ATMOSPHERIC SCIENCE LETTERS
Atmos. Sci. Let. **11**: 83–91 (2010)
Published online 8 January 2010 in Wiley InterScience
(www.interscience.wiley.com) **DOI:** 10.1002/asl.248

RMetS
Royal Meteorological Society

Propagation of uncertainty from observing systems and NWP into hydrological models: COST-731 Working Group 2

Massimiliano Zappa,[1]* Keith J. Beven,[2,3,4] Michael Bruen,[5] Antonio S. Cofiño,[6] Kees Kok,[7] Eric Martin,[8] Pertti Nurmi,[9] Bartlomé Orfila,[10] Emmanuel Roulin,[11] Kai Schröter,[12] Alan Seed,[13] Jan Szturc,[14] Bertel Vehviläinen,[15] Urs Germann[16] and Andrea Rossa[17]

[1] *Swiss Federal Research Institute WSL, Birmensdorf, Switzerland*
[2] *Lancaster Environment Centre, Lancaster, UK*
[3] *GeoCentrum, Uppsala University, Uppsala, Sweden*
[4] *ECHO/ISTE/ENAC, EPFL, Lausanne, Switzerland*
[5] *UCD Centre for Water Resources Research, Dublin, Ireland*
[6] *Department of Applied Mathematics and Computer Sciences, University of Cantabria, Cantabria, Spain*
[7] *Royal Netherlands Meteorological Institute (KNMI), De Bilt, Netherlands*
[8] *CNRM-GAME/GMME/MOSAYC, Méteo-France, Toulouse, France*
[9] *Finnish Meteorological Institute, Helsinki, Finland*
[10] *State Meteorological Agency of Spain (AEMET), Madrid, Spain*
[11] *Royal Meteorological Institute of Belgium, Brussels, Belgium*
[12] *BWS GmbH, Hamburg, Germany*
[13] *Centre for Australian Weather and Climate Research, Melbourne, Australia*
[14] *Institute of Meteorology and Water Management, Warszawa, Poland*
[15] *Finnish Environment Institute, Finnish Meteorological Institute, Helsinki, Finland*
[16] *Federal Office for Meteorology and Climatology, MeteoSwiss, Zürich, Switzerland*
[17] *ARPA Veneto, Teolo, Italy*

Correspondence to: Massimiliano Zappa, Swiss Federal Research Institute WSL, Zürcherstrasse 111, 8903 Birmensdorf, Switzerland. E-mail: massimiliano.zappa@wsl.ch

Received: 30 September 2009
Revised: 26 October 2009
Accepted: 26 October 2009

Abstract

The COST-731 action is focused on uncertainty propagation in hydrometeorological forecasting chains. Goals and activities of the action Working Group 2 are presented. Five foci for discussion and research have been identified: (1) understand uncertainties, (2) exploring, designing and comparing methodologies for the use of uncertainty in hydrological models, (3) providing feedback on sensitivity to data and forecast providers, (4) transferring methodologies among the different communities involved and (5) setting up test-beds and perform proof-of-concepts. Current examples of different perspectives on uncertainty propagation are presented. Copyright © 2010 Royal Meteorological Society

Keywords: **COST-731; uncertainty; NWP; weather radar; hydrological modeling**

1. Introduction

Operational flood forecasting systems rely on data from observing systems to generate initial conditions required for predicting discharge for some hours and days in advance, depending on the lead time required for different types of operational decision in relation to the response time of a basin. For many flood warning purposes in mesoscale to macroscale basins, a flood forecasting system based only on observed precipitation data might be all that is needed. In small river basins, however, and for flash flood warnings, this may not give sufficient lead time to be useful for operational warnings so that some prediction of future rainfalls will be required, either from the propagation of weather radar rainfall estimates or from numerical weather predictions (NWP). Other purposes might also require the forecasting of future rainfall inflows such as for decisions about moving to flood alert status in larger basins (Thielen *et al.*, 2009), long lead time decisions about the employment of mobile flood defenses or predictions of longer term (even seasonal) hydrological responses for water resource management.

In recent years many efforts have been undertaken in order to improve both the quality of data from observing systems (discharge gauges, hydrometeorological networks and weather radar) and in NWP. Despite large improvements it is nowadays recognized that many of the processes linked with the triggering of (flash-)floods (local thunderstorms, generation of surface runoff) suffer from low predictability (Collier, 2007; Pappenberger *et al.*, 2009) and there is consequently a serious need for quantifying predictive uncertainty of the model involved (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 NWP 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 of HEPS. Such systems propagate the input uncertainty as determined by applying global and limited-area atmospheric ensemble prediction systems (LEPS) through a hydrological model. This raises some interesting issues about how such information should be interpreted and communicated to end-users (Faulkner *et al.*, 2007; Bruen *et al.*, 2009).

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). Recent progresses on coupling ensemble weather radar QPE with hydrological models have been proposed by Szturc *et al.* (2008b) and Germann *et al.* (2009).

In hydrological modeling 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, 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).

Working Group 2 of the COST-731 Action (Rossa *et al.*, 2009b; http://COST-731.bafg.de) deals with the assessment and propagation of the three aforementioned sources of uncertainty: uncertainty in NWP, uncertainty in meteorological information from observing platforms and uncertainty in hydrological models. The next sections will present an overview on goals and activities of COST-731 Working Group 2. The text includes many acronyms, which are declared in alphabetical order in Appendix.

