Towards a probabilistic hydrological forecasting and data assimilation system

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Outline

- Hydrological forecasting
- Data assimilation framework
- Data assimilation experiments
- Concluding remarks

Hydrological Forecasting

Hydrological forecasting to support water management at different time scales

Short – medium range

< 10-15 days

- Flood forecasting
- Early warning
- Emergency management
- Flood control
- …

Monthly – seasonal range

1-6 months

- Reservoir operation
- Water allocation
- Drought management
- …

Long-term

> 1 year

- Infrastructure development
- Climate change adaptation
- Water and environmental planning
- …

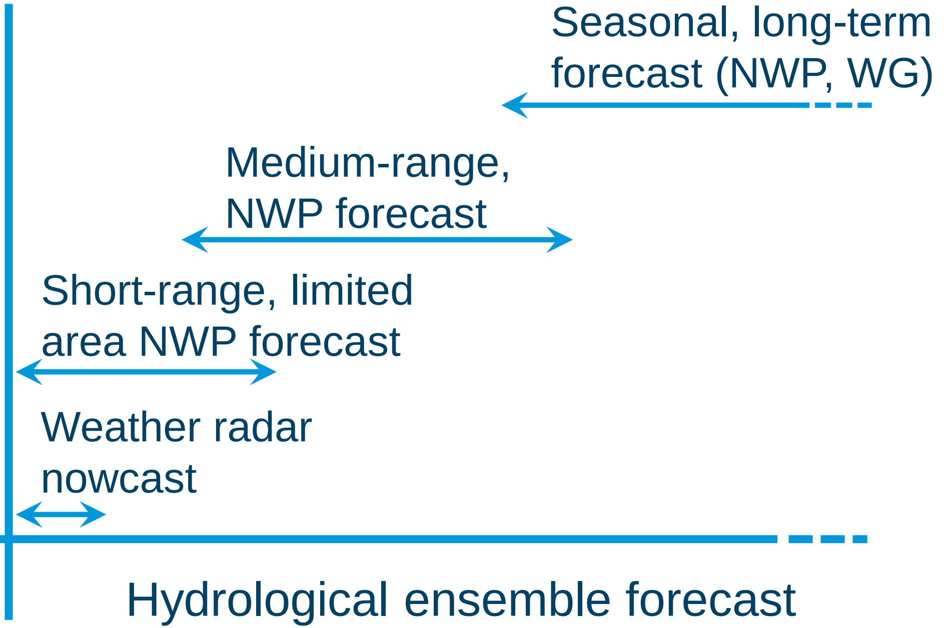
Hydrological forecasting and data assimilation

On-line measurements

In-situ:
- River water levels / discharges
- Groundwater levels
- Soil moisture profiles

Remote sensing:
- Land surface temperature
- Soil moisture
- Snow water equivalent
- River/lake water levels

Ensemble weather forecasting



Data assimilation

Hydrological ensemble forecast

Time of forecast

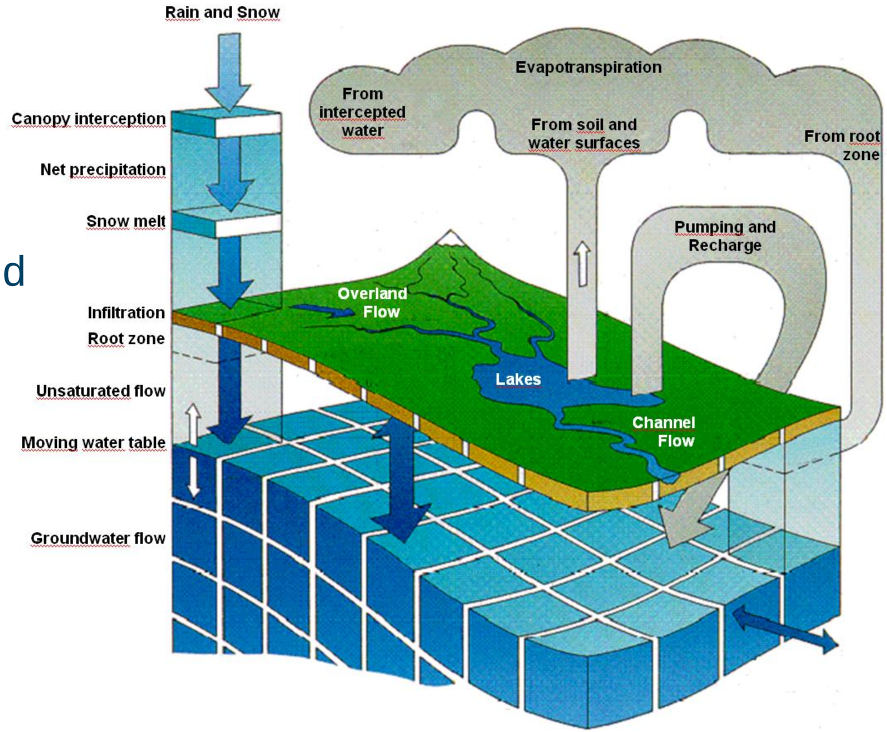
Integrated hydrological modelling – MIKE SHE

Precipitation and snowmelt

Vegetation-based evapotranspiration and infiltration

Unsaturated groundwater flow

Saturated groundwater flow



Channel flow in rivers and lakes

(MIKE 11)

