Multi-variate hydrological data assimilation – opportunities and challenges

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Outline

• Introduction to multi-variate hydrological data assimilation
  – Opportunities and challenges
• Data assimilation framework
• Applications
  – Assimilation of SMOS soil moisture
  – Multivariate data assimilation (incl. cosmic ray soil moisture)
  – Assimilation of CryoSat-2 altimetry
• Concluding remarks
Introduction
Hydrological data assimilation

• Assimilation of single data sources in single compartment models, e.g.
  − Assimilation of river water level/discharge in river models
  − Assimilation of groundwater levels in groundwater models
  − Assimilation of soil moisture data in land-surface models

• Multivariate data assimilation
  − Assimilation of multiple data types and sources in integrated hydrological modelling
Multivariate data assimilation in integrated hydrological modelling

Precipitation and snowmelt

Vegetation-based evapotranspiration and infiltration

Unsaturated groundwater flow

Saturated groundwater flow

Channel flow in rivers and lakes

Overland surface flow and flooding

Water demands

Integrated water quality

MIKE SHE
Opportunities

SMOS soil moisture

UAV

Sentinel-1 soil moisture

In-situ sensors

Sentinel-3 altimetry
Challenges

- Assimilation and combination of different data sources that represent
  - Different temporal dynamics
  - Different spatial resolution (supporting scale)
  - Different measurement uncertainties and representation errors
Challenges (SMOS soil moisture)

Coarse resolution (~44 km)

Bias (0.02 – 0.23 $m^3/m^3$)
Data assimilation framework
Generic data assimilation framework

- Generic run-time interface to models
- Assimilation of multiple observation sources and types
- Library of assimilation methods (ensemble-based KF)
- Joint state-parameter estimation
- Bias-aware filtering
- Localisation / Statistical regularisation
- Asynchronous updating

User Configuration
- PFS File (XML like)

Filters
- Ensemble KF (EnKF)
- Ensemble Transform KF (ETKF)
- Bias Corrections
- Localization

Observations
- Time series (point, 2D, 3D)

Error Models
- Initial conditions
- Input data
  - (Gaussian, AR1, ...)

Model Interface
- Model Factory
- Create Ensemble of model instances
- Time Stepping
- Mapping Observation to Model Space
- Localization scheme
- Getting / Setting model state
- Writing results
OpenMI – OpenDA data assimilation framework

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

Observations
- Time, data, uncertainty

Ridler et al. (2014)
Localisation (statistical regularisation)

- Localisation is used to reduce the model domain influenced by observations
- Normally a distance-based localisation approach is applied
- Additional regularisation between different types of state variables

In-situ soil moisture DA

Soil moisture measurements

UZ

Vegetation

Zhang et al. (2016)
Variable regularisation

Zhang et al. (2016)
Adaptive localisation

The localisation factor is calculated by two adaptive components

• Cross-validation of observation-state correlations

\[
Cor(\delta X, \delta y) \quad c_1 \\
\text{m/2-member correl.} \\
Cor(\delta X, \delta y) \quad c_2
\]

\[
w_a = \left(1 - \frac{|c_1 - c_2|}{2}\right)^{s_a}
\]

• Weighting observation-state correlations

High sample correlation = more reliable = more weight

\[
w_b = |C|^s_b
\]

m-member correl.

Rasmussen et al. (2015)
Covariance or Kalman gain temporal smoothing

• Temporal smoothing of covariance or Kalman gain

\[ K_{k}^{\text{smooth}} = (1 - \alpha)K_{k-1}^{\text{smooth}} + \alpha K_{k} \] , \( 0 < \alpha < 1 \)

\( \alpha = 0 \): Steady-state Kalman filter
\( \alpha = 1 \): Normal Kalman filter

Sørensen et al. (2004)
Applications
Assimilation of SMOS soil moisture
Assimilation of SMOS soil moisture

Ahlergaarde catchment, Denmark

Integrated MIKE SHE – SVAT model

Ridler et al. (2014)
Challenges

Coarse resolution (~44 km)

Bias (0.02 – 0.23 m³/m³)
Data assimilation approach

- Downscaling based on land cover classification
- Bias-aware Kalman Filter (ETKF) to update bias estimates for each land cover class
- Vertical localisation for Kalman filter update of soil moisture states
Results