2. COST-731 and Working Group 2

Individual efforts seldom lead to innovative ideas in scientific research. This is the reason why the European Community offers different instruments in order to promote cooperation in research. While European framework program projects are meant to support targeted research and development efforts, COST Actions (http://www.cost.esf.org/about_cost) are means to focus and coordinate existing research efforts supported by national funding agencies. By means of those actions scientists and students working in the same research field are connected to each other and can start collaborations. COST-731 is a network for scientists dealing with the propagation of uncertainty in end-to-end hydrometeorological forecasting chains (Rossa *et al.*, 2009b). Three working groups (WG) deal with different aspects of this chain. WG-1 focuses on the propagation of uncertainty from observing systems (e.g. radars) into NWP models (Rossa *et al.*, 2009a). WG-3 makes use of uncertainty information for issuing warnings and improving decision making (Bruen *et al.*, 2009). This paper describes the activities of WG-2, which coordinates research efforts on the propagation of uncertainty from observing systems and NWP into hydrological models. Figure 1 shows a simplified sketch of input and outputs in a hydrometeorological forecasting chain needing to assess and communicate uncertainty all along the path from the observation to the issuing of warning for end-users. Five main objectives have been defined when designing WG-2:

1. Understand and evaluate the uncertainty associated with different observed or forecast variables for which different methodologies may be used;
2. Explore and design methodologies for the estimation and propagation of uncertainty in hydrological models and try to establish a standard methodology or guidelines for good practice to be a reference in the future;
3. Explore and design methodologies for assessing the hydrological impact of the different sources of observation and forecast uncertainty in order to give a feedback to the data providers;
4. Explore the transfer of verification methodologies commonly used in meteorology for hydrological purposes;

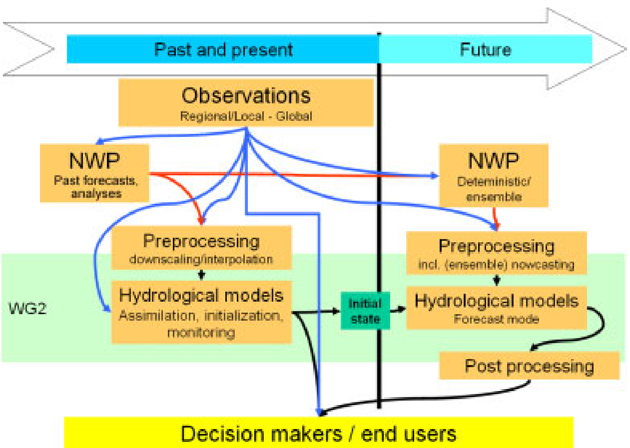

Figure 1. The COST-731 WG2 position on uncertainty propagation of observed (blue arrows) and forecasted (red arrows) meteorological and hydrological (black arrows) information in operational forecasting chains. This figure was drawn after a discussion round at the COST-731 mid-term seminar in Bologna (June 2008).

5. Set up a European test-bed in which to run a demonstration project as a proof-of-concept to the hydrological community, not yet used to dealing with uncertainties in operational forecasting chains. Examples of test-beds are presented in Bruen *et al.* (2009).

3. Selected ongoing discussion and applications

3.1. QPE/QPF uncertainties and verification

An underlying uncertainty is inherent in all observing systems and instruments of meteorological variables. This is possibly most pronounced in the precipitation observations. There are many sources of error in the estimation of rainfall volumes and intensities for both the tipping bucket rain gauge (Sevruk, 1996) and weather radar (Germann *et al.*, 2006; Villarini and Krajewski, 2008). The reduction of such errors would make weather radar QPE much more appealing for hydrology in the future (Collier, 2009a; Germann *et al.*, 2009). Thus, ideas are needed to quantify the uncertainty in radar QPE.

A contribution from Poland to COST-731 is the concept of the quality index (QI) as a measure of data quality to characterise the weather radar data quality quantitatively, e.g. using numbers in range from zero (bad data) to one or one hundred (excellent data). The index is computed from a set of selected individual quality factors that are estimated in real time. Operationally the QI is calculated for surface precipitation estimates since this is the radar-based data most often required by hydrologists (Szturc *et al.*, 2009). QI is calculated in real-time mode in following COST-731 member countries: Germany (Friedrich *et al.*, 2006), Poland (Szturc *et al.*, 2008a), France (Tabary *et al.*, 2007) and in the Emilia-Romagna region (Italy). Further ideas on assessing the quality of weather radar information for hydrological application are presented by Collier (2009b).

A number of different contributors to the COST-731 project are working on the estimation of uncertainty and verification issues for NWP QPF at the scale of mesoscale to macroscale river basins (Casati *et al.*, 2008; Ebert *et al.*, 2008; Wernli *et al.*, 2008). A team from the Czech Republic focuses its research on the use of weather radar QPE for the deterministic and probabilistic verification of NPW QPF in case of convective rainfall events (Rezacova *et al.*, 2009; Zacharov *et al.*, 2009).

A team from Belgium has investigated the merging of precipitation data from weather radar and from spaceborne microwave cross-track scanners using the scale-recursive estimation (SRE) methodology (Van de Vyver and Roulin, 2009) allowing the assimilation of noisy measurements at different spatial scales.

New, innovative object or feature-based forecast verification techniques have proven to be useful tools in identifying QPE/QPF uncertainties. Techniques like the Contiguous Rain Area (CRA) and the Structure–Amplitude–Location (SAL) (Wernli *et al.*, 2008) have been utilized to evaluate the effects of the observation data source on the eventual quality of QPF. Radar-derived quantitative QPE and the more conventional rain gauge data have been the main source of information applied as the 'observed truth', focusing on rainfall forecasts within hydrological basins. This kind of analysis is, moreover, valuable in addressing the overall quality of different forecast models within the meteorological–hydrological forecast chain. Such studies are also beneficial in the choice of proper forecast verification measures for given forecast applications. As part of its efforts in COST-731 the Finnish Meteorological Institute is implementing the novel object-based verification measure SAL for hydrological applications. The procedure has been adapted for the verification of NWP QPF in river basins in Finland (Nurmi and Nasman, 2009; http://www.ecmwf.int/products/greenbook/2008/GB_2008_Finland.pdf). So far, SAL has been only applied for large river basins (>40 000 km^2). The ultimate goal is to provide a measure of forecast quality for small-scale river basins.

