Deltares

Enabling Delta Life

2009.06.08 Postprocessing of Hydrological Ensemble Forecasts

Report on HEPEX activities

Flood Control 2015

Deltares

Title
2009.06.08 Postprocessing of Hydrological Ensemble Forecasts

Client	**Project**	**Reference**	**Pages**
Deltares	1200379-002	1200379-002-ZWS-0001	45

Keywords
HEPEX, Flood Control 2015, Workshop, Meeting, Uncertainty, Flood forecasting

Summary
This research was carried out within the Flood Control 2015 program. The present report summarizes the activities performed in the context of the HEPEX initiative. The documents contains a science plan on post-processing of ensemble streamflow forecasts that has been written as result of the 2008 HEPEX workshop hosted at Deltares in June 2008. The HEPEX initiative involves attendance of workshops that are held on a two-yearly basis. The full Deltares contribution presented during the latest HEPEX conference held in Toulouse (France) in June 2009 is reported in the Appendix. The aim of the science plan is to develop and test methods for conditioning hydrological ensemble forecasts so that they can support decision making.

Version	**Date**	**Author**	**Initials**	**Review**	**Initials**	**Approval**	**Initials**
	dec. 2009	Paolo Reggiani		Joost Beckers		Toon Segeren	

State
final

Contents

1 Report HEPEX activities 1

2 Introduction 3

3 Motivation and Goals 5

4 Background 7
4.1 Description of Typical Current Operational System (including Mod Practices) 7
4.2 Predictive Uncertainty 8
4.3 Discussion of Forecast Limitations 9
4.4 Importance of Forecast Verification 10

5 Requirements for a Hydrological Post-Processing System 13

6 Science Questions 15

7 Near-Term (Phase I) Objectives and Proposed Activities 17
7.1 Activities 17

8 Project Schedule 19

9 Longer Term Objectives and Expected Results 21

10 Literature 23

Appendices

A Presentation HEPEX meeting Toulouse 15-18 June 2009 A-1

1 Report HEPEX activities

The present report summarizes the activities pursued under the Hydrological Ensemble prediction Experiment (HEPEX) initiative during the year 2008/2009. The activities are focused on improving knowledge on the handling of forecasting uncertainty and thus improving flood forecasts capabilities at Deltares. The contributions of Deltares to the HEPEX initiative fall under the Flood Control 2015 (FC2015) program.

2 Introduction

A workshop on hydrologic ensemble post-processing was held as a subgroup activity of HEPEX (the Hydrologic Ensemble Prediction Experiment). The goal of the workshop was to identify opportunities to develop international scientific collaboration to improve hydrologic ensemble forecasts through statistical post-processing of the output from hydrologic ensemble forecast models. The invitation-only workshop was hosted by Deltares (formerly WL Delft Hydraulics) in Delft, June 23-25, 2008, and approximately 25 individuals from the U.S. and Europe participated. Participants agreed to initiate an ongoing collaborative effort focused on the post-processing subtopic, and this science plan, which is based on discussions and findings at the workshop, outlines the motivation, goals, science questions, activities and structure of that effort.

3 Motivation and Goals

The Hydrologic Ensemble Prediction Experiment (HEPEX) Uncertainty Post-processing Project (HUPP) is motivated by the broad recognition in the hydrologic prediction community that: (a) hydrologic models are generally unable to reproduce observed streamflow behavior with zero error even when forced with high quality met
eorological inputs, after extensive calibration using the latest and most sophisticated techniques, and when run using comprehensive and frequent assimilation of observations to adjust and theoretically reduce errors in simulated states; and (b) that these simulation errors translate into forecast errors that are further compounded by the inherent uncertainty of future meteorological forcing. The basic assumption or requirement of many follow-on applications that hydrologic forecasts must be unbiased and statistically reliable necessitates the consideration of approaches (generally statistical and applied as a post-process to hydrologic forecasting) to remove bias and spread errors (while maintaining or improving forecast skill) from hydrologic forecasting system output. This general need applies equally to deterministic hydrologic forecasting systems (which are common in operations), but we here focus on ensemble predictions.

The HUPP goal is to gather a community of researchers and practitioners in the hydrologic forecasting area to explore alternative post-processing techniques, identify common science issues and develop a shared vision of a conceptual framework for evaluating post-processing techniques. This work is expected to lead to development of practical but sound solutions to the ensemble bias and spread problem that can be implemented in an operational setting to produce reliable, bias-free ensemble forecasts.

HUPP is only one component of the larger HEPEX effort, which is depicted in Figure 3.1. The overarching goal for HEPEX is “to develop and test procedures to produce reliable hydrological ensemble forecasts, and to demonstrate their utility in decision making related to the water, environmental and emergency management sectors.” (HEPEX Implementation Plan, 2007).

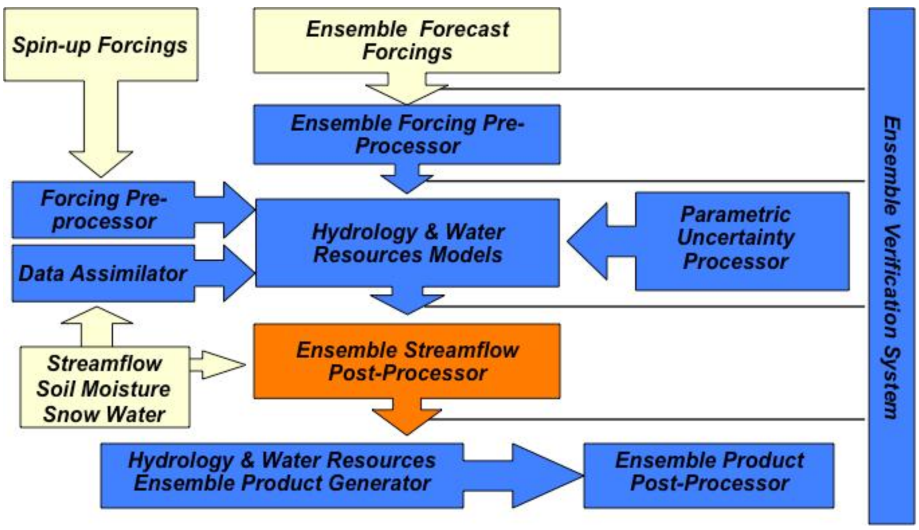


Figure 3.1 *Schematic of a hydrological ensemble prediction system, showing the integration of the ensemble streamflow forecast post-processing component (in orange)*

4 Background

Increasingly, users of hydrologic forecasts want quantitative estimates of forecast uncertainty rather than only an approximation of the single most probable scenario. In response, operational agencies are beginning to employ ensemble forecast techniques for hydrologic predictions. Ensemble forecast systems provide an estimate of the most probable future scenario, and also offer a wide range of possible outcomes that account for all sources of forecast uncertainty. These sources include precipitation and other meteorological inputs, estimates of boundary/initial hydrological conditions, the hydrologic forecast models, and model parameters. [copied from implementation plan]

4.1 Description of Typical Current Operational System (including Mod Practices)

Current operational forecasting systems consist of a chain of hydrological and hydraulic models, that are connected in series and are integrated with live data streams. The data streams include observations of precipitation, temperature and water levels, as well as precipitation forecast products from numerical weather prediction models and in some cases weather radar now-casts.

The hydrological models simulate the rainfall-runoff response of the land phase, while water in the river network is propagated by means of channel hydraulics models. The modelling system is operated in two modes: in *i) historical mode* and in *ii) forecast mode*.

i) The historical mode of operation consists in running the model chain over a historic period up to the onset of the forecast. The meteorological input is provided by observed precipitation, temperature and evaporation. During the historic run, observations of water levels or discharges are assimilated into the hydrological and hydraulic models, in order to correct internal model states and create optimal model initial conditions for the forecast.

ii) In forecast mode the model chain is driven by precipitation, temperature as well as evaporation forecasts form either now-casting systems (weather radars) or numerical weather prediction (NWP). The lead time of these forecasting products can range between a few hours up to 10 days ahead. The NWP products can be either deterministic, or entail probabilistic products such as ensemble weather forecasts form ensemble prediction systems (EPS). Ensemble weather predictions are obtained by perturbing the initial conditions vectors for numerical weather models. Currently used ensemble weather forecasts can include up to 50 weather forecasts.