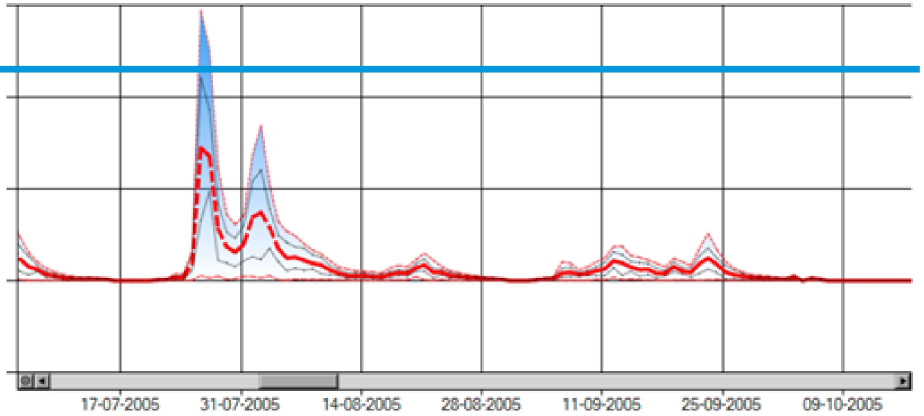
Overland surface flow and flooding

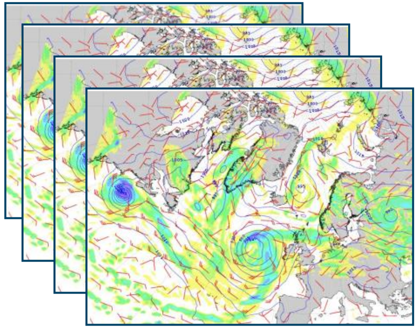
Water demands

Integrated water quality

Ensemble forecasting

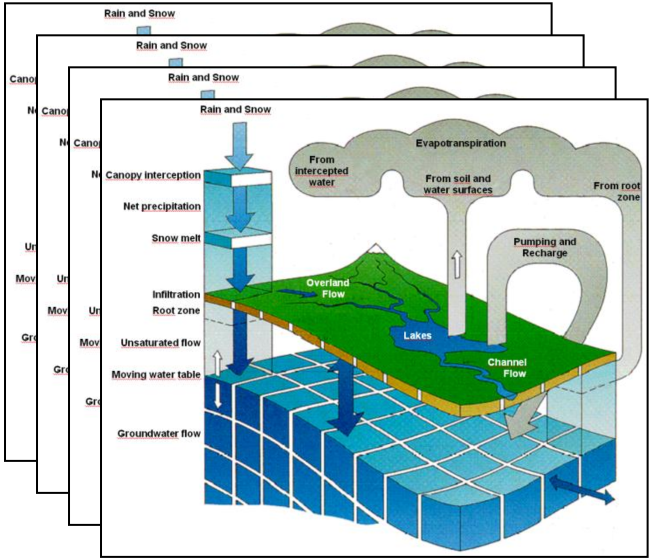
Alarm
WL





Ensemble
Weather
Forecast

Ensemble
pre-processing

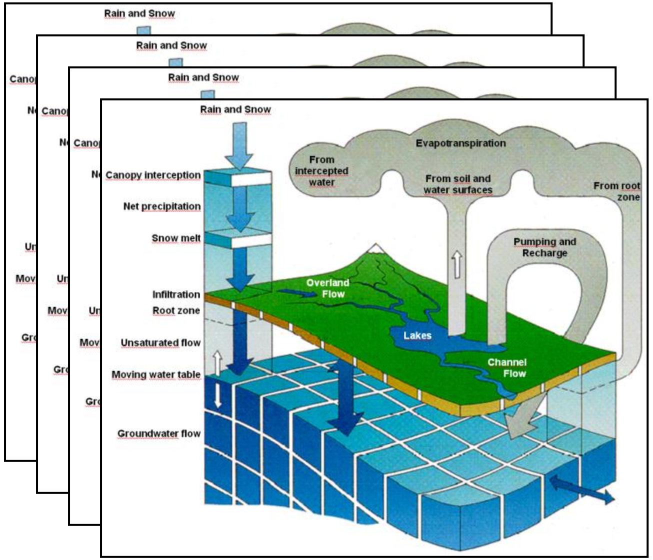


Ensemble
post-processing

Ensemble
Hydrological
Forecast

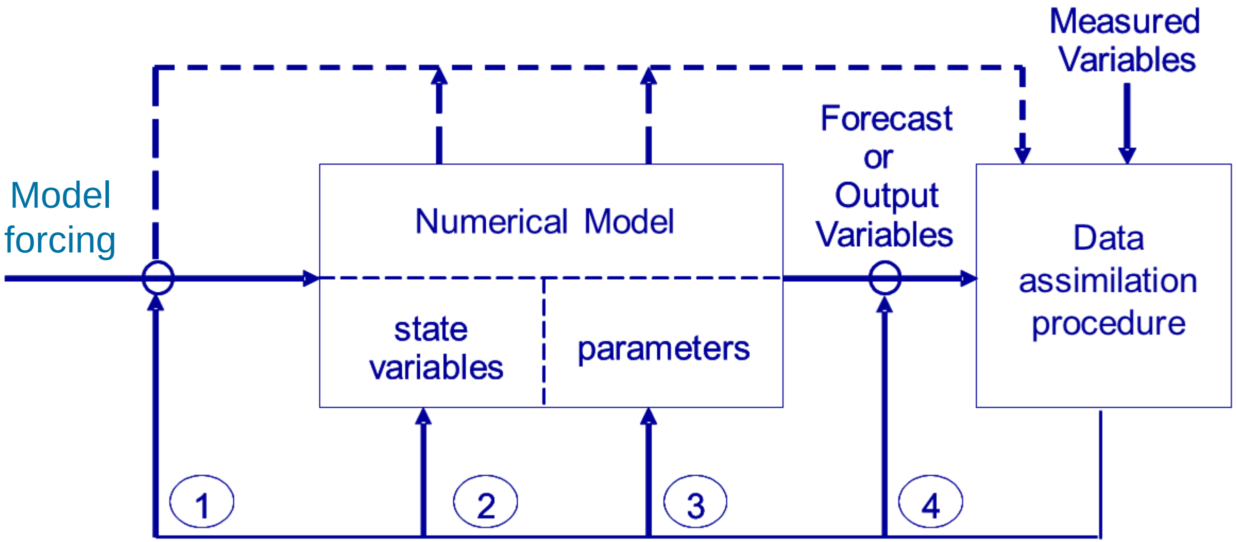
Ensemble hydrological forecasting

- Multiple model simulations with an ensemble of weather forecasts
- Ensemble of multiple models, e.g.
  - ➢ Different model structures
  - ➢ Different model parameterizations
  - ➢ Different model schematisations (e.g. embankment breaches)



Data Assimilation Framework

Data assimilation framework

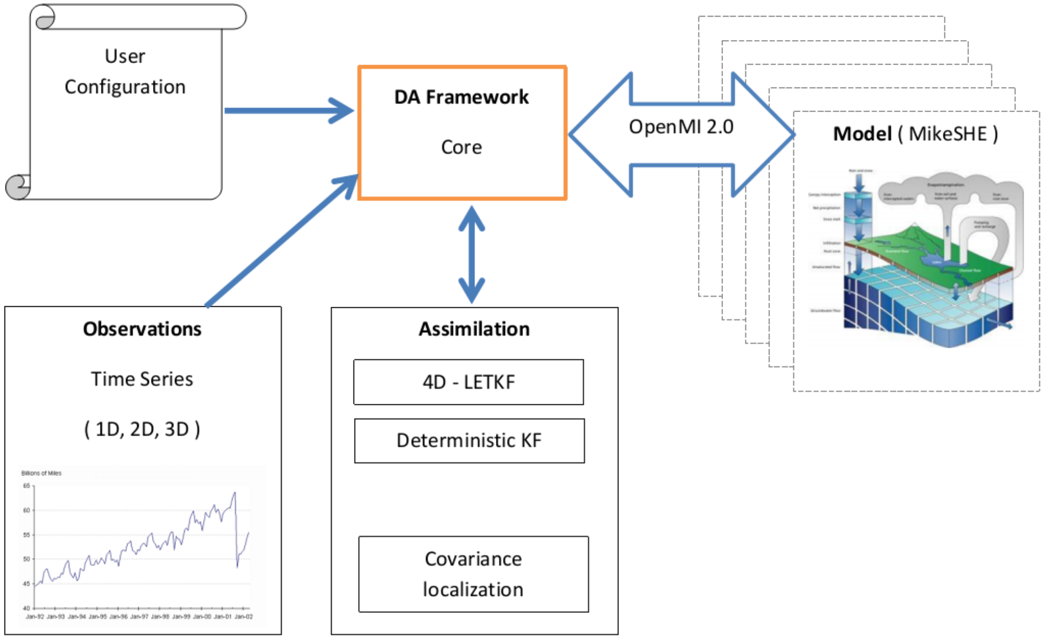


1. Correction of model forcing
2. State updating
3. Parameter estimation
4. Error forecasting

Data assimilation framework

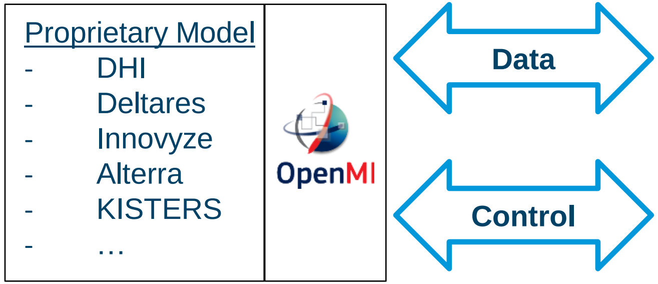
Basic features

- Generic run-time interface to models
- Assimilation of multivariate observations from in-situ and remote sensing
- Library of assimilation methods
- Feasible for real-time application



OpenMI

http://www.openmi.org/



Open “Model Interface” Standard

- Exchange data with a model during run time
  - ➢ get / set variable (state)
  - ➢ spatial information (location)
- Control
  - ➢ create instance
  - ➢ time step propagation

