# Impact of data assimilation on the usage of multiple models


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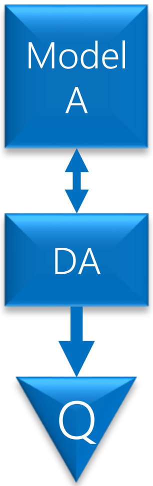
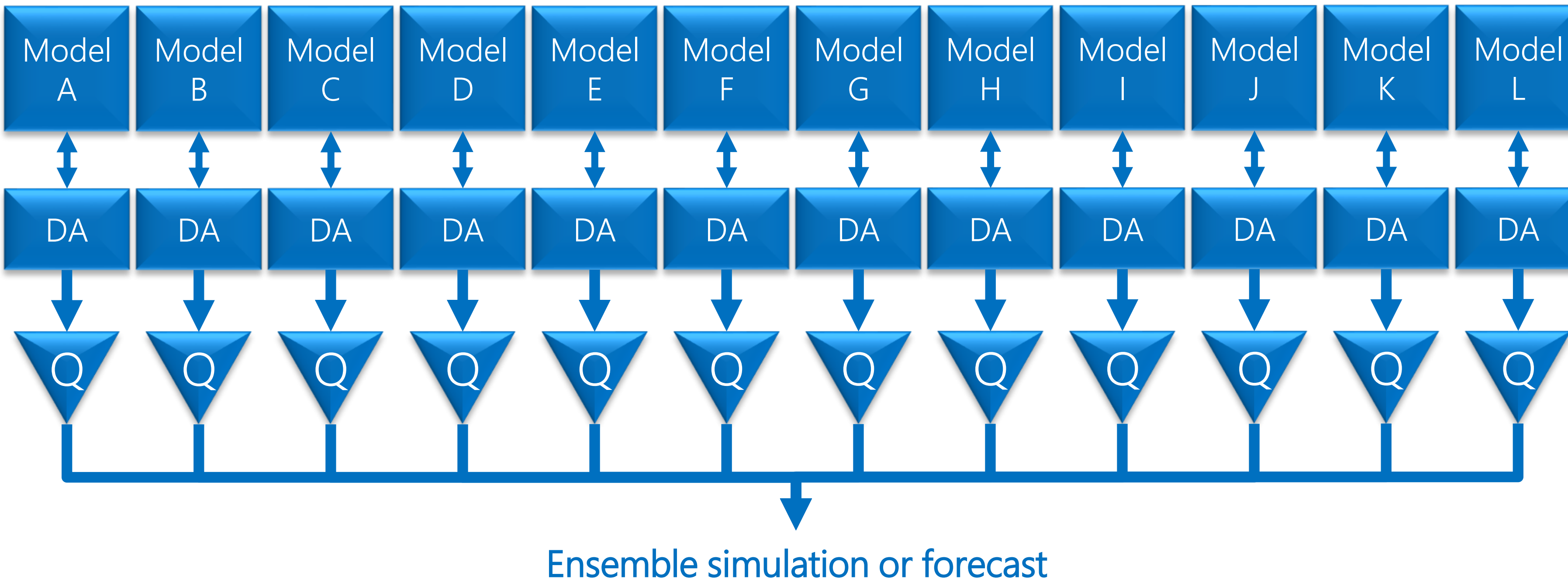
# Standard H-EPS



