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Probabilistic forecasting and the reshaping of flood risk management

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Abstract
Advances in probabilistic forecasting, notably based on ensemble prediction systems, are transforming flood risk management. Four trends shaping the assimilation of probabilistic flood forecasting into flood risk management are longer forecasting lead times, advances in decision-making aids, inclusion of probabilistic forecasting in hazard mitigation and collaboration between researchers and managers. Confronting how to use probabilistic flood forecasts to make binary management decisions for reducing flood losses requires developing institutional capacity while acknowledging flood risk estimation is one component of decision making under uncertainty in an evolving policy landscape.

Keywords: flood risk management; flood forecasting; water resources management; probabilistic forecasting; uncertainty in decision making; ensemble prediction systems

1. Introduction

Advances in probabilistic forecasting are altering flood risk management profoundly. Forecasting, for de Franco and Meyer (2011), consists of all activities people engage in to make sense of the future. Since any 'rational' policy of prevention or mitigation is based on knowledge claims about what will happen and what the consequences will be, they consider forecasting to be an essential management activity. Yet, with notable exceptions, such as Dale et al. (2014), Demeritt, Nobert, Cloke, and Pappenberger (2013), Demeritt, Nobert, Cloke, and Pappenberger (2010), and Stephens and Cloke (2014), much of the discussion on forecasting focuses on scientific and technical advances rather than on the prospect for appropriately and effectively incorporating them into flood risk management. What counts when it comes to information is not the information *per se,* rather it is how the information is used (Ramos, Mathevet, Thielen, & Pappenberger, 2010). Consequently, the contribution of this paper is to set out from a practitioner perspective some key considerations in the current state of employing probabilistic flood forecasting in flood risk management.

To get the most out of flood forecasting requires understanding and quantifying the associated uncertainties curtailing their operational value (Schumann, Wang, & Dietrich, 2011). Yet making and living with the consequences of specific, binary decisions on behalf of others, such as whether to close floodgates or to issue a flood warning, based on probabilistic information, is not easy. This is especially so when the outcome of a decision appears as a mismatch with the reality experienced; for example, failing to issue a flood warning when serious flooding occurs.

Using probabilistic forecasting to operationalize risk as a core decision-making criterion involves considering the odds an outcome will happen and the consequences of that outcome. In probabilistic flood forecasting, two components are involved: (1) estimating the spectrum of potential peak levels of water predicted, which determines the likelihood of flooding, and (2) determining the impact of flooding caused when water reaches the predicted levels (Dale et al., 2014).

Ensemble forecasts, by distinguishing where forecast uncertainties come from (Schumann et al., 2011), are one means for formally incorporating uncertainty (Pagano, Shrestha, Wang, Robertson, & Hapuarachchi, 2013). Ensemble forecast systems indicate uncertainties in input data, parameters, and models (Schumann et al., 2011); they are run many times, each time beginning with slightly altered starting conditions and with small perturbations to the model (Bowler, Arribas, Mylne, Robertson, & Beare, 2008; Cloke & Pappenberger, 2009). Rather than generating one value for the variable being investigated, a range of values are created (Dietrich, Denhard, & Schumann, 2009). Data and information generated by imperfect models and uncertain data can be merged using ensembles (Schumann et al., 2011). A key intent of ensemble flood forecasting is to array the complete range of forecast uncertainty and/or predictability by presenting various hydrological responses to different inputs generated from atmospheric ensemble prediction systems (Zappa, Fundel, & Jaun, 2013). Since not all forecast users have the same risk tolerance, ensemble prediction systems are useful because they generate information applicable to different decision thresholds. For the same flood event, different people experience different costs of flooding (Pappenberger, Cloke, et al. 2011). For example, a user confronted by high costs of taking protective action compared to prospective loss may well require more certainty to act than a user facing a lower ratio (Zhu, Toth, Wobus, Richardson, & Mylne, 2002).

Advances in probabilistic flood forecasting are among the converging circumstances making it timely to consider the implications for flood risk management of incorporating flood forecasting uncertainties. These are discussed in the next section followed by an examination of what makes forecasts with uncertainty useful to practitioners. After that, four trends shaping the incorporation of probabilistic forecasting into flood risk management are identified. Before concluding, selected challenges facing practitioners interested in incorporating probabilistic forecasting into flood risk management are reviewed.

2. Why it is timely to consider incorporating flood forecasting uncertainties in flood risk management

A convergence of five circumstances makes it timely to consider the implications for flood management of incorporating uncertainties in flood forecasting.