DHI

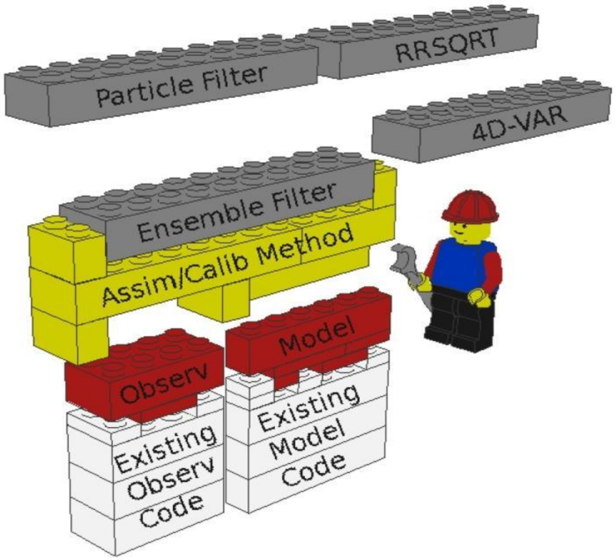
OpenDA

http://www.openda.org

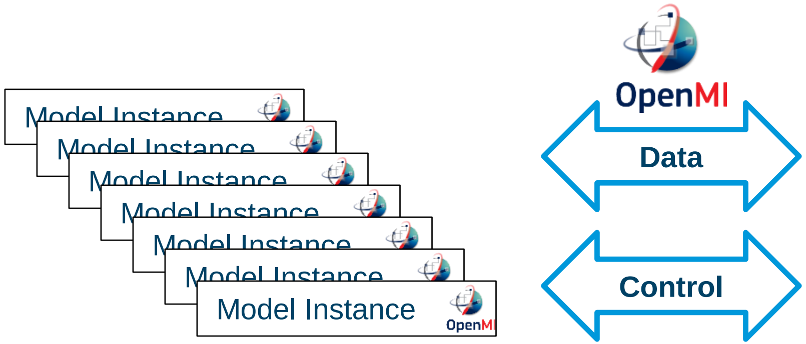
Free open-source Data Assimilation library

Methods available

- Ensemble KF (EnKF)
- Ensemble Square Root KF (EnSR)
- Steady State KF
- Particle Filter
- 3DVar
- … and more in development.



Open DA-MI Framework – tying the two together



OpenDA

- Creates ensemble of model instances
- Runs ensemble based filter
- Perturb models (noise model)
- Results (Matlab, Octave)

Observation

- time, data, confidence

<u>Note</u>

- IKVM automatic translation of OpenDA to C#
- OpenMI 2.0
- Will be freely available (with DHI example)
- Very little is model specific
    - observation operator
    - model factory

Statistical regularisation

- Localisation (distance regularisation)
  - Update state only in local region around measurement

- Covariance or Kalman gain smoothing
  - Temporal smoothing of covariance or Kalman gain

$$K_k^{smooth} = (1-\alpha)K_{k-1}^{smooth} + \alpha K_k \quad , 0 < \alpha < 1$$

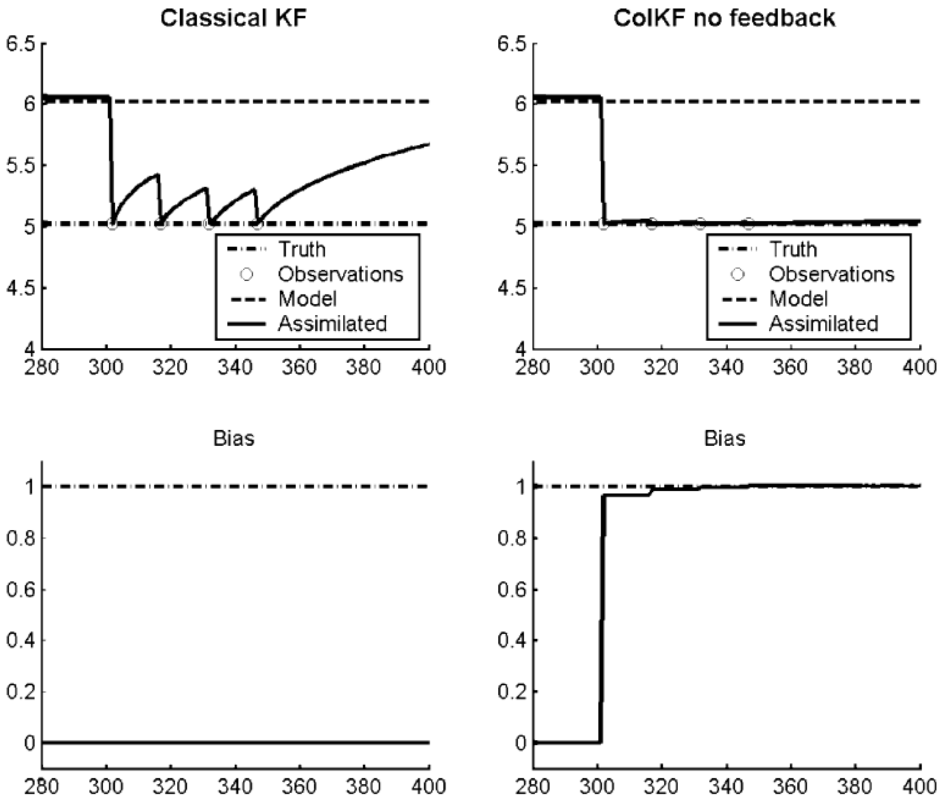
α = 0: Steady-state Kalman filter

α = 1: Normal Kalman filter

Sørensen et al. (2004)

Bias aware Kalman filter

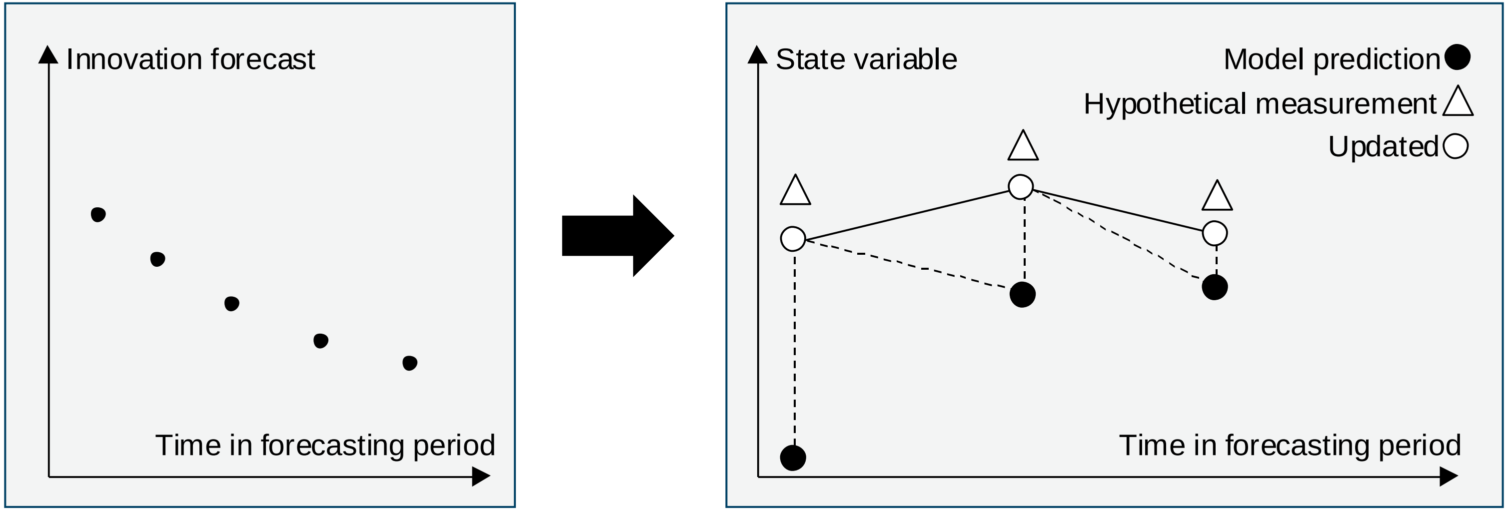
- Account for bias in measurements (or in model)
- Include bias using augmented state formulation
- Separate bias Kalman filter (Dual Kalman filter)



