Overview and Main Results on the interdisciplinary effort in flood forecasting COST 731 – Propagation of Uncertainty in Advanced Meteo-Hydrological Forecast Systems

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1. Introduction

Floods are among the most commonly occurring types of natural disasters in Europe and their frequency and people’s vulnerability is increasing across Europe (Barredo, 2007). This is because of increased development pressures on floodplains with more and more people and valuable infrastructure moving into flood-prone areas. The European Commission recognized the paramount importance of the natural hazards issue for the protection of the environment and the citizens and made significant investments in associated research and development ever since the 4th Framework Programme in 1994. One particular focus is the real-time forecasting of extreme events with significant flooding potential, which is the basis for triggering a range of mitigating actions. This is a difficult task for many reasons, a main one being related to successfully integrating the contribution of the different ‘spheres’ (atmosphere, hydrosphere) each of which with its different modelling approaches, inherent uncertainties, limitations and, not least, paradigms of application.

Uncertainty recognizes a certain amount of fuzziness in the forecasts which contrasts with the definitive, categorical, decisions that flood relief managers have to take in order to launch mitigating actions. Significant effort is needed towards reconciling this apparent clash of paradigms by working on the conceptual and communication issues between scientists and decision makers related to uncertainty information (e.g. Demeritt et al., 2007). Such clarification is necessary even on a purely scientific level, in that uncertainty information seems to be perceived fundamentally differently by weather forecasters and flood forecasters. Full-fledged flood forecasting systems which make use of meteorological forecasts to extend warning lead times are relatively recent and many operational centers around the world are increasingly moving towards such systems (e.g. Cloke and Pappenberger, 2009). In these, testbeds are often developed and play an important role in exploring the potential of integrated probabilistic flood forecasting systems (Schaake et al., 2007; Rotach et al., 2009). Also, they are indispensable opportunities for gathering hands-on experience and provide training for operational staff, without which it will be very hard to resolve the communication and paradigm difficulties.

The COST 731 Action, of the latest in a series of COST Actions related to radar meteorology, can be seen as the expression of the will of a large number of European meteorological and hydrological services to further both understanding and, even more so, application of systematic uncertainty information. The Action hence focuses on hydro-meteorological forecasting and how to deal with the uncertainties inherent in the entire forecast chain. The COST 731 Action was proposed within the ESSEM Domain and launched mid 2005 for a five-year period as an offspring of a series of COST Actions related to radar meteorology (Rossa et al., 2005a). While the COST Actions 72, 73, and 75 dealt with pure scientific issues related to single weather radars, radar networking, and advanced capabilities (Meischner et al., 1997), Action 717 focused on the application of radars in hydrological and NWP models (Rossa et al., 2005b). In these earlier Actions, the unparalleled ability
of the radar to observe precipitation in 3+1 dimensions was explored and used for validating NWP precipitation forecasts and improving the model’s initial conditions. In addition, COST 717 sought to promote the use of radar quantitative precipitation estimates (QPE) for hydrological modelling. On a non-technical level, two issues stood out: the need for a clearer communication between the participating scientific groups, and the necessity to quantify, or at least describe, the variable quality of the radar-derived QPE. The lack of understanding of this uncertainty often led to the exclusion of these data. COST 731 was, therefore, designed to address the quantification and communication of the uncertainty in meteorological observation and forecasting along with their effect on hydrological forecasting, and the subsequent impact on the decision making process. An extensive review on the propagation of uncertainty in flood forecasting systems be found in Rossa (2010b). The Action was strongly linked to the MAP D-PHASE initiative (Rotach et al. 2009, Zappa et al. 2008).

The aim of this contribution is to describe the structure and participation of the COST 731 Action, as well as summarize their objectives and main achievements.