# Multimodel H-EPS




**On what basis do we select multiple models ?**

**Is it best to perform model selection after DA ?**

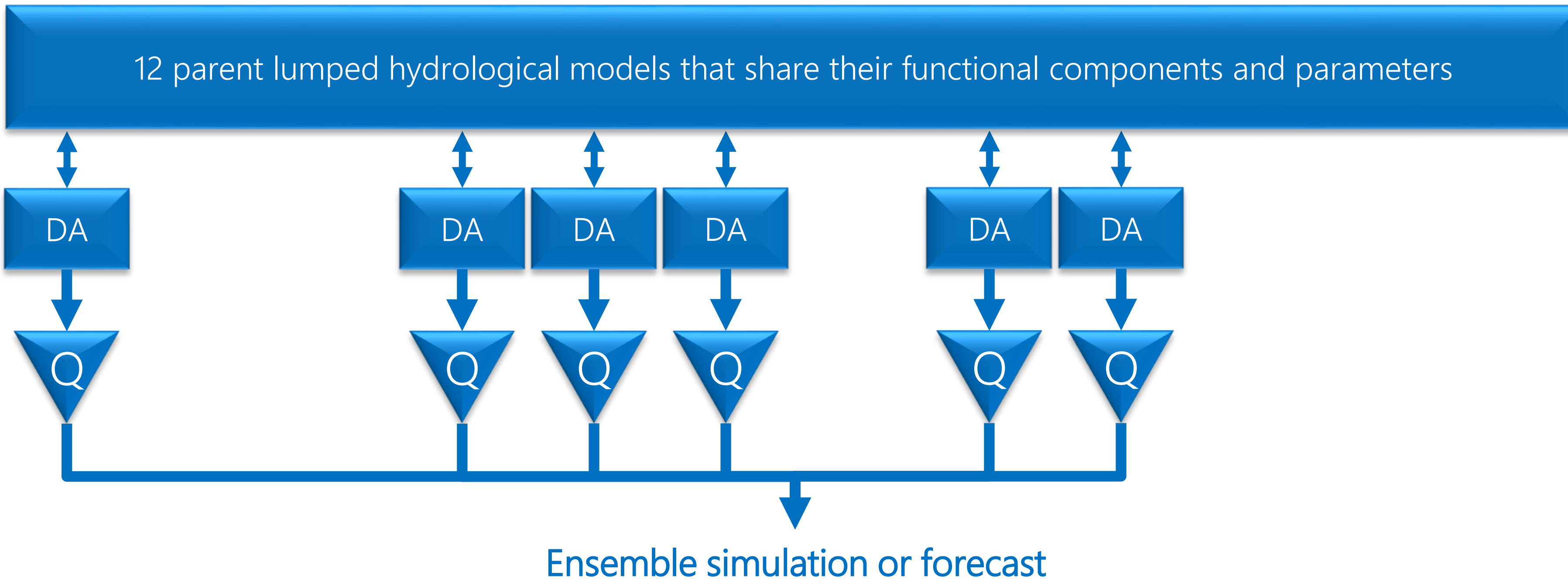
# Working hypotheses

- 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

**Seiller G**, Anctil F, Roy R. 2017. Design and experimentation of an empirical multistructure framework for accurate, sharp and reliable hydrological ensembles. Journal of Hydrology 552, 313-340.

# Main inspirations for EMF

## Flexible modelling

- Modular Modeling System: Leavesley et al. (1996)
- Rainfall-Runoff Modeling Toolkit: Wagener et al. (2002)
- FLEX and SUPERFLEX: Fenicia et al. (2008; 2011)
- Framework for Understanding Structral 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