Drecourt et al. (2006)

Hybrid data assimilation and error forecasting

- Error forecast model applied to forecast innovation in measurement points -> virtual measurement
- Filtering using virtual measurements

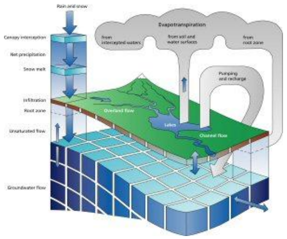


Madsen and Skotner (2005)

DA Experiment

1. State updating in integrated hydrological modelling

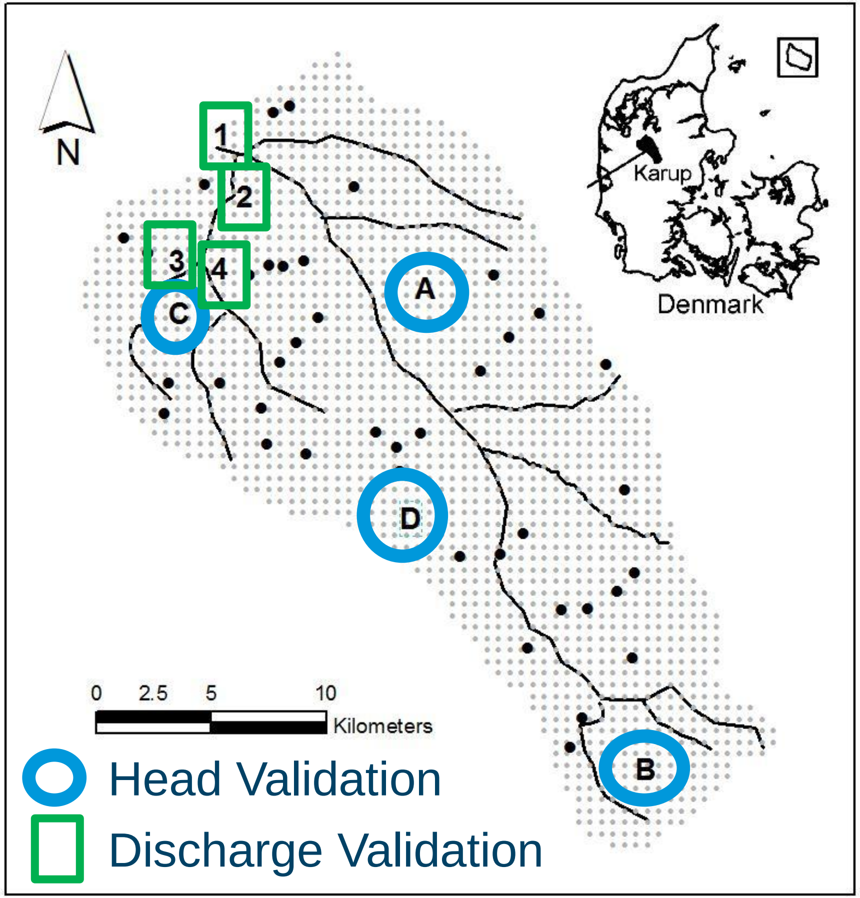
Karup Catchment



MIKESHE
- unsaturated
- saturated
- overland flow

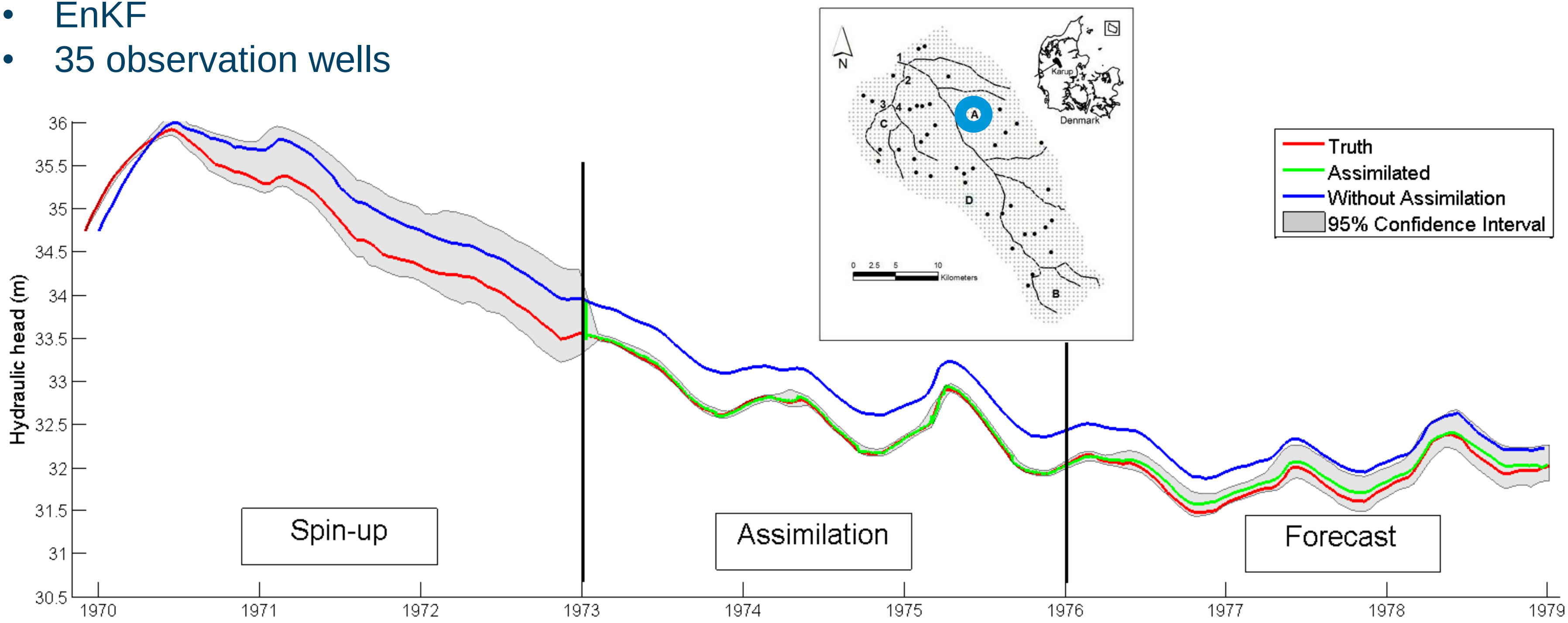
MIKE11
- river

<u>Setup</u>
- Assimilate groundwater levels
  → 35 observation wells, 2 obs. / month
- Model uncertainty
  → forcing (precipitation, reference ET)
  → parameters
- 9 years (3 spin-up, 3 assimilation, 3 forecast)
- Validation: groundwater level and discharge



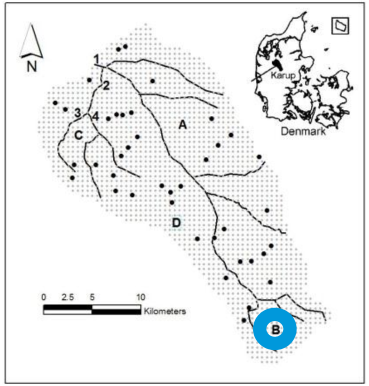
Results: groundwater level at validation point 'A'

