

OVERVIEW

Operational and emerging capabilities for surface water flood forecasting

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Abstract

Surface water (or pluvial) flooding is caused by intense rainfall before it enters rivers or drainage systems. As the climate changes and urban populations grow, the number of people around the world at risk of surface water flooding is increasing. Although it may not be possible to prevent such flooding, reliable and timely flood forecasts can help improve preparedness and recovery. Unlike riverine and coastal flooding where forecasting methods are well established, surface water flood forecasting presents a unique challenge due to the high uncertainties around predicting the location, timing, and impact of what are typically localized events. Over the past 5 years, there has been rapid development of convection-permitting numerical weather prediction models, ensemble forecasting, and computational ability. It is now theoretically feasible to develop operational surface water forecasting systems. This paper identifies three approaches to surface water forecasting utilizing state-of-the-art meteorological forecasts: empirical-based scenarios, hydrological forecasts linked to presimulated impact scenarios, and real-time hydrodynamic simulation. Reviewing operational examples of each approach provides an opportunity to learn from international best practice to develop targeted, impact-based, surface water forecasts to support informed decision-making. Although the emergence of new meteorological and hydrological forecasting capabilities is promising, there remains a scientific limit to the predictability of convective rainfall. To overcome this challenge, we suggest that a rethink of the established role of flood forecasting is needed, alongside the development of interdisciplinary solutions for communicating uncertainty and making the best use of all available data to increase preparedness.

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Engineering Water > Engineering Water

KEYWORDS

decision making, flood forecasting, operational, pluvial, surface water

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1 | INTRODUCTION

Surface water flooding, or pluvial flooding, is defined as “flooding as a result of rainfall when water ponds or flows over the ground before it enters a natural or man-made drainage system or watercourse, or when it cannot enter because the system is already full to capacity” (SEPA, 2009). Surface water flooding in this context is usually the result of convective weather systems that cause intense rainfall over short periods of time. In the United Kingdom, this type of rainfall typically occurs in the summer months but can occur at any time of the year (Blenkinsop, Lewis, Chan, & Fowler, 2016; Flack et al., 2019; Hand, Fox, & Collier, 2004). Flash floods resulting from rapidly developing convection systems or alignment of storm cells can be particularly dangerous (Pilling, Dodds, Cranston, Price, & How, 2016) and affect large numbers of people if they occur over urban areas. For example, in England, there are more properties at risk of surface water flooding than river and coastal flooding combined (Environment Agency, 2009). The United Kingdom as a whole is relatively unique in its flood risk management approach as they consider surface water flooding separately to flash flooding in steep small catchments; other countries forecast these events on a continuous scale using the same system. Although the main focus of this paper is on surface water flood forecasting, the content is largely applicable to forecasting flooding from any short-duration rainfall event.

Surface water flooding presents unique challenges to decision-makers due to high uncertainties around predicting the location, timing, and impact of what are typically localized events. Increasing urban populations and aging drainage systems, combined with an increase in intense rainfall events as the climate changes, will result in increasing risk of surface water flooding in the future. Although it may not be possible to prevent flooding from intense rainfall, reliable real-time forecasts are crucial to support improved preparedness and response (Flood Forecasting Centre, 2018). A real-time surface water flooding forecasting system requires a combination of hydrological and meteorological modeling. For example, hydrological models are required to represent surface runoff, inundation, and water movement and show how water travels via surface, subsurface, urban sewerage, and drainage networks. High-resolution probabilistic rainfall forecast models are required to quantify the uncertainty in forecasting the rainfall, which causes surface water flooding.

In this paper, we review the recent UK and international developments in hydrometeorological forecasting and consider how they support decision-making by first responders and emergency managers. This includes the emergence of operational surface water flood forecasting systems and the increased use of crowdsourced data to support such systems. This review is part of a project funded by the Scottish Environment Protection Agency (SEPA) to inform their decision-making around the development of future surface water flood forecasting tools in Scotland (Speight, Cranston, Kelly, & White, 2019). It is based on a literature review of international examples of operational surface water flood forecasting tools with a strong focus on examples from the United Kingdom. The analysis was supported by discussions with industry experts and leading academics (as listed in the acknowledgments) to incorporate emerging capabilities and recent applications on new operational systems.

The structure of this paper is as follows. First, we discuss the importance of effective surface water flood forecasting to support decision-making (Section 2). Section 3 details the step change in convection-permitting numerical weather prediction (NWP), which has enabled the development of surface water flood forecasting. Section 4 provides examples of operational and near operational surface water flood forecasting tools. This is followed by a comparison of the different approaches and a review of their suitability in different operational scenarios. Section 5 considers the benefits of including “nontraditional” sources of observation data in forecasting systems. Finally in Section 6, based on the findings of this review, we identify five grand challenges for operational surface water flood forecasting.

2 | THE CHALLENGE OF SURFACE WATER FLOOD FORECASTING

Given the potentially high impact of surface water flooding, there is a growing need to make the best use of available and emerging science to develop surface water forecasting tools. Effective forecasts at national and local scales are crucial to saving lives and livelihoods during flood events. Surface water flooding presents a challenge for forecasters because the events are often very localized, develop quickly and only last for short periods of time. This results in uncertainties around predicting the location and timing of convective events (Flack, Skinner, et al., 2019). The introduction of convection-permitting NWP and ensemble forecasts (Golding et al., 2014; Golding, Roberts, Leoncini, Mylne, & Swinbank, 2016) resulted in a step change in rainfall forecasting capabilities (Clark, Roberts, Lean, Ballard, & Charlton-Perez, 2016). It is now theoretically possible to forecast surface water flooding in urban areas. However, the probability of occurrence for any given location is likely to remain low at lead times beyond a few hours (Speight et al., 2018).

2.1 | A universal framework for surface water forecasting systems

In this review, surface water forecasting systems are considered as an end-to-end framework (see Flack, Skinner, et al., 2019). They incorporate

1. meteorological observation and forecasting;
2. a form of hydrological or hydrodynamic modeling to calculate flood hazard, which may also include an assessment of potential impact; and
3. postprocessing of the model output and visualizations used to inform the hydrometeorological assessment. This is then communicated to decision-makers who take action based on the forecast.

This process is illustrated in Figure 1. Previously the main challenge of completing this chain was computational ability (which still remains significant and should not be taken lightly). Today, however, the main challenges are representing the uncertainties around the location and timing of the heavy rainfall forecasts, understanding how this uncertainty propagates through the forecasting chain and impacts decision-making, and communication of the risk to first responders and the public, particularly when probabilities of impact may remain low until very close to the event. Beyond the forecasting timeframe presented in Figure 1, validation and verification of forecast models is an essential component of any forecasting system. The validation and verification of risk-based forecasts is an emerging research topic in its own right particularly due to the complication that such systems are designed to promote actions to mitigate the forecasted impacts and challenge of collecting observation data on impacts (Harrowsmith et al., 2020; Robbins & Titley, 2018). The topic of verification is not explicitly covered in this paper beyond consideration of the potential of alternative data sources to be used for this purpose.

Before developing a surface water forecasting system, it is important to establish realistic aims for the system that balance the end-user requirements and the scientific and practicality feasibility (Flack, Skinner, et al., 2019). There are two recent developments that have been fundamental to making these discussions possible. First, the growth of impact-based forecasting (e.g., Dale et al., 2014; Harrowsmith et al., 2020; Hemingway & Robbins, 2020; Neal, Boyle, Grahame, Mylne, & Sharpe, 2014; Potter et al., 2018; World Meteorological Organisation, 2015) has helped focus the attention of decision-makers on areas with the highest expected impacts. This enables efficient resource management decisions to be made despite potential high uncertainties in the spatial location of rainfall. Second, there has been a growing acceptance of the need for probabilistic forecasts for surface water flood forecasting (Clark et al., 2016; Golding et al., 2014) and a growing familiarity among decision-makers of using probabilistic forecasts (Arnal et al., 2019; Rabb, Boeing, Shelton, & Birch, 2019). Combined this has resulted in decision-makers improving their skills and confidences in making decisions under uncertainty.

2.2 | What type of information is needed from a surface water flood forecasting system to support decision-making?

Fluvial and coastal flood warning systems offer long lead times and bespoke local information for individual at-risk areas (for details of the UK system see Cranston & Tavendale, 2012; Dale, Davies, & Harrison, 2012, Price et al., 2012;

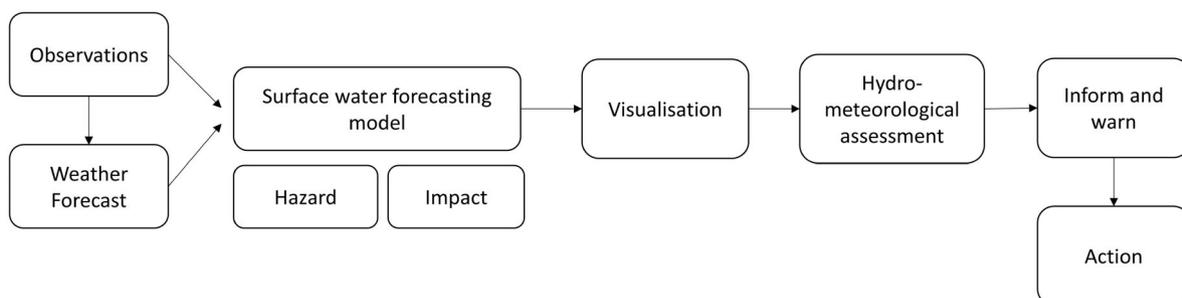


FIGURE 1 Typical structure of an end-to-end surface water flood forecasting system

Werner, Cranston, Harrison, Whitfield, & Schellekens, 2009). Due to the challenges of forecasting surface water flooding, the same level of information is not available for pluvial events.

