boelee@hrwallingford.com; d.lumbroso@hrwallingford.com; p.samuels@hrwallingford.com)
[2] University of Reading, Reading, United Kingdom
(Email:.l.cloke@reading.ac.uk; elisabeth.stephens@reading.ac.uk

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Abstract

The increased availability and application of probabilistic weather forecasts in flood forecasting means that the uncertainty arising from the precipitation forecast can be assessed. This has led to a wider interest in how uncertainty is affecting flood forecast systems. In literature there are general techniques and principles available on how to deal with uncertainty. However, there are no of well-accepted guidelines on the implementation these principles and techniques. There is neither coherent terminology nor a systematic approach which means that it is difficult and perhaps even impossible to assess the characteristics and limitations of uncertainty quantification methods. Selecting the most appropriate method to match a specific flood forecasting system is therefore a challenge. The main findings of this review are that there are remaining mathematical and theoretical challenges in uncertainty quantification methods and that this leads to the use of assumptions which in turn could lead to a misrepresentation of the predictive uncertainty.

Keywords
Ensembles; Flood forecasting; hydrological modelling; hydraulic modelling; uncertainty.

1. Introduction

Flooding affects an average of 520 million people a year and is one of the most frequently occurring and deadly natural phenomena (James *et al.*, 2007). Flood warning is a non-structural measure which has proved to be efficient and cost effective in minimizing negative impacts of flooding (WMO & GWP, 2013;Mishra and Singh, 2011; Mishra and Singh, 201; Pappenberger *et al.*, 2015). Flood forecasting systems rely on a combination of historical observed data, in-situ measurements and models to produce forecasts. This paper focusses on fluvial flood forecasting systems. Operational flood forecasting systems, or real-time flood forecasting systems, are continuously running systems that forecast at a point in real time (defined as the forecast time origin) for a future time (WMO & GWP, 2013). They consist of four main components (Zappa *et al.*, 2011):

I. **Numerical Weather Predictions (NWP)** can be deterministic or probabilistic; atmospheric observations are assimilated into NWP systems to produce forecasts (Rossa *et al.*, 2011). Although this is highlighted by Zappa *et al.* (2011) as a main component of a flood forecasting system, not all systems have a NWP component, for example basic flood forecasting systems can use a river level to river level correlation between an upstream gauge and downstream point(s) of interest. For more details on NWP prediction systems the reader is referred to Palmer (2000).
II. **Hydrological initial conditions** from observations or models for a flood forecasting system represent soil moisture, snow cover, the river and other waterbodies (Li *et al.*, 2009 and Madsen and Skotner, 2005). Initial conditions can be either observed or estimated using models. If observations are available, data assimilation can be used to update the model. The subject of data assimilation is outside of the scope of this paper, for more information on this the reader is referred to (Liu *et al.*, 2012).
III. **Flood prediction systems** use models to predict the state of the river; often a combination of model types are used. Available models for flood prediction include physically based models, conceptual models and data-driven techni ques (Mure-Ravaud *et al.*, 2016). At the end of the modelling chain the flood prediction system will predict the variable (e.g. simulated discharge, water level) at the point(s) of interest.
IV. **Warnings for end users**; the communication of uncertainty is beyond the scope of this paper and the reader is referred to Kreibich *et al.* (2016).

Historically, many flood forecasting systems produced deterministic forecasts. Ensembles of Numerical Weather Predictions (NWPs) are being increasingly used in flood forecasting systems. This allows the uncertainty of the meteorological forecast input data to be assessed, examples of this development include The Hydrological Ensemble Prediction Experiment (HEPEX, 2017) initiative (Cloke and Pappenberger, 2009). Recently, there has been more emphasis on the presence of uncertainty in all components of the forecasting system (Krzysztofowicz, 2002; Pappenberger *et al.*, 2005). Research with end-users has found that there is an appetite for uncertainty information if improvements in accuracy and lead time can be achieved (Lumbroso *et al.*, 2009). Powerful techniques are becoming more widely available within flood forecasting systems and these allow the quantification of uncertainty, sensitivity analysis, risk analysis and decision analysis. However, there are no of guidelines on how to implement these principles and techniques in complex flood forecasting systems where there are multiple sources of uncertainty to consider (Zappa *et al.*, 2010; Liu and Gupta, 2007). There is a lack of coherent terminology and systematic approaches which leads to difficulty in assessing characteristics and limitations of individual methods. This makes selecting the most appropriate method for practical problems difficult and perhaps impossible (Montanari, 2007). Within flood forecasting systems Liu and Gupta (2007) highlight four areas that need to be addressed:

I. Understanding of uncertainty
II. Quantifying uncertainty
III. Reducing uncertainty
IV. Communication of uncertainty.

This paper focusses on areas one and two: the understanding and quantification of uncertainty. More explicitly, the aim of this paper is to provide a review of the understanding of uncertainty in flood forecasting systems and the available methods of dealing with it. Further, this paper identifies gaps and limitations with regards to the understanding and quantification of uncertainty.

2. Understanding uncertainty

2.1. Definitions of uncertainty

Uncertainty indicates that something is not able to be relied on, is not known or not definite (Oxford English Dictionary, 2017). Two well-known types of uncertainty are: aleatory and epistemic. Aleatory uncertainty is uncertainty resulting from natural variability and randomness and epistemic uncertainty is uncertainty due to lack of knowledge (Li, Chen and Feng, 2013). In flood forecasting systems uncertainty can be referred to in terms of 'predictive uncertainty' or 'predicting the uncertainty', (Todini, 2008; Weerts, Winsemius and Verkade, 2011; Palmer, 2000; Van Steenbergen and Willems, 2015; Zappa *et al.*, 2011), which is defined by Todini, (2008) as "the probability of any future (real) value, conditional upon all the knowledge and information, available up to the present.".

2.2. The sources of uncertainty

Sources of uncertainty in a flood forecasting system are linked to the elements that are included in the chain of models and will vary for different forecast setups. For example, the inclusion of a hydraulic model to estimate the levels and extent of flooding would add additional sources of uncertainty to a forecasting system which are only relevant if this element is part of the model chain. Krysztofowicz (1999) identifies input uncertainty and all other uncertainties in the aggregate (e.g. hydrological uncertainty). Table 1 shows the varying sources of uncertainty that can affect a flood forecasting system.

Table 1: Varying sources of uncertainty that can affect a flood forecasting system

Sources of uncertainty according to (Pappenberger *et al.*, 2005)	**Sources of uncertainty according to** (Cloke and Pappenberger, 2009)	**Sources of uncertainty according to** (Zappa *et al.*, 2011)	**Sources of uncertainty according to** (Klein *et al.*, 2016)
Rainfall forecast	Correction and downscaling	Forecast data	NWP
Runoff model	Spatial and temporal owing to initial conditions and data assimilation	Initial conditions	Initial and boundary conditions of hydrological and hydraulic models
Hydraulic model	Model unable to fully represent processes	Model unable to represent processes	Meteorological observations
	Infrastructure failure	Observed data	Model parameters
	Model parameters		
	Geometry of the system		

Being explicit in naming sources of uncertainty is challenging owing to the wide variety of flood forecasting systems. The most prevalent sources of uncertainty affecting flood forecasting systems have been identified as: uncertainty resulting from NWP forecasts, uncertainty from issues with measurements and observations, uncertainty due to initial conditions, uncertainty due to the model being unable to fully represent processes and uncertainty due to parameters. In this paper NWP forecasts are classified as input data and the uncertainties are treated as a single source of uncertainty. The authors are aware that NWP originates from atmospheric prediction models and uncertainty sources can be separated out in more detail; however, this is outside the scope of this paper.

2.2.1. Uncertainty due to using NWP forecasts

Atmospheric variables that are used in flood forecasting systems include precipitation, temperature and evaporation. Precipitation is considered to be the variable that has most effect on a flood forecasting systems outputs (e.g. water level, flow) (Strauch *et al.*, 2012). Excluding seasonal forecasts, there are three types of precipitation forecasts that are typically applied to flood forecasting systems:

I. Short to mid-range precipitation forecasts for NWP.
II. Short term rainfall forecasts and nowcasts (e.g. 0 to 9 hours) from extrapolation from weather radar rainfall estimations (Liguori and Rico-Ramirez, 2014).
III. Merged NWP with radar products have been developed which combine the high spatial temporal resolution of radar nowcasting with the longer lead times of NWP forecasts.