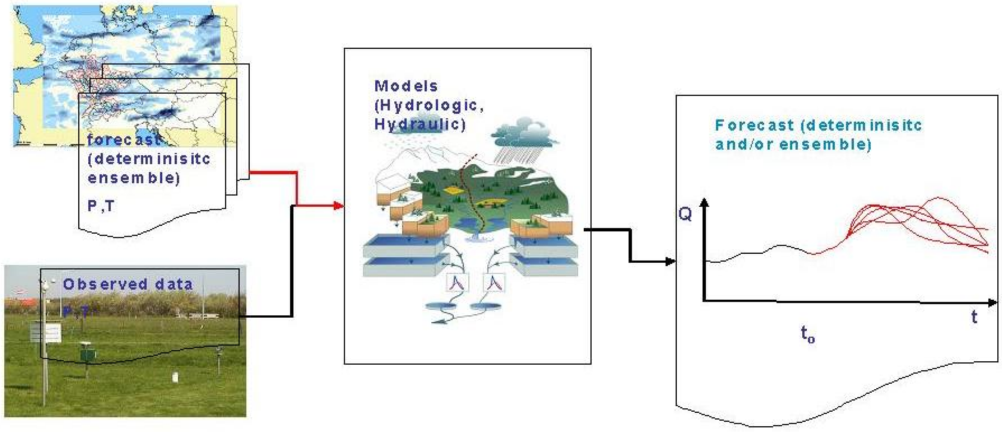


Figure 4.1 Schematic view of the structure of conventional flood forecasting systems

The observed meteorological data are imported into the system and validated. Outliers or unreliable data values are identified and replaced by interpolation.

Subsequently precipitation and temperature series are mapped from the sparse grid of station locations towards the locations that correspond to the input points for the hydrological models. The NWP output is supplied in grid format. The respective values need to be averaged over basin shapes a subsequently mapped to the basin centres.

Cases of missing data are handled via appropriate selection hierarchies, which assign different priorities to a range of possible procedures for data filling and data exploration/interpolation. In this way an availability of continuous data series with a seamless transition between observations and forecasts is ensured.

The forecasts are performed at regular intervals during the day. The models calculate forecasted flow rates at critical locations, which are then disseminated to decision-makers.

4.2 Predictive Uncertainty

The *predictive uncertainty* (Krzysztofowicz [2001a]) can be defined as a measure of the degree of certitude on the occurrence of a flood event, conditional on all information available at the start of the forecast.

In operational river flow forecasting, an "event" consists of the exceedance of a critical stream flow rate or water level at the control section of the basin.

The predictive uncertainty on the forecasted flow (expressed in terms of discharge or water level) for a given lead time can be expressed in terms of a conditional probability density function ϕ:

$$\phi\left(h_n \mid s_n, h_0, h_{0-1}, ..., h_{0-k}\right)$$

where h_n is the water level at lead time t_{0+n}, s_n is the water level at the same lead time forecasted by the model, h_0 is the water level observed at the forecasting location at the forecast base time t_0. The quantities h_{0-k} are water levels observed at the forecasting location at time t_{0-k} ahead of the forecast.

The predictive uncertainty represents a family of probability density functions on future flow, conditional on the model forecasts and on past observations. We note that conditioning on additional variables such as flow observations at locations further upstream or precipitation is in principle possible.

The basic concept underlying the definition of *predictive uncertainty* is that the uncertainty on future water level observations is conditioned on all possible information available to the forecaster, including model predictions and a range of historical observations up to the forecast base time.

The challenge consists in finding methods to estimate ϕ in real-time, and to be able to attribute a probability of occurrence to a forecasted event. Estimating the predictive uncertainty constitutes the central task of post-processing flow forecasts.

One possibility for specifying the predictive uncertainty has been laid out by Krzystofowicz (1999). He proposes to use Bayesian inference, by updating a prior density. Bayes theorem is by combining a prior probability density on flow with a stochastic specification of the model error, which is expressed in terms of a likelihood function. The revised posterior distribution constitutes an estimate of the predictive uncertainty.

It is important to point out, that the predictive uncertainty itself does *not* represent a description of the model error, but rather a probability on the future flow, conditional on a model forecast and past flow observations.

4.3 Discussion of Forecast Limitations

Forecasts produced by integrated data-modelling systems can be affected by limitations due to a series of reasons, which we will address next:

Input uncertainty:
Forecast of precipitation is uncertain at best. The uncertain input into hydrological prediction models leads to an uncertain output (river stages, discharges), which is most suitably quantified in terms of a probability distribution for the forecasted quantity conditional on other variables (see previous section). The input uncertainty weights in much more prominently than other sources uncertainties, such as uncertainty on model states and boundary conditions. A significant input uncertainty seriously compromises the value of a forecast and imposes limitations on the forecasting product.

Poor model performance:
Models are affected by errors. There can be *i)* systematic errors attributable to poor model conceptualizations, leading to a model bias, or *ii)* sporadic errors attributable to lack of initial data and model initialization as well as errors due to absence or poor estimates of boundary and initial conditions. In either case error correction methods need to be applied at the onset of a forecast.
Error correction can work at different levels of complexity and can start with simple output or input correction, and go all the way to more complex procedures aiming at adjusting internal model states and parameters. The error correction is based on comparisons of model output against observations over a historical period of observations preceding the forecast base time.

A postprocessor for forecasts should enable a forecaster to asses the information content of a model and the limitations it poses on the forecast. In case of a particularly poor performing model the information content of a model-based forecast could be less than just using historical information.

Lead time

In some situations, a too short lead time can pose severe limitations on the actual value of a forecast. The lead-time is the time horizon over which a critical variable such as a river stage can be forecasted. Especially in small river basins with a short contraction time the forecast lead time can be too short to take any actions and therefore provide no added value in terms of disaster reduction. Extension of lead-time can be achieved to some extent by combining weather forecasts, radar now-casts and observations and use fast forecasting models (e.g. simple regression models). In particular situations simple approaches, based on precipitation thresholds can provide significant benefits. Urban settings, in which flooding occurs due to heavy precipitation in combination with sealed surfaces are typical environments in which forecasting is limited due to short lead times.

4.4 Importance of Forecast Verification

Hydrologic Post-Processing methods are used to improve the reliability, skill and resolution of probabilistic hydrological forecasts. Forecast verification techniques may be applied to assess these attributes. As with the ensemble forecasting approach, these techniques have been developed primarily within the atmospheric sciences, but are often equally applicable to other disciplines, such as the hydrological sciences (Wilks, 2006).

From the viewpoint of operational hydrologic forecasting, there are at least three types of verification of interest: 1) diagnostic, 2) trend and 3) prognostic. Diagnostic verification is concerned with assessing different attributes of ensemble forecasts, such as reliability, skill, resolution, discrimination, etc., to diagnose the performance of the forecast system and process so that cost-effective improvements may be made. Trend analysis is concerned with being able to discern and assess improvement in forecast quality over time. Prognostic verification is concerned with being able to provide the users of the forecast, such as the forecasters and the emergency managers, with verification information that may directly be used for decision making. Such verification information would come from translating and casting all available verification information into the context of the forecasting and decision-making problem at hand.

Methods for verification of forecasts are well established (Wilks, 2006), and such verification provides clear insight into value and skill of the ensemble predictions at different lead times, giving valuable information to the forecaster in interpreting the forecast products.

Skill measures for assessing ensemble forecasts include the Brier score, which measures the mean squared error in the probability space. The Brier skill score (BSS) measures skill relative to a reference forecast (usually climatology or naïve forecast). The ranked probability score (RPS) is another way of determining the accuracy of the probabilistic forecast. RPS measures the squared difference in probability space when there are multiple categories (when there are only two categories RPS is equal to the BS). As with the Brier Skill Score, the Ranked probability skill score measures skill relative to a reference forecast. RPS applies when there is a discrete number of categories, but can be extended to continuous categories as the Continuous Ranked Probability Score (CRPS). CRPS is particularly attractive in that it does not depend on the particular choice of thresholds and that it allows comparative verification with single-value forecasts, for which CRPS reduces to absolute mean error. The relative operation characteristic (ROC) is a measure to assess the ability of the forecast to discriminate between events and non-events. The ROC curve plots the hit rate (POD) against the false alarm rate (POFD). The curve is created using increasing probability thresholds to make the yes/no decision (WMO, 2007).