For the purpose of this review, decision-makers are considered to be people who take proactive action based on the flood forecast. For surface water flooding, action may include clearing trash screens in urban areas, calling in additional staff to respond to incidents, activating community response mechanisms, and installing property-level protection. Once flooding occurs, reactive actions dominate such as rescuing people and vehicles from inundated areas or activating pumps (see Dale et al., 2013; Ochoa-Rodríguez, et al., 2018; Rabb et al., 2019 for other examples). Different decision-makers have different requirements from a flood forecasting system. The actions they take may require different lead times to activate (Kox, Kempf, Lüder, Hagedorn, & Gerhold, 2018), and they may be willing to act at different levels of probability based on their acceptance of “acting in vain” (Coughlan de Perez et al., 2016) should an event not occur following the forecast. There is not a one-size-fits-all solution (Kox et al., 2018; Priest, Parker, Hurford, Walker, & Evans, 2011; Rothfus et al., 2018), yet there is a growing need to provide targeted surface water forecasts to support informed decision-making (DEFRA, 2018; Halcrow, 2011; Ochoa-Rodríguez et al., 2018; Pitt, 2008; Priest et al., 2011; Rabb et al., 2019; Speight et al., 2018).

The development of impact-based forecasting has shifted the focus away from providing details of “what the weather will be,” which can be meaningless without further context, to warning of “what the weather will do” (Harrowsmith et al., 2020); for example, saying there will be fast flowing water, damage to property, or risk to life. Two recent studies have sought to identify the specific needs of decision-makers at the city and local scale for surface water flood forecasting in the United Kingdom. Speight et al. (2018) established a steering group of key responders in Glasgow, including SEPA, the City Council, Scottish Water, and Transport Scotland. Rabb et al. (2019) surveyed a similar group of responders in Yorkshire, which included the Environment Agency, multiple city and local councils, Yorkshire Ambulance Service, and Yorkshire Water. Both groups identified similar end-user requirements from a surface water flood forecasting system, which were as follows:

1. To focus on the 6–24-hr lead time to enable proactive preparations; with 12 hr seen as a critical forecast horizon although some organizations such as the emergency services were happy with a 1–2-hr lead time.
2. To provide guidance on event timings, specific locations that might be affected, and possible impacts and severity.
3. To include relatively low-likelihood but high-impact events to enable proactive low-regret actions to be taken
4. To communicate a stand-down message when the event is over or the risk level reduced.

These priorities are reflected in other European studies and international reviews (Harrowsmith et al., 2020; Zhang et al., 2019). For example, during workshops with emergency responders about the usefulness of weather warnings from the German Weather Service (DWD), Kox et al. (2018) identified requirements for details of expected impacts over relevant temporal and spatial domains; “intensification of warning” messages as an event develops and expected end time of the event. German emergency responders responsible for proactive preparations required lead times of over 12 hr, while those such as the fire service who were involved in event response were happy with lead times of 6 hr or less. In France, the ongoing PICS project (Prévision immédiate intégrée des impacts des crues soudaines, <https://pics.ifsttar.fr/en/>), which aims to integrate flash flood models and impact assessment, held a workshop with end users to identify user priorities for the new model. Again, the priorities were for detailed forecasts at a 6-hr lead time with frequent updates and real-time inundation maps showing the expected impact area at a detailed spatial resolution (PICS, 2018). The findings of the above reviews are of significant value as they highlight areas for forecasts to focus on and so improve the overall usefulness of surface water flood forecasts within decision-making.

3 | ADVANCES IN METEOROLOGICAL MONITORING AND FORECASTING

Accurate and reliable rainfall observations and forecasts are crucial for effective forecasting of surface water flooding. Surface water flooding is often caused by small-scale thunderstorms whose magnitude and distribution are difficult to monitor and predict. As such, rainfall observations and forecasts are thus required at high spatial and temporal scales.

3.1 | Rainfall monitoring

Rainfall observations can be used either directly in the surface water forecasting system or to provide initial conditions to improve precipitation forecasts. In the context of surface water flood forecasting, a major challenge for the use of rain gauge data is maintaining a dense enough spatial coverage of gauges to observe localized intense rainfall. The literature suggests a density of one gauge per 1 km² is needed to support accurate urban hydrological modeling and forecasting (Liguori, Rico-Ramirez, Schellart, & Saul, 2012; Schilling, 1991). In the United Kingdom, the rain gauge network is not sufficient for this purpose. For example, on 18th July 2017, Coverack (in southwestern England) experienced what is understood to be one of the most extreme short-duration rainfall events ever seen in the United Kingdom. However, while 44 properties were flooded and fast flowing water and debris presented a significant risk to life, the nearest Environment Agency rain gauge located 8 km away showed no recorded rainfall (JBA Consulting, 2018; Flack, Skinner, et al., 2019).

Unlike rainfall gauges, rainfall radars can survey large areas and capture the spatial variability of the rainfall. Radars also provide real-time data and can calculate the motion, intensity, and type of precipitation falling. Modern dual polarization radars (see Darlington et al., 2016) enable more information about the size and composition of precipitation to be captured and processed (Dance et al., 2019; Darlington et al., 2016; Flack, Skinner, et al., 2019). This has led to improvements in radar-observed rainfall rates either for use directly in rainfall monitoring or as input to forecasting and nowcasting systems. This has enabled more accurate and timely warnings, particularly in very intense rainfall events.

Despite these improvements, rainfall radar cannot guarantee to capture high intensities and local conditions accurately. There are known issues with radars poorly representing intense rainfall from convective precipitation when hail forms a part of the precipitation, and this continues to be an active research area for meteorologists. There are also regions that are not well covered by the existing radar network, for example, the central belt in Scotland (Worsfold, Norman, & Harrison, 2014). The use of high-resolution X-band radars is starting to be used to improve rainfall detection in urban flood environments, for example, in Japan (Kimura, Kido, & Nakakita, 2012), Europe (Reinoso-Rondinel, Bruni, ten Veldhuis, & Russchenberg, 2013), and the United Kingdom (Neely III et al., 2018). In regions of the world where the radar network is limited or poorly maintained, satellite-observed rainfall products such as EUMETSAT H-SAF in Europe (Mugnai et al., 2013) or NASA's Global Precipitation Modeling (GPM) mission (Mazzoglio, Laio, Balbo, Boccoardo, & Disabato, 2019) can provide an alternative source of rainfall observations. Satellite data have been used to develop extreme-rainfall-alerting products, although these are at a coarse temporal and spatial resolution. The potential of satellite data for improving km-scale model forecasts (as needed for surface water forecasting) is an active research topic in the World Meteorological Organizations HiWeather program (Zhang et al., 2019).

Another emerging alternative is the use of crowdsourced weather data (Zhang et al., 2019) including from personal weather stations, vehicles, and smart phones (Hintz et al., 2019). For example, the FloodCitiSense research project (which can be accessed via <https://jpi-rbaneurope.eu/project/floodcitisense/>) aims to develop urban pluvial flood early warning services for, and by, citizens and city authorities in Brussels, Rotterdam, and Birmingham through a network of low-cost, self-built rain gauges and a new pluvial flooding app.

3.2 | Numerical weather prediction

NWP uses mathematical models of the atmosphere to predict future precipitation based on current weather conditions. Current weather observations are input to the models through a process known as data assimilation, which is a technique where observational data from different sources are processed and adjusted. The aim of data assimilation is to provide as close to initial conditions as possible (Asch, Bocquet, & Nodet, 2016). The different sources of data typically include recent measurements of precipitation and a previous forecast valid at the same time the measurements are made (Dance et al., 2019). The development of convection-permitting NWP models has necessitated international research efforts in data assimilation over the past few years (Dance et al., 2019; Flack, Skinner, et al., 2019; Hintz et al., 2019). Unlike large-scale models that rely on some form of parametrisation process to add in convective features, convection-permitting NWP models can represent convective structures directly (Clark et al., 2016). To do this well, existing convective features need to be represented in the initial conditions.

One example of a world-leading convection-permitting NWP model is the UK Met Office UKV model. Its current configuration provides forecasts on a 1.5-km grid across the United Kingdom for up to 120 hr ahead (5 days) with

frequent updates for up to 54 hr ahead (<https://www.metoffice.gov.uk/research/approach/modelling-systems/unified-model/weather-forecasting>). The UKV model can produce very realistic looking showers, which is a considerable improvement over larger-scale model configurations (Clark et al., 2016). While the development in precipitation forecasting has led to a significant improvement in the ability of hydrometeorologists to forecast surface water flooding, the size of typical convective features is smaller than the 1.5-km grid length, meaning that showers (especially small rain showers) are still under-resolved (Clark et al., 2016).