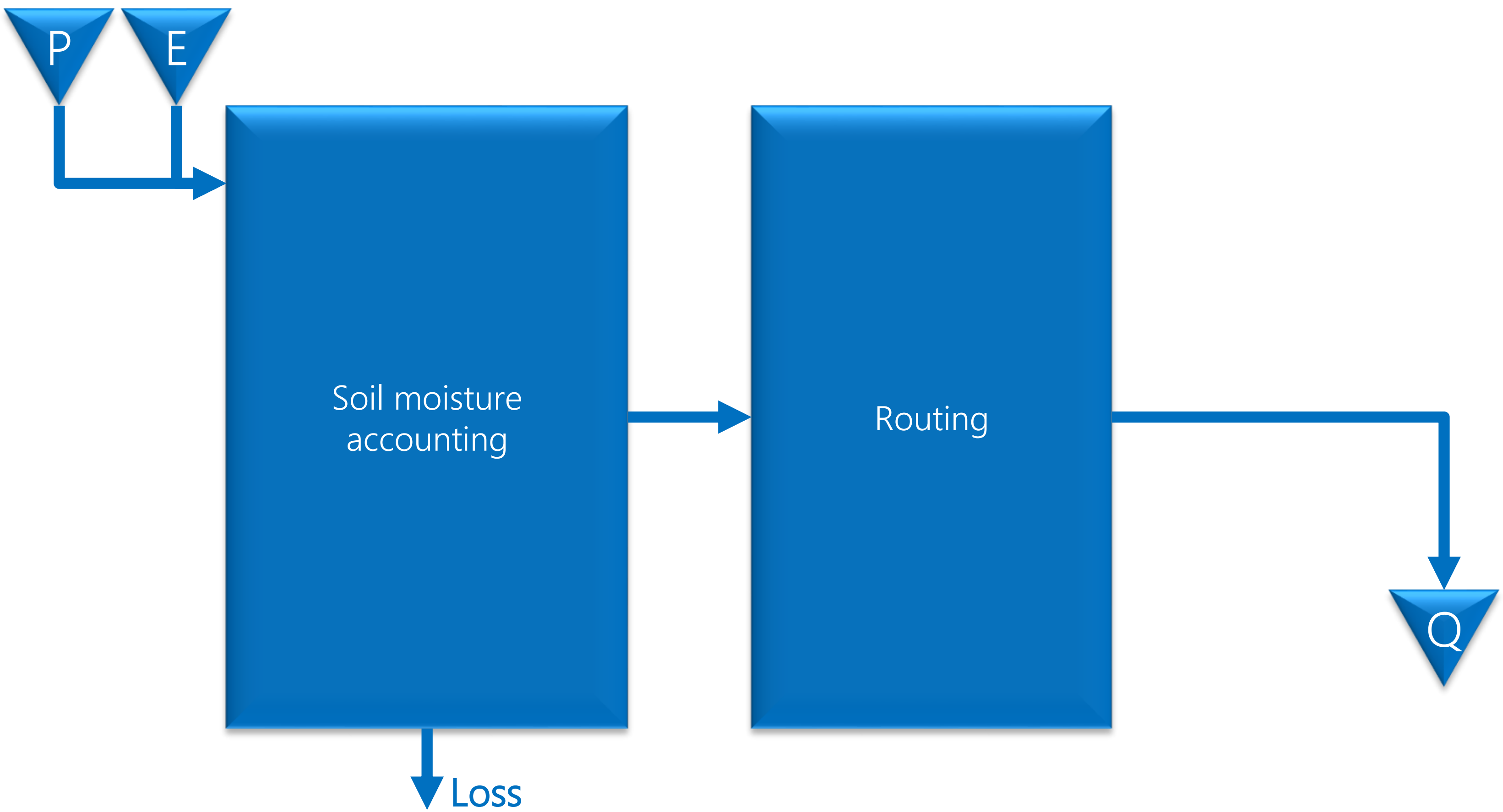
# How EMF was put together ?