2. COST 731 structure, participation, and objectives

COST is an intergovernmental framework for European Cooperation in Science and Technology, allowing the coordination of nationally-funded research on a European level. COST contributes to reducing the fragmentation in European research investments and opens the European Research Area to worldwide cooperation, thus ensuring that Europe holds a strong position in the field of scientific and technical research for peaceful purposes, by increasing European cooperation and interaction in nine key domains, one of which is the Earth System Science and Environmental Management (ESSEM, see www.cost.eu). A total of 23 countries participated in the Action: Australia, Belgium, Cyprus, Czech Republic, Denmark, Finland, France, Germany, Greece, Hungary, Ireland, Israel, Italy, Luxembourg, The Netherlands, Norway, Poland, Portugal, Romania, Spain, Sweden, Switzerland, United Kingdom.

Dealing with uncertainties in a flood forecasting and warning production chain in a consistent way requires the following general stages (see also Figure 1):

- atmospheric observation (e.g. precipitation by radar) and quality characterization;
- assimilation of atmospheric observations into a NWP system;
- probabilistic atmospheric forecasting in a NWP system (ensembles, neural networks, others);
- hydrological modelling with atmospheric observations and forecasts, including their associated uncertainties;
- flood response decision making (especially protection vs. evacuation), management decisions during the event and public warnings.

Radar scientists are mainly concerned with stage 1, NWP modellers with stages 2 and 3. Hydrologists deal with stage 4 but, at present, without making extensive use of radar precipitation estimates and NWP precipitation forecasts. Learning from the COST 717 experience and recognizing the need for an effective interdisciplinary collaboration in order to deal with the propagation of uncertainty from one part of the forecasting/warning system to the next in a coherent way, Working Groups (WGs) were defined on the interfaces between the participating communities to maximize the interactions; these are:

![Figure 1 Schematic representation of a flood forecasting chain coupling the atmosphere to the hydrosphere, eventually feeding the end users and decision makers with flood forecasting and uncertainty information. Verification is a vital element in ensuring that the realism of the uncertainty information can assessed. Extension of warning lead time in flood forecasting can be achieved by including atmospheric forecasting through observation-based nowcasting (NWC) or numerical weather prediction (NWP).](image-url)
• **WG-1:** Propagation of uncertainty from observing systems (radars) into NWP;
• **WG-2:** Propagation of uncertainty from observing systems and NWP into hydrological models;
• **WG-3:** Use of uncertainty in warnings and decision making.

A number of interdisciplinary links were implemented to guarantee the transfer of knowledge among the different communities on an appropriate level and allow for an effective modelling/decision making chain. The main objective of the Action is to address issues intimately associated with the quality and uncertainty of meteorological observations from remote sensing and other potentially valuable instrumentation, along with their impacts on hydro-meteorological outputs from advanced forecast systems. This will be achieved through specific objectives which can be summarized as follows:

- **Radar data assimilation in NWP:** provide radar data errors in a form suitable for assimilation schemes, and compare different assimilation techniques for the cloud resolving scale, including nudging, 3- and 4-dimensional variational assimilation and the ensemble Kalman filter techniques and establish their sensitivity to the specification of radar uncertainty.
- **Radar data quality description:** in collaboration with OPERA (Holleman, 2006), update the NWP user requirement for radar data to assist operational data providers.
- **Radar ensembles:** Investigate methods for generation of ensembles based on uncertainty in radar observations.
- **Understand Uncertainty:** clarify and understand the meaning of uncertainty and to establish and agree upon ways to measure and express them.
- **Use of uncertainty in hydrological models:** establish a standard methodology which has the potential to be a reference in the future, and to provide feedback for improvement of meteorological input data (Section 2.4).
- **Methodology transfer:** explore the potential of techniques used to quantify uncertainty commonly used in meteorology applied to hydrology, and promote them to end users.
- **Test beds as proof of concept:** set up European test bed(s) in which to run a demonstration project as a proof of concept for probabilistic flood forecasting systems. Test beds integrate observation and forecast uncertainty into a hydrological forecast to provide warning uncertainty. A “simulation package” including a hydrological model and all aspects of decision making can be used for presentation, education and training as well as for sensitivity studies.