3.2.1 | Nowcasting

Nowcasting is the term given to weather forecasting on a very short-term period of 0–6 hr. It uses surface weather station data (radar echo maps and rain gauge data), wind profiler data, and any other weather data available blended with NWP models. The value of nowcasts is their ability to represent the development of convective rainfall features over small areas and short lead times (Liguori & Rico-Ramirez, 2014). As the reliability of nowcasts improves so will the reliability of short-term surface water flood forecasting.

One example that shows the potential of this approach is the development of the UK Met Office very short-range forecasts system. The system, known as NIMROD, was first developed in the mid-1990s (Golding, 1998). Ten years later, a stochastic element was introduced known as the Short-Term Ensemble Prediction System (STEPS) that allowed features smaller than the NWP resolution to be represented while also representing the spatial and temporal uncertainty of such features (Bowler, Pierce, & Seed, 2006). The STEPS system is discussed here as it was developed in conjunction with the Australian Bureau of Meteorology and has been integrated into other operational nowcasting system, for example, in Belgium (Foresti, Reyniers, Seed, & Delobbe, 2016). It, therefore, provided a good example of an internationally recognized system. Other countries have also developed ensemble nowcasting systems, for example, in Switzerland (Sideris, Foresti, Nerini, & Germann, 2020) and the Netherlands (Heuvelink, Berenguer, Brauer, & Uijlenhoet, 2020). A Nowcast Demonstration Project for the 2012 Olympics developed hourly cycling, 1.5-km resolution nowcast with four-dimensional variational data assimilation (4D-Var). The skill of the Nowcast Demonstration Project was shown to be greater than the UKV NWP forecast for the 6-hr nowcast period and better than the operational nowcast at times beyond $T + 2$ hr (Ballard, Li, Simonin, & Caron, 2015). Work is ongoing to implement the 4D-Var nowcast system for the whole of the United Kingdom. Despite these improvements, comparisons between the Nowcast Demonstration Project, the STEPS nowcast, and the UKV forecast all showed issues forecasting light, scattered showers (Clark et al., 2016) illustrating the ongoing forecasting challenge. The Met Office “seamless” Unified Model harnesses the relative advantages of nowcasts and high-resolution NWP by blending from forecasts heavily weighted on observations at $T + 0$, through nowcasts, to forecasts heavily weighted toward the high-resolution NWP model at $T + 6$ hr (Met Office, 2018). A similar approach to forecasting high-impact weather events from minutes to days in advance is being developed through the Forecasting a Continuum of Environmental Threats (FACETs) project in America (Rothfus et al., 2018).

3.2.2 | Probabilistic forecasting

Convection-permitting forecasts are known to be sensitive to uncertainties in the initial conditions, boundary conditions, and physical processes (Hagelin et al., 2017). It is largely accepted that it is not possible to rely on deterministic forecasts of convective rainfall at a grid scale and a probabilistic approach is needed (Clark et al., 2016; Golding et al., 2014).

Ensemble (or probabilistic) forecasts comprise a set of forecasts using slightly different input conditions or varying the representation of physical processes to account for uncertainty (Box 1). Ensemble predictions are commonly made at the major operational weather prediction facilities worldwide. For example, the German COSMO-DE-EPS model runs on a 2.8-km resolution with 30 members providing a 21-hr lead time eight times a day, and Meteo France runs a 2.5-km ensemble with 12 members twice a day (Hagelin et al., 2017). The UK Met Office Global and Regional Ensemble Prediction System (MOGREPS-UK) provides an ensemble of short-range convective-scale NWP forecasts (Bowler et al., 2006; Hagelin et al., 2017). The MOGREPS-UK system has been running since 2012. It provides a 54-hr-lead time, 12-member ensemble forecast based on the UKV model at a 2.2-km resolution. As computational power increases it will be possible to further increase the ensemble size, resolution, domain size, and forecast length of ensemble forecasts.

BOX 1 ENSEMBLE FLOOD FORECASTING

The development of surface water flood forecasting is linked to wider developments in ensemble forecasting. Ensemble (or probabilistic) forecasts comprise a set of forecasts using slightly different input conditions or varying the representation of physical processes to account for uncertainty. In an EPS, each forecast run is equally likely to occur and represents a different possible rainfall scenario. Considering the full ensemble provides a range of possible future outcomes and allows forecasters to assess the probability of different scenarios. This contrasts with a deterministic forecast, which produces one single best estimate prediction.

The use of ensembles in flood forecasting has been continually reviewed in the academic literature (Cloke & Pappenberger, 2009; Emerton et al., 2016; Pagano et al., 2014; Wu et al., 2020). The majority of studies to date have focused on forecasting of flooding associated with fluvial processes at the catchment scale for lead times of up to 15 days rather than short-duration surface water events. The most recent example by Wu et al. (2020) reviewed 70 papers on ensemble flood forecasting between 2001 and 2019 and found urban flooding was the focus of only 12 of these papers (including flash flooding in small urban catchments). Of all 70 papers reviewed, worryingly, only 30% considered the application of ensemble flood forecasting to solve real-world problems. The use of probabilistic forecasting is increasingly considered essential to produce useful surface water flood forecasts.

Decisions need to be made about how best to optimize the use of computational resource to support forecasting. Hagelin et al. (2017) showed more benefit in running a larger-member ensemble for MOGREPS-UK (24 opposed to 12) over increasing the model resolution. Since 2017, the MOGREPS-UK system has been increased to 18 members using a time-lagging technique with a 120-hr lead time. It is also able to provide hourly updates (compared to the previous 6 hourly updating cycle), which allows close monitoring of the development of convective showers (latest configuration details for MOGREPS-UK are given here <https://www.metoffice.gov.uk/research/weather/ensemble-forecasting/mogreps>).

Studies have shown that the predictability of convective precipitation depends on whether it is controlled by large-scale or local factors (Flack, Gray, Plant, Lean, & Craig, 2018). Flack et al. found that for 85% of convective precipitation events in the United Kingdom, the convection-driving process resulted in scattered showers (rather than organized convection) and displayed relatively large uncertainty in the rainfall locations but higher confidence in the total rainfall. In contrast, the other 15% showed confidence in the location of the rainfall but lack of confidence in the amount (Flack et al., 2016, 2018; Flack, Gray, & Plant, 2019; Flack, Skinner, et al., 2019). The limited number of ensemble members in an operational convective-permitting ensemble prediction system (EPS) means that in these situations the ensemble may not capture the full range of uncertainty. Understanding the limits of predictability of convection-permitting NWP enables hydrometeorologists to make informed assessments of forecast skill in different weather situations. This is particularly important when ensemble rainfall forecasts are being used further down the chain, for example, to drive flood inundation and impact assessments (e.g., in Cole et al., n.d. and Speight et al., 2018 and other approaches described in Section 4).

3.2.3 | Postprocessing

Postprocessing is defined as the processing of data after other processes have been completed. Postprocessing converts rainfall predictions from forecasting systems (i.e., ensemble NWP model outputs and nowcasting outputs) into forecast products. They add value to the raw data, correcting bias and producing forecasts that reliably quantify uncertainty.

Postprocessing for intense rainfall is particularly challenging due to the small-scale nature of the features of interest (Clark et al., 2010; Leoncini, Plant, Gray, & Clark, 2013). This means that probabilities for specific locations will remain very low and may not alert meteorologists or flood forecasters to the risk of an event, and may remain below the probability threshold at which decision-makers are willing to take action (Golding et al., 2016; Kox, Gerhold, & Ulbrich, 2015). To help account for this, neighborhood processing is often used to search for events within a spatial and temporal search window that could be considered equally likely to occur anywhere within the window (see Golding

et al., 2016 for a description of the process). This process changes the low point probabilities of occurrence to show higher probabilities of an event occurring somewhere within the specified spatial area or temporal time frame. The neighborhood sampling technique removes some of the noise of the result and effectively increases the ensemble size. The noise is a result of the ensemble not being large enough to convey the uncertainty in the process (Hagelin et al., 2017). The use of different postprocessing techniques can influence how forecasts are presented and hence how decisions are made. Hydrometeorologists need to understand the postprocessing method and ideally be involved in discussions around what metrics, time frames, and neighborhood sizes are most useful for their purpose. Flack, Skinner, et al. (2019) and Speight et al. (2018) report on research projects where this has successfully occurred.

3.3 | The future of convection-permitting NWP for surface water flood forecasting

The introduction of convection-permitting NWP models has led to a step change in the ability to forecast the type of rainfall events that lead to surface water flooding. However, although the output from the models looks realistic, users need to remain mindful that NWP at a 1.5-km resolution is unable to accurately forecast the timing and location of convective rainfall. Although ongoing scientific developments will improve the skill of the forecasts, there is likely to remain a limit to the deterministic predictability of convective rainfall. Golding (2009), (also discussed in Speight et al., 2018) estimates this to be 3 hr ahead for a 10-km by 10-km rainstorm and just 30 minutes ahead for the most intense 1-km by 1-km part of the storm. The use of probabilistic forecasts is therefore essential to support surface water flood forecasting. The interpretation of probabilistic forecasts requires user expertise. It is known that in some situations the skill of the forecast is better than others. The interpretation of probabilistic forecast also requires knowledge of the postprocessing technique as this can have a large influence on how the probability of heavy rainfall is presented.