(1) People and property are increasingly exposed to flooding (Gopalakrishnan, 2013; Stephens & Cloke, 2014; United Nations International Strategy for Disaster Reduction [UNISDR], 2012). There is mounting concern about how vulnerable water resources are to fast-changing conditions and our collective capacity to mitigate the impacts of extreme events on what people care about (Ramos, van Andel, & Pappenberger, 2013).

(2) Capabilities for forecasting are improving (UNISDR, 2012). More attention is being paid to how ensemble prediction systems can be used to advance operational flood warning and flood risk management (Cloke & Pappenberger, 2009; Demeritt et al., 2013). Lessons are being drawn from the successful use of ensemble prediction systems in weather

forecasting (Cloke & Pappenberger, 2009) and climate prediction (Collins, 2007). Consequently, beginning in the late 1990s, hydrological applications of ensemble-based meteorological forecasts have been developed (Schumann et al., 2011). Doing so captures such benefits as improving forecasting skill (Nobert, Demeritt, & Cloke, 2010). For hydrological ensemble prediction systems (HEPS) this means extending the lead-time for predicting floods (Pappenberger et al., 2013). Especially over the medium range of 3–10 days, ensemble prediction systems demonstrate greater skill than conventional deterministic forecasting systems in forecasting rainfall and related fluvial flooding (Richardson, 2000; Roulin, 2007; Pappenberger, Thielen, & Del Medico, 2011).

To advance operational water management and better anticipate hydrologic extremes, meteorological and hydrologic prediction models have been coupled. Based on these coupled models, forecasting and warning systems have been developed to improve flood and drought risk planning and response, and to optimize managing and regulating water use for purposes ranging from domestic consumption to supplying thermal power plants (Ramos et al., 2013).

Advances in applying ensemble prediction systems to flood forecasting may give people more confidence in forecasts and make them more willing to act on forecasts than they are currently (Demeritt et al., 2010). Still, applying meteorological ensemble forecasts to flood forecasting is not unproblematic. For example, there are few options to validate them because data is limited and the reforecasting of past flood events is costly (Schumann et al., 2011). Generating large ensembles is restricted by the extent of model complexity and high model resolution (Curry & Webster, 2011). Probabilistic techniques are often focused on selected sources of uncertainty, such as in model parameters, and on reducing them in selective ways (Pappenberger & Brown, 2013). As a result, the uncertainties of models are not fully represented by ensemble forecasting systems (Schumann et al., 2011). Advances in post-processing of forecasts are making headway, however, in ameliorating this situation (Cloke et al., 2013). Nonetheless, methods and techniques to cascade uncertainties are not yet fully developed and tested in operational meteohydrology (Ramos et al., 2010).

(3) The scientific community envisions contributing to improved decision making by providing users with probabilistic weather information (Marimo, Kaplan, Mylne, & Sharpe, 2012). Indeed forecasts that do not include uncertainty information are now considered incomplete. Providing an estimate of uncertainty is regarded as being as important as increasing accuracy and timeliness (National Research Council, 2006). The weather, climate and hydrology communities are more interested in effectively conveying uncertainty as the capacity to estimate uncertainty in hydro-meteorological forecasts has improved (National Research Council, 2006; Pappenberger & Beven, 2006). Part of this enlarged capacity stems from employing an increasingly broad array of models in a framework for estimating uncertainty. This has been made possible by greater capacity in computational power, parallel processes, and software (Juston et al., 2013).

(4) At the turn of the twenty-first century there has been notable progress in understanding how individuals grasp uncertainty and probabilistic information (Marx et al., 2007). What is becoming apparent through empirical research is study participants make better decisions when provided with information about uncertainty than when they are not provided with it (Marimo et al., 2012; Roulston & Kaplan, 2009).

(5) Decision makers are expressing interest in gaining a sense of the range of uncertainties they face and the risks associated with the consequences of their choices (Pappenberger & Beven, 2006). Civil protection authorities will employ ensemble prediction systems if they can see how these systems will help optimize their operational options for managing risk (Nobert et al., 2010). Users prefer to make their own situational assessments, and as demonstrated by the public's preference when it comes to weather forecasts, do appreciate probabilistic information (Frick & Hegg, 2011; Handmer & Proudley, 2007). The use of probabilistic flood forecasts is in tune with the wider trend in public policy to employ riskbased decision making. For example, the United Kingdom government has been a leading proponent of embedding risk as a core decision-making consideration (Rothstein & Downer, 2012), thereby making risk management an integral component of government planning (Massey & Rentoul, 2007).

