Overview of Forecast Communication and Use of Ensemble Hydrometeorological Forecasts

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Abstract

Over the last few decades, hydrometeorological forecasting, warning and decision making has benefited greatly from advances in the natural, physical, computing and social sciences. A fast developing computing capability has enabled meteorologists to produce ensemble prediction systems (EPS) that quantify the uncertainty in forecasting and simulating floods, droughts, and in water management decision making. At the same time, the social sciences have helped to understand the human perceptions of risk information and how different actors communicate hazard, risk and uncertainty information. Ultimately hydrometeorological forecasts are used in making decisions. However, to be effective, such decisions must be communicated to the hazard response organisations and to the general public. For this, the communication must be simple and clear, it must be relevant and should come from a trusted source. This overview summarises how such communication is organised for a variety of applications in different countries. It is the effectiveness of the entire system which must be considered and assessed. As ensembles are increasingly used in increasingly longer term management and policy decisions, the range of end-users and their differing requirements can only expand and flexibility and adaptability to individual circumstances will be required from both the natural and social scientists involved.

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Ensemble prediction systems (EPS) · Flood · Forecast communication · Hydrometeorological forecasts

Over the last few decades, hydrometeorological forecasting, warning, and decision making have benefited greatly from advances in the natural, physical, computing, and social sciences. A fast developing computing capability has enabled meteorologists to produce ensemble prediction systems (EPS) that are now applied in various sectors including hydrological applications for the forecasting and simulation of floods, flash floods, droughts, and water management decision making. Ensemble prediction systems allow us to quantify the uncertainty in our forecasts in a meaningful way and to better understand the limits of predictability (Thielen et al. 2009; Rossa et al. 2010; Zappa et al. 2010) and so provide decision makers with longer useful lead times to prepare for the event. The amount and breath of material in this handbook is evidence of the importance that hydrological ensemble prediction systems are playing in various applications in hydrology.

At the same time as the natural and technical sciences improved forecasting technology, the social sciences have helped to understand the human perceptions of risk information and how different actors communicate and respond to hazard, risk, and uncertainty information between peers (horizontally) as well as within a hierarchy (vertically) (e.g., Drobot and Parker 2007; Demeritt et al. 2007). The natural sciences and social sciences communities are united in the realization that uncertainties must be managed rather than ignored or eradicated at all cost (Drobot and Parker 2007), a view that is also shared within the response community (IFRCRC 2012).

Ultimately, hydrometeorological forecasts are used in making decisions. Decision making or planning under uncertain conditions can be a complex, yet everyday, experience that people encounter. *"Uncertainties exist when details of situations are ambiguous, complex, unpredictable, or probabilistic; when information is unavailable or inconsistent"* (Brasher 2011, p. 478). In addition to the uncertainty of whether a predicted future event, e.g., a flood or drought, will occur, forecasters are also faced with the uncertainty an individual person feels about taking the right or wrong decision on a course of action.

Decisions could be urgent ones, i.e., related to immediate emergency response, where life is at risk, or less time-sensitive ones possibly relating to the longer term management of resources or the formulation of policy. The most important requirement is that the decisions are effective. This means they save lives, reduce damage to health, property or quality of life, or improve the management of infrastructure and resources. Hydrometeorological forecasts are just one source of information available to the decision maker who must take all other types of information from many other sources into account in deciding what should be done. Examples of other sources of information could be (i) the demographics of populations at risk for instance their age profile – the very young and very old may be particularly vulnerable or their health/disability status, (ii) hydropower energy demand, (iii) temporal variations in requirements for irrigation water or public water supply, and (iv) transport traffic on water ways, just to name a few. Some indication of the reliability or uncertainty in each data source is essential to guide their influence on the final decisions. This is straightforward if the information is a direct measurement, e.g., of flows, water levels, or precipitation, for which the measurement uncertainties are well understood. However, it is much more problematic when the information is a forecast and even more so when it involves such complex system and models as for the atmosphere or a river basin. Nevertheless, such information is essential if the decision maker is expected to consistently make good decisions. While forecasters tend to want this information, they find it difficult to quantify any improvement in skill due to having this information, Frick and Hegg (2011).