3.2. Weather radar ensembles for hydrology

When COST-731 started in 2005 there were no established techniques for estimating uncertainty in weather radar QPE and no probabilistic weather radar product was operational in Europe. Four years later at least three of the WG2 contributors have implemented and published new methods for the application of ensemble radar QPE in hydrology.

The first approach, not working in real-time mode yet, implements the above introduced 'QI' as a radar QPE/QPF uncertainty metric. Having a QI map attached to radar-based precipitation data, the next step is to express precipitation field in a probabilistic manner with uncertainty resulting from the QI. The precipitation uncertainty is estimated by applying a probability density function (PDF) that is a function of the QI value (Szturc *et al.*, 2008b). The PDF parameters must be estimated in each time step for all pixels of radar-based data which are treated as independent. These parameters are obtained from radar deterministic measurement and the QI information. Percentiles of the PDFs can be considered as a probabilistic set of rainfall fields. A proof-of-concept of this procedure including propagation through a hydrological model is presented in detail by Szturc *et al.* (2008b) and shown in Figure 2.

Germann *et al.* (2009) from Switzerland presented an operationally running prototype, an ensemble generator for radar precipitation estimation called REAL (Figure 3). REAL uses the operational MeteoSwiss radar precipitation fields (Germann *et al.*, 2006) as a deterministic component. Perturbations for the radar ensemble are generated by means of singular value decomposition of the full radar error covariance matrix

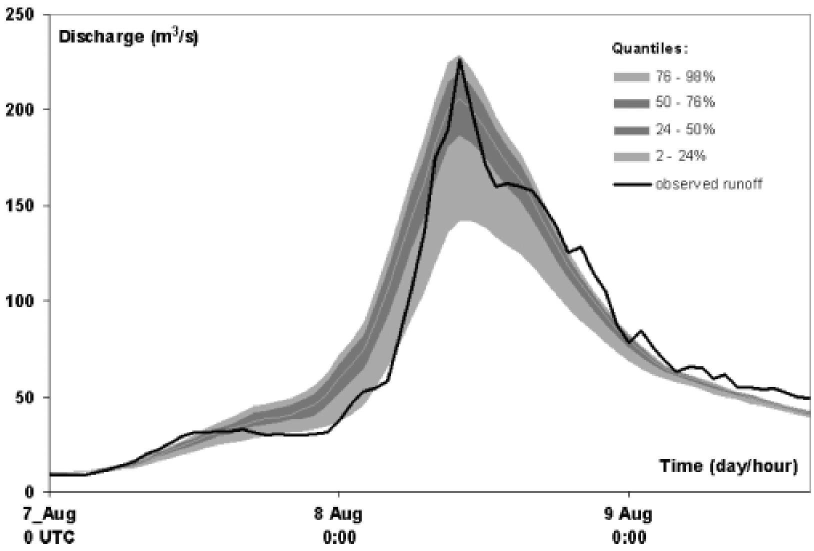

Figure 2. Hydrological ensemble nowcasting as described by Szturc *et al.* (2008b, modified) starting on 7 August 2006 for the Mała Wisła River basin in Poland (297 km^2). Different percentiles of ensemble of hydrographs generated are shown with different gray. The median of the obtained ensemble is shown as thin light gray line. The observed discharge is plotted as thick black line.

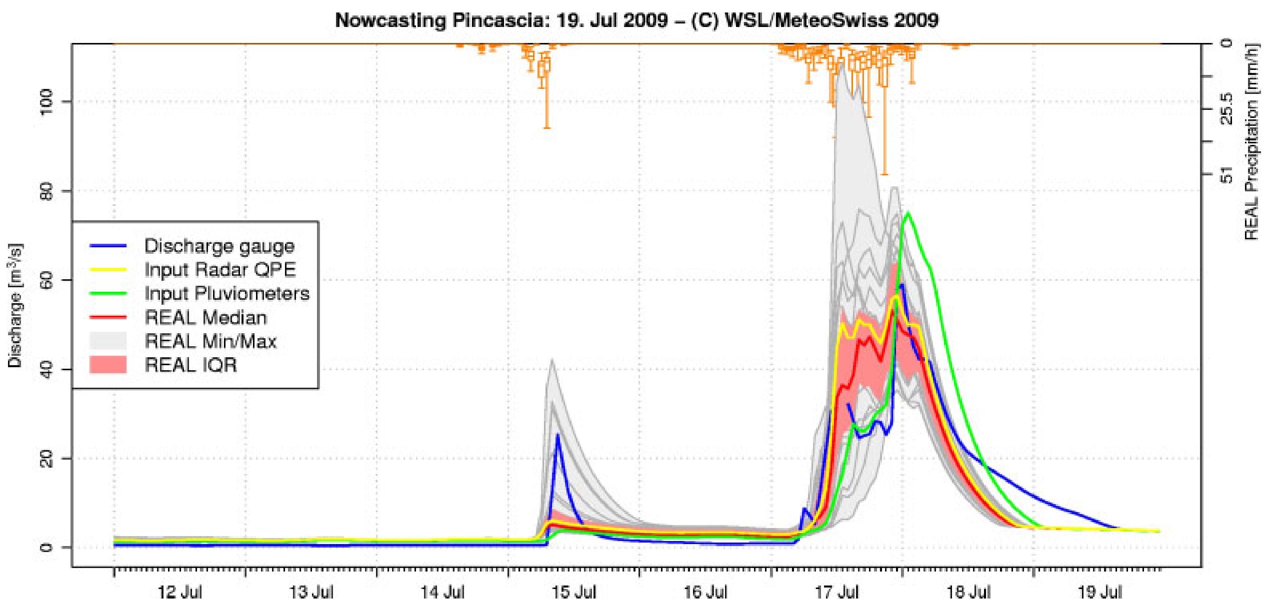

Figure 3. Operational hydrological ensemble nowcasting with REAL and PREVAH (Germann *et al.*, 2009), starting on 12 July 2009 for the Pincascia basin in Southern Switzerland (44.4 km^2). The 25 members from REAL (light gray) are shown with corresponding interquartile range (REAL IQR, red area) and the median (red line). Additionally, two deterministic runs are shown: deterministic radar QPE (yellow line) and forcing with interpolated pluviometer data (green line). The observed runoff is shown in blue. Spatially interpolated observed precipitation as ensemble precipitation from the REAL members (orange whisker-plots).