3. Making forecasts with uncertainty useful to practitioners

When users receive a forecast including upper and lower bounds of the predictive interval they may conclude forecast providers acknowledge the forecast's uncertainty and still consider taking protective action is justified. This is particularly important for extreme events when it is vital for people to trust the forecast and to take the recommended actions (Joslyn, Savelli, & Nadav-Greenberg, 2011). A key determinant of the palatability of warnings to decision makers is whether or not they perceive there are feasible actions they can take at a cost they can afford (Meyer & de Franco, 2011).

When people are not provided with estimates of forecast uncertainty they attempt to take uncertainty into account on their own (Joslyn et al., 2011). In doing so they may make serious errors (Joslyn & Savelli, 2010). Ramos et al. (2013) found when people are not provided with uncertainty information, they move towards risk-averse positions.

Providing uncertainty information contributes to more optimal decisions and tends to result in individuals making convergent decisions (Ramos et al., 2013). Conveying the uncertainties surrounding scientific knowledge and admitting the limitations of that knowledge helps gain and retain decision makers' and the public's trust (Juston et al., 2013; Ramos et al., 2013).

While technical qualities provide one framework for assessing the overall value of hydrometeorological forecasts, a second framework emphasizing functional qualities, such as how forecast products, characteristics and metrics are communicated (Buizza et al., 2007) is of direct interest to decision makers. Forecast system utility is about measuring how valuable forecasts are for practical applications. This depends on forecast system attributes such as space-time scale and quality. Are forecasts issued at usable scales and lead-time? Are they provided in a timely manner? Are uncertainties communicated appropriately? (Pappenberger & Brown, 2013). What will help increase the use of probabilistic forecasts generated by ensemble prediction systems are advances in how these forecasts are presented and the means to evaluate the ensemble forecasts from the users' perspectives (Cloke et al., 2013). The value of a forecast is a function of the extent to which it shapes decisions where uncertainty is a major concern (Handmer & Proudley, 2007; Murphy, 1993). Ultimately what matters is the extent to which a forecast results in benefits accrued, or losses avoided, that would not have occurred if it was not employed (Schumann et al., 2011; Zhu et al., 2002).

Different users make use of different forecasts. Given the array of needs, users value forecasts they can adapt appropriately to their individual circumstances (Handmer &

Proudley, 2007 citing McDavitt, 1998). Ideally, ensemble-based operational flood management systems should reflect the differing needs different operational functions, such as controlling reservoirs, releasing flood warnings, and triggering flood defense measures, have for varying extents of forecast accuracy and lead times (Dietrich et al., 2009). Total discharge volume forecasts are valuable to lake managers and hydropower dam operators. For flood planning and relief, the timing of peak flow and volume of peak discharge are key (Zappa et al., 2013). Reservoir management and early warning systems for potential extreme flood events make use of medium-range forecasts with lead times of 3–5 days. Flood alerts are delivered, and flood defense measures are initiated, based on short to very short-range forecasts that include detailed information about peak time, peak discharge and possible inundation areas, and into which observed data can be assimilated. Hydrological uncertainty is a critical consideration in short-range forecasting (Schumann et al., 2011).

Under a number of circumstances decisions based on probabilistic rather than deterministic forecasts are advantageous. Yet it is less clear whether this holds when forecast error increases or action is required when the probability of an event occurring is low. While there are benefits to quantifying uncertainty in many circumstances, emergency managers contend that, when the probability of an adverse weather event is low, specifying the low probability will discourage compliance with warnings. For example, to enable a successful evacuation severe weather warnings must be released early. Yet, the probability of adverse weather in a given region may be less than 20% just a few days before the event is anticipated to strike. It is tempting for decision makers to withhold uncertainty information because of the perceived need to reduce the complexity of information being presented (Joslyn et al., 2011). It is unclear, though, whether better decisions are procured by providing people with uncertainty forecasts or by providing them with explicit instructions (Joslyn & LeClerc, 2012).

4. Trends to watch

The world of incorporating probabilistic forecasting into flood risk management is fast evolving. Four trends are contributing to the shape and pace of this evolution.

(1) Creating longer forecast lead times provides an essential underpinning for improving early warning systems, investing in flood mitigation, advancing preparedness and furthering risk awareness. One promising means for doing so in hydrological forecasting is using coupled meteohydrological forecasting systems (Ramos et al., 2010).