Ensemble verification as it is applied in operational hydrology today borrows heavily from the atmospheric science community. One of the distinguishing aspects of streamflow or precipitation ensembles is that they are multi-scale in nature, and hence should be verified over a wide range of spatio-temporal scales of aggregation. Unlike verification measures for single-value forecasts, most of the measures for ensemble forecasts are not expressed in physically meaningful units. While this poses little problem for diagnostic verification, it makes the use of verification information for real-time forecasting and decision making very difficult. This is an extremely important aspect of hydrologic ensemble forecasting; its promise can be realized only if the user is able to use the probabilistic information with ease and clarity in real-time decision making.

5 Requirements for a Hydrological Post-Processing System

Workshop participants discussed practical requirements and/or principles that forecast systems should strive to meet and maintain, and agreed upon the following key elements:

1. Post-processing must achieve forecasts that are:
   - unbiased, reliable, and have the highest skill possible (which implies bias and spread correction and resolution improvement).
   - coherent (default to climatology when they have no skill)

2. Post-processing must be able to combine forecasts from multiple sources

3. Forecasters must understand the general principles of the post-processing techniques and/or be persuaded that they work – hence post-processing techniques must either be straightforward and accessible to forecasters who may only know basic statistics, or must be supported by ample training and demonstration material.

4. The post-processing system must be compatible with and/or offer an avenue for forecaster modification.

5. A post-processor must be able to transition easily between distribution representation and trace representation (both directions) and be consistent in both perspectives across time and space scales

6. Post-processing approaches should be extensible where possible from flow variables to related quantities, ie, stage, reservoir releases.

7. Post-processing techniques should be adaptive to incorporate lead-time, state (ie, high flows, low flows) and other dependencies, as warranted by the performance of the forecast system.

8. Although hindcasts may not be required to support some of the goals of a post-processing system (e.g., a retrospective model run in lieu of hindcasts may supply sufficient statistical context for bias and spread correction), hindcasts are almost certainly required for verification of the post-processing approach’s performance. Hindcasts are therefore promoted as a requirement.

6 Science Questions

The requirements and principles listed above reflect the immediate concerns and interests of operational forecasters, but the development of approaches to meet them depends on the exploration and resolution of a number of outstanding scientific issues. For this reason, the workshop concluded by advanced a number of explicit science questions as potential focus areas of further study. These included the following:

1. How can forecasts from multiple models be combined?
2. What is the role of updating vs. post-processing?
3. To what extent are hydrologic hindcasts required, versus retrospective simulations of the type traditionally used for model calibration?
4. What performance measures are appropriate for expressing the error characteristics of operational hydrologic ensemble forecasts? For diagnosis of forecast system behavior?
5. What is the value of using recent observations in post-processing, and what methods apply?
6. What is the effect of temporal scale dependency on forecast skill and implications for post-processing techniques to produce reliable multi-scale predictive uncertainty.
7. Can the effects of reservoir operations and upstream diversions be incorporated?
8. Can we make ensemble hydrological simulations (with reliable predictive uncertainty) from single-value model simulations?
9. Can we develop conditional post-processing techniques (that recognize differences in hydrological uncertainty for different hydrological conditions, and handle extremes)?
10. What is the potential role of scaling theory in hydrological post-processing?
11. What verification procedures/statistics are needed (or should be used) for different kinds of events? What events should be verified?
12. What is the potential role of wavelet and other variance decomposition techniques?
13. What is the role of the forecaster?
14. Are there differences in the way post-processing addresses continuous versus binary processes?
15. What are the effects of non-stationarity (including climate variability and change as well as river basin changes) in applying post-processing techniques?
16. What approaches are most appropriate for short, medium and long range forecast periods?
17. Are there differences between post-processing stage versus flow forecasts?
18. How can we account for possible levee failures in post-processing flow or stage forecasts?

7 Near-Term (Phase I) Objectives and Proposed Activities

Given the broad scope of the science focus areas and potential supporting activities illustrated by the range of questions above, HUPP objectives and activities are broken into a near-term Phase 1 (leading up to the next HUPP meeting) and a longer-term phase to ensue following that meeting. The near-term objectives are the following:

1. …the establishment of a handful of testbed datasets focusing on short to medium range flow prediction that can be used for the development, demonstration, evaluation and comparison of post-processing techniques. The datasets will include retrospective simulations, observations, and hindcasts.

2. … the development of methods which meet Requirements 1, 2, 5, 6 and 7 as detailed previously.

3. …development and illustration of a concept of operations that addresses the role and implications of forecaster modifications.

4. …the development of a bibliography related to post-processing techniques.

To achieve these objectives, several targeted activities have been identified. These activities advance our understanding of the objectives' underlying science questions (note that science questions may apply to more than one activity and objective), as well as provide concrete results in the form of collaboration-supporting archives of methods and forecast-related datasets. The activities are generally to be carried out within the larger HEPEX project testbeds, making use of knowledge and datasets of those testbeds.

7.1 Activities

Multi-model ensembles, Po Basin - Ezio Todini (*Objectives 1, 2*)
Ensemble forecasts and re-forecasts from ECMWF, Florian Pappenberger
Experimental Ensemble Forecasting System, XEFS – Dong Gjun Seo
Bayesian Model Averaging, Rhine Basin – Albrecht Weerts, Paolo Reggiani
Bayesian Ensemble & Deterministic Post processor, Rhine Basin– Albrecht Weerts & Paolo Reggiani
Ensemble Data Assimilation Rhine and Meuse Basin (Hydraulic & Hydrologic) – Albrecht Weerts
End user perspective, forecast datasets, Western US & BC Testbeds– Rob Hartman (*Objectives 1, 3*)
Collation of model datasets – Feather Basin, Western US & BC Testbeds – Andy Wood (*Objectives 1, maybe 2*)
NSSC, training?– Jonathan Gourley
Information content of flashy catchments – Enda O'Connel
Multi-model and challenging datasets, Peace River & Mica Basin – Sean Fleming
Bayesian Ensemble Post processor (links NCEP & XEFS), Bayesian verification, Scientific conscience – Roman Krzystofowicz

Verification Methods & Performance Indicators (Micha Werner, Christel Prudomme)
The activity targets methods suitable for the verification of both deterministic and probabilistic hydrological forecasting. Many of these methods have their foundation in the atmospheric sciences, but their applicability in verification of hydrological forecasts is not always equally obvious. The activity will align closely with the development of a verification framework/tools in associated work that can be easily applied to different datasets on the one hand, as well as allowing extension with verification methods on the other.

Several datasets will be considered,

- Datasets of longer range forecasts at daily time steps (UK? Christel?)
- Datasets of short-medium range flow forecasts at synoptic time steps (NWS, CNRFC?)
- Datasets of short range forecasts for fast responding basins (MAP-D Phase, Switzerland?)

8 Project Schedule

- Complete draft science plan by Dec 31, 2009
- Progress Reports from each project activity due every 6 months:
  - June, 2009
  - December, 2009
  - June, 2010
  - December, 2011
  - June, 2011
- Web access to project information to be available – continuing
- Follow-up Workshop ~ June 2010 To be decided.

9 Longer Term Objectives and Expected Results

The project expects to produce the following results:

- Hydrological post-processing procedures produced by project participants will begin to be used by operational hydrological services, hydrological forecast users and/or private sector support organizations with 2 years.
- Example operational applications of hydrological post-processing procedures will be available for users to review within 3 years.
- A follow-up workshop to assess progress and plan for future activities will be held within 2-3 years.
- Supporting data sets to support continued development and assessment of hydrological post-processing procedures will be developed and made freely available to the scientific community.