This review has focused on the scientific developments in convection-permitting NWP. Alongside this, there have also been rapid developments in computational capacity and data availability, which have been essential to support the forecasting science. We cannot expect processing power to continue to increase at the rate required to support the growing requirements of NWP (Bauer, Thorpe, & Brunet, 2015). Instead, we need to make more use of both parallel computing and new forecasting techniques, for example, machine learning. One example of this is Google's development of MetNet (Sønderby et al., 2020). MetNet is a neural network that forecasts precipitation up to 8 hr into the future at the high-spatial resolution of 1 km². It has been shown to outperform traditional NWP forecasts in the United States for these short-lead time forecasts. Machine learning approaches such as this will emerge from the research arena in the near future and offer much potential to address some of the challenges of surface water forecasting. As concluded by Clark et al. (2016, p178) "the current state of the art [of convection-permitting NWP] represents a beginning, not a conclusion, and it is anticipated that many advances in various directions will be possible in the future."

4 | APPROACHES TO SURFACE WATER FLOOD FORECASTING

In their scoping review of potential options for surface water flood forecasting and warning for the United Kingdom, Priest et al. (2011) presented a spectrum of possible approaches ranging from simple rainfall-based alerts at large scales to more complex and targeted impact-based flood warnings at local scales. In this updated review, we examine the models and forecasting systems that have been developed over the past ~10 years to support operational surface water flood forecasting. Multiple approaches have developed based on different forecasting scales, end-user needs, and data and resource availability. Broadly based on Henonin, Russo, Mark, and Gourbesville (2013) who classified available approaches based on the use (or not) of hydraulic models, our review is structured using a three-type classification of real-time flood forecasting systems as follows:

1. Empirical-based scenarios: Surface water flood forecasting based on observed or forecast rainfall scenarios, typically based on historical data and evidence of pluvial flooding
2. Hydrological forecasting linked to presimulated impact scenarios: Real-time flood forecasts using hydrological modeling with warning triggers based on scenarios or results catalogue built from offline hydraulic simulations, applied at either a national or regional scale
3. Hydrological forecasting linked to real-time hydrodynamic simulations at the urban scale: Real-time operation and simulation of hydraulic model(s).

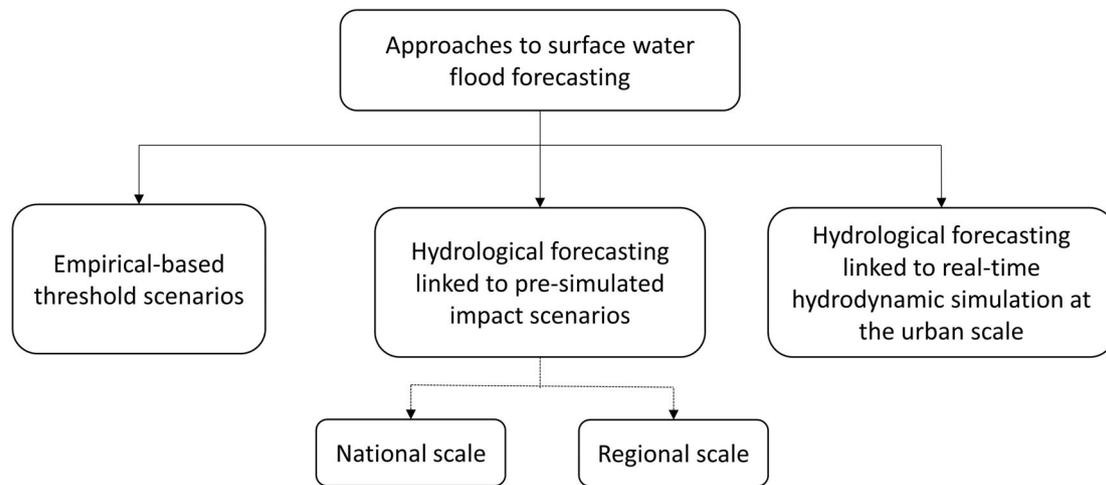


FIGURE 2 Conceptual approaches to surface water flood forecasting

BOX 2 RISK BASED FORECASTING

Instead of just reporting the expected inundation area, risk-based flood forecasts combine information about the probability of an event and the severity of potential impacts. Flood forecasting in the United Kingdom, particularly at national scales, is increasingly risk-based. The UK Met Office National Severe Weather Warning Service (NSWWS), the FFC (for England and Wales), and the Scottish Flood Forecasting Service (for Scotland) communicate the flood risk for all sources of flooding using a matrix of impact and likelihood. The overall flood risk could be reported as “medium” for both a forecast showing a high probability of significant impacts or a forecast showing a low probability of severe impacts. Further details of the flood risk matrix are available here http://www.ffc-environment-agency.metoffice.gov.uk/services/FGS_User_Guide.pdf.

Figure 2 presents the conceptual approaches to surface water flood forecasting in a systematic diagram. The output from each system can range from a simple alert that flooding is possible to a full-risk-based forecast incorporating assessment of both the probability of an event occurring and the likely impacts (Box 2).

4.1 | Empirical-based threshold scenarios

The use of precalculated rainfall thresholds to identify the risk of pluvial flooding is a quick means of postprocessing NWP output, radar rainfall rates or gauged data to support decision-making. Depth–duration thresholds are set based on existing knowledge of the amount of rainfall falling within a specified time period or water level that could cause flooding impacts. The thresholds are then validated against observed events. Due to their low development and running costs, such systems are in widespread use.

The simplest form of such systems (Figure 3) can be found at city and local scales. For example, in Bonn in Germany, water levels in a local stream are continually monitored and sent in real time to the fire brigade who issue a warning if the specified thresholds are exceeded (Hofmann & Schüttrumpf, 2019). Acosta-Coll, Ballester-Merelo, Matrinez-Peiro, and De la Hoz-Franco (2018) describe other examples of systems from across the world where simple triggers linked to rain gauges, radar systems, or sewer sensors provide pluvial flooding alerts directly to the authorities or the public usually through web apps or mobile phones. Accepting that the density of formal discharge and rainfall gauges is not always sufficient to support such systems, there is a strong link between the developments of local threshold-based systems and crowdsourced or community data (see Section 5). Since these local systems are based on observed rainfall or flow, they offer limited lead time to prepare for surface water flooding. However, they do provide

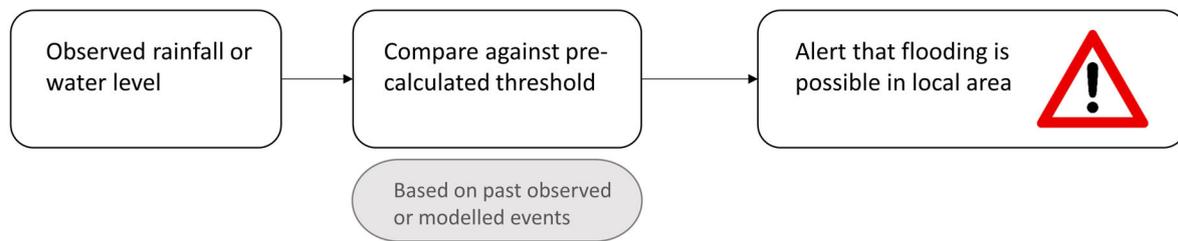


FIGURE 3 Schematic of a local-observed empirical-based system for surface water flood forecasting

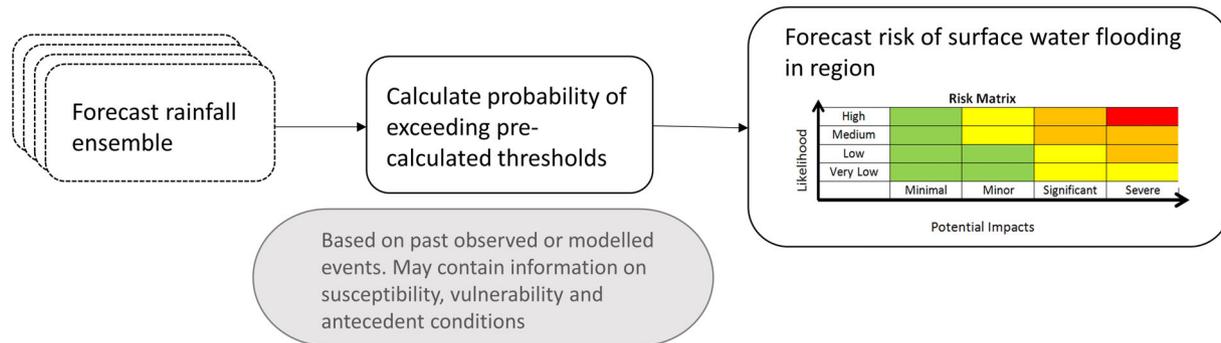


FIGURE 4 Regional ensemble forecast empirical-based system for surface water flood forecasting

an opportunity for increased community-level awareness and encourage individuals to be proactive in taking actions to reduce their own flood risk (Starkey et al., 2017).