(2) While decision-making aids for exploiting probabilistic flood forecasting are in their infancy (Dale et al., 2014), the search is on for promising means to incorporate new decision support technologies into practice (Demeritt et al., 2010; Frick & Hegg, 2011). This includes how to assimilate ensemble prediction systems, touted as the best available science for operational flood forecasting, effectively and appropriately into decision support for flood risk management (Demeritt et al., 2013). If forecasts are to be valuable in time-sensitive situations, such as managing flood incidents, developing visualization tools and forecast products that effectively and appropriately convey uncertainty becomes critical (Cloke et al., 2013).

(3) While much attention has focused understandably on using probabilistic flood forecasting for real time flood management (Cloke et al., 2013), incorporating such forecasting

into long-term hazard mitigation and adaptation will have profound implications. For example, the full potential of incorporating ensemble models into maps indicating risk to floodplains has yet to be realized. In the immediate, the inherent uncertainty in these maps pose challenges for planners (Faulkner, Parker, Green, & Beven, 2007) and others attempting to use them to guide decision making.

(4) Reflecting a broad trend towards inclusive decision making, there is growing interest in collaboration as an important means for incorporating probabilistic forecasting into flood risk management. Collaboration ideally involves scientists, forecasters and end-users (Pappenberger, Cloke, et al. 2011). A powerful reason to collaborate is to provide operational forecasts predicting the variables of greatest salience to the decision being made in the form and time scale of most value to users (Wilks, 1997). It is also helpful if joint decisions are made by producers and users about how to illustrate and demonstrate inconsistency in forecast products (Pappenberger, Cloke, et al. 2011).

The process of designing ensemble prediction systems benefits from users being involved in the very early stages (Nobert et al., 2010). Likewise it is valuable for information providers to partner with the decision maker to reach decisions using the new information. A prerequisite is having information providers appreciate how the targeted recipients interpret and intend to use the information received (Morss, Lazo, & Demuth, 2010) and how the information contributes to shaping the decision makers' beliefs.

How probabilistic forecasts can be communicated effectively to nonscientists engaged in flood risk reduction is still being worked out (Nobert et al., 2010). While promising visualization tools are being employed, there are not yet agreed upon best-practices for communicating ensemble flood forecasts. This reflects both (1) the relative novelty of such flood forecasts (Lumbroso & von Christierson, 2009) and (2) the lag between generating the science and its utilization. An overarching frustration is the delay between gains in forecasting and the uptake of state of the science forecasts by decision makers (Demeritt et al., 2013).

5. Challenges

Technical challenges remain in designing and generating ensemble prediction systems for flood forecasts (Cloke & Pappenberger, 2009; Demeritt et al., 2010; Ramos et al., 2010). Our interest in this paper, however, is on challenges to incorporating probabilistic forecasts into flood risk management from the vantage of practitioners. However uncertain is the forecasting, flood managers must make categorical decisions for specific places often in a pressurized setting, frequently in advance of a potentially damaging event (Cloke & Pappenberger, 2009; Dale et al., 2014). For example, managers must decide whether to close flood gates or not, to erect temporary flood barriers or not, to issue warnings or not (Dale et al., 2014; Penning-Rowsell, Tunstall, Tapsell, & Parker, 2000; Werner, Cranston, Harrison, Whitfield, & Schellekens, 2009). The question for decision makers in such circumstances is how in real-time to use probabilistic flood forecasts to make binary decisions. Practitioners must choose which one or a combination of forecasts from among the range of possible probabilistic forecasts is most helpful in addressing a particular decision (Dale et al., 2014). Probability-based decision making is challenging in the context of situation-specific settings (Handmer & Proudley, 2007). It is one reason Nobert et al. (2010) recommend ensemble prediction system training be custom designed and delivered locally.

Moving to probabilistic forecasting from deterministic forecasting may trigger an institutional shift in who is responsible for decision making under uncertainty (Dale et al., 2014). Who owns the uncertainty judgment has implications for the relationship between forecast producers and users. The outcome determines who will be blamed (De Franco & Meyer, 2011).

Accountability is also a concern among forecast producers. National flood forecasting agencies in Europe that have public safety statutory mandates and value certainty over advance notice may be cautious about employing the European Commission's European Flood Alert System (EFAS) alerts generated from medium-term ensemble forecasts. They are concerned about being held responsible if EFAS alerts are wrong (Demeritt & Nobert, 2011).