as obtained by comparing the deterministic weather radar QPE with a dense network of rain gauges. Twenty-five members are generated at an hourly time step and used for ensemble runoff nowcasting by forcing the semi-distributed hydrological model PREVAH (Viviroli *et al.*, 2009).

The third approach for estimating weather radar ensembles has been developed in Spain (Llort *et al.*, 2008; Figure 4). Their approach relies on the generation of a best estimate of the rain fields by blending the weather radar QPE with rainfall fields obtained from quality checked rain gauge records using external drift Kriging (Llort *et al.*, 2008). This best guess is used for estimating the error structure (including bias, random variability and spatial correlation) of the weather radar QPE. Finally the errors structures are sampled to generate perturbation fields to be added to the original radar QPE. Several equally probable perturbation fields are generated and used as the forcing input data for hydrological simulations using the fully distributed model WBrM model (Schröter *et al.*, 2009).

3.3. Observation-based ensembles for hydrology

When dealing with observational estimates of rainfall, the rainfall gauge observation error is not the only

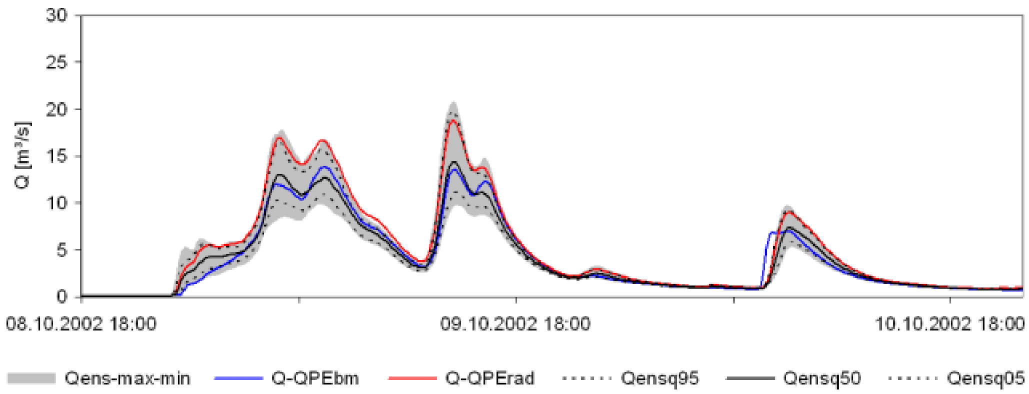

Figure 4. Hydrological ensemble nowcasting as described by Schröter *et al.* (2009) starting on 8 October 2002 for the Besòs river basin in Spain (1020 km^2). Qens-max-min shows the maximum and minimum range of ensemble hydrographs. The 5% (Qensq05), 50% (Qensq50) and 95% (Qensq95) percentiles of the ensemble hydrographs obtained using an ensemble of precipitation fields are also plotted. Q-QPEBm is the simulated hydrograph using the benchmark precipitation field (radar observations blended with rain gauges using external drift Kriging) as forcing, while Q-QPErad is the simulated hydrograph using the radar rainfall field as forcing.

source of uncertainty. The spatial interpolation of the available (real time) point observations is also an important source of uncertainty. Ahrens and Jaun (2007) designed a verification technique for ensemble NWP QPF based on a comparison with a synthetic observation-based precipitation ensemble reference. This observational reference is generated by applying ordinary Kriging as a deterministic reference. For the generation of ensemble precipitation fields a stochastic simulation technique is adopted. The procedure was tested for estimating the quality of COSMO-LEPS rainfall forecasts on Switzerland in 2005.

Moulin *et al.* (2009) go a step further: they propose a technique for computing ensemble precipitation information by generating an error model for rainfall estimation. To achieve this result, they combine an interpolation technique based on ordinary Kriging and Monte Carlo sampling of error fields. Finally they propagate the obtained ensemble through a rainfall–runoff model and estimate the spread of the obtained ensemble discharge simulations for an upper Loire river basin (France). The lead author of this last study was invited to give a talk for the WG-2 members during the 2009 HEPEX Workshop in Toulouse.

3.4. Downscaling of precipitation fields

When precipitation forecasts from meteorological EPS are available, efforts should conduct to propagate its PDF through hydrological models. This is more appropriate than using deterministic forecasts based on some form of aggregation of the members of the meteorological EPS because the response of a river basin to precipitation events is not linearly related to the intensity of the events, but strongly depends on topography and dimensions of the river basin, on the antecedent wetness prior to an event and on the time and space characteristics of the event itself. The same is true for perturbations (uncertainties) in the (forecast) precipitation in that any perturbations will be damped if they are integrated over space and/or time scales that are larger than the characteristic scales of the perturbations. Some basins show high sensitivity to a limited range of scales that may be present in the perturbations and resonance-like behavior may be observed.

3.5. Ensemble NWP for medium-range hydrological forecasts

We pointed out in the introduction that the propagation of atmospheric EPS through hydrological models is a research field that has seen a lot of recent research activity, as thoroughly summarized by Cloke and Pappenberger (2009).