At national scales, precalculated threshold systems can be used to identify regions of the country most at risk of surface water flooding based on forecast rainfall. Where an ensemble forecast is used as input this enables a risk-based forecast to be produced as shown in Figure 4.

Using forecast rainfall in flood forecasting increases the available lead time but reduces the spatial fidelity and hence the regional application. The UK Met Office refers to the use of this type of threshold system as a “first-guess early warning” and uses it for multiple weather-driven hazards (Neal et al., 2014). The complexity of such systems has evolved alongside developing rainfall forecasting capabilities and understanding of surface water hazard and impact. For example, France has developed a system called Vigiecrues Flash (Javelle et al., 2016; Javelle, Saint-Martin, Garandeau, & Janet, 2019) that combines a simple 1 km² distributed hydrological model for rivers, with radar rainfall to identify rivers exceeding high-impact or very-high-impact thresholds (associated with return period). It is aimed at flash flooding in ungauged catchments but is also a surrogate for identifying the potential for pluvial flooding in communities (Dermagne & Javelle, personal communication, 2019). The United States has had a flash flood guidance system warning of flooding in small river basins from rainfall of less than 6-hr duration since 1971 (Mogil, Monro, & Groper, 1978). Recognizing that flash flooding occurs on smaller scales, the Flash Flood Potential Index was developed to determine the gridded susceptibility of flooding (Clark, Gourley, Flamig, Hong, & Clark, 2014; Gourley, Hong, & Wells, 2012). Further developments to this system are ongoing through the FACETS research program. The program aims to deliver detailed hazard information through the use of “threat grids” and will be applied to severe convective and flash flooding events. Currently, the approach to flash flood guidance in the United States is “warn on detection”; however, the new approach of “warn on forecast” will combine satellite, NWP, and radar data to forecast the future track of severe convection (Rothfusz et al., 2014, 2018).

In the United Kingdom, the first system for surface water flooding was the extreme rainfall alert (ERA) system introduced by the UK Met Office and the Environment Agency in 2009 (Hurford, Priest, Parker, & Lumbroso, 2012; Priest et al., 2011). The service was based on the likelihood of exceeding depth–duration thresholds for a 30-year return period event, but it did not consider surface–subsurface processes or vulnerability (Pilling et al., 2016). In 2010, the Flood Forecasting Centre (FFC) launched the Surface Water Flooding Decision Support Tool (SWFDST) for England and Wales. Details of the SWFDST are given by Pilling et al. (2016) and Ochoa-Rodríguez, Wang, Thraves, Johnston,

and Onof (2018). The SWFDST is a more targeted system than the ERA as it takes account of urbanization and antecedent conditions. It uses forecast rainfall from MOGREPS-UK to assess the probability of exceeding six different rainfall thresholds (for different durations and severities). This is then combined with information on the soil moisture deficit, the rainfall spatial extent, and potential impacts on the ground based on 1 km² from static flood risk maps. Each county is assigned a surface water flooding risk category of very low, low, medium, or high.

While threshold-based approaches such as these are valuable (particularly at broad scales), there appears to be limited confidence in the use of this type of system as a standalone approach. Instead, they are usually used alongside other sources of information, including expert judgment, to inform end-user facing products (Rothfusz et al., 2018). For example, the chief forecaster has the capability to vary the thresholds used in the UK Met Office system to account for varying seasons or antecedent conditions (Neal et al., 2014). Similarly, Cole, Moore, Aldridge, Lane, and Laeger (2013) state the SWFDST is used alongside “expert judgment and feedback from local Environment Agency flood teams, public weather service civil contingency advisers, and the Met Office chief forecaster to produce the surface water flooding element of the FGS.” The reasons for this include concerns about uncertainty due to the relatively small ensemble sizes, the need to maintain consistency with other products, offline inclusion of hydrological and hydraulic processes rather than just a rainfall-based assessment, and a need to be able to vary thresholds to account for changes in vulnerability of antecedent conditions.

4.2 | Hydrological forecasting linked to presimulated impact scenarios

Thanks to the development of surface water flood risk mapping activities in recent years (De Moel, Van Alphen, & Aerts, 2009), the use of presimulated scenarios for flood forecasting is becoming an acceptable compromise between benefiting from the detail available from detailed hydraulic inundation mapping and allowing a direct link to the assessment of impacts while reducing the operational computation time. There are examples at a city scale (Speight et al., 2018), at regional scales (Cole et al., n.d.), at national scales (Saint-Martin, Fouchier, Javelle, Douvinet, & Vinet, 2016; Saint-Martin, Javelle, & Vinet, 2018), and at international scales (Dottori et al., 2017). The approach is based on the assumption that a link can be made between the real-time forecasting model and the static inundation and impact assessment. For example, in Speight et al. (2018) and Cole et al. (n.d.), the assumption is made that the effective rainfall used to produce the static flood maps is equivalent to the surface runoff from the real-time hydrological model. This enables the most appropriate flood and impact maps from a library of static maps to be selected based on the forecast rainfall scenario as per Figure 5. A strength of this approach is that the spatial variability of rainfall can be accounted for by selecting a different hazard map and associated impacts for each grid cell (Aldridge et al., 2020). Repeating this process for each ensemble members gives the probability of impact exceeding a given threshold within each grid cell and thus overall flood risk (Speight et al., 2018).

The success of the approach relies on (a) the quality of the original hydraulic inundation modeling, (b) the representation of urban drainage capacity, and (c) having a large enough library of events (in terms of return periods and event durations) to be able to reflect the varying response to the forecast rainfall event. Unlike the threshold scenario approaches (Section 4.1), the spatial variability of rainfall is accounted for by linking forecast rainfall and effective rainfall at a grid cell level as well as the spatial variability of impacts using spatial impact databases. The use of a real-time hydrological model allows the incorporation of antecedent conditions. Using a library of inundation maps and impact assessments allows for full consideration of rainfall forecast ensembles rather than focusing only on deterministic forecasts or short-range nowcasts. The static inundation maps and impact assessments have often been made at a finer resolution than the predictability of the forecast rainfall; therefore, consideration must be made of an appropriate reporting scale that meets end-user needs but also reflects the uncertainty in forecasts of convective rainfall.

Speight et al. (2018) discuss the operational experience of using a city-scale surface water forecasting model during the summer of 2014 (in particular for the Commonwealth Games held in Glasgow, Scotland). The output from the city-scale forecasting system was challenging to communicate due to the low probabilities of impact for the specific areas of interest to end users. This also led to a challenge of maintaining a consistent message between the Glasgow city-scale forecast and the national flood guidance and weather warnings. For example, on one occasion, the national flood guidance statement highlighted a risk of surface water flooding across south west Scotland, but the Glasgow forecasts identified that the chance of any impact in Glasgow itself was very low. A high level of hydromet staff time was found to be needed to interpret and communicate the output from the Glasgow surface water forecasting pilot (Speight et al., 2018). In parallel to the Glasgow trial, the FFC has developed a similar system to forecast surface water flood risk (Cole

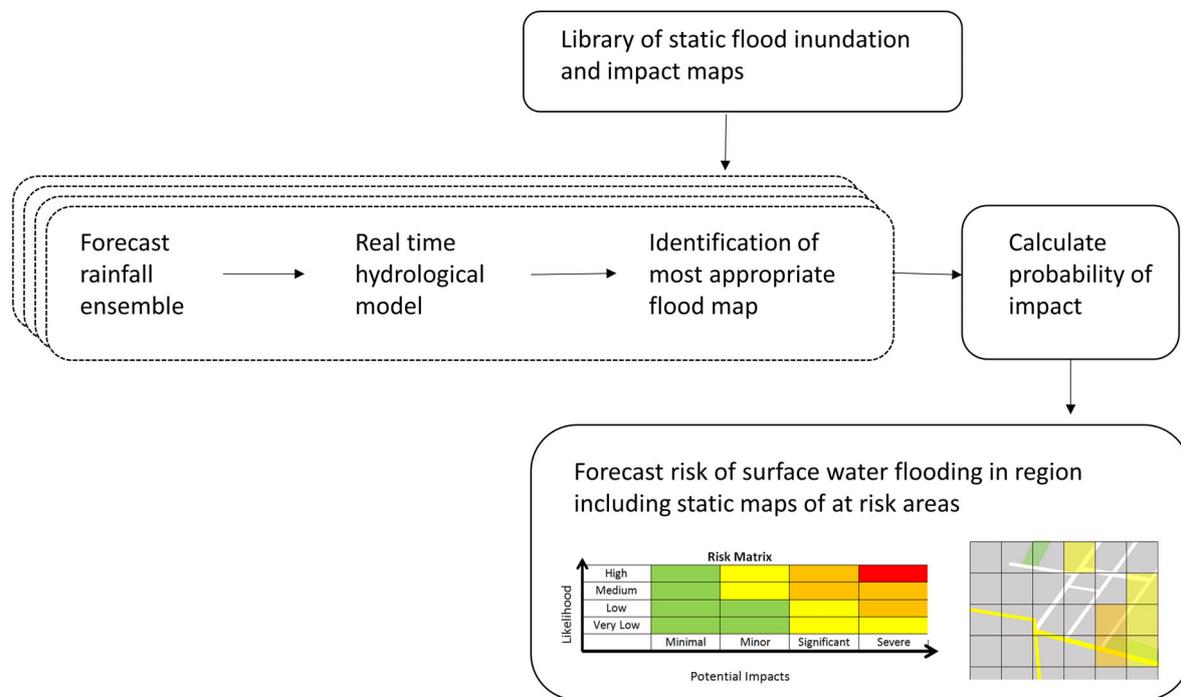


FIGURE 5 Hydrological forecasting linked to presimulated impact scenarios for surface water flood forecasting (based on Speight et al., 2018)