10 Literature

Krzysztofowicz, R. (2001a), The case for probabilistic forecasting in hydrology, *J. of Hydrol*, **249**, 2--9.

Wilks, D. S., 2006, Statistical methods in the atmospheric sciences Second edition, International geophysics series, v. 91. Academic Press, San Diego.

WMO, 2007, Forecast verification – issues, methods and faq, WWRP/WGNE Joint working group on verification. URL:
http//www.bom.gov.au/bmrc/wefor/staff/eee/verif/verif_web_page.html .

A Presentation HEPEX meeting Toulouse 15-18 June 2009

To : HYD and OWB
From :
Subject : Hepex meeting Tolouse 15-18 June 2009
Date : 28 September, 2009
Cc :
Action:

Between 15 and 18 of June 2009 the yearly HEPEX meeting was held, this time at the premises of Meteo France, Toulouse. Two Deltares representatives were present: 1) Albrecht Weerts and 2) Paolo Reggiani. Albrecht Weerts joined the meeting on June the 15th and stayed until Wednesday 17th. Paolo Reggiani joined the meeting on the 16th of June and stayed until Thursday the 18th.

The programme of the workshop can be downloaded form the following URL:

http://www.meteo.fr/cic/meetings/HEPEX09/HEPEX_Program_V1.pdf

Paolo Reggiani held a presentation about Bayesian post processing on ensemble forecasts for the river Rhine forecasting system. The presentation was received very well and was followed up by a series of questions by workshop participants.

During the afternoon of the 17th of June and the last day of the conference, the 18th of June Breakout groups were organized. The breakout groups focussed on forecast uncertainty, with a principal focus on meteorology. One particular breakout group focussed on streamflow uncertainty. Paolo Reggiani participated in the breakout groups and contributed to the scientific discussions.

The conference closed on Thursday afternoon, the 18th of June.

The slides of the presentations given by Paolo Reggiani are attached to this document

Deltares
Enabling Delta Life

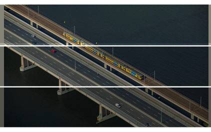
Uncertainty assessment of ensemble flow forecasts for the River Rhine

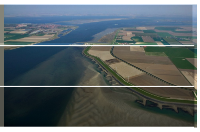
HEPEX Meeting Toulouse, France
15-18 June 2009

Paolo Reggiani, Maik Renner, A. Weerts, P. Van Gelder

17 June 2009

Acknowledgements





- BFG (Bundesanstalt für Gewässerkunde), Koblenz, Germany
- Water Management Centre Netherlands
- Flood Control 2015
- TU Delft

17 June 2009

Deltares

Motivation

Aims:

- Probability density function of the expected flow, conditional on a given ensemble flow forecast (= predictive uncertainty).
- derive probabilities of occurrence of a water level level conditional on a forecast.

Method used:

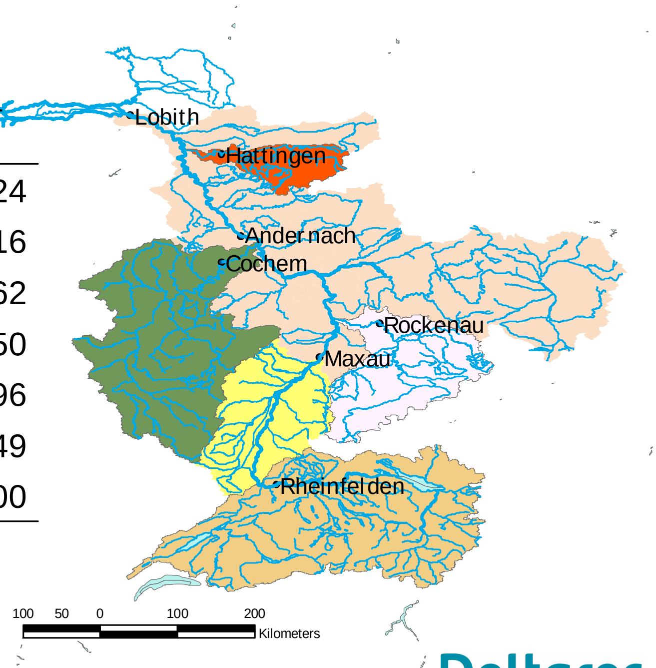
- Bayesian Revision
  - use Bayesian inference to derive probability of occurrence of an event on the basis of past experience.

17 June 2009

Deltares

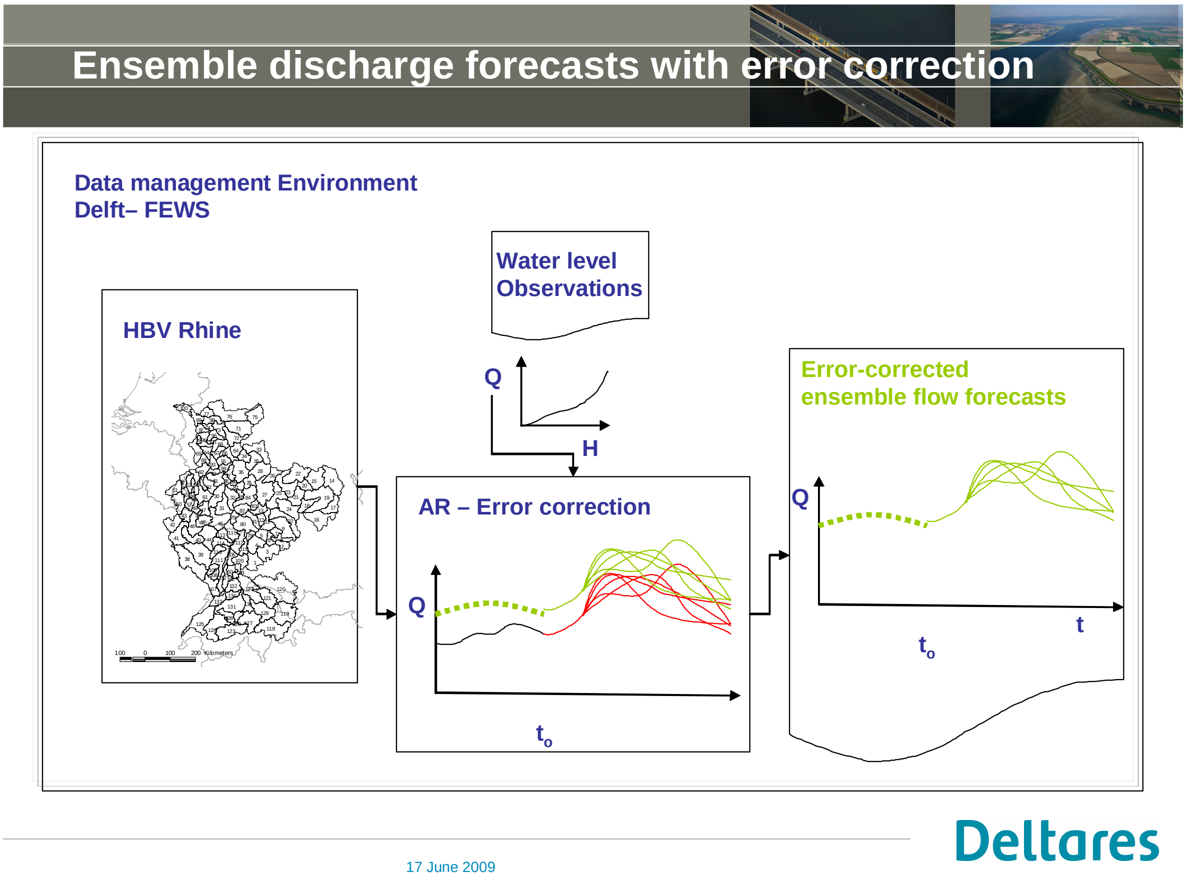
Forecasting locations along the Rhine river

Discharge	Basin area [km²]
Hattingen/Ruhr	4124
Rockenau/Neckar	12616
Cochem/Mosel	27262
Rheinfelden	34550
Maxau	50196
Andernach	139549
Lobith	160800