COST-731 WG-2 also contributes to this research area. Thirel *et al.* (2008) present an ensemble streamflow prediction system that has been built using data from both the ECMWF EPS and the French short time ensemble prediction product PEARP. The system adopts the French hydrometeorological SAFRAN-ISBA-MODCOU chain for the hydrological model component. In a first step, a post-processing of the meteorological ensemble has been calibrated, and then the atmospheric EPS have been used to feed the hydrometeorological model. The impact of the input from the EPS systems on discharge prediction has been assessed by adopting probabilistic measures of skill (Laio and Tamea, 2007). The short-term forecast performance for small basins was better when using PEARP, while the ECMWF EPS results were better for large scale basins.

A system based on the ECMWF EPS and the SCHEME hydrological model has been evaluated for two test basins in Belgium using the Brier Skill Score (Roulin and Vannitsem, 2005) and the Relative Economic Value (Roulin, 2007, and presented at the join COST-731 – NetFAM Workshop, in Vilnius, Lithuania). This system was made operational and then extended to the basins of the Meuse and Scheldt in Belgium and France (Van den Bergh and Roulin, 2009).

The European hydrometeorological test-bed MAP D-PHASE was the starting point for many operational implementations of HEPS. In Switzerland the experimental HEPS system described in Jaun *et al.* (2008) has been put into operational use (Zappa *et al.*, 2008). In parallel the Swiss Federal Office for Environment first adopted their operational ensemble modeling framework. Thus, two distinct forecasting chains with a complete time series between 1 June 2007 and 30 November 2008 are available for more than 20 basins, some of them shared by the two systems. A systematic verification is still ongoing and is addressing the challenging task of applying meteorological verification measures for evaluating hydrological ensembles (Cloke and Pappenberger, 2008; Demargne *et al.*, 2009; Jaun and Ahrens, 2009).

3.6. Ensemble seasonal hydrological forecasts

There are only very few contributions dealing with seasonal hydrological forecasts in the scientific literature (Wood *et al.*, 2002). Operational applications are slowly emerging but are still far from being established. There is a large gap between the number of studies of medium-range flood forecasting (up to 10 days lead time) and the number of seasonal hydrological forecasting system for water resources management. This low popularity of seasonal hydrological forecasts is not owed to disinterest '*a priori*' by the community. Seasonal forecasts suffer from the scarce predictability of precipitation patterns and intensities. Anyway, two currently running systems have been implemented by WG-2 contributors and are briefly defined here.

The same SAFRAN-ISBA-MODCOU chain used for medium-range forecasts over France has been applied using the DEMETER database of ensemble seasonal forecasts (Céron *et al.*, 2009). In a first test focused on the spring period, the initial state of the hydrological model was extracted from the chain forced by observations in mid-February and ran 3 months with seasonal forecasts. The scores on snow cover, soil wetness index and discharges showed an improvement when compared to the scores for meteorological variables alone (e.g. precipitations), showing that there is an added value of using of hydrological models in seasonal forecast applications.

The Finnish Environment Institute makes operational use of monthly and seasonal lake inflow forecasts in large lake rich watersheds with long delays in Finland. Combined monthly and seasonal meteorological EPS forecasts from ECMWF have been verified as inputs for lake inflow forecasting in some Finnish river basins since 2007. Weather forecasts with lead times of 30 and 100 days are available from ECMWF. Winter 2008–2009 was warm and wet in southern Finland. The inflow forecasts for Lake Saimaa (4300 km^2) at Vuoksi basin (61 000 km^2) based on monthly and seasonal weather EPS forecasts from ECMWF were better than climatology based inflow forecasts. Also during autumn 2008 the combined monthly and seasonal precipitation forecasts were better than climatological precipitation as 'forecast' giving better inflow forecast to Lake Saimaa as well. After the positive experience during these test periods, the monthly weather EPS from ECMWF have been taken into operational use for lake management in Finland. The coming years will show if a successful operation of such forecasts is possible even if the predictability of precipitation at the seasonal time scale is poor.

3.7. Use the adjoint method in hydrology

Too often forecasts from the flood modeling chain are used without any concern for their uncertainty and/or their sensitivity to perturbations in inputs (e.g. data quality issues) or to fitted parameter values. Proper use of numerical model outputs requires this type of assessment, but the techniques available are limited. Monte Carlo simulation is computationally expensive for complex models so alternative techniques are sought to address this need. Variational methods using the model adjoint show promise for this purpose as they allow the tracking of influences backwards through the model (Penenko *et al.*, 2002). However, although the technique is used in the meteorological and oceanography domain (Moore 1991; Rabier *et al.*, 1996), very little work has been done in the physical infrastructure environmental/water or hydrological/floods areas, although it has potential, e.g. for the sensitivity analysis of distributed catchment models (Castaings *et al.*, 2009) or of pipe network models (Liggett and Chen, 1994), and for estuary management applications (Sanders and Piasecki, 2002) and effluent control (Piasecki, 2003).

The adjoint method provides a useful way of calculating the local sensitivity of a model (Errico, 1997). Effectively, it provides a local linearized inverse model, that can (1) show the sensitivity of some useful property, possibly an objective function as used in optimization, of the model's output to variations in inputs or parameters and (2) provide gradient information for use in optimizing model fit (White *et al.*, 2003; Belanger and Vincent, 2005) or backward-in-time model runs (Neupauer and Wilson, 1999; Penenko *et al.*, 2002). It is an alternative to the forward calculation of partial derivatives, and is particularly useful and computationally efficient for spatially distributed models. The power of adjoint methods lies in that a single (backward) integration of the adjoint model yields all spatial and temporal sensitivities. The main difficulty consists in the differentiation and transposition of complex operators. Although, for simple models, the adjoint equations can be derived analytically using variational methods (Sun and Yeh, 1990), for more complex models computer codes for numerical differentiation are available for the automatic calculation of the required relationships.