Significant uncertainty is associated with forecasting precipitation (Bauer, *et al.*, 2015). In radar nowcasting, uncertainty is due to a combination of uncertainty in the observations of the radar data and uncertainty in estimations in modelling the movement of the precipitation field in space and time (Liguori and Rico-Ramirez, 2014). In the NWP predictions uncertainty is due to model uncertainty, boundary and initial conditions. These uncertainties can be assessed using an ensemble (Palmer, 2000). A mismatch between the scale of the atmospheric model outputs and the required scale of the hydrological model can be solved by using downscaling techniques (Rodriquez-Rincon, *et al.*, 2015). However, these techniques lead to uncertainties and have limitations (Fowler and Wilby, 2007).

2.2.2. Uncertainty due to measurement and observations

Observations are essential to the calibration and validation of flood forecasting systems but are uncertain themselves (Gotzinger and Bardossy, 2007). Observed data are affected by both random and systematic errors varying over time. Frequently occurring uncertainties relating to the difference between the spatial and temporal characteristics of the observations compared to the model include:

I. Uncertainty due to the interpolation techniques used for applying a point measurement to areal or volumetric model inputs (Gotzinger and Bardossy, 2007).
II. Uncertainty due to using a rating curve to convert water level into a discharge, for more details the reader is referred to McMillan *et al.*, (2012) and Di Baldassarre and Montanari (2009).
III. Uncertainty in remote sensing data due to the sensing and retrieval techniques used (Li *et al.*, 2016).
IV. Uncertainty in radar rainfall observations due to the difficulties in distinguishing solid precipitation (e.g. snowflakes and hailstones), the effect of terrain blocking and inaccuracies in the reflectivity-rain rate relationship (McMillan *et al.*, 2012).

The reader is referred to (McMillan, *et al.*, 2012) and (Li *et al.*, 2016) for a comprehensive review of uncertainty in measurements.

2.2.3. Uncertainty due to initial conditions

The initial conditions in flood forecasting systems include the soil moisture, snow cover, initial state of the rivers and other waterbodies in the catchment (Li *et al.*, 2009; Madsen and Skotner, 2005). Not all initial conditions can be observed or will have data available. As a solution these conditions are estimated using models, which leads to uncertainty. The continuous simulation of a flood forecast system will also inherit state uncertainty from preceding time steps (Gotzinger and Bardossy, 2007). Initial conditions that are especially associated with large uncertainty are soil moisture and snow cover (Li *et al.*, 2009).

2.2.4. Uncertainty owing to the model unable to fully represent processes

The inherent simplifications of the model to represent the more complex real system leads to uncertainty. For example, distributed hydrological models use polygons or grids to represent the catchment, this will lead to uncertainty, as the physical processes (e.g. related to soil structure) often occur on smaller scales than the model elements (Gotzinger and Bardossy, 2007). An overview of different models in hydrology is provided by Todini (2007) for hydrological models and (Knight, 2013). An example of the range of uncertainty in hydrological models is presented by Haddeland *et al.* (2011) where 11 global models were forced with the same data. The results had significantly different results ranging from 290 to 457 mm/year depending upon the partitioning of evaporation and runoff year.

2.2.5. Uncertainty due to model parameters

Model parameters are related to the input data (Matott *et al.*, 2009) but are not necessarily actual physical variables or are not directly measurable, which means they need to be calibrated to find values that are able to match the input-output behaviour of the model to the real system (Vrugt *et al.*, 2003). The estimation or calibration processes inevitably leads to uncertainty. Parameter uncertainty will be different due to using different types of models available, e.g. conceptual, physical and black box. The parameters of a hydrological model (conceptual model) relate to catchment characteristics such as soil type, vegetation, antecedent moisture conditions. Variation in catchment characteristics leads to variation of the parameters. These local spatial heterogeneities and non-stationarities in the catchments affect the parameters, making them difficult to estimated effectively (Gupta *et al.*, 2003). This leads to a lack of transferability of the parameters across the catchment, which will inevitably lead to uncertainty of the runoff prediction (Pappenberger *et al.*, 2005). In the case of hydraulic models (physically based) local heterogeneities in the channel and floodplain geometry and cover will affect the parameters. Local parameters will need to be calibrated using observed data, of which are often limited. As a result there will be uncertainty with respect to the hydraulic model outputs, which can include flood inundation and the flood wave propagation (Pappenberger *et al.*, 2005). Of course the parameters themselves can never represent reality which brings additional uncertainty due to e.g. equifinality (Beven and Freer, 2001) .