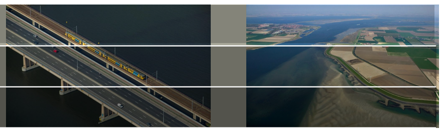


17 June 2009

Deltares


Ensemble discharge forecasts with error correction
Data management Environment
Delft– FEWS
Water level
Observations
HBV Rhine
Q
H
AR – Error correction
Q
t
o
Error-corrected
ensemble flow forecasts
Q
t
t
o
17 June 2009
Deltares

Bayes’ theorem for forecasting



Approach:

- Describe the joint distribution of observation and forecasts

$$\frac{\overbrace{P(H_n)}^{priori}\ \overbrace{P(S_n \mid H_n)}^{likelihood\ Funktion}}{\underbrace{P(S_n)}_{totale\ Wahrscheinlichkeit}} = \underbrace{P(H_n \mid S_n)}_{posteriori}$$

Re-analysed forecasts (hindcast) and observations

Current forecast

H_n … flow n- days ahead

S_n … forecasted flow n – days ahead

a-priori distribution:
Prior knowledge about upcoming flow
e.g. historic flow distribution

likelihood function:
conditional distribution of (previous) forecasts, for a given observation

a-posteriori distribution:
revised distribution of upcoming flow, conditional on a current forecast

17 June 2009

Deltares

Development of a Bayesian Ensemble Uncertainty Processors (BEUP)

Theory based on:

- Bayesian Theory of probabilistic forecasting
Krzysztofowicz(1999)
- Hydrological Uncertainty Processors (HUP)
Krzysztofowicz (2000)

BEUP extensions here:

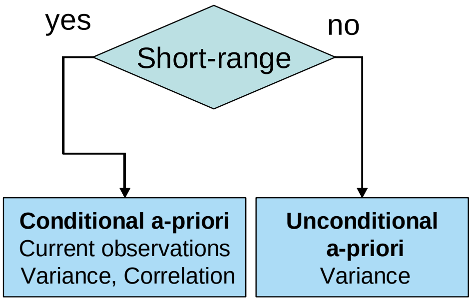
- Medium range forecasts
- Ensemble flow forecasts