Other methods based on multiple forward runs are easier to implement and take proper account of model nonlinearities but at the expense of requiring more computational resources. In COST-731, the focus is primarily on determining the sensitivity of flood forecasts derived from linked meteorological and hydrological models to variations in inputs and/or parameters of both models. A presentation on Castaings *et al.* (2009) achievements during a COST-731 meeting in Koblenz (Germany) provided very enriching information for all contributors of WG-2.

4. Summary and outlook

This paper summarized some of the current research efforts and topics that Working Group 2 of COST-731 is addressing since the start of the Action in 2005. Concerning the WG-2 topics we observe that the contributors are active in many branches of a common research filed. There is common wish and effort of toward improving knowledge on uncertainties in operational hydrometeorological forecasting chains.

So far, most examples consider only one member of the uncertainty chain (Figure 1). In the future test-beds are needed in order to evaluate how different sources of uncertainty can 'interact' and superpose. First examples in this direction are found in Pappenberger *et al.* (2005) and Zappa *et al.* (2009).

Many of the presented examples are also a result of short-term scientific missions completed by a scientist and PhD students of one research group in the research unit of a second member of COST-731 WG2. COST confirms being a valuable platform for realizing scientific exchange within Europe. Since few years also Australia, New Zealand and other countries have agreements with the COST administration and can regularly send scientist in Europe for starting collaborations. With one more year left in the schedule of COST-731 it has been observed that numerous collaborations have been starting between participants. This led among others to the successful acquisition of joint projects in calls of the Seventh Framework Program.

Acknowledgements

The authors would like to thank Carine Petit, Lucia Forzi and the COST Office staff for their support in the management of COST-731. M. Z. profited from funding Swiss State Secretariat for Education and Research SER (C05.0105) through the COST Programme. M. Z., K. J. B. and U. G. profited from grants through the EU FP7 Project IMPRINTS (Grant agreement no.: 226555/FP7-ENV-2008-1-226555).

A. Appendix: Abbreviations in Alphabetical Order

COSMO: Consortium for Small-scale Modeling
COST: European Cooperation in Science and Technology
CRA: Contiguous Rain Area (verification method)
DEMETER: Development of a European Multimodel Ensemble system for seasonal to inTERannual prediction
D-PHASE: Demonstration of Probabilistic Hydrological and Atmospheric Simulation of flood Events in the Alpine region
ECMWF: European Centre for Medium-Range Weather Forecasts
EPS: Ensemble Prediction System
GLUE: Generalized Likelihood Uncertainty Estimation
HEPEX: The Hydrologic Ensemble Prediction Experiment (http://hydis8.eng.uci.edu/hepex/)
HEPS: Hydrological Ensemble Prediction System
ISBA: Interactions Soil–Biosphere–Atmosphere Model
LEPS: Limited-Area Ensemble Prediction System
MAP: Mesoscale Alpine Programme (http://www.map.meteoswiss.ch/)
MODCOU: Coupled Model
NWP: Numerical weather prediction model
PDF: Probability Density Function
PEARP: Prévision Ensemble ARPEGE
PREVAH: PREecipitation-Runoff-EVApotranspiration HRU Model
QI: Quality Index
QPE/QPF: quantitative precipitation estimation/ prediction
REAL: Radar Ensemble generator designed for usage in the Alps using LU decomposition
SAFRAN: meteorological analysis system
SAL: Structure-Amplitude-Location (verification method)
SCHEME: SCHEldt and MEuse semi-distributed hydrological model
SRE: Scale-Recursive Estimation (data assimilation method)
WBrM: Water Balance raster Model
WG: Working Group

References

Ahrens B, Jaun S. 2007. On evaluation of ensemble precipitation forecasts with observation-based ensembles. *Advances in Geosciences* **10**: 139–144.

Belanger E, Vincent A. 2005. Data assimilation (4D-VAR) to forecast flood in shallow-waters with sediment erosion. *Journal of Hydrology* **300**: 114–125.

Beven K. 2006. On undermining the science? *Hydrological Processes* **20**: 3141–3146.

Beven KJ. 2009. *Environmental Modelling: An Uncertain Future?* Routledge: London.

Beven K, Binley A. 1992. The future of distributed models – model calibration and uncertainty prediction. *Hydrological Processes* **6**: 279–298.

Bruen M, Krahe P, Zappa M, Olsson J, Vehviläinen B, Kok K, Daamen K. 2009. Flood forecasting: communicating uncertainty information to end-users. *Atmospheric Science Letters* (submitted).

Casati B, Wilson LJ, Stephenson DB, Nurmi P, Ghelli A, Pocernich M, Damrath U, Ebert EE, Brown BG, Mason S. 2008. Forecast verification: current status and future directions. *Meteorological Applications* **15**: 3–18.

Castaings W, Dartus D, Le Dimet FX, Saulnier GM. 2009. Sensitivity analysis and parameter estimation for distributed hydrological modeling: potential of variational methods. *Hydrology and Earth System Sciences* **13**: 503–517.

Céron J-P, Tanguy G, Franchistéguy L, Martin E, Regimbeau R. 2009. Hydrological seasonal forecast over France : feasibility and potentialities. *Atmospheric Science Letters* (submitted).

Cloke HL, Pappenberger F. 2008. Evaluating forecasts of extreme events for hydrological applications: an approach for screening unfamiliar performance measures. *Meteorological Applications* **15**: 181–197.

Cloke HL, Pappenberger F. 2009. Ensemble flood forecasting: a review. *Journal of Hydrology* **375**(3–4): 613–626.