### 3. Main achievements

A recent review of the main activities and achievements of the three COST 731 Working Groups can be found in Rossa et al. (2010), Zappa et al. (2010), and Bruen et al. (2010) for WG1, WG2, and WG3, respectively. Here selected highlights will be presented and the breadth of the progress illustrated that was witnessed over the lifetime of the Action in quantifying and communicating uncertainty, especially in operational flood forecasting.

#### 3.1 Radar data quality description and probabilistic radar-based QPE through ensembles

Meteorological observations have an uncertainty which should be assessed and expressed in a suitable way. Quantitative precipitation estimation (QPE), both from rain gauge networks and meteorological radars, are traditionally expressed in a deterministic way, i.e. without specifying any ‘error bars’. Recently, several approaches to estimating the uncertainties in radar QPE have been proposed. They are all based on the recognition that the number of error sources limits the accuracy with which radars can measure both reflectivity and Doppler velocities. Such errors are discussed by Joe (1996), Saltikoff et al. (2004), and Michelson et al. (2005) among others. In recent years advanced quality control and characterization schemes for radar data have been developed (e.g. Friedrich et al., 2006; Parent du Châtelet et al. 2006). These schemes are now ready to be applied in NWP and hydrological models. Also, there is a WMO project on Radar Quality and Quantitative Precipitation Estimation Intercomparison (RQOI) with the aim of identifying best practices in QPE. Germann et al. (2006) derived an error climatology for precipitation estimates using a high-resolution rain gauge network, which served as a basis for the construction of an radar precipitation error covariance matrix (Germann et al. 2009), while Sempere-Torres et al. (2008) propose a real time error estimation comparing precipitation estimates against a benchmark, i.e. two different stages of their quality control cascade.

Several groups within COST 731 have proposed methods of making use of the quality description or error characteristics of the radar QPE to formulate a probabilistic, or ensemble, QPE (e.g. Krajewski and Georgakakos, 1985 for an early attempt in this direction). The originally retrieved precipitation field is perturbed with a stochastic component, which has the appropriate space–time covariance structure. To determine this error structure Germann et al. (2009) utilize the error climatology of radar QPE assessed by comparison with a dense rain gauge network, while Sempere et al. (2008) attempt a real time comparison against a best possible, or benchmark, QPE field. Szturc et al. (2008) circumvent the challenge of defining the actual precipitation error by using a radar data quality index from which then an error is parameterized. The main headline here is that radar QPE goes probabilistic, a result that can be considered a major conceptual leap, and which can be further detailed as follows:
Figure 2 Output taken from an innovative hydrometeorological platform for a small Alpine catchment which is driven with radar-derived ensemble QPE to yield probabilistic river flows (Germann et al. 2009). To the knowledge of the authors this may well be the first real-time example worldwide! On the right, the verification of the runoff simulated with radar QPE, radar ensemble QPE, and raingauges, for the sub-catchment of the Pincascia creek is presented for a one year period.

- Radar QPE ensembles are meaningful when the prediction of hydro-geological response is sensitive to space-time structures of the radar uncertainty, i.e. for catchment sizes of the order of 1000 km² or less and concentration times of a few hours.
- It is conceptually clear how to generate radar QPE ensembles; the big trick is to provide a suitable description of the residual radar errors, possibly in real time.
- A number of different radar error models have been proposed, none of which provides a complete account.
- There are various statistical techniques that have been developed and tested with individual strengths and limitations. None of these methods is obviously superior, and a number of statistical aspects can be further refined. Rigorously speaking, these methods work, or are designed, only for ‘nicely’ behaving Gaussian errors.
- Open issues include the conservation of the frequency distribution and the variance of the rainfall ensembles, as well as the treatment of ‘nasty’ radar errors like ground clutter or other sharply varying structures.