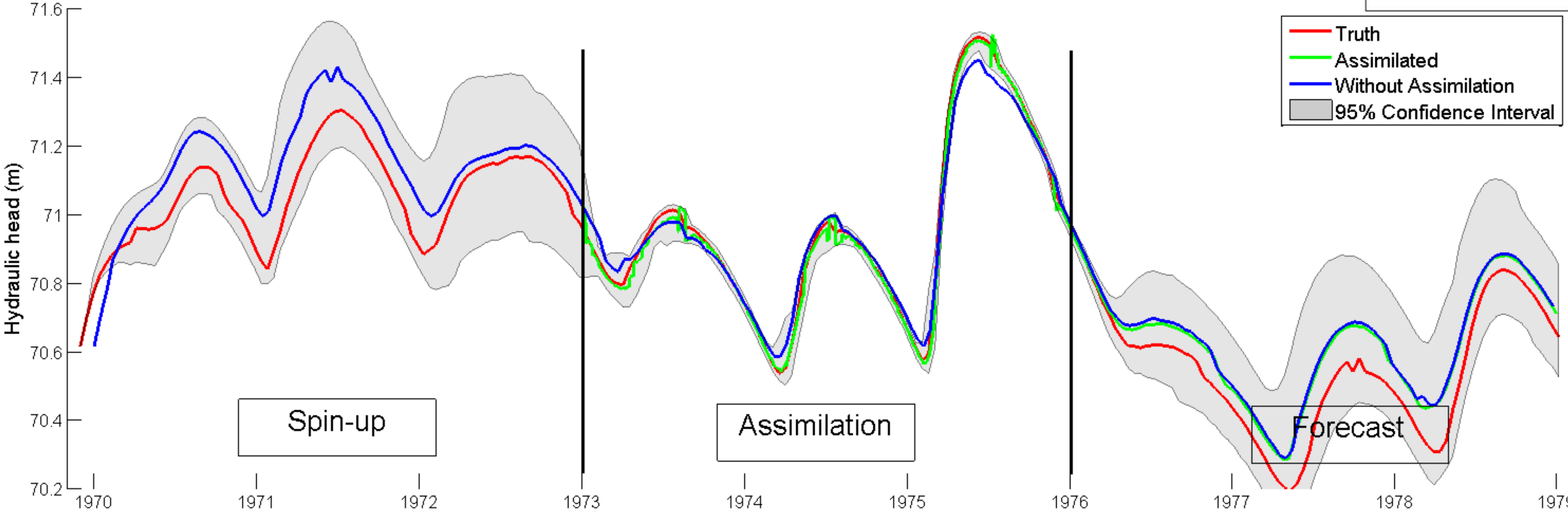
- EnKF
- 35 observation wells



Results: groundwater level at validation point ‘B’

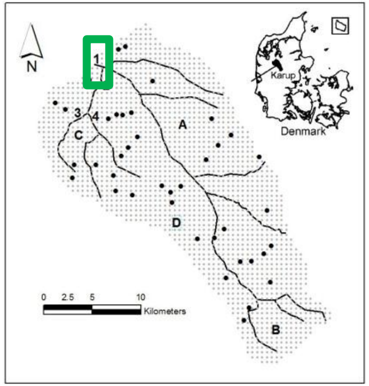
- EnKF
- 35 observation wells

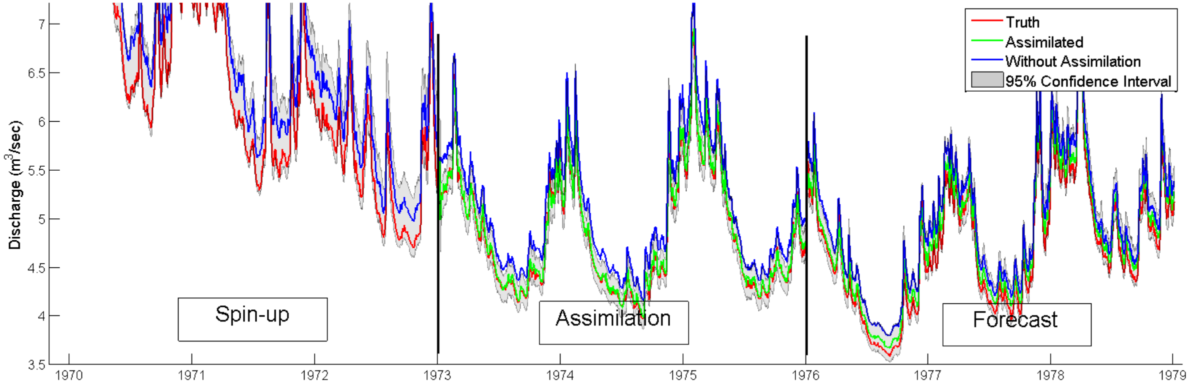


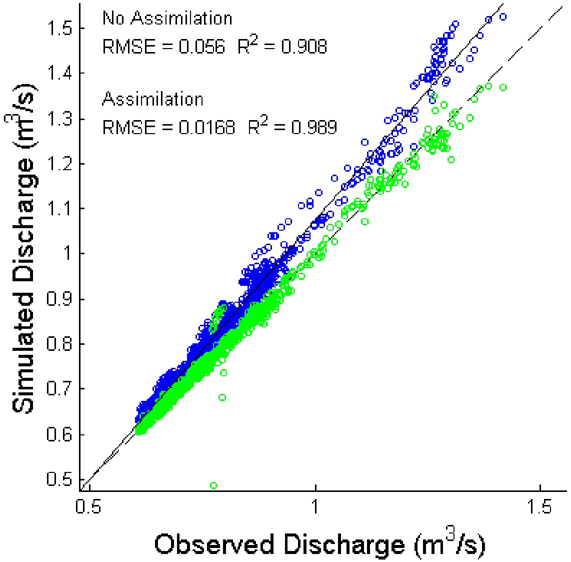


Results: discharge at validation station '1'

- EnKF
- 35 observation wells (Not assimilating discharge)