3. Quantifying uncertainty

To understand, analyse and compare different types of uncertainty, quantification methods are helpful to classify them into different categories. Montanari (2007) distinguishes four types of uncertainty quantification methods:

I. Approximate analytical methods; deriving uncertainty using known statistical properties of the system and input data.
II. Approximate numerical methods/sensitivity analysis; define the system space as a collection of all possible modelling solutions that can be obtained by varying the parameters and model structure. Multiple runs can then be performed randomly sampling the system and input data space, the uncertainty can be derived from the collection of outputs.
III. Techniques based on the statistical analysis of model error; statistical analysis of the model residuals of the forecast value compared to the observed values.
IV. Non-probabilistic methods; based on random set theory, evidence theory, fuzzy set theory or possibility theory which provide possibilistic information.

Methods from the first category are limited in flood forecasting due to the statistical properties of the input space being mostly unknown (Van Steenbergen *et al.*, 2012). The fourth category is mostly relevant to situations with very limited data availability where human reasoning (possibilistic information) is used to assess the likelihood of a scenario taking place. The most common methods in flood forecasting to quantify uncertainty fall into categories two and three. Methods do not necessarily fall into a single category, but can fall across several categories (Montanari, 2007).

3.1. Approximate numerical methods and sensitivity analysis

The approximate numerical methods and sensitivity analysis aims to move away from the principle of a single optimum model setup, in which the model setup includes both model structure and model parameters. The philosophy behind this is that there are multiple model structures and parameters within these structure, that will provide an equally acceptable representation of the complex environment (Beven and Freer, 2001). The defined system and input space should cover all model parameters, structure and input uncertainty. Random sampling over the space is applied, allowing multiple model runs to take place (Van Steenbergen and Willems, 2015) . Observed data are not required as a direct input in this methods. The multiple model runs that are part of this methods will require additional computational power and data management resources compared to traditional deterministic methods of forecasting.

The main challenge when applying this method is defining the input and system space so that it will cover all aspects of uncertainty. Two approaches are available to this: 1) importance sampling (Kuczera and Parent, 1998); and 2) using a response surface with weights, the most common method to do this is the generalised likelihood uncertainty estimator GLUE (Beven and Freer, 2001).

An example of using resampling and multiple model runs is where the uncertainty of all model components of the flood forecasting chain were quantified (Pappenberger *et al.*, 2005); a probabilistic weather forecast containing 50 members and one control was used. The parameter uncertainty of the rainfall-runoff model was quantified using GLUE. GLUE was also applied to the flood inundation model in order to get ten different sets of roughness coefficients. This uncertainty analysis was applied to the European Flood Awareness System (EFAS); more details about EFAS are provided in Figure 1.

3.2. Techniques based on the statistical analysis of model error

Techniques based on the statistical analysis of model uncertainty use statistics derived from comparing the forecast values to observed values. An example of this is the probability distribution of model residuals which can be derived by comparing, for example, forecast value of river discharge to observations (Montanari and Brath, 2004). This method assumes that the future uncertainty can be represented using the model residuals of past forecasts. This method is attractive due to the low requirements with regards to computational power and data management, because multiple model runs are not required. When dealing with data scarce locations the application of this method is limited, due to observed data being directly used. From the perspective of observed data being in itself uncertain, this method has a limited ability quantify uncertainty correctly (Montanari and Brath, 2004). Assumptions regarding stationarity and ergodicity of the model residuals are often required, but remain disputed for different systems and for different states of a system.

Box 1 Uncertainty in the European Flood Awareness system

Operating Authority: European Flood Alert system (EFAS)

Models used: LISFLOOD, a GIS based distributed hydrological rainfall runoff routing model on a 5km grid with six hourly time steps. (Van Der Knijff et al., 2010)

Forecast rainfall: Deterministic forecast rainfall from the Deutsche Wetterdienst, ECMWF deterministic and ensembles (VAREPS) and Ensembles from Consortium for Small-scale Modelling (COSMO).

Uncertainty method: The uncertainty method is based on the atmospheric uncertainty which is quantified using ensembles and weather prediction from different models. The weather predictions from the different models and the ensembles are push through the hydrological model (LISFLOOD). Warnings are probabilistic based on return period threshold exceedance.