Figure 2 shows a COST 731 testbed example which consists in a real-time implementation of the semi-distributed rainfall-runoff model PREVAH (Viviroli et al., 2009, Germann et al., 2009) for flash flood modelling in a small, steep Alpine catchment with a probabilistic radar rainfall input. It is one of the first experiments of its kind worldwide producing radar-driven operational ensemble runoff nowcasting. The verification of the runoff simulations driven with deterministic and probabilistic radar QPE, and rain gauge input reveal that the radar ensemble has a very reasonable performance, and that the radar information apparently reduced the negative bias which results in the simulations with rain gauge input.

3.2 Storm-scale radar data assimilation (see also Rossa et al., 2010)

Assimilation of radar data is a major challenge for high-resolution numerical weather prediction models, especially the newest generation of models that explicitly simulate cumulus convection. Nevertheless, it is considered a promising avenue for hydrological applications in small river catchments, as it has the potential to bridge the gap between radar-derived QPE and nowcasts and short-range NWP QPF (Collier, 2007), both in terms of forecast range and spatial localization. As a matter of fact, radar reflectivity is the standard data source for characterizing the spatial distribution of precipitation, and one would expect significant benefits from using this information in the initial conditions of an NWP forecast, particularly in convective conditions. However, the nonlinear relationship between reflectivity and the NWP model variables that describe precipitation, the lack of observations that provide a consistent description of the cloud-scale dynamics, and the generally low predictability of the atmosphere at small scales, combine to make it difficult to assimilate reflectivity in such a way that the model will retain the information and produce an improved forecast over a longer period of time (e.g. Sun, 2005; Macpherson et al. 2004). The most common method in operational use at the time of writing is the latent heat nudging (LHN: Jones and Macpherson, 1997; Leuenberger, 2005; Leuenberger and Rossa, 2007; Stephan et al., 2008; Dixon et al., 2009), although a variety of more advanced techniques have been studied in various contexts (e.g. Jakubiak 2008; Caumont et al. 2009).
Operational experience suggests that the impact of the assimilated radar data is often short-lived, e.g. a couple of hours, although individual cases can show a much longer lasting positive impact. The fact that the impact of the radar data normally decreased rapidly in the first 4 hours of the free forecast is likely to be linked to the short lifetimes and predictability of cumulus convection, an inappropriate representation of the convective environment, as well as to deficiencies in current data assimilation methods. Figure 3 shows the potential of even simple schemes as LHN in assimilating extreme convective events and the corresponding benefits in hydrological forecasting in small catchments, where the capacity of localizing the storm is particularly essential (Rossa et al., 2010). In this case the potential gain in warning lead time based on hydrological simulations is 2-3 hours when using forecasts based on LHN analyses, when compared to hydrological simulations based on observed rainfall input, which for the studied catchments means 10 instead of 7 hours lead time until the flow peaked.

The assimilation of reflectivity instead of derived surface rain rates is being explored in a few centres. The UK Met Office are pursuing both direct assimilation of reflectivity in 4DVAR and also indirect assimilation of temperature and humidity profiles derived from applying a variational analysis along azimuth height sections. At Météo France 3-dimensional reflectivity is used to derive humidity profiles which then are assimilated in a 3DVAR framework (Caumont et al. 2009), while a similar method is in development at ARPA-SIMC (Poli 2009). The use of 4DVAR methods at the convective scale is still under investigation. The COSMO (Consortium for Small scale MOdelling) is currently investing in the development of an ensemble Kalman filter type of assimilation framework, while research on this subject is done in Poland (Jakubiak 2008). In the HIRLAM (High Resolution Limited Area Model) variational data assimilation framework the work has concentrated on exploiting radar radial wind observations in the model analysis. The HIRLAM reference system includes all needed tools for modelling the radial wind observation (Järvinen et al., 2009; Salonen et al, 2009). Preliminary results indicate that the use of radial winds in the model analysis has a positive impact on wind and temperature forecasts. More extensive data assimilation experiments are ongoing both with 3D-Var and 4D-Var to confirm the results and to study in more detail the impact of using radial winds in convective cases. In the UK a collaboration between Reading University and the Met Office is ongoing to investigate the potential for derivation of changes in near-surface air refractive index from the operational radars based on earlier work by Fabry et al (1997). The changes have been compared with refractivity and humidity derived from near surface screen observations of temperature and humidity (Nicol et al 2008). This approach bears great potential for improving the initialization of the convective environment and may contribute to a better description of low-level moisture convergence undetected by conventional observing networks.
3.4 Hydrometeorological forecast chains (see also Zappa et al., 2010)