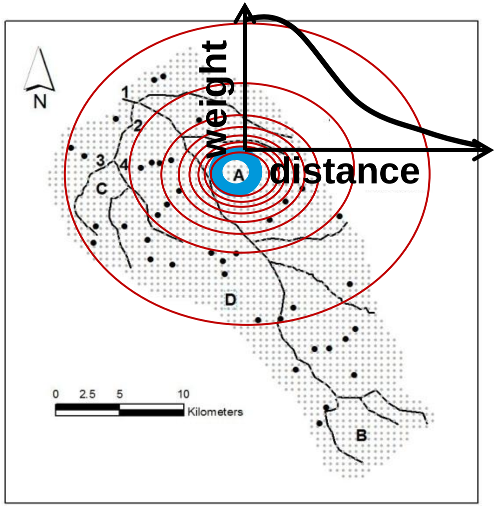


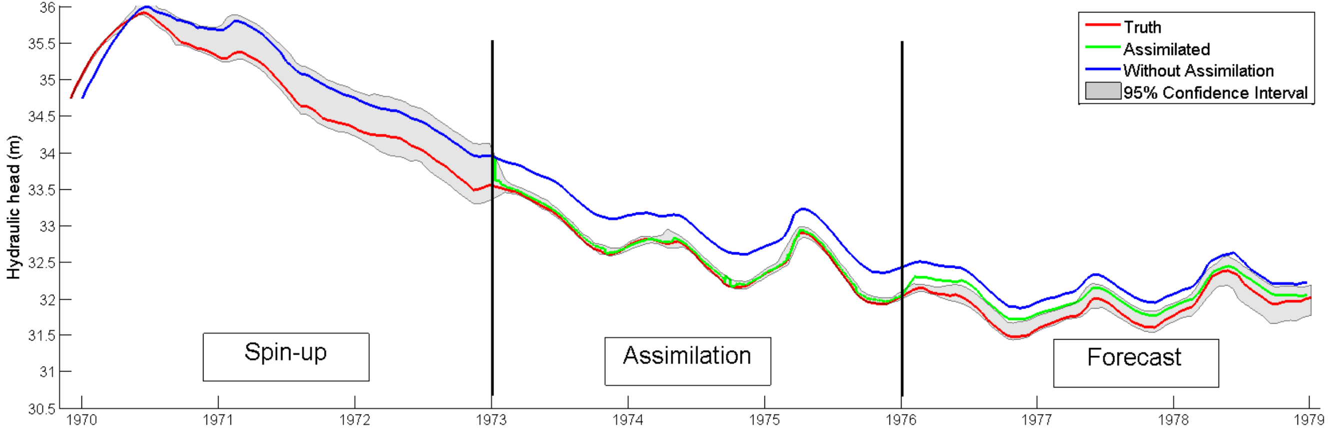




Results with localization groundwater level at validation point 'A'

- Distance-dependent scheme
  →Gaussian scale (radius of 5000 m)
- Avoids spurious correlations
- Smaller ensemble size (**50**)



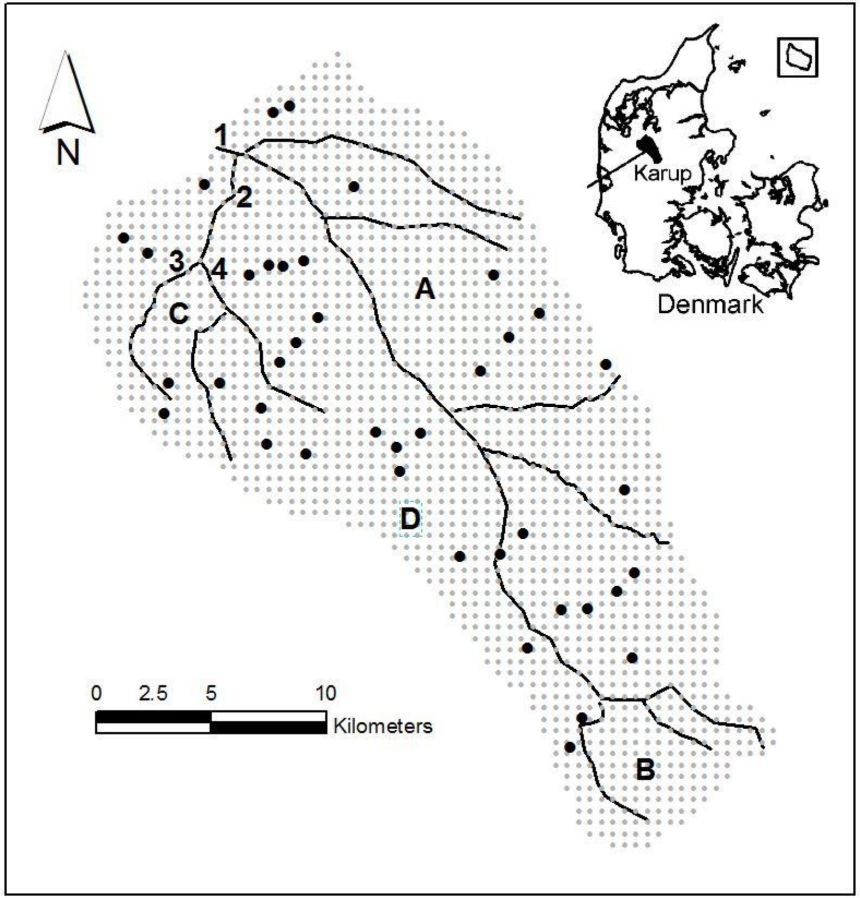


DA Experiment

2. Joint state updating and parameter estimation in integrated hydrological modelling

Setup

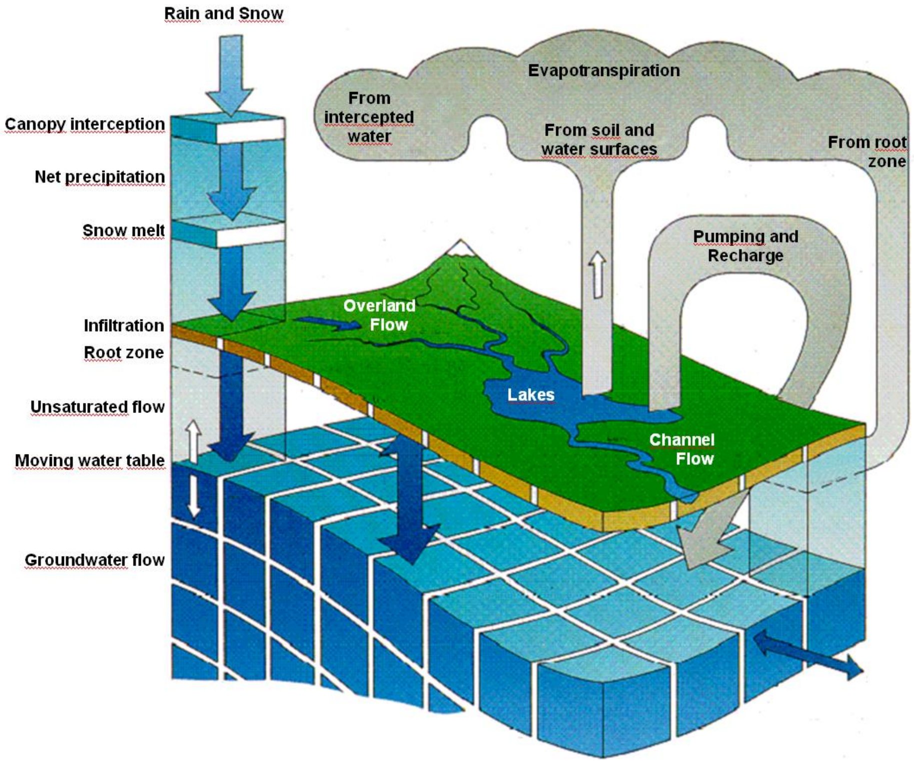
- Karup catchment
- Assimilation data
  - ➢35 groundwater head observations (weekly)
  - ➢4 stream discharge observations (daily)
- Perturbed Asynchronous EnKF
  - ➢Update frequency = 1 week
- Model uncertainty
  - ➢Precipitation and potential ET
  - ➢Model parameters



Jørn Rasmussen, PhD student, University of Copenhagen

Setup

- Updated state variables:
  - ➢ Hydraulic head
  - ➢ Stream discharge
  - ➢ Stream water level
- Estimated parameters
  - ➢ Hydraulic conductivity
  - ➢ Stream leakage coefficient
- Experiments:
  - ➢ Groundwater level observations only
  - ➢ Both groundwater level and discharge observations



