Impact of data assimilation on the usage of multiple models

Carine Poncelet
François Anctil
Antoine Thiboult
Grégory Seiller
Standard H-EPS
On what basis do we select multiple models?
Is it best to perform model selection after DA?
Working hypotheses

- Model selection impacts H-EPS performance
- Data assimilation (DA) improves performance
  - But not similarly from one model to the other

On what basis do we select multiple models?
Is it best to perform model selection after DA?
Empirical Multistructure Framework

Overproduce and select paradigm → Select candidates out of 108 852 possibilities

Main inspirations for EMF

Flexible modelling
- Modular Modeling System: Leavesley et al. (1996)
- FLEX and SUPERFLEX: Fenicia et al. (2008; 2011)
- Framework for Understanding Structural Errors: Clark et al. (2008)
- Structure for Unifying Multiple Modeling Alternatives: Clark et al. (2015)

Ensemble modelling
- Reduce the predictive error
- Quantify the predictive uncertainty
  - Accuracy, sharpness, and reliability
How EMF was put together?
Phase 1 – Parent model selection

12 dissimilar lumped hydrological models, out of more than 30 candidates (Perrin, 2000; Mathevet 2005; Seiller et al. 2012; 2015)

<table>
<thead>
<tr>
<th>Name</th>
<th>Free parameters</th>
<th>Storages</th>
<th>Derived from</th>
</tr>
</thead>
<tbody>
<tr>
<td>A</td>
<td>6</td>
<td>3</td>
<td>BUCKET (Thornthwaite and Mather, 1955)</td>
</tr>
<tr>
<td>B</td>
<td>6</td>
<td>3</td>
<td>CREC (Cormary and Guilbot, 1973)</td>
</tr>
<tr>
<td>C</td>
<td>6</td>
<td>3</td>
<td>GARDENIA (Thiery, 1982)</td>
</tr>
<tr>
<td>D</td>
<td>4</td>
<td>2</td>
<td>GR4J (Perrin et al., 2003)</td>
</tr>
<tr>
<td>E</td>
<td>7</td>
<td>4</td>
<td>MARTINE (Mazenc et al., 1984)</td>
</tr>
<tr>
<td>F</td>
<td>7</td>
<td>2</td>
<td>MOHYSE (Fortin and Turcotte, 2006)</td>
</tr>
<tr>
<td>G</td>
<td>6</td>
<td>4</td>
<td>MORDOR (Garçon, 1999)</td>
</tr>
<tr>
<td>H</td>
<td>9</td>
<td>5</td>
<td>SACRAMENTO (Burnash et al., 1973)</td>
</tr>
<tr>
<td>I</td>
<td>8</td>
<td>3</td>
<td>SIMHYD (Chiew et al., 2002)</td>
</tr>
<tr>
<td>J</td>
<td>7</td>
<td>4</td>
<td>TANK (Sugarawa, 1979)</td>
</tr>
<tr>
<td>K</td>
<td>8</td>
<td>3</td>
<td>WAGENINGEN (Warmerdam et al., 1997)</td>
</tr>
<tr>
<td>L</td>
<td>8</td>
<td>4</td>
<td>XINANJIAN (Zhao et al., 1980)</td>
</tr>
</tbody>
</table>
Phase 2 – Isolate their functional components

Soil moisture accounting → Routing

P, E → Soil moisture accounting

Loss → Soil moisture accounting

Routing → Q

Soil moisture accounting
Phase 2 – Isolate their functional components

- Surface processes \([S_f]\)
- Soil moisture accounting \([S_o]\)
- Groundwater \([G_w]\)
- Overland flow routing \([R_{of}]\)
- Interflow routing \([R_{if}]\)
- Baseflow routing \([R_{bf}]\)
- Total flow routing \([R_{tf}]\)
- Loss

\(P\) to \(E\):

\(Q\)
Phase 2 – Isolate their functional components

39 functional components are identified; some are shared by 2 or more models

<table>
<thead>
<tr>
<th>Name</th>
<th>Sf</th>
<th>So</th>
<th>Gw</th>
<th>Rof</th>
<th>Rif</th>
<th>Rbf</th>
<th>Rtf</th>
</tr>
</thead>
<tbody>
<tr>
<td>A</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>B</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>C</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>D</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>E</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>F</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>G</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>H</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>J</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>K</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>L</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>I</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

|   | 11+0 | 12  | 6+0 | 2+0 | 2+0 | 1+0 | 5   |

108 852 potential models
Phase 3 – Share parameters whenever possible

Many functional components resort to a similar parameter
- 10 use a maximum capacity storage (mm) for soil moisture accounting
- 8 use a Percolation residence time (days)
- 5 use a Interflow residence time (days)
- 5 use a Baseflow residence time (days)
- 4 use a Maximum capacity storage of Sf (mm) for surface processes
- And so on ...

Ultimately, the number of free parameter has been reduced from 82 to 38
Phase 4 – Calibrate the Empirical multistructure

Dynamically Dimensioned Search (DDS) algorithm
   - Tolson and Shoemaker (2007)

Minimise the error of the simple average of the 12 parent time series
   - Which cover all 38 parameters

One obtains 108 852 child models
   - Many of which are very bad
EnKF Experiment
Step 1 – EMF Calibration, Initial selection

EMF Calibration
- Matapédia River, Québec, Canada
- 2730 km², P = 1001 mm, ETP = 665 mm, Q = 483mm
- 3-h time step, from 2003/01 to 2009/12
- NSE

Initial selection
- Eliminate duplicates
- Retain best 1600 child models
Step 2 – Individual calibration, Data assimilation

Individual calibration of the 1600 models

Data assimilation
  - Applied to EMF-calibrated and individually-calibrated models
    - EnKF (50 members)
    - OpenLoop (50 members), which inputs are perturbed as for EnKF
Step 3 – Ensemble constitutive members selection

Reliability is attained when the ensemble spread ($\sigma$) is close to the $\text{RMSE}$

- Fortin et al. (2014); Abaza et al. (2015)

So, we are seeking a $\text{NRD}'$ value close to 0 %

$$\text{NRD}' = 100 \times \frac{\text{RMSE} - \sigma}{\text{RMSE}}$$

Selection procedure

- All child time series are ranked per individual $\text{NSE}$ values
- Starting from the best time series, the next best one is retained only if it improves $\text{NRD}'$ by more than 1%
  - Favors diversity
  - Limits the number of time series (models) to 100
Results
EMF- vs individually-calibrated MCRPS

OpenLoop

- Models perform better when individually-calibrated (96%)
EnKF impact on MCRPS

OpenLoop
- Models perform better when individually calibrated (96%)

EnKF
- Largely improves MCRPS but not systematically
- Does not compensate for suboptimal parameters
  - Larger chance of EnKF underperformance
OpenLoop model selection

Some lesser models are needed to attain the desired spread.

EnKF applied after OpenLoop selection

- Largely improves MCRPS
- Offers no control on spread
  - See poster tomorrow on multimodel DA
EnKF model selection

- Individual models are better
  - A lower spread is needed
- OpenLoop ordering offers no clue how to optimally select models
- Performs better than when EnKF is applied after the OpenLoop selection (in red)
Based on 1600 EMF- and individually-calibrated models, EnKF improves model performance in a non systematic way

Which complicates model selection for multimodel H-EPS
Impact of data assimilation on the usage of multiple models

Carine Poncelet
François Anctil
Antoine Thiboult
Grégory Seiller