17 June 2009

Deltares

2. Method

Determination of the prior distribution



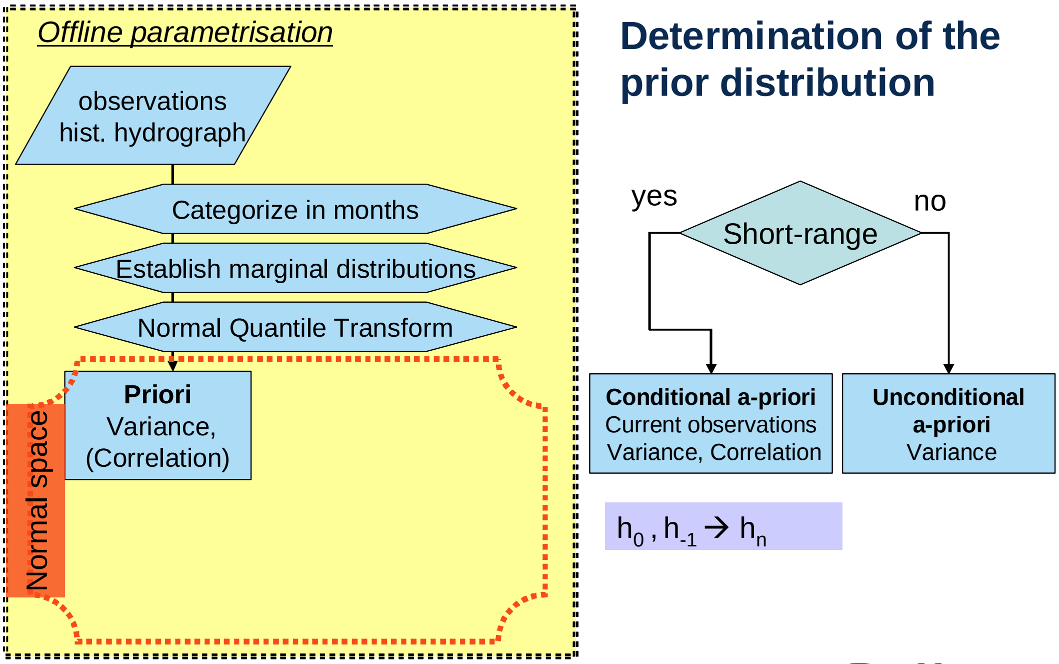
$h_0 , h_{-1} \rightarrow h_n$

17 June 2009

Deltares

2. Method

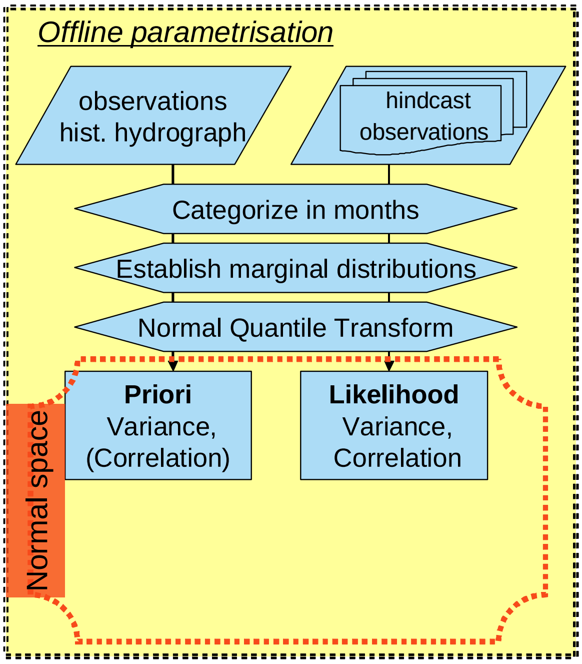
Determination of the prior distribution



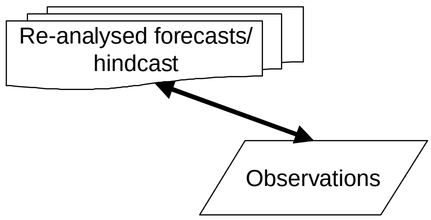
17 June 2009

Deltares

2. Method



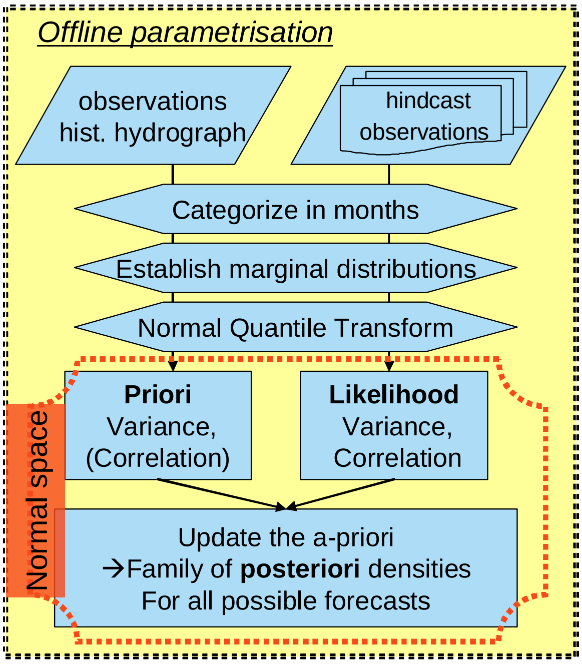
Estimation of the likelihood function



17 June 2009

Deltares

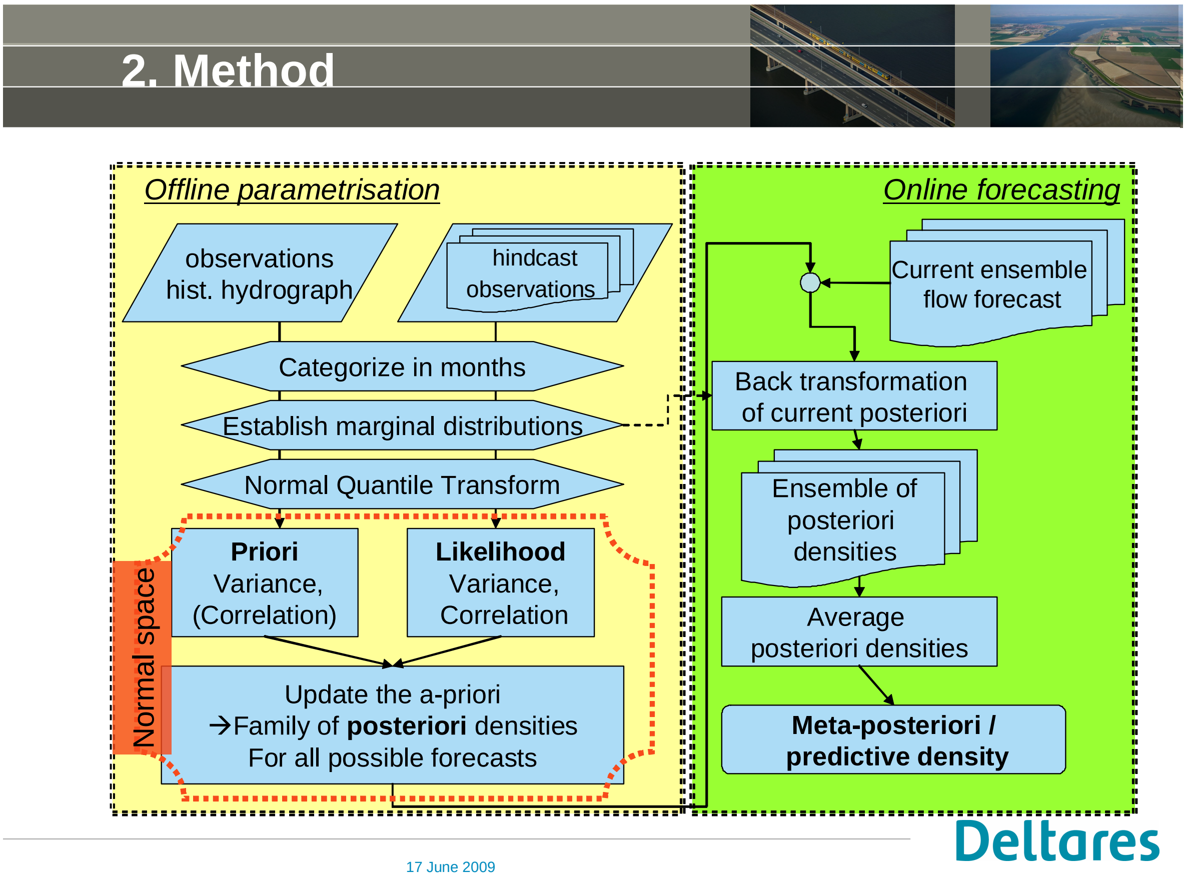
2. Method



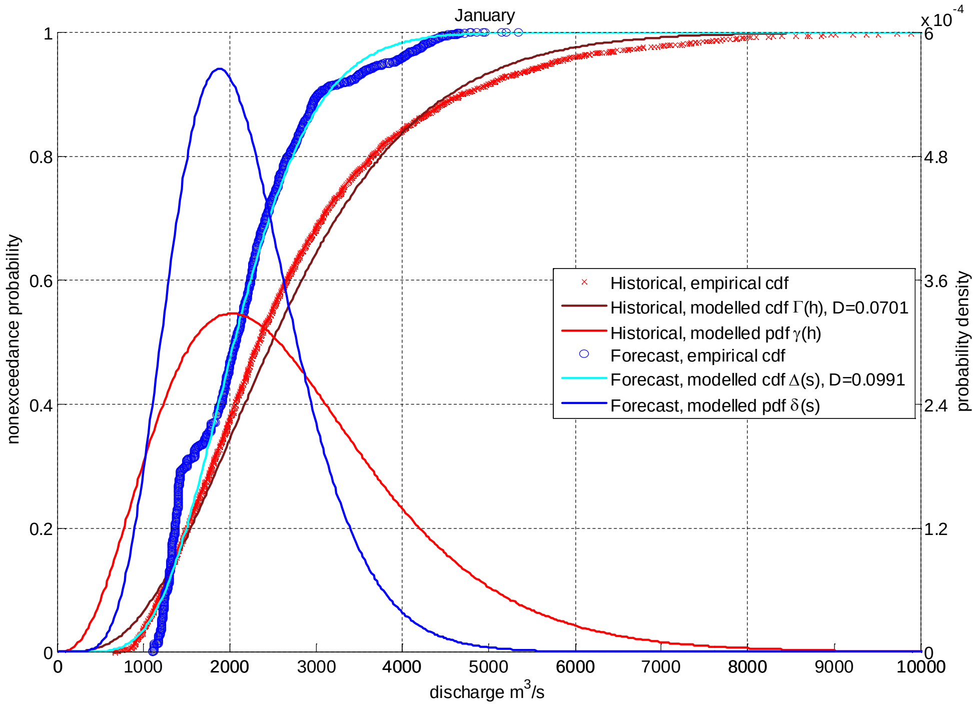
Derivation of the posterior density in normal space

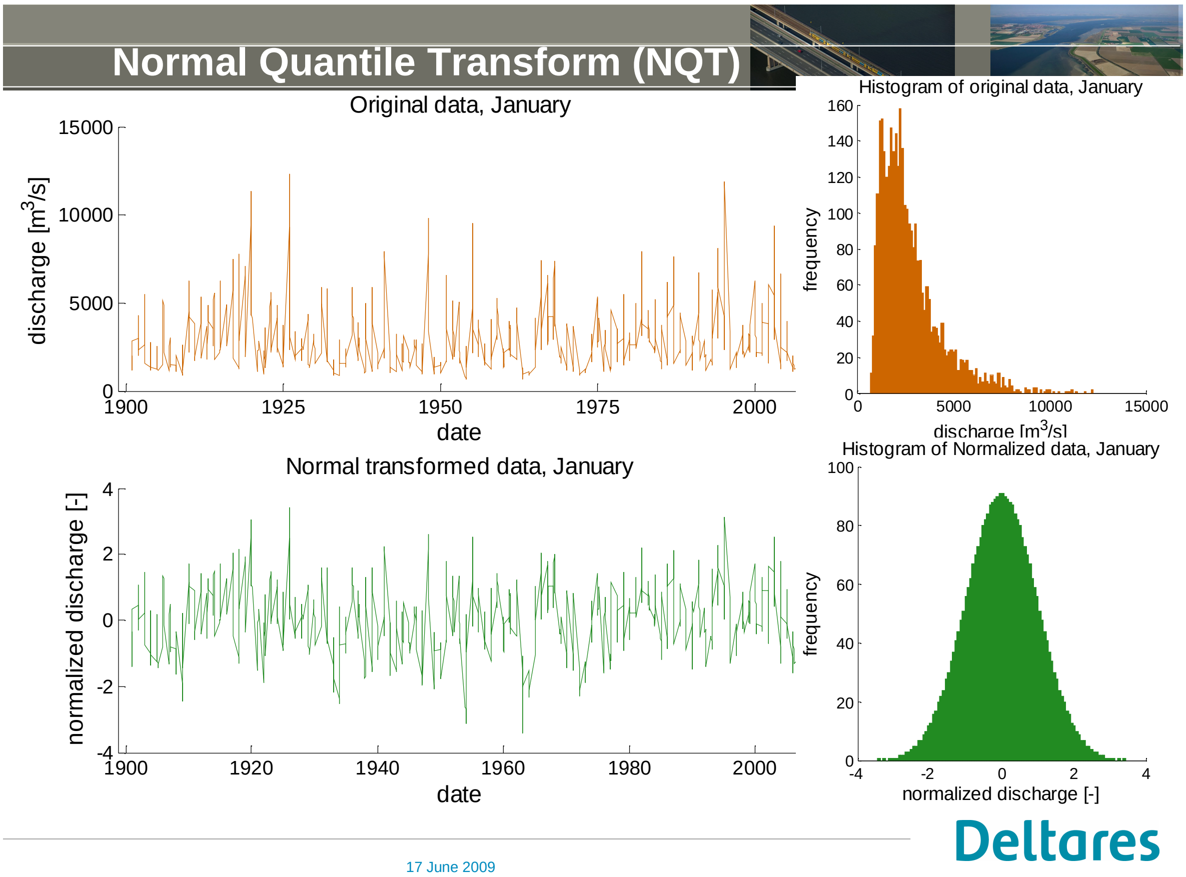
Deltares

17 June 2009


2. Method
Offline parametrisation
Online forecasting
observations
hist. hydrograph
hindcast
observations
Categorize in months
Establish marginal distributions
Normal Quantile Transform
Priori
Variance,
(Correlation)
Likelihood
Variance,
Correlation
Normal space
Update the a-priori
→Family of posteriori densities
For all possible forecasts
Current ensemble
flow forecast
Back transformation
of current posteriori
Ensemble of
posteriori
densities
Average
posteriori densities
Meta-posteriori /
predictive density
Deltares
17 June 2009