# Phase 1 – Parent model selection

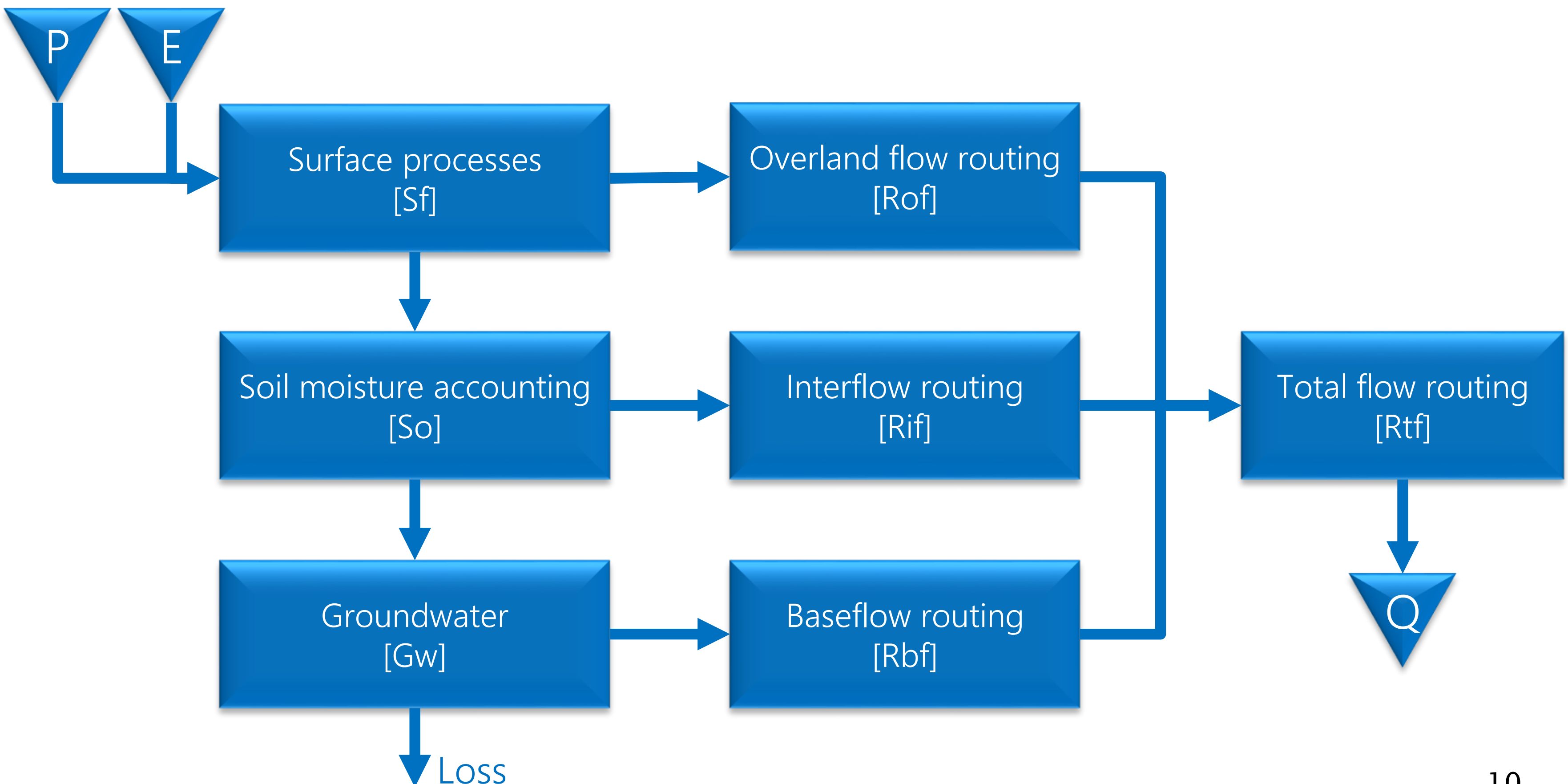
12 dissimilar lumped hydrological models, out of more than 30 candidates
(Perrin, 2000; Mathevet 2005; Seiller et al. 2012; 2015)

| Name | Free parameters | Storages | Derived from |
|---|---|---|---|
| A | 6 | 3 | BUCKET (Thornthwaite and Mather, 1955) |
| B | 6 | 3 | CREC (Cormary and Guilbot, 1973) |
| C | 6 | 3 | GARDENIA (Thiery, 1982) |
| D | 4 | 2 | GR4J (Perrin et al., 2003) |
| E | 7 | 4 | MARTINE (Mazenc et al., 1984) |
| F | 7 | 2 | MOHYSE (Fortin and Turcotte, 2006) |
| G | 6 | 4 | MORDOR (Garçon, 1999) |
| H | 9 | 5 | SACRAMENTO (Burnash et al., 1973) |
| I | 8 | 3 | SIMHYD (Chiew et al., 2002) |
| J | 7 | 4 | TANK (