et al., n.d.). This system incorporates static flood inundation and impact maps at a 1-km resolution but mitigates the challenge of low small-scale probabilities by aggregating the forecast up to a regional scale to inform the national flood guidance statement support (see Gunawan and Aldridge (2016) and Aldridge et al. (2020) for details of the method and development of the supporting impact databases). Rabb et al. (2019) explored through a flood exercise how this additional detail on risk, presented at different spatial and temporal scales, might be used by decision-makers. Echoing the findings of Arnal et al. (2019), Rabb et al. reported a “degree of caution” (p. 28) over the usefulness of new enhanced information over existing data sources, particularly where full training had not been given on how to use the new products. More technical users did find it a helpful addition to the existing flood forecasting information available, but, like Speight et al. (2018), cited the need for expertise and local knowledge to interpret and communicate the forecasts successfully.

4.3 | Hydrological forecasting linked to real-time hydrodynamic simulations

Moore et al. (2015) concluded that due to run time constraints, there were limited linked hydrological and hydrodynamic models that had the potential to run in real time and those that could potentially be used in this way had not been developed with continuous updating of the system states in mind (Moore, Bell, Cole, & Jones, 2007; Speight et al., 2018). As computational power has increased over the past few years and cloud computing and graphical processing units (GPUs) have developed rapidly, these new technologies have emerged as a realistic and affordable way to run computationally demanding surface water flooding models in less time (see Flack, Skinner, et al., 2019; Glenis, Kutija, & Kilsby, 2018; Xia, Liang, Ming, & Hou, 2017). The benefit of real-time hydrodynamic simulations is the ability to directly model the forecast spatial variability of rainfall on inundation and impacts at a city scale. Another potential benefit is the ability to set thresholds based on the velocity of flow as this is known to be important when considering a danger to people, movement of vehicles, or damage to property (Hofmann & Schüttrumpf, 2019). Despite the growing potential of real-time hydrodynamic simulation, the run time remains a barrier to use. In Germany, a research project compared the runtime for a hydrodynamic pluvial flooding model of a 36-km² area of the city of Aachen on a 1–3-m grid and showed that the computational time using the GPU was 10.5 times faster than a standalone CPU, but at 4,610 and 439 min, respectively (Hofmann & Schüttrumpf, 2019), neither would be suitable for operational surface water

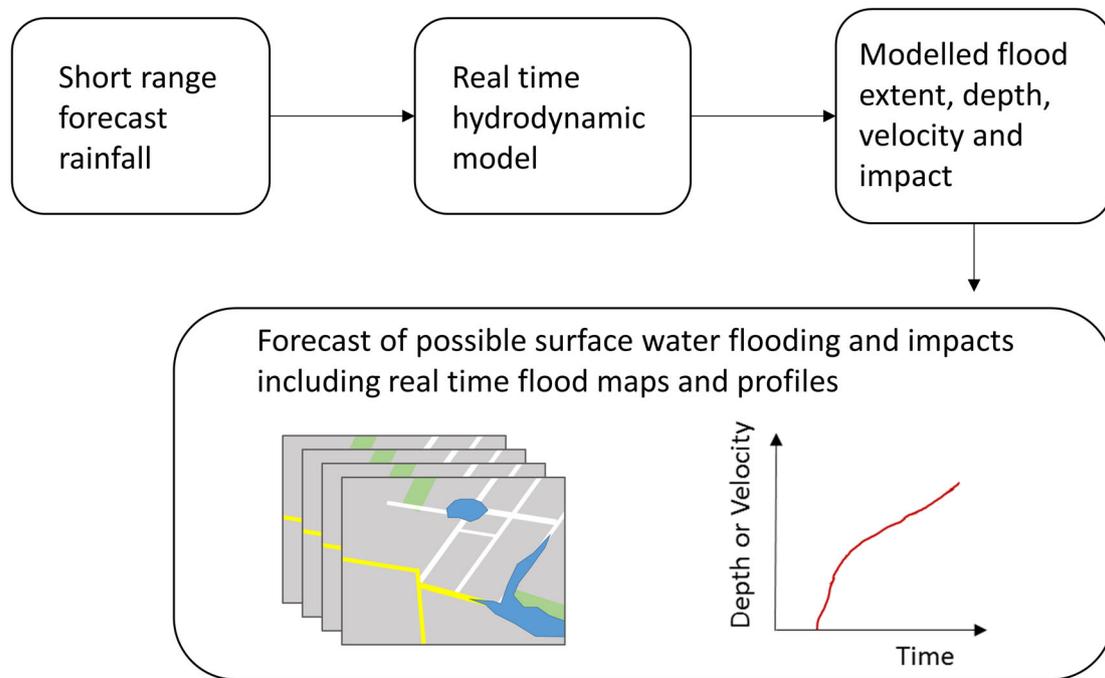


FIGURE 6 Hydrological forecasting linked to real-time hydrodynamic simulations for surface water flood forecasting

forecasting. In this instance, Hofmann and Schüttrumpf (2019) envisage a multifunctional system whereby full hydrodynamic simulations are used to understand more about the flood hazard and validate the model, but a presimulated library of flood inundation maps (as per Section 4.2) is used in real time.

The use of real-time hydrodynamic models is currently possible at shorter lead times and without using a full ensemble of forecast rainfall (Figure 6). Flood nowcasting refers to forecasting urban flooding in real-time using the rainfall nowcast as input to a city-scale hydrodynamic model. This term was first coined by Willems, Delobbe, and Reyniers (2016) who describe an application in Ghent, Belgium, using the probabilistic STEPS nowcast as input. In the United Kingdom and China, FloodMap-HydroInundation2D (Yu & Coulthard, 2015) has been used to provide high-resolution flood mapping at a street-level resolution (2–50 m). FloodMap integrates surface water runoff modeling with a simplified representation of sewer surcharge in an urban area and also represents hydrological inflow to the urban area from multiple upstream sources. The flood nowcasting system was originally developed to help identify access routes for emergency responders during flood events in Leicester using rainfall input from the Met Office 6-hr nowcast (Green et al., 2017) and illustrates a good example of developing a workable solution in partnership with end users. The system has been well received, the Chief Constable of Leicestershire Police said, “It’s passed the ultimate test for me which is its met the real people, who do the real stuff, who will be up to their ankles and knees in water at the time, and they thought it was useful” (Loughborough University, 2017).

Although there is now the emerging potential to use real-time hydrodynamic simulation at the urban scale, there remains a key research question around how much detail can decision-makers use effectively on an operational time-scale, given the computational costs involved. Like the presimulated inundation scenarios, real-time hydrodynamic modeling also has the potential to display results at a more detailed resolution than is appropriate, given the known uncertainty in the rainfall forecasts.

4.4 | Machine learning

In addition to the approaches identified in Figure 2, machine learning and artificial intelligence models offer a means of reducing simulation times by seeking to extract significant patterns in large historical data sets and use these patterns to make predictions about the future (Chang et al., 2019). They are becoming popular with hydrologists (Wu et al., 2020) and could provide a valuable means of linking ensemble rainfall forecasts with inundation and impact maps. For example, Chang et al. (2019) describe an intelligent hydroinformatics integration platform that utilizes the

Google Maps interface to provide real-time flood-related information such as rainfall data and regional flood inundation maps in the Tainan city of Taiwan. However, “the current state of Machine Learning modelling for flood prediction is quite young and in the early stage of advancement” (Mosavi, Ozturk, & Chau, 2018). To fully understand their potential requires close cooperation between hydrologists and machine learning specialists (Mosavi et al., 2018). In our opinion, the operational uptake of machine learning approaches is likely to be further delayed by concerns about using new types of models (Arnal et al., 2019), a general mistrust of “black box”-type approaches in hydrology (Wu et al., 2020) and the need for observed inundation data to train the models on (Chu, Wu, Wang, Nathan, & Wei, 2020). Machine learning approaches have not been considered further in this paper as the authors are not aware of any operational machine learning approaches to surface water flood forecasting.

4.5 | Comparison of surface water forecasting approaches

Tables 1–3 provide a comparison of the advantages and disadvantages of the operational flood forecasting methodological approaches reviewed in this paper, including comments on the operational challenges of each. The selection of the most suitable approach for particular applications will depend on the requirements and budget of the operational organization for development and delivery.