Cumulative distributions: 100+ years empirical data and modelled distributions



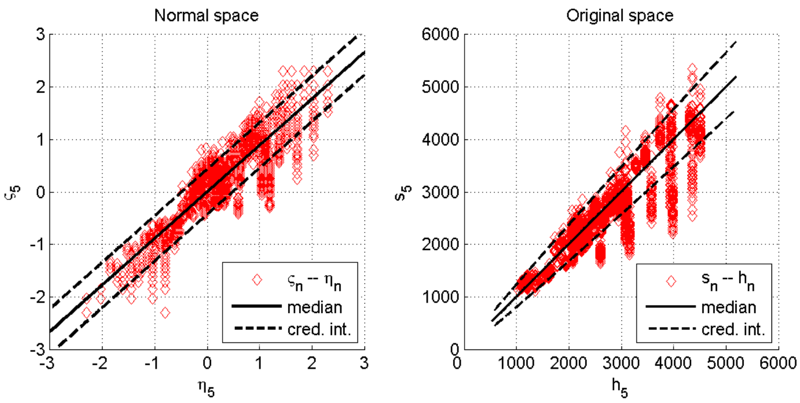

Normal Quantile Transform (NQT)
Original data, January
discharge [m3/s]
date
Histogram of original data, January
frequency
discharge [m3/s]
Normal transformed data, January
normalized discharge [-]
date
Histogram of Normalized data, January
frequency
normalized discharge [-]
Deltares
17 June 2009

Derivation of linear regression in the Gaussian space

Assumptions

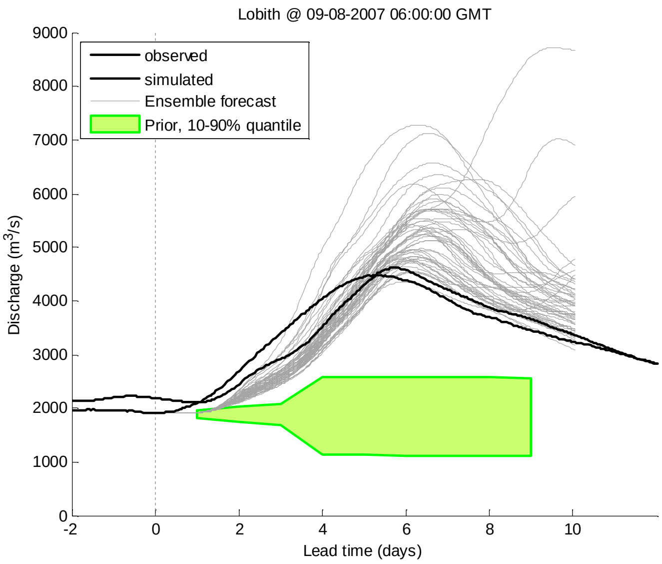
- Linear relation between random variables in the normal space.
- Priori, Likelihood Function and Posteriori Distribution are normally distributed.

→ Derive parameterized posterior distributions on the basis of property of conjugated distributions.