Interpreting flood forecast uncertainties generated through the scientific enterprise may not be a responsibility with which those who have not generated the forecasts are comfortable. Practitioners may be reluctant to interpret uncertainty tools (Faulkner et al., 2007 citing Handmer et al., 2003). Emergency managers may struggle at the outset to understand probabilistic forecasts especially when probabilistic forecasts may seem to be at odds with what some flood professionals regard as their primary need, accurate information (McCarthy, Tunstall, Parker, Faulkner, & Howe, 2007).

While operational flood forecasters seek greater certainty at the local scale, mediumterm forecasts by their construction are coarse in scale and often uncertain. Forecasters confront the tension between competing and incompatible policy demands for earlier warnings and more certain ones. The uncertainty of medium-term flood forecasts requires users to weigh the opportunity costs of precautionary action and false alarms. While advances in ensemble prediction systems hold out the promise of increasing the predictability and foresight offered by medium-range (3–7 days) forecasts, what is not in place is the institutional capacity to utilize fully such forecast outputs in flood risk management (Demeritt et al., 2013).

As flood forecasters understand it, the preferences of those in civil protection authorities is for 'deterministic forecasts issued with a high degree of certainty' (Demeritt et al., 2013, p. 155). This reflects an institutional culture seeking to avoid false alarms, and the associated harmed reputations and disinclination of individuals to respond to future warnings (Nobert et al., 2010). There is concern a series of false alarms will result in individuals no longer responding to warnings and in so doing increase the consequences of a damaging event when it does happen. Conversely, a failure to warn individuals about a flood event that does occur can be devastating to those directly impacted by the flooding and for the authority that did not provide the alert (Dedieu, 2010).

Institutional mandates understandably dictate what staff members emphasize. For example, historically European flood forecasting agencies because of their public safety statutory responsibility focused on very short term warnings in the zero to 48 hour range to facilitate public evacuation rather than medium-term forecasting valuable for mitigating flood damage. This responsibility meant that, when it came to issuing flood warnings, they set high confidence thresholds more achievable in the very short term than for longer time horizons (Demeritt et al., 2013).

Estimating flood risk is one component of the wider challenge of making decisions under uncertainty in an evolving policy landscape (Faulkner et al., 2007). For example, to incorporate climate change into planning activities, water managers must include uncertain information derived from a range of projections from climate models into the management and operation models they already use. Uncertainty around individual considerations increases concurrently with consideration over time of different issues (Barsugli et al., 2012). Flood risk managers must consider the natural indeterminism of whether a flood will occur or not, along with associated social indeterminism, such as how an issued warning will be interpreted and the implications of an issued warning not being justified (Demeritt et al., 2010; Michaels & Tyre, 2012). Uncertainty about human behavior may result from the diverse perspectives individuals and communities bring to the situations they face. It may also be a function of conflicting interests, varying standards for evidence, and differing degrees of risk aversion (Casman, Morgan, & Dowlatabadi, 1999; Morgan, 1998; Moss, 2007).

People with different attitudes process evidence, including uncertain and conflicting evidence, in different ways (Corner, Whitmarsh, & Xenias, 2012). The critical point for forecasts is the one at which individuals alter their plans (Handmer & Proudley, 2007); however, there may not be a universal critical point. In making tradeoffs required in decision making, such as between current and future risks, people may benefit less from more facts and more from different perspectives that help them clarify the implications of a decision on what they value (Pidgeon & Fischhoff, 2011).

6. Conclusion

Our ability to leverage the considerable advances in probabilistic flood forecasting is contingent on being able to apply them in decisions that ultimately reduce losses from flood risk. From a practitioner perspective, one of the most demanding aspects of applying probabilistic forecasting is how to consider constructively the uncertainty articulated in such forecasts. Doing so involves reconfiguring entrenched patterns of interaction between model developers, model users, those making decisions based on model outputs, and those affected by such decisions. With earlier, deterministic models it was easier to consider that a linear approach to forecast transmission was adequate and to down play subjective considerations, such as risk tolerance. With probabilistic forecasts generating a range of possibilities, the advantages of ongoing interaction between development, use and exploitation of forecasts come to the fore. Probabilistic forecasting highlights there is no single output satisfying the needs of all users. A critical, ongoing search in practitionerengaged probabilistic forecasting is underway to develop forecasts that generate the outputs needed for decision making. In the long lead-up to this ideal state, we must explore how best to bridge what we can do with what is needed.

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