For hydrometeorological forecasts, based on ensembles of simulations, possibly with multiple models, some uncertainty information is already implicit in the ensembles. The critical issue is how to extract the uncertainty information and how to present it to the decision maker. It is important that the decision maker is not overburdened with unnecessary information nor is expected to do complex analyses in a hurry, particularly in emergency response situations. Many approaches have been suggested, including some based on a cost-benefit analysis (Dale et al. 2014) and others based on a decision scaling method(Turner et al. 2014). Simplicity, clarity, relevance, and trust are thus the ideal characteristics of the way ensemble information is presented to a decision maker. Their resulting actions may be instrumental in saving lives and property, and they may, after an event, be held accountable for the decisions. This serious responsibility has a large influence on their approach to making decisions, often characterized by a risk-averse conservatism (Block 2011) and a tendency towards institutional inertia (Rayner et al. 2005). The different attitudes of the decision maker to costs and losses can lead to suboptimal decisions (Millner 2009) so there is a complex challenge to demonstrate the effectiveness of model-based decision support systems, Moser (2009). Millner (2008) develops a decision model for use with ensembles which incorporates the user's cost-loss profile. Weaver et al. (2013) identifies one barrier to the increased use of climate models as a failure to incorporate information from the decision science and social science disciplines and argue for a paradigm shift towards a multidisciplinary decision support framework. Marshall et al. (2011) maintain that social factors are important in the take-up of climate model information and Renn (2011) identifies the perception of risk information and its social amplification as an important issue. End users' requirements span many factors other than technical model or resolution improvements and include education and training (Wetterhall et al. 2013).

The characteristics of good forecast communication, mentioned above, are:

(i) **Simplicity and Clarity**: Spaghetti plots are too complex and potentially confusing (Zappa et al. 2013). This has been recognized by forecasters for some time, e.g., WMO (2003). Demeritt et al. (2010) explain the particular issues that decision makers have with spaghetti plots. Stephens et al. (2012) reviews methods of visualization and Bruen et al. (2010) describe the visualization strategies of some operational systems.

(ii) **Relevance**: This depends on the use of the forecast, e.g., emergency response, hazard warning, or water resources management. The timescale may be immediate, medium or longer term, typically ranging from single event scales to climate change impacts on water resources. Actively seeking end user feedback and responding accordingly is a key element of maintaining relevance (Demeritt et al. 2013). Contextually sensitive approaches to presenting information are important (PytlikZillig et al. 2010).

(iii) **Trust:** Sector-specific and local sources of information are most likely to be trusted. However, in order for persons to respond correctly to a warning, it is also important that they are familiar with the event, e.g., occupants of a house that has recently been flooded will most likely act differently to a flood warning compared with occupants who have never experienced this threat. The social aspects of warning are very important and must be correctly understood (Drabek 1999). Individual relationships can be important (Lackstrom et al. 2014), and also the use of established networks (Kirchhoff 2013).