Empirical-based rainfall scenarios (Table 1) are widely used and provide a good “first-guess” early warning of the potential for surface water flooding. Recent improvements to convection-permitting NWP have improved their reliability; however, they do not take account of real-time changes to vulnerability and cannot provide details at the local scale. In most cases, they are used alongside other sources of information. There is potential to link empirical-based solutions, which can provide early warnings at lead times of up to 5 days, with local sensor-based systems to provide updated local warnings at lead times of less than 6 hr.

Hydrological forecasting linked to presimulated impact scenarios (Table 2) is becoming popular for both surface water and fluvial flood forecasting at a range of scales. This approach provides a compromise between incorporating the spatial and temporal variability of rainfall and impacts with limited computational resources. By using a presimulated impact scenario approach, it is possible to provide a fully risk-based forecast 5 days in advance. At a national scale, this approach has been shown to provide a more targeted forecast than empirical-based rainfall scenarios alone. The approach is sensitive to the way that impact and probability thresholds are calculated, which can result in reporting inconsistencies between scales.

While hydrological forecasting linked to real-time hydrodynamic simulations at the urban scale (Table 3) potentially enables a fully hydrodynamic real-time simulation of rainfall, inundation, and impact, it remains an emerging

TABLE 1 Advantages, disadvantages, and operational challenges of forecasting surface water flooding using empirical-based rainfall scenarios

| Advantages | Disadvantages | Operational challenges |
|--|---|---|
| <ul style="list-style-type: none"> • Low development and computational costs • Quick to use • Probabilistic approaches possible • Allows immediate use of improvements to NWP • Continual validation against observed events possible • At a local scale, can encourage community engagement | <ul style="list-style-type: none"> • Systems using deterministic forecasts provide no account of uncertainty • Probabilistic systems are reliant on postprocessing that can make them difficult to interpret • Thresholds are static and do not take account of hydrological or hydraulic process or changes in vulnerability • Trigger-based systems using observed rainfall or water level offer limited lead times | <ul style="list-style-type: none"> • Usually used alongside other approaches • Usually require expert knowledge and experience to interpret • Maintaining consistency across multiple products |

Note: Operational examples - UK Flood Forecasting Centre Extreme Rainfall Alert (Hurford et al., 2012, Priest et al., 2011), UK Flood Forecasting Centre Surface Water Flooding Decision Support Tool (Pilling et al., 2016), UK Met Office MOGREPS-W system to inform the National Severe Weather Warning Service (Neal et al., 2014), USA Flash Flood Guidance System (Clark et al., 2014; Gourley et al., 2012), French Vigicrues Flash System (Javelle et al., 2019), and Local trigger-/sensor-based warning systems (Acosta-Coll et al., 2018).

TABLE 2 Advantages, disadvantages, and operational challenges of forecasting surface water flooding using presimulated impact scenarios

| Advantages | Disadvantages | Operational challenges |
|--|--|--|
| <ul style="list-style-type: none"> Offers compromise between computation requirements, lead time, and detailed assessment Makes good use of existing maps and data Allows consideration of probabilistic forecasts in a risk-based approach Accounts for spatial variability of rainfall, antecedent conditions, and impacts Allow full use of convection-permitting NWP providing lead times of up to 5 days Suitable for providing information on regional-level timings and impacts to support responders | <ul style="list-style-type: none"> Reliant on quality of existing hydraulic modeling and inundation mapping Limited lead times if only observed rainfall or nowcasts are used Reliant on having a large enough library of presimulated scenarios to represent the forecast rainfall event No direct accounting for real-time hydraulic processes or changes in vulnerability Challenging to aggregate between finer-scale detail of presimulated inundation and impact scenarios and regional-scale reporting framework Limited local detail | <ul style="list-style-type: none"> Existing inundation mapping and impact assessments are at a finer resolution than can be justified by the uncertainty in rainfall forecasts Consideration of appropriate reporting scales requires aggregation of impacts Ongoing research need to identify the level of information needed from the system to support decision-making |
| <p>At city/local scales</p> <ul style="list-style-type: none"> Supports city-scale decision-making by providing information on location and timing of impacts | <p>At city/local scales</p> <ul style="list-style-type: none"> May provide more detail at the local scale than can be justified by science Probabilities will be low for small areas resulting in a communication challenge | <p>At city/local scales</p> <ul style="list-style-type: none"> Operational experience suggests a high staff resource is needed to interpret and communicate the output and explain inconsistencies between scales |

Note: Operational examples-UK Natural Hazard Partnership Surface Water Hazard Impact Model (Cole et al., n.d.) and Glasgow surface water flood forecasting pilot for the 2014 Commonwealth Games (Speight et al., 2018).

TABLE 3 Advantages, disadvantages, and operational challenges of forecasting surface water flooding using real-time hydrodynamic simulation at the urban scale

| Advantages | Disadvantages | Operational challenges |
|---|---|---|
| <ul style="list-style-type: none"> Designed to support city-scale decision-making including providing detail at street level Demonstrated to run fast enough to support real-time decision-making Includes real-time hydraulic modeling Directly models spatial variability of rainfall on inundation and impact at city scale Potential to set warning thresholds based on the velocity of flow | <ul style="list-style-type: none"> Computational requirement challenging for longer lead times The scientific need for use of probability forecasts to account for uncertainty in convective rainfall currently not met Requires flood forecasters to understand the modeling assumptions of new hydraulic modeling approaches | <ul style="list-style-type: none"> Still an emerging capability Computational run-time remains high Benefits of approach compared to presimulated scenarios have not been demonstrated |

Note: Operational examples - Surface water nowcasting (Green et al., 2017; Willems et al., 2016).

computational capability. There are a number of models that could be used to generate forecasts for individual cities that have been proven to accurately model the inundation extent and impacts from past events. Significant investment in computational resources is required for this approach to meet the scientific requirements of using ensembles to account for forecast uncertainty or to provide forecasts with lead times of greater than 6 hr.

5 | MONITORING SURFACE WATER FLOOD IMPACTS IN REAL TIME

NWP and large catchment river models use a process of real-time updating (or data assimilation) to incorporate current conditions into the forecast. The lack of surface water flooding observations in real-time means limited feedback for operational models. It also restricts the options for forecasters to review their decision-making and for forecast verification and future development.

Monitoring using sensors, for example, in small urban watercourses, is a traditional means of capturing and detecting flooding impacts. A review of real-time early warning systems by Acosta-Coll et al. (2018) includes examples from Florida, Columbia, the Philippines, and Thailand, which use sensors to support pluvial early warning systems. Sensors are useful for small-scale systems; however, the cost of large-scale formal monitoring networks often restricts meaningful observations of urban flooding.

Remote sensing offers a potentially valuable source of monitoring flood extent data without relying on formal monitoring networks or social media. Given the decline of field observations, this could be of value especially in remote areas and developing countries (Domeneghetti, Schumman, & Tarpanelli, 2019). There are examples of satellite data being used to identify fluvial flood water in urban areas (e.g., Boccardo & Tonolo, 2015; Mason, Dance, Vetre-Carvalho, & Cloke, 2018), which could potentially be applied for severe surface water flooding. However, for short-duration pluvial flooding, limitations would include immediate availability of satellites, the potential processing time, cloud cover, and smaller flood extents. Another emerging approach to remotely capture flood extent information is through the use of unmanned aerial vehicles as demonstrated by Perks, Russell, and Large (2016) for flash flooding. However, as with the use of satellites, being able to quickly deploy equipment and capture pluvial flood extents remains a challenge.

While using sensors and remote sensing provides a structured approach to monitoring in support of surface water early warning, it is potentially crowdsourced information that offers the greatest potential to support operational response (See, 2019; Starkey et al., 2017; Zhang et al., 2019). There are various national and international scale systems that have been set up to crowdsource data on flood events. Some of these encourage users to directly input local observations into the system, for example, the UK Met Office Weather Observations Website (Kirk, Clark, & Creed, 2020) and SEPA's Report a Flood system (<http://www.floodlinescotland.org.uk/report-a-flood/>). Others approaches trawl other sources of data to collate information on flooding; for example, Global Flood Monitor provides a real-time overview and historical report of flooding based on data filtered from Twitter (de Bruijn, de Moel, Jongman, Wagemaker, & Aerts, 2018; de Bruijn et al., 2019).

The number and variety of systems in use indicates that the optimal use of crowdsourced data has yet to be found. The challenge is how to extract usable information from the data, particularly when using social media-derived data that do not follow a consistent format. Witherow, Elbakary, Iftekharuddin, and Cetin (2018) and Witherow et al. (2018) proposed a method for extracting street inundation information from crowdsourced images taken at near ground level in the city of Norfolk, Virginia, but found this challenging due to the lack of a fixed camera with a known location. Smith, Liang, James, and Lin (2017) present a real-time modeling framework in Newcastle upon Tyne, the United Kingdom, to identify areas likely to have flooded using data obtained through social media (Twitter). Their methodology involves a process to extract georeferenced information from tweets on flooding (i.e., locations, flood depth, and disruption), compare the results with a hydrodynamic inundation model, and infer other flooded locations in the city where no tweets were available. Brouwer et al. (2017) concluded that crowdsourcing social media reports of flooding can provide useful estimates of flood extents and could aid operational response and decision-making. However, there are limitations associated with extracting information, and as Smith et al. (2017) note the approach may be better suited to incident management applications rather than forecasting. The potential of crowdsourced data to support the validation and verification of forecasts is also widely acknowledged (Harrowsmith et al., 2020; Zhang et al., 2019) particularly for impact-based models where evaluation methods of forecast success from a socioeconomic perspective remain under developed (Robbins & Titley, 2018).