Rainfall observation is a key input for hydrological modelling (see also Section 3.1) and, therefore, for any kind of hydrological prediction. Rainfall forecasts are especially valuable for small river basins and for flash flood forecasting in producing operationally useful warnings, but show promise also for decisions to move to flood alert status in larger basins, employ mobile flood defence infrastructure or in water resource management. Limited predictability of precipitation, especially at the convective scale (e.g. Collier, 2007), increase uncertainty of hydrological forecasts significantly, so that there is a serious need for quantifying the resulting predictive uncertainty (Pappenberger and Beven, 2006; Beven, 2006, 2009; Todini and Mantovan, 2007).

In meteorological sciences the problem of predictive uncertainty has been addressed by developing and implementing ensemble numerical weather prediction systems (EPS) at the global (ECMWF EPS, Molteni et al., 1996) and regional scale (COSMO-LEPS, Marsigli et al., 2005). There has also been some progress in the development of both operational and experimental end-to-end hydrological ensemble prediction systems (HEPS). A recent review by Cloke and Pappenberger (2009) compiled a list of examples from numerous countries of operational and nearly operational implementation HEPS. Such systems propagate the input uncertainty as determined by applying global and limited-area atmospheric ensemble prediction systems (LEPS) through a hydrological model. The obtained information can be interpreted and communicated to end-users (Beven et al., 2008). Concerning the uncertainty of observing systems, there has been some recent experience in propagating observation-based precipitation ensembles through hydrological models (e.g. Moulin et al., 2009). Similar approaches are also emerging in the field of weather radar quantitative precipitation estimation (QPE).

Table 1 List of research and operational hydrometeorological forecast chains developed in the framework of COST 731. They systems are loosely listed in from small to large catchments. The components of the chains are labeled QPE (radar), NWP, where (e) means also probabilistic, EPS the ECMWF ensemble prediction system, HYD for hydrological model, and EU for end users for whom the chain was tailored. The status of these chains is either operational (op.) or experimental (exp.). List may not be complete.