Methods of communicating probabilistic forecasts and their use are as many as their applications on the short, medium, and long ranges as well as for local, national, continental, and global scales. A comprehensive review is provided in this handbook by Pappenberger et al. in Part 10 "Ensemble Forecast Application and Showcases." In addition, Alfieri et al. "*Flash flood early warning based on precipitation-indices: three examples at the European and regional scale*" highlight the growing trend of the hydrological community to increasingly use ensemble prediction systems based on radar, nowcasting, and high-resolution short-term forecasting data or combinations thereof to improve the prediction of flash floods. Both information from regional monitoring networks and the expertise of local flood forecasters are being integrated for better forecasting of location and intensity of the events (cf. Alfieri), which is also important information to translate the hazard forecasts into impact-based forecasting and risk information as described by Wittwer et al. "*Challenges of decision making in the context of uncertain forecasts in France"(Section 10).* Such information is crucial for the translation of hydrological forecasts into actionable warnings which serve as guidance for decision makers, the response community and the public. Bates et al. illustrate in "*Probabilistic Inundation Modelling*" (Section 10) how the recent advances in computing power and high-resolution mapping have made probabilistic forecasting of flood inundation possible, allowing now to quantify the probability of flood occurrences with sufficient advanced warning for taking useful preventive actions. Taking for example the June 2013 floods in Central Europe, Bates et al. demonstrate how such applications can work across scales, e.g., how input from a medium-range, continental system such as the European Flood Awareness System (Thielen et al., Section 10) can be successfully combined with a high-resolution hydraulic model (LISFLOOD-FP) to derive probabilistic inundation maps. Such maps could provide important guidance to decision makers and provide information on the temporal as well as spatial uncertainty on expected flood extent. Thus, the range of examples provided in section 10 shows that ensemble prediction systems have become a trusted and well-established feature for flood forecasting on the short ranges as well as medium range, for local systems as well as global systems. However, the application of ensemble prediction systems is by far not limited to flood forecasting only but extends for example also to shipping ("*Probabilistic shipping forecast*" by Meissner et al., Section 10), prediction of droughts ("*Seasonal drought forecasting*" by Wood et al., Section 10), hydropower ("*Hydro-power forecasting in Brazil*" by Tucci et al., and "*Ensemble forecasting for hydropower in Canada*" by Boucher and Ramos, Section 10), or generally water resource management.

The chapters in this section of the handbook aim at summarizing at a few key issues which are illustrated with concrete examples: These complement the examples in Section 10 and present a snapshot of methods of communication of EPS in forecasting at a number of locations in three very different continents, Australia, Asia, and the USA. A broad range of challenges, both in climate and computational resources, is represented. A number of different timescales are involved, varying between shorter term flood forecasting for emergency response to longer term streamflow forecasting for water resources planning.

Tuteja, Zhou, Lerat, Wang, Shin, and Robertson explain that because of the very high variability in stream flows in Australia, seasonal forecasts, which are used in practical water resources applications, have a high degree of uncertainty which must be communicated with the forecasts. The focus is on minimizing the risks of misunderstanding as well as on communicating the forecast skill. A Bayesian Joint Probability model is used (Wang et al. 2009) with a 5000 member ensemble (some results are sensitive to ensemble size) generated from an empirical multivariate model of stream flows. A number of different forecast skill metrics were evaluated. There is some variation of forecast skill with season, but the best forecasts are for the latter half of the year when storages are filling.

Hartman describes different approaches to the specific forecast information communicated in the USA. There, the resources to generate ensemble flood forecasts are widely available, and the issue is whether to generate an uncertainty product from the ensembles and deliver this to the end user or to deliver all of the raw, unprocessed, ensemble forecasts to the end user, allowing them to analyze them in whatever way they deem appropriate. Usually the provider of the forecasts is best placed to produce the decision support "tool" for the end user. Use of ensembles in longer range water resources forecasting in the USA is complicated by the attenuating effects of its many reservoirs. The management of (and releases from) each must be included in the simulations. Interestingly, end users often want to see the related input data, such as precipitation and snowpack forecasts, as these convey significant information for the longer term predictions. Considerable emphasis is placed on validating EPS forecasts using hindcasts, e.g., simulating what forecasts the system would have made for past weather. This helps to identify bias in an EPS system, but is computationally demanding.

The following chapter, consisting of a number of forecast communicating examples from around the world, addresses the requirements for communicating ensembles and uncertainty for short-term, medium-term, and long-term applications and decision making. They address the issues of (i) how the information is produced and used at different scales? (ii) how the specific needs of decision makers, forecasters, and water managers are reflected in the set-up of the early warning systems, and (iii) identifying where ensemble prediction systems can play a useful role and where their application is limited.

Pegram highlights the importance of robust and reliable information for disaster managers when emergency actions such as evacuations are required. Repeated false alarms result in lack of trust between the public and the decision makers which is particularly critical when the time to react is limited, e.g., in urban and flash flood prone areas. He gives the example of the city of Durham in South Africa and explains how ensembles are generated from radar data to quantify the uncertainty in the rainfall and hydrological response to produce reliable forecasts for the decision makers.