Example output – Probabilistic threshold exceedance warnings. (ECMWF, 2016; Smith *et al.*, 2016) More information available: https://www.efas.eu/user-information.html and Thielen 2009

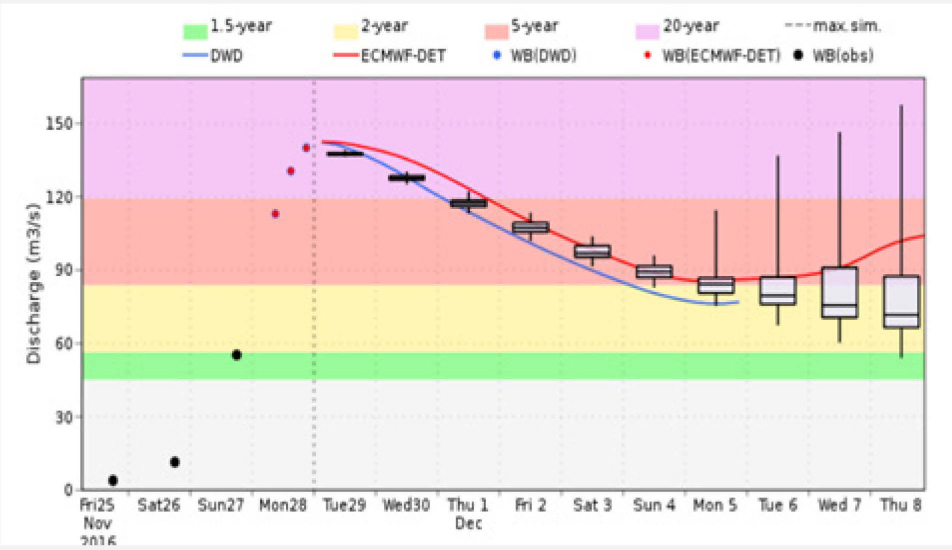

Figure 1: Box 1: Uncertainty in the European Flood Awareness system

An example of the application of this method is given by Weerts *et al.* (2011) when they aim to quantify the predictive uncertainty of the rainfall-runoff and hydraulic forecasts. A retrospective quantile regression is applied to the hindcast water level. Independent sources of uncertainty are not considered, instead the effective uncertainty of the forecast process is considered, which can be a result of input or output uncertainty, model structural uncertainty or parameter uncertainty. The method has been tested for robustness on catchments across England and Wales of different sizes and hydrological characteristics (Weerts *et al.*, 2011).

3.3. Combining the methods

These two methods represent two different approaches to quantifying uncertainty in flood forecast systems. However, due to the fact that flood forecasting systems consist of multiple components, there are forecasting systems that use a combination of these two methods. An example is described by Krzysztofwicz and Herr

(2001), where a Bayesian formulation of a Hydrological Uncertainty Processor (HUP) was used in combination with probabilistic precipitation forecast. The HUP aims to quantify the aggregate of all uncertainties arising from sources other than those quantified by the probabilistic precipitation forecast. This system has been applied to the National Weather Service for a 1,430km^2 catchment in Pennsylvania, USA. The probabilistic precipitation forecast was generated using the first method, but the HUP is part of the second method.

4. Conclusions

Two main challenges have been identified as part of this review on the understanding and quantification of uncertainty for flood forecasting systems. The first challenge is that there is a lack of coherent terminology around uncertainty in flood forecasting. Calls for a more coherent terminology, for example by Montanari (2007), have thus far proven difficult to achieve. It could be that the difficulty lies in finding terminology around uncertainty that will be applicable to the wide variety of systems within flood forecasting. Another difficulty lies in the fact that flood forecasting brings together a wide variety of different disciplines, including meteorologists, hydrologists, geographers, mathematicians, engineers and social scientists.

The second challenge that has been identified is that the remaining mathematical and theoretical challenges in the quantification of uncertainty requires assumptions to be made that could be leading to a misrepresentation of the predictive uncertainty. More specifically for approximate numerical methods and sensitivity analysis creating a usable ensemble that covers the input and system space remains a challenge. In the case of techniques based on the statistical analysis of model uncertainty the questions around how representative the historical model residuals are for the future uncertainty remain unanswered.

Opportunities to improve uncertainty quantification methods can be found for example in the field of data assimilation and in many cases the coming together of research form different disciplines can be instrumental in developing better methods.

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