<table>
<thead>
<tr>
<th>Country</th>
<th>Platform</th>
<th>Status</th>
<th>Chains</th>
<th>End users</th>
<th>Scale (km²)</th>
<th>Fc range</th>
</tr>
</thead>
<tbody>
<tr>
<td>CH</td>
<td>Verzasca</td>
<td>op.</td>
<td>(e)QPE, (e)NWP, HYD</td>
<td>scientific, hydro power</td>
<td>300</td>
<td>case study</td>
</tr>
<tr>
<td>PL</td>
<td>IMGW, Szterruc</td>
<td>exp</td>
<td>(e)QPE, QPF, HYD</td>
<td>scientific</td>
<td>330</td>
<td>hrs – 5d</td>
</tr>
<tr>
<td>CH</td>
<td>Sihl</td>
<td>exp.</td>
<td>QPE, (e)NWP, HYD, EU</td>
<td>city, canton, railway, hydro power</td>
<td>1020</td>
<td>case study</td>
</tr>
<tr>
<td>E</td>
<td>Besos</td>
<td>exp.</td>
<td>(e)QPE, HYD</td>
<td>scientific</td>
<td>5</td>
<td></td>
</tr>
<tr>
<td>E</td>
<td>Catalunya</td>
<td>exp.</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>E</td>
<td>Andalucia</td>
<td>exp.</td>
<td>EPS, statistics, HYD</td>
<td>water agency</td>
<td>1175</td>
<td>5d?</td>
</tr>
<tr>
<td>LU</td>
<td>Alzette</td>
<td>exp.</td>
<td>EPS, HYD</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>D</td>
<td>Donau (Preview)</td>
<td>exp./exp.</td>
<td>(e)NWP, HYD</td>
<td>public, authorities, etc.</td>
<td>300-10^4</td>
<td>3d, 5d</td>
</tr>
<tr>
<td>CH, Alps</td>
<td>D-PHASE</td>
<td>exp.</td>
<td>QPE, TRT, many (e)NWP, many HYD</td>
<td>large demonstr. project</td>
<td></td>
<td></td>
</tr>
<tr>
<td>CH</td>
<td>GIN</td>
<td>exp.</td>
<td>(e)NWP, HYD</td>
<td>authorities</td>
<td>small-Swiss</td>
<td>hrs – 5d</td>
</tr>
<tr>
<td>B</td>
<td>RMiB</td>
<td>exp.</td>
<td>EPS, HYD</td>
<td>regional authorities</td>
<td>6 10^2 – 2 10^4</td>
<td>10d</td>
</tr>
<tr>
<td>SF</td>
<td>SYKE</td>
<td>exp.</td>
<td>EPS (10,30,100d), HYD</td>
<td>flood mitigation, hydro power, public</td>
<td>&gt; 1000</td>
<td>days, months, seasons</td>
</tr>
<tr>
<td>N</td>
<td>NVE</td>
<td>exp.</td>
<td>EPS, HYD</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>S</td>
<td>WebHyPro</td>
<td>exp.</td>
<td>EPS, HYD</td>
<td>hydro power, public</td>
<td>10-10^5</td>
<td>10d</td>
</tr>
<tr>
<td>F</td>
<td>Safran-Isba- Modcou (Météo France)</td>
<td>exp./exp.</td>
<td>EPS, HYD</td>
<td>Schapi (flood forecasting)</td>
<td>&gt;1000 km</td>
<td>1-10 days</td>
</tr>
<tr>
<td>F</td>
<td>Safran-Isba- Modcou (Météo France)</td>
<td>exp.</td>
<td>EPS, HYD</td>
<td>scientific</td>
<td>&gt; 100 km</td>
<td>Months seasons</td>
</tr>
<tr>
<td>F</td>
<td>AROME-Isba- TopModel (Météo-France)</td>
<td>exp.</td>
<td>EPS, HYD</td>
<td>scientific</td>
<td>&lt;100km2</td>
<td>0-2 days</td>
</tr>
<tr>
<td>NL</td>
<td>KNMI</td>
<td>exp.</td>
<td>EPS-based warning system</td>
<td>waterboard</td>
<td>2000 – Dutch</td>
<td>10d</td>
</tr>
<tr>
<td>D</td>
<td>BaF, Rhein</td>
<td>exp.</td>
<td>(e)NWP, HYD</td>
<td>scientific</td>
<td>10^4 – 10^5</td>
<td>5d</td>
</tr>
<tr>
<td>UK</td>
<td>K. Beven</td>
<td>exp.</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>E</td>
<td>INM B. Orfila</td>
<td>exp.</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>CZ</td>
<td>Daniela Rezacova</td>
<td>exp.</td>
<td>NWP: COSMO + assim. radar, HYD: HYDROG</td>
<td>scientific – flash flood warning small CR catchments</td>
<td>10^3</td>
<td></td>
</tr>
<tr>
<td>IR</td>
<td>M. Bruen</td>
<td>exp.</td>
<td></td>
<td></td>
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</tbody>
</table>
In hydrological modelling the estimation of model uncertainty has emerged as one of the most prolific research fields in recent years (in terms of number of published papers on the topic). Since the presentation of the “Generalized Likelihood Uncertainty Estimation” GLUE by Beven and Binley (1992) numerous algorithms have been developed and adopted for estimation uncertainty of environmental models in general and of hydrological models in particular (Beven, 2006 and 2009; Liu and Gupta, 2007; Matott et al., 2009; Montanari et al., 2009). A transfer of these methods for estimating uncertainty in observed precipitation fields has been recently realized by Pappenberger et al. (2009). Over the lifetime of COST 731 a very significant number of operational and research implementations of more or less full-fledged hydrometeorological forecast chain have been implemented, when prior to COST 731 especially operational hydrologist were known to be reluctant to using radar QPE and NWP QPF, much less in probabilistic form. Table 1 gives a tentative, yet incomplete list of systems that are directly related to the Action.