While early warning based on radar ensembles is typically limited in lead time from 0 to 6 h, high-resolution EPS from numerical weather prediction can be useful to provide an early warning indication that potentially critical conditions are possible within a time frame of 1–3 days as illustrated in the second section by Raynaud. Although not sufficiently precise in terms of location and timing for local civil protection to take specific actions, such indicators can be useful for local authorities to be prewarned, take precautionary actions, and put staff and equipment on standby.

In particular for trans-national river basins, where typically different agencies and multiple authorities are involved in monitoring, forecasting and decision making, the additional lead times gained through HEPS proves to be important. For instance, *Sprokkereef, Ebel & Rademacher* illustrate how HEPS have been used for the Rhine, a river basin shared by nine countries, for more than 10 years to calculate probabilistic water levels and discharges and they describe how they are communicated and distributed on a daily basis to expert users. The added value of the probabilistic forecasts in comparison to deterministic ones has been demonstrated especially for navigation-related water-level forecast.

Finally, longer term EPS such as monthly and seasonal forecasts find application more in water resources and hydropower management than in emergency response. Being the most common form of renewable energy worldwide, it is not surprising that the optimization of hydropower output is of particular interest for different sectors. Olsson, Alionte-Eklund, Johansson, Lindström, and Spångmyr describe how HEPS are used in Sweden for hydropower optimization. The added value of hydrological probability forecasts as support in decision making to hydropower plant operators is demonstrated, but also the limitations with regard to spatio-temporal resolution are also highlighted.

Hirpa, Fagbemi, Afiesimam, Shuaib, and Salamon highlight the special challenges of translating scientific information into practical operations in developing countries where hydrometeorological disasters have profound impacts on human lives. While, for example, the previous chapters illustrate advanced early warning systems benefiting from high-density observational networks, skillful weather forecasts and ensemble systems as well as state-of-the-art web technologies for communication and information sharing, there are still many places in the world where such levels of sophistication and technology are not yet utilized.

The use and communication of ensemble predictions and uncertainty require a minimum data sharing and IT infrastructure, while for communities without Internet there is a need for a different means of information dissemination such as by phone or through a face-to-face conversation. Trans-disciplinary and multistakeholder partnerships offering global solutions for basic coverage and provision for medium-range forecasts and near-real-time remote sensing detection of events can play a major role in accelerating the process of incorporating science into more effective disaster planning to save human lives and protect the economy.

Demeritt, Stephens, Créton-Cazanave, Lutoff, Ruin, and Nobert conclude this section by investigating the practical challenges of communicating and using ensemble forecasts at the example of operational flood incident management. Based on recent social science research on the variety and effectiveness of visualizing hydrological ensemble prediction, the chapter highlights cognitive and other difficulties experienced by the users of probabilistic forecasts to understand the information correctly. Recognizing that the way uncertainty information is presented has influence on its perception, this chapter illustrates the most common way of communicating EPS to different users with varying level of expertise in probabilistic forecasting. It also highlights that probabilistic information can be misunderstood, for example, by the general public but equally by expert users, if the underlying concept of probability is not fully understood. Dialogue between the producers of HEPS and the users, for example, through repeated discussions or training is identified key action for the correct uptake of the information by the decision makers.

However, even if the information is well communicated and received, there remains the issue that anticipatory actions and decisions based on uncertain forecasts will always be associated with a risk and different mechanisms for an improved management still need to be further explored.

Accepting that there is not a single solution to fit all applications, it emerges that the visualization and the communication of HEPS need to be tailored to the respective end users. This is particularly challenging the less defined the end user community is, e.g., in continental and global systems.

Scientists and engineers involved in hydrometeorological forecasting have realized for some time now that their role is not confined to the generation of forecasts and associated uncertainty information. To be effective and make a real difference in the lives of people, this information must be communicated in a convincing way to the right decision makers whether these are civil protection, water resource managers, or the public. It is the effectiveness of the entire system which must be considered and assessed. Different approaches to what is communicated and how such communication takes place, described above, illustrate how diverse the area can be, how much progress has already been made, and how much more there is to be done. As ensembles are increasingly used in longer term management and policy decisions, the range of end users and their differing requirements can only expand and flexibility and adaptability to individual circumstances will be required.

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