6 | GRAND CHALLENGES FOR SURFACE WATER FLOOD FORECASTING

While the scientific and computational advances discussed in this paper will continue to improve our ability to forecasts surface water flooding, we must accept that there will remain a limit to the lead time that it is possible to forecast intense rainfall with useful spatial and temporal certainty. Waiting for science or technology to be able to generate equivalent solutions to those we have come to expect for fluvial and coastal flooding is unrealistic. Instead, there is a

need to develop innovative and interdisciplinary solutions that meet the needs of end users and embrace the changing role of forecasters (Stuart et al., 2006). We have identified five “grand challenges” that should be addressed to advance this endeavor. There is inevitably some overlap between these challenges and those previously identified for fluvial flood forecasting (Cloke & Pappenberger, 2009; Emerton et al., 2016; Pagano et al., 2014; Wu et al., 2020), but, as identified in this review, the short lead times and low probabilities associated with surface water flood forecasting necessitate special attention.

6.1 | Grand challenge 1: Dealing with low probabilities of occurrence

Current operational (or near operational) surface water flood forecasting systems offer forecasts for either focused areas with short lead times or for larger regions at longer lead times. In all cases, due to the high spatial and temporal uncertainty of convective rainfall, probabilities of occurrence for specific locations will remain low and may not trigger action. Consideration is also needed of how new approaches will integrate with existing forecast products to produce a consistent “weather story” at different spatial and temporal scales. While this review discusses possible approaches to surface water flood forecasting at discrete scales (national, regional, and city), in reality, operational flood forecasting centers have responsibility across all of these scales. Like the difference in rainfall occurrence probability at point scale and larger spatial regions (Section 3.2.3), the probability of surface water flooding occurring somewhere within a region will be higher than for a particular city, which will in turn be higher than for a particular location within that city. While it is assumed that flood warnings are issued using the best available information for the location of interest, using different approaches can create an apparent disconnect between forecasting systems, leading to communication challenges (Weyrich, Scolobig, & Patt, 2019).

There are two established options for dealing with these issues, either aggregating the point rainfall probabilities to larger spatial scales (Section 3.2.3) or utilizing the benefits of risk-based forecasting to focus on “what the weather will do” and reporting the flood impacts across larger regions (Section 4.2). Questions remain over whether this aggregation should be done by forecast organizations, such as for the Natural Hazard Partnership Surface Water Hazard Impact Model for the FFC (Aldridge et al., 2020; Cole et al., n.d.; Gunawan & Aldridge, 2016), or be transparent to help meet differing needs of end users. The experience of city-scale forecasting alongside national-scale forecasts for the Glasgow Commonwealth Games (Speight et al., 2019) highlighted the need to consider the additional staff resource required to communicate spatial uncertainty at multiple forecast scales. Further research is required on seamless flood forecasting for convective events across all spatial scales. Flood forecasters should seek to learn from the meteorological endeavors to produce seamless forecasting models. This would have the additional benefit of alleviating the need to explicitly identify the source of flooding (surface water, flash flooding, fluvial flooding, etc.), which is of little relevance to decision-makers dealing with impacts.

6.2 | Grand challenge 2: Developing interdisciplinary solutions

Short lead times mean it is even more important that hydrologists and meteorologists work together and communicate a consistent message (Flack, Skinner, et al., 2019; Pagano et al., 2016). To do this effectively, there is a requirement to understand what is needed by decision-makers for effective flood risk management while ensuring hydrometeorological expertise remains at the heart of the solution (Rothfusz et al., 2018). Example key questions are what lead time is useful?, what forecast probabilities would initiate action?, and does focusing on impact rather than hazard help? Answering these questions requires input from everyone in the forecasting chain (scientists, operational end-users, hydrologists, meteorologists, social scientists) at the beginning of developing a new system (Speight et al., 2018, Wu et al., 2020). For example, in the surface water nowcasting approach (Section 4.3, Green et al., 2017), the original objective was to provide targeted advice to emergency responders trying to access the city during a flood event. This enabled a clear partnership to be developed between the users and the developers of the forecast, resulting in a product that met operational needs and was quickly transferred from research to an operational tool. Initiatives such as the one by SEPA which funded this review are essential to ensure that operational end-users are able to make the best use of new and emerging science. Similarly, academic scientists should actively seek to engage with end users to ensure that their science is able to answer real-world needs.

6.3 | Grand challenge 3: Communicating uncertainty and limitations

Surface water flood forecasts are intrinsically uncertain, and their effective use requires a realistic understanding of their limitations from end users. We may need to accept that further improvements to the current “state of the art” may not be feasible; however, we can aim to communicate more efficiently and make better use of the products that we already have. While it is acknowledged that probabilistic forecasting is required (Clark et al., 2016; Golding et al., 2014), there remains a need to support decision-makers in dealing with the probabilistic information provided to them (Arnal et al., 2019; Rabb et al., 2019). This should include providing comprehensive training on new models and systems before they are introduced and providing support during high-impact events. As Pagano et al. (2016) observed, flash flood forecasts are a suitable candidate for automation as there is little forecasters can do to improve the forecast in the short time frames available. This would free up forecasters time to use their expertise to advise on the confidence of the forecast, given the wider-scale weather situation (Flack et al., 2016; Flack et al., 2018) and on the effect of post-processing techniques on the forecast for particular locations or spatial/temporal scales.

This review has focused on the needs of decision-makers; the responsibility of communicating uncertain flood forecasts to the public (through weather and flood warnings or increasingly social media) is an additional challenge that is discussed elsewhere (e.g., Cranston, Cuthill, Smith, Black, & Malcolm, 2018; Meléndez-Landaverde, Werner, & Verkade, 2020; Parker, Priest, & Tapsell, 2009).

6.4 | Grand challenge 4: Making the best use of all sources of data

Given the high uncertainties in surface water flood forecasts, all data are valuable to help understand the localized nature of surface water flooding. New computational methods (e.g., GPUs or machine learning) offer the potential to make better use of existing data such as building footprints or high-resolution topographic data, either in real time or to build up more detailed libraries of inundation maps that better reflect the complex flow pathways of water in urban areas. There is a need for an increased acceptance of the value of “alternative” data sources and active community involvement to increase the evidence of flood inundation and impacts in urban areas. The growing number of websites and apps that encourage the public to report severe weather and impacts is encouraging, as is the increasing use of crowdsourced data to verify and validate flood models. However, work is still required to develop a consistent approach and identify how these data could be used in real time to improve surface water flood forecasts.

6.5 | Grand challenge 5: Increasing preparedness at longer lead times

While it is beyond the scope of this review to discuss flood risk management beyond the forecasting scale, it is important to note that people living in urban areas away from visible watercourses often do not realize they are at risk of flooding (Bevan, 2018). Combined with short lead times, this leads to a reduced ability for proactive community response. Surface water flood forecasting, therefore, needs to be considered as part of a package of urban flood resilience measures including the use of sustainable urban drainage systems and community readiness (e.g., property-level resilience) and a planned interorganizational response.

7 | CONCLUSIONS

Surface water flood forecasting can save lives and livelihoods by increasing preparedness before flooding occurs. The step change in convection-permitting NWP, ensemble forecasts, and computational ability over the past decade means that it is now possible to forecast and warn for surface water flooding in urban areas to support informed decision-making. However, such forecasts will remain uncertain at lead times beyond a few hours and at spatial scales less than ~ 10 km². Therefore, we suggest that the adoption of new approaches will require rethinking of established fluvial and coastal flood forecasting practices to deal with short lead times and uncertainty in surface water decision-making.

The applications cited in this review demonstrate the range of approaches that have been developed for surface water flood forecasting from simple trigger-based systems to real-time hydrodynamic modeling with integrated impact assessment. When developing new surface water forecasting systems, decisions need to be made around appropriate

modeling scales, available computational ability, integration with existing systems, attitudes to risk, and available staff support time. It is important to remember that one size will not fit all. The ability to make flood risk management decisions based on surface water flood forecasts depends on an interdisciplinary understanding of the strengths and limitations at all points through the forecasting chain. The most effective examples of this are based on a clear partnership of codevelopment between users and forecast developers, resulting in products that make the best use of available science, techniques, and data to meet operational needs.

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CONFLICT OF INTEREST

The authors have declared no conflicts of interest for this article.

AUTHOR CONTRIBUTIONS

Linda Speight: Conceptualization; funding acquisition; investigation; methodology; writing-original draft; writing-review and editing. **Michael Cranston:** Conceptualization; funding acquisition; investigation; methodology; project administration; writing-review and editing. **Christopher White:** Conceptualization; funding acquisition; investigation; methodology; project administration; writing-review and editing. **Laura Kelly:** Investigation; methodology; writing-review and editing.

DATA AVAILABILITY STATEMENT

Data sharing not applicable to this article as no datasets were generated or analyzed during the current study.

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