Collier CG. 2007. Flash flood forecasting: what are the limits of predictability? *Quarterly Journal of the Royal Meteorological Society* **133**: 3–23.

Collier CG. 2009a. On the propagation of uncertainty in weather radar estimates of rainfall through hydrological models. *Meteorological Applications* **16**: 35–40.

Collier CG. 2009b. On quality indicators for radar-based river flow forecasts. *Proceedings of the Institution of Civil Engineers: Water Management* **162**: 115–123.

Demargne J, Mullusky M, Werner K, Adams T, Lindsey S, Schwein N, Marosi W, Welles E. 2009. Application of forecast verification science to operational river forecasting in the US national weather service. *Bulletin of the American Meteorological Society* **90**: 779–784.

Ebert EE. 2008. Fuzzy verification of high-resolution gridded forecasts: a review and proposed framework. *Meteorological Applications* **15**: 51–64.

Errico RM. 1997. What is an adjoint model? *Bulletin of the American Meteorological Society* **78**: 2577–2591.

Faulkner H, Parker D, Green C, Beven K. 2007. Developing a translational discourse to communicate uncertainty in flood risk between science and the practitioner. *Ambio J* **36**: 692–703.

Friedrich K, Hagen M, Einfalt T. 2006. A quality control concept for radar reflectivity, polarimetric parameters, and Doppler velocity. *Journal of Atmospheric and Oceanic Technology* **23**: 865–887.

Germann U, Berenguer M, Sempere-Torres D, Zappa M. 2009. REAL – Ensemble radar precipitation estimation for hydrology in a mountainous region. *Quarterly Journal of the Royal Meteorological Society* **135**: 445–456.

Germann U, Galli G, Boscacci M, Bolliger M. 2006. Radar precipitation measurement in a mountainous region. *Quarterly Journal of the Royal Meteorological Society* **132**: 1669–1692.

Jaun S, Ahrens B. 2009. Evaluation of a probabilistic hydrometeorological forecast system. *Hydrology and Earth System Sciences* **13**: 1031–1043.

Jaun S, Ahrens B, Walser A, Ewen T, Schar C. 2008. A probabilistic view on the August 2005 floods in the upper Rhine catchment. *Natural Hazards and Earth System Sciences* **8**: 281–291.

Laio F, Tamea S. 2007. Verification tools for probabilistic forecasts of continuous hydrological variables. *Hydrology and Earth System Sciences* **11**: 1267–1277.

Liggett JA, Chen LC. 1994. Inverse Transient analysis in pipe networks. *Journal of Hydraulic Engineering: ASCE* **120**: 934–955.

Liu YQ, Gupta HV. 2007. Uncertainty in hydrologic modeling: toward an integrated data assimilation framework. *Water Resources Research* **43**: W07401. DOI:10.1029/2006WR005756.

Llort X, Velasco-Forero C, Roca-Sancho J, Sempere-Torres D. 2008. 2008: Characterization of uncertainty in radar-based precipitation estimates and ensemble generation. *Fifth European Conference on Radar in Meteorology and Hydrology*, Helsinki, Finland.

Marsigli C, Boccanera F, Montani A, Paccagnella T. 2005. The COSMO-LEPS mesoscale ensemble system: validation of the methodology and verification. *Nonlinear Processes in Geophysics* **12**: 527–536.

Matott LS, Babendreier JE, Purucker ST. 2009. Evaluating uncertainty in integrated environmental models: a review of concepts and tools. *Water Resources Research* **45**: W06421. DOI:10.1029/2008WR007301.

Molteni F, Buizza R, Palmer TN, Petroliagis T. 1996. The ECMWF ensemble prediction system: Methodology and validation. *Quarterly Journal of the Royal Meteorological Society* **122**: 73–119.

Montanari A, Shoemaker CA, van de Giesen N. 2009. Introduction to special section on uncertainty assessment in surface and subsurface hydrology. *Water Resources Research* **45**: W00B00. DOI:10.1029/2009WR008471.

Moore AM. 1991. Data assimilation in a quasi-geostrophic open-ocean model of the gulf-stream region using the adjoint method. *Journal of Physical Oceanography* **21**: 398–427.

Moulin L, Gaume E, Obled C. 2009. Uncertainties on mean areal precipitation: assessment and impact on streamflow simulations. *Hydrology and Earth System Sciences* **13**: 99–114.

Neupauer RM, Wilson JL. 1999. Adjoint method for obtaining backward-in-time location and travel time probabilities of a conservative groundwater contaminant. *Water Resources Research* **35**: 3389–3398.

Nurmi P, Nasman S. 2009. SAL in hydrological catchments. 4th Internaional Verification Methods Workshop, Helsinki, Finland, 8–10 June 2009. http://space.fmi.fi/Verification2009/Booklet_FINAL_2009-05-09.pdf.

Pappenberger F, Beven KJ. 2006. Ignorance is bliss: or seven reasons not to use uncertainty analysis. *Water Resources Research* **42** W05302. DOI:10.1029/2005WR004820.

Pappenberger F, Beven KJ, Hunter NM, Bates PD, Gouweleeuw BT, Thielen J, de Roo APJ. 2005. Cascading model uncertainty from medium range weather forecasts (10 days) through a rainfall-runoff model to flood inundation predictions within the European Flood Forecasting System (EFFS). *Hydrology and Earth System Sciences* **9**: 381–393.

Pappenberger F, Ghelli A, Buizza R, Bodis K. 2009. The skill of probabilistic precipitation forecasts under observational uncertainties within the generalized likelihood uncertainty estimation framework for hydrological applications. *Journal of Hydrometeorology* **10**: 807–819.

Penenko V, Baklanov A, Tsvetova E. 2002. Methods of sensitivity theory and inverse modeling for estimation of source parameters. *Future Generation Computer Systems* **18**: 661–671.