17 June 2009

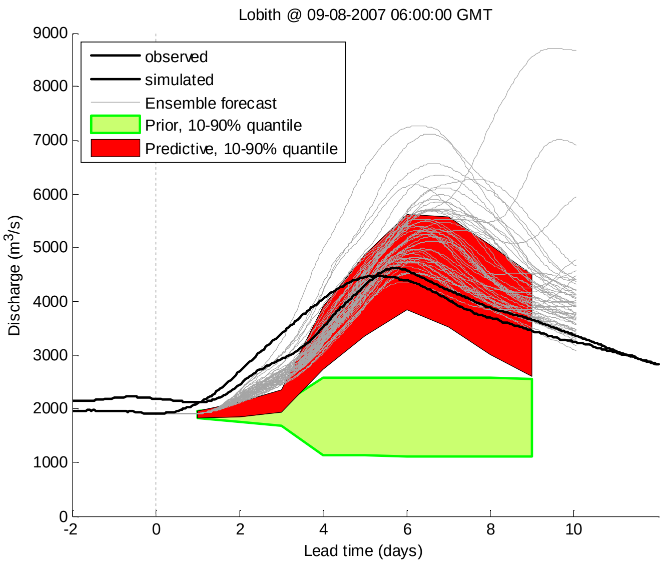
BEUP – forecast example 9th August 2007



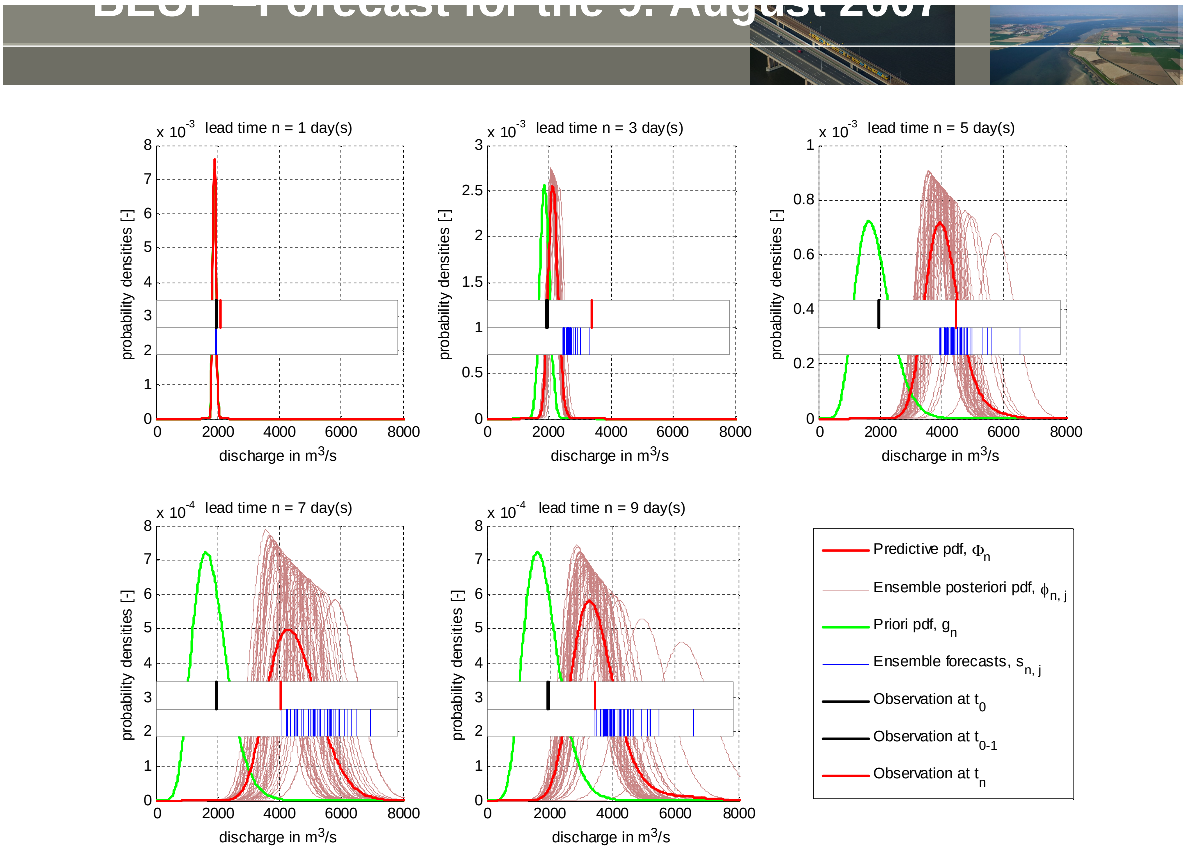
Deltares

17 June 2009

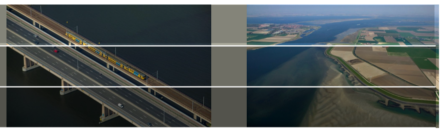
BEUP – forecast example 9th August 2007

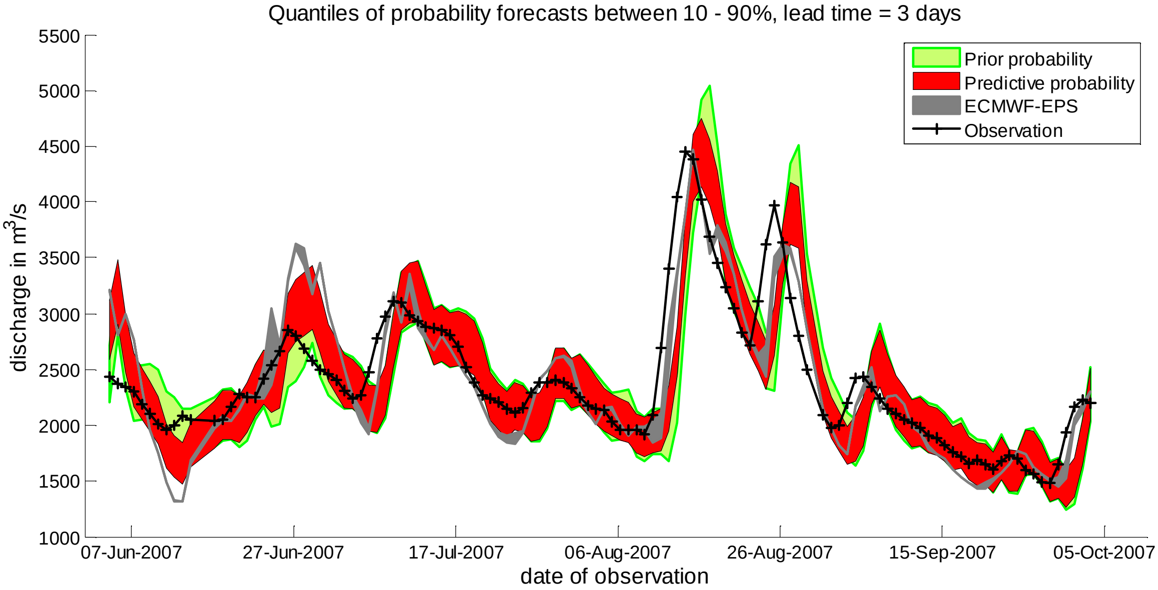


17 June 2009


x 10^-3 lead time n = 1 day(s)
x 10^-3 lead time n = 3 day(s)
x 10^-3 lead time n = 5 day(s)
x 10^-4 lead time n = 7 day(s)
x 10^-4 lead time n = 9 day(s)
probability densities [-]
discharge in m³/s
Predictive pdf, Φn
Ensemble posteriori pdf, φn, j
Priori pdf, gn
Ensemble forecasts, sn, j
Observation at t0
Observation at t0-1
Observation at tn

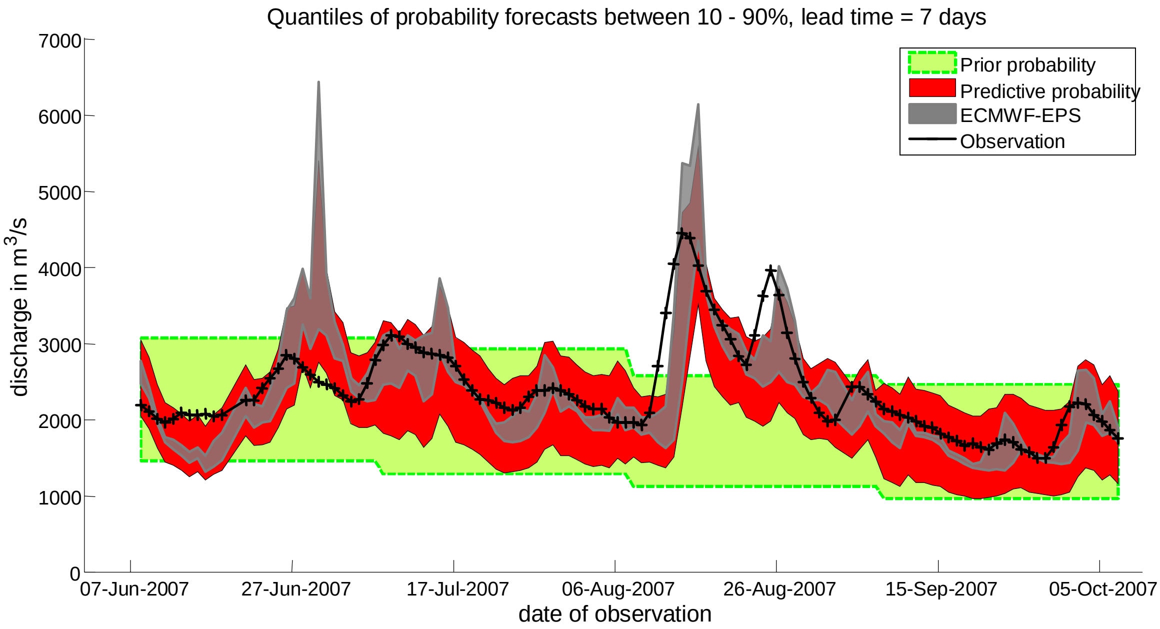
Results: lead-time 3 days





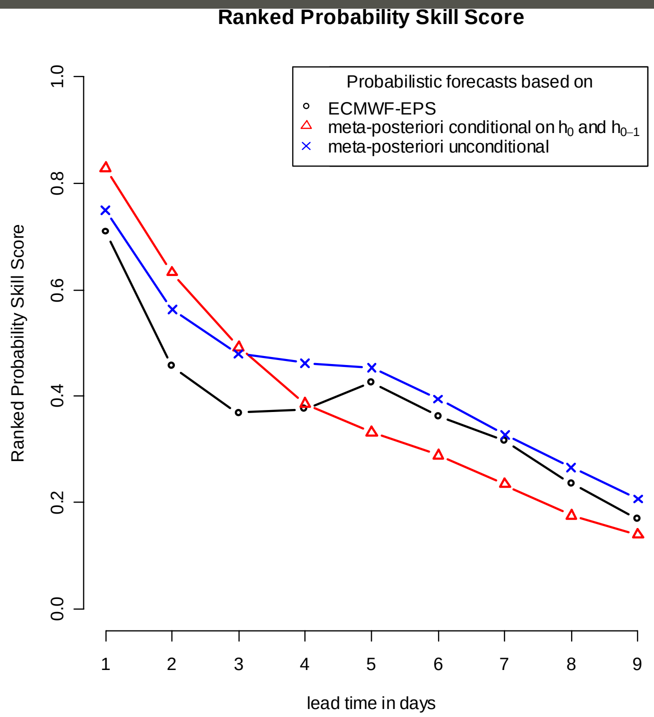
17 June 2009

Results: Lead time > 3 days (7 days)



17 June 2009

Comparison with ECMWF-EPS and different a-priori assumptions



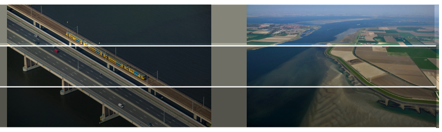
Verification period:

01.06.2007 –

01.10.2007

17 June 2009

Deltares



Thank you!

17 June 2009