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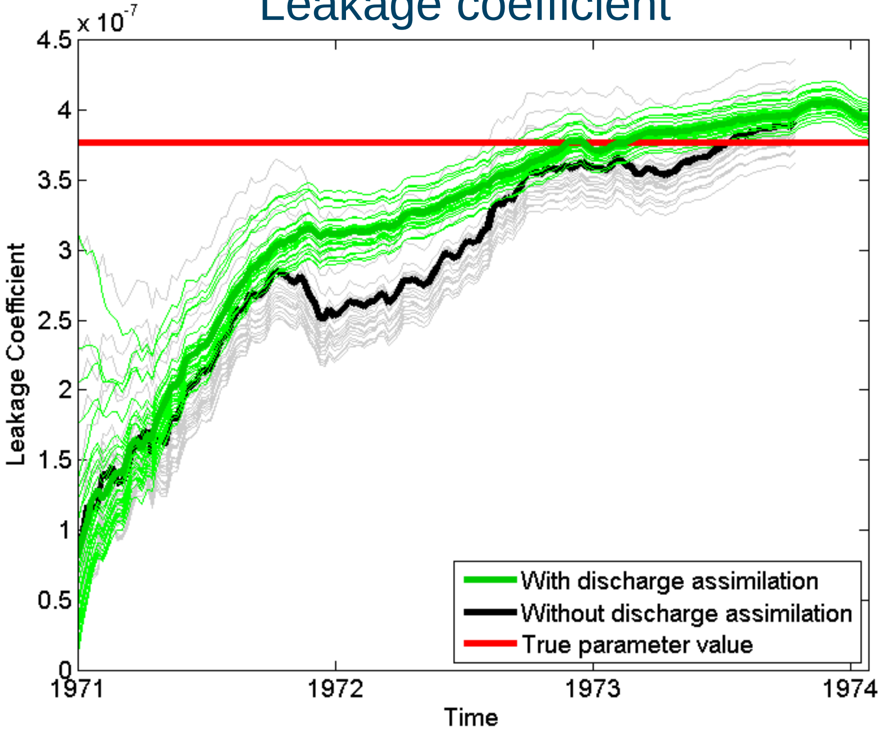
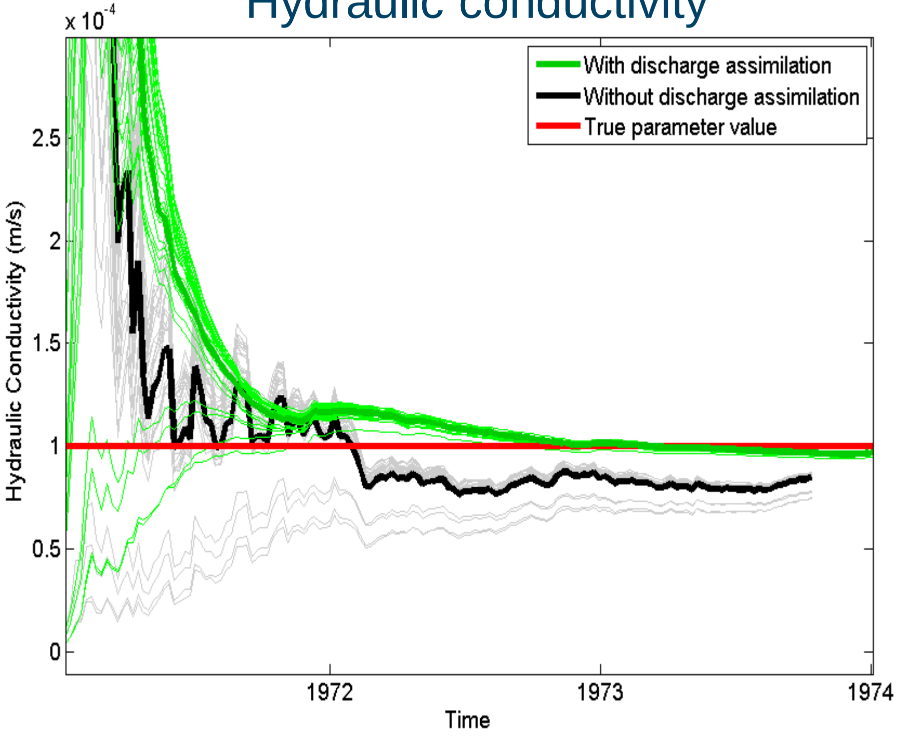
Parameter convergence

Leakage coefficient



Hydraulic conductivity



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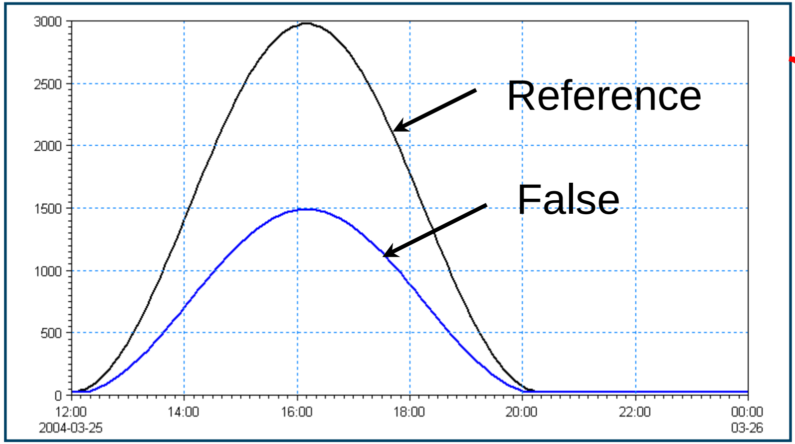
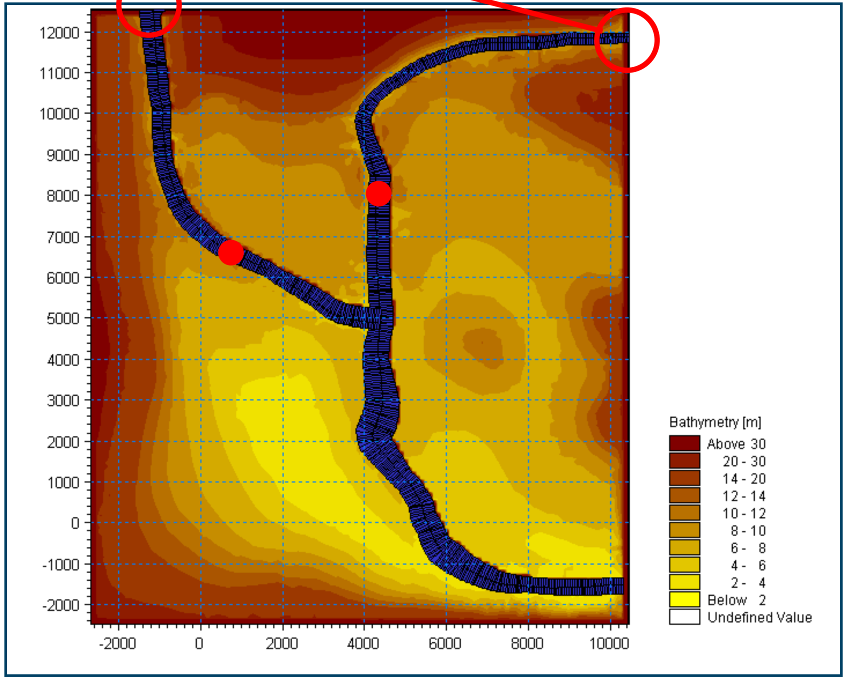
DA Experiment