3.5 Visualization platforms, test beds, and end users (see also Bruen et al., 2010)

A most notable example for an operational test bed has been set up for the down-town area of Zurich, Switzerland. The hydrological catchment is that of the river Sihl (336 km$^2$), a very challenging and flood prone river basin that constitutes a serious threat to the central railway station of Zurich. For construction work in Central Station the flow capacity below the station had to be reduced by 40%, so that the return period for critical flow conditions are reduced down to 2 years. If an unexpected flood occurs during the works, the potential for damages exceeds 1 billion Euros and the lives of the people living, traveling, and working in the environs of the station would be endangered. In the upstream part of the basin, a concrete dam impounds waters from a headwater sub-basin of about 155 km$^2$. The waters in the dam are managed by a private hydropower company, however, the other headwater sub-basins are prone to flash-floods. For this reason, the local authorities decided to implement a real-time flood warning system associated with the construction works.

The flood forecast system is an operational implementation of the hydrological model PREVAH (Viviroli et al., 2009) is forced by the output from both deterministic and ensemble numerical weather prediction models. Once a flood forecast is produced, the various options for flood control and protection at Zurich Central Station are evaluated by experts. When necessary, decisions are taken by the local administration following discussions with a panel of persons composed of stakeholders, meteorologists, and hydrologists. One option is to order a controlled drawdown of the upstream lake. However, to be effective, this should be ordered at least 2 or 3 days before the serious flood is expected and it may trigger substantial financial penalties if no storm occurs because of the energy lost. A second option for flood mitigation is controlled flooding of two sections of the five channels below the railway station that are normally closed to allow construction work in these channels. In this case, the building contractor could lose up to 2 weeks of work, which would also incur significant financial loss. Figure 4 shows verification results in terms of Brier skill scores for simulations driven by the deterministic NWP model COSMO-7 (forecast range out to 3 days) and the probabilistic version COSMO-LEPS (out to 5 days, Addor et al., 2010). One can appreciate that the probabilistic version is superior for all lead times and for rainfall intensities that range from moderate (Q0.75) to heavy (Q0.99).
Verification is a very important aspect in promoting advanced forecast systems, such as high-resolution NWP, both in deterministic and probabilistic form. Ament et al. (2010) performed a massive verification task in the framework of the MAP D-PHASE, in which they evaluated the performance of 13 mesoscale atmospheric models regarding heavy precipitation alerts issued in medium-sized river catchments by these models in Switzerland during the summer 2007. As a highlight seven of the considered models are deep convection resolving systems with grid spacings equal or smaller than 3 km. Although the accuracy of these alerts is poor they are still skillful. An analysis of relative value diagrams (Figure 4) reveals a clear tendency of deep convection resolving models to produce more useful alerts. The benefit of high resolution systems can partly be attributed to the higher update frequency of these models, even without any direct assimilation of precipitation observations. Probabilistic forecasts allow for a significant gain in relative value by choosing user dependent probability thresholds.

MAP D-PHASE (Demonstration of Probabilistic Hydrological and Atmospheric Simulation of floodEvents in the Alpine region) was a project focused on demonstrating progresses in forecasting heavy rainfall and flood in the alpine region (Rotach et al., 2009; Zappa et al., 2008). The project had an explicit focus on the involvement of end users and developed an innovative visualization platform that was run during the whole demonstration period (June to November 2007) and which, with reduced content, continued beyond the end of the project. This visualization platform has three different levels of warnings and a level of direct access to forecast products:

- **Level 1**: General alerts based on heavy rainfall for all target areas in the Alpine region;
- **Level 2**: General alerts based on heavy rainfall for all target areas in an Alpine subregion Visualizing flood forecasting uncertainty accompanied by a table displaying the alert of each individual atmospheric model for every target area;
- **Level 3**: Detailed alerts on heavy rainfall and discharge for an individual hydrological impact area. A table displays the detailed alert status of every hydrological and atmospheric model for each forecast hour;
- **Forecast product level**: Online model outputs in the form of weather maps and discharge hydrographs.