Piasecki M. 2003. Optimal control of effluents using the adjoint method. *Wasser und Boden* **55**(3): 37–41.

Rabier F, Klinker E, Courtier P, Hollingsworth A. 1996. Sensitivity of forecast errors to initial conditions. *Quarterly Journal of the Royal Meteorological Society* **122**: 121–150.

Rezacova D, Zacharov P, Sokol Z. 2009. Uncertainty in the area-related QPF for heavy convective precipitation. *Atmospheric Research* **93**: 238–246.

Rossa A, Haase G, Keil C, Pfeifer M, Bech J, Ballard S, Alberoni P. 2009a. Propagation of uncertainty from observing systems into NWP:COST-731 Working Group 1. *Atmospheric Science Letters* (submitted).

Rossa A, Liechti K, Bruen M, Germann U, Haase G, Keil C, Krahe P, Zappa M. 2009b. Uncertainty propagation in advanced hydro-meteorological forecast systems: the COST 731 Action. *Atmospheric Research* (submitted).

Roulin E. 2007. Skill and relative economic value of medium-range hydrological ensemble predictions. *Hydrology and Earth System Sciences* **11**: 725–737.

Roulin E, Vannitsem S. 2005. Skill of medium-range hydrological ensemble predictions. *Journal of Hydrometeorology* **6**: 729–744.

Sanders BF, Piasecki M. 2002. Mitigation of salinity intrusion in well-mixed estuaries by optimization of freshwater diversion rates. *Journal of Hydraulic Engineering: ASCE* **128**: 64–77.

Schröter K, Llort X, Velasco-Forero C, Ostrowski M, Sempere-Torres D. 2009. Implications of radar rainfall estimates uncertainty on distributed hydrological model predictions. *Atmospheric Research* (submitted).

Sevruk B. 1996. Adjustment of tipping-bucket precipitation gauge measurements. *Atmospheric Research* **42**: 237–246.

Sun NZ, Yeh WWG. 1990. Coupled inverse problems in groundwater modeling. 1. Sensitivity analysis and parameter-identification. *Water Resources Research* **26**: 2507–2525.

Szturc J, Einfalt T, Osródka K, Jurczyk A. 2009. Rainfall and runoff ensembles based on the quality index of radar precipitation data. *Atmospheric Research* (submitted).

Szturc J, Osrodka K, Jurczyk A. 2008a. Parameterization of QI scheme for radar-based precipitation data. *Proceedings of ERAD 2008 (on CD)*, Helsinki, Finland, 267–279.

Szturc J, Osrodka K, Jurczyk A, Jelonek L. 2008b. Concept of dealing with uncertainty in radar-based data for hydrological purpose. *Natural Hazards and Earth System Sciences* **8**: 267–279.

Tabary P, Desplats J, Do Khac K, Eideliman F, Gueguen C, Heinrich JC. 2007. The new French operational radar rainfall product. Part II: validation. *Weather and Forecasting* **22**: 409–427.

Thielen J, Bartholmes J, Ramos MH, de Roo A. 2009. The European Flood Alert System – Part 1: concept and development. *Hydrology and Earth System Sciences* **13**: 125–140.

Thirel G, Rousset-Regimbeau F, Martin E, Habets F. 2008. On the impact of short-range meteorological forecasts for ensemble streamflow predictions. *Journal of Hydrometeorology* **9**: 1301–1317.

Todini E, Mantovan P. 2007. Comment on: 'On undermining the science?' by Keith Beven. *Hydrological Processes* **21**: 1633–1638.

Van de Vyver V, Roulin E. 2009. Scale-recursive estimation for merging precipitation data from radar and microwave cross-track scanners. *Journal of Geophysical Research: Atmospheres* **114**: D08104. DOI:10.1029/2008JD010709.

Van den Bergh J, Roulin E. 2009. Hydrological ensemble prediction and verification for the Meuse and Scheldt basins. *Atmospheric Science Letters* (submitted).

Villarini G, Krajewski WF. 2008. Empirically-based modeling of spatial sampling uncertainties associated with rainfall measurements by rain gauges. *Advances in Water Resources* **31**: 1015–1023.

Viviroli D, Zappa M, Gurtz J, Weingartner R. 2009. An introduction to the hydrological modelling system PREVAH and its pre- and post-processing-tools. *Environmental Modelling and Software* **24**(10): 1209–1222. DOI:1210.1016/j.envsoft.2009.1204.1001.

Wernli H, Paulat M, Hagen M, Frei C. 2008. SAL-A novel quality measure for the verification of quantitative precipitation forecasts. *Monthly Weather Review* **136**: 4470–4487.

White LW, Vieux B, Armand D, LeDimet FX. 2003. Estimation of optimal parameters for a surface hydrology model. *Advances in Water Resources* **26**: 337–348.

Wood AW, Maurer EP, Kumar A, Lettenmaier DP. 2002. Long-range experimental hydrologic forecasting for the eastern United States. *Journal of Geophysical Research: Atmospheres* **107**(D20): 4429. DOI:10.1029/2001JD000659.

Zacharov P, Rezacova D. 2009. Using the fractions skill score to assess the relationship between an ensemble QPF spread and skill. *Atmospheric Research* (in press).

Zappa M, Jaun S, Germann U, Walser A. 2009. Superposition of three sources of uncertainties in operational flood forecasting chains in mountainous areas. *Atmospheric Research* (submitted).

Zappa M, Rotach MW, Arpagaus M, Dorninger M, Hegg C, Montani A, Ranzi R, Ament F, Germann U, Grossi G, Jaun S, Rossa A, Vogt S, Walser A, Wehrhan J, Wunram C. 2008. MAP D-PHASE: real-time demonstration of hydrological ensemble prediction systems. *Atmospheric Science Letters* **9**: 80–87.