(a) 5 cm

(b) 25 cm

(c) 50 cm

Soil moisture (m³/m³)

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## Results

<table>
<thead>
<tr>
<th>Land cover</th>
<th>Open-loop</th>
<th>Assimilation (SMOS)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>5 cm</td>
<td>25 cm</td>
</tr>
<tr>
<td></td>
<td>RMSE</td>
<td>Bias</td>
</tr>
<tr>
<td>Heath</td>
<td>0.060</td>
<td>-0.056</td>
</tr>
<tr>
<td>Forest</td>
<td>0.038</td>
<td>0.010</td>
</tr>
<tr>
<td>Winter cereal</td>
<td>0.040</td>
<td>0.034</td>
</tr>
<tr>
<td>Grass</td>
<td>0.049</td>
<td>-0.041</td>
</tr>
<tr>
<td>Potato</td>
<td>0.067</td>
<td>0.051</td>
</tr>
<tr>
<td>Spring cereal</td>
<td>0.060</td>
<td>0.033</td>
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<tr>
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<td>0.041</td>
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<tr>
<td>Grass</td>
<td>0.044</td>
<td>-0.037</td>
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<tr>
<td>Potato</td>
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<td>Spring cereal</td>
<td>0.060</td>
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</tbody>
</table>

- **Improved statistics**
- **Worsened statistics**
Multivariate data assimilation
Hydraulic Head
Cosmic Ray
Soil Moisture (3 layers)
River Discharge

Ahlergaarde, West Denmark
1055 km²
Assimilation Setup

- Ensemble size: 50  ➔  Size of State Vector: 710,000
- Filter: ETKF
- Simulation period: 1 year (excluding winter) with 4 year spin-up

Model Uncertainty
- Parameters
  - Hydraulic conductivities (Saturated zone)
  - van Genuchten parameters (Unsaturated zone)
- Forcing
  - Precipitation
Adaptive localisation

- Measurement: Cosmic Ray in agricultural field
- State: Soil moisture in upper soil layer
- Related to:
  - Soil type
  - Vegetation type
  - Precipitation

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Results: Groundwater elevations
### Results: Soil moisture

<table>
<thead>
<tr>
<th>Depth</th>
<th>Without Data Assimilation</th>
<th>Data Assimilation</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>RMSE</td>
<td>R²</td>
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<tr>
<td>2.5 cm</td>
<td>0.055</td>
<td>0.58</td>
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<tr>
<td>25 cm</td>
<td>0.024</td>
<td>0.95</td>
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<tr>
<td>50 cm</td>
<td>0.033</td>
<td>0.61</td>
</tr>
</tbody>
</table>
Results: Discharge

Discharge at catchment outlet

RMSE: 6.6 → 4.6 (m³/sec)
Assimilation of CryoSat-2 altimetry
Assimilation of CryoSat-2 altimetry

CryoSat-2 ground tracks for one 369-day cycle over the Assam Valley, India

Envisat 35-day repeat tracks over the Assam Valley, India, with virtual stations along Brahmaputra

Schneider et al. (2016)
Brahmaputra river basin
CryoSat-2 data processing – river mask filtering
Assimilation of synthetic CryoSat-2 data

Discharge at Bahadurabad

<table>
<thead>
<tr>
<th></th>
<th>CRPS [m3/s]</th>
<th>Sharpness [m3/s]</th>
</tr>
</thead>
<tbody>
<tr>
<td>Open loop</td>
<td>5475</td>
<td>16369</td>
</tr>
<tr>
<td>DA with ETKF</td>
<td>3444</td>
<td>10658</td>
</tr>
</tbody>
</table>
Concluding remarks
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• Increasing amount of hydrological data from different sensors offers new opportunities for data assimilation in integrated hydrological modelling
• Optimal combination and assimilation of different data sources and data types is challenging
• Use of localisation (and other statistical regularisation techniques) required to obtain physically consistent updates
References


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• 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

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This work was carried out with the support of
• Innovation Fund Denmark as part of the project “HydroCast – Hydrological Forecasting and Data Assimilation”
• NordForsk as part of the Nordic Centre of Excellence ”EmblA - Ensemble-based data assimilation for environmental monitoring and prediction”