In addition, a series of nowcasting platforms were linked to the platform to provide support for real-time decision making during an event. The end user opinions on the platform were collected in a series of workshops and they appreciated the real-time availability of high-end weather radar information (Germann et al., 2009).

Figure 6 shows another two examples of operational visualization platforms for hydrometeorological forecast information that includes quantified uncertainty. KNMI operates a warning system for the Dutch Union of Water Boards (Kok et al., 2010). An example is given in Figure 5 (left panels) for which the estimated ‘instantaneous’ exceedance probability of 10 mm/12 h (black line) and the probability of having this intensity somewhere in a period of 48 h (green line). The latter probability exceeds the 25% threshold for which warnings are issued. It is interesting to note that the two probabilities differ by a factor of 3 in this case. About 40% of the EPS ensemble members, used in this system, agreed on having the intensity in the day 3 to day 4 range but they differ quite substantially on the exact timing of the event, another useful example of how to make better use of the available probabilistic information. A similar procedure can be used to present simulation information on combined probabilities, e.g. for wind stress and surge levels which determine the amount of water that can be drained to the North Sea. By tailoring the risk conditions more accurately (e.g. by including surge and other meteorological information), the predicted exceedance probabilities can be conveniently linked to the decision models of the user. This will eventually improve the use (and acceptance) and usefulness of uncertainty information.
SMHI operates a flood forecasting platform based on the HBV model (Lindstrom et al., 1997) and the ECMWF EPS. For each forecast catchment, the precipitation and temperature in the ECMWF forecasts from the model grid box covering the catchment are directly applied as inputs to the HBV model, set up and calibrated (using historical observations) for the catchment. The HBV model is run using all 51 ECMWF precipitation and temperature forecasts as input, generating an ensemble forecast for up to 9 days ahead, which is processed statistically to derive five quantiles, representing 2, 25, 50, 75, and 98% non-exceedance probabilities, respectively. These quantiles are transferred to the graphical interface WebHyPro, which is used to visualize discharge forecasts. Figure 5 (right panels) shows the two main ways in which ensemble discharge forecasts are displayed, i.e. time series of discharge in a single catchment and a map showing the areas in which a certain warning level is reached. The ensemble forecasts have been recently evaluated, by (1) comparing them with an operational deterministic forecast and (2) by evaluating the statistical properties of any bias in the calculated quantiles (Olsson and Lindstrom, 2008). A general conclusion was that the spread in the ensemble of discharge forecasts is systematically underestimated, and different post-processing methods are being explored to adjust the estimated quantiles.

4. Conclusions and outlook

Efforts like the COST 731 Action suggest that a systematic treatment of uncertainty is a prerequisite for information produced by advance hydrometeorological forecast systems to be used in operational contexts by practitioners and decision makers. In this contribution selected results of the COST 731 Action were presented and some context was given. The main outcome may be headlined as follows. COST 731:

- acted as a ‘door-opener’ for dealing with uncertainty in a systematic way, especially in operational settings;
- witnessed the development and evaluation of several integrated, end-to-end forecasts systems;
- provided information and hands-on training on visualization platforms of probabilistic information based on huge amounts of observational and forecast data;
- learnt to express uncertainty in directly usable forms, i.e. QPE ensembles;
- promoted convection-permitting NWP and convective-scale radar data assimilation.

Work on quantifying uncertainty has just begun, and much more work is ahead to tap the potential that lies in the systematic exploitation of uncertainty information, while improving the quality of radar QPE and NWP QPF.
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References


Papenberger F, Beven KJ. 2006. Ignorance is bliss: Or seven reasons not to use uncertainty analysis. Water Resources Research 42.