3. Flood inundation modelling

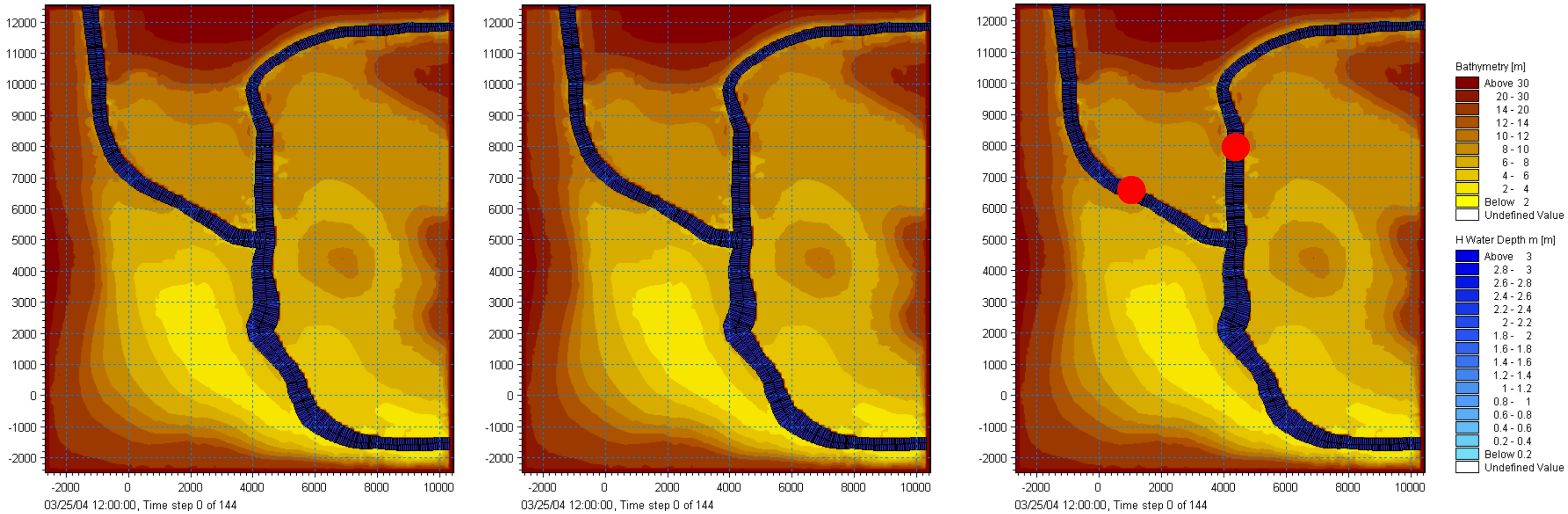




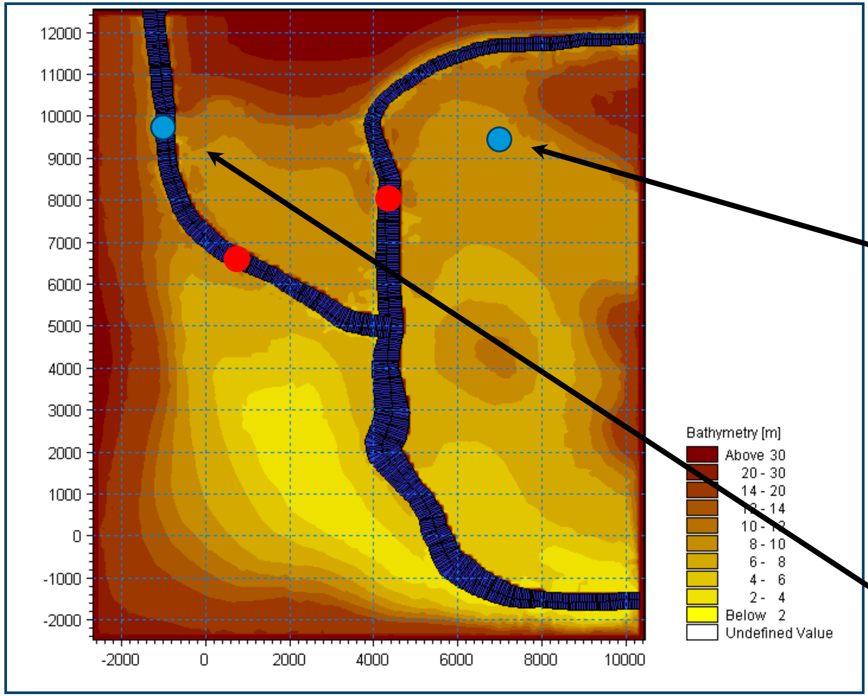
Twin test experiment

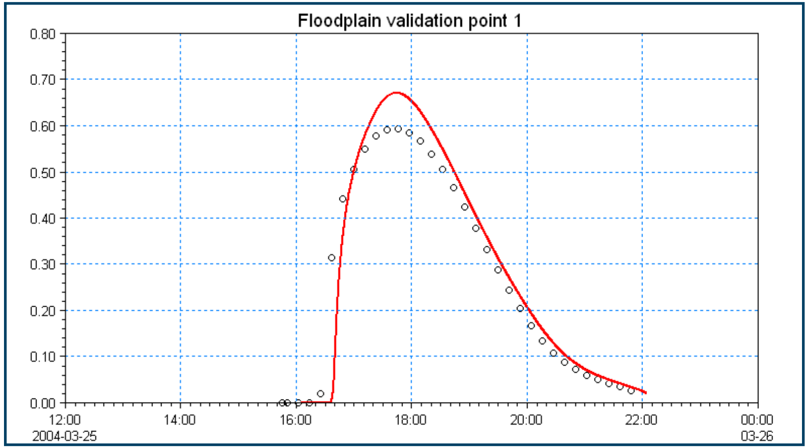
- False run: Model forced with erroneous boundary conditions
- Update of false model using water level measurements at two locations (from reference run)

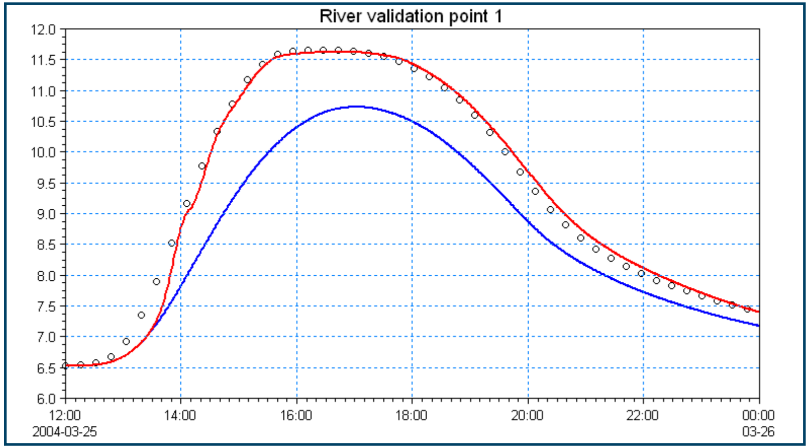
Reference | False | Update



● Assimilated water levels







○ ○ ○ Reference

False

Update

Concluding Remarks

Concluding remarks

- Hydrological forecasting supports water management at different time scales
- Probabilistic forecasting provides information about confidence of model predictions which is important for operational risk assessment and decision making
- Data assimilation in integrated hydrological modelling utilises multivariate measurements from in-situ and remote sensing
- Generic data assimilation framework based on open modelling standards (OpenMI) and supports open-source data assimilation library (OpenDA)
- General Kalman filter framework allows joint updating and estimation of model state, forcing, parameters and bias

References

- Drécourt, J.P., Madsen, H., Rosbjerg, D., 2006, Bias aware Kalman filters: Comparison and improvements, *Advances in Water Resources*, 29, 707-718.
- Madsen, H., and Skotner, C., 2005, Adaptive state updating in real-time river flow forecasting - A combined filtering and error forecasting procedure, *Journal of Hydrology*, 308, 302-312.
- Sørensen, J.V.T., Madsen H. and Madsen H., 2004, Efficient sequential techniques for the assimilation of tide gauge data in three dimensional modeling of the North Sea and Baltic Sea system, *Journal of Geophysical Research*, 109, 10.1029/2003JC002144.

Thank you for your attention

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This work was carried out with the support of the Danish Council for Strategic Research as part of the project "HydroCast – Hydrological Forecasting and Data Assimilation", Contract No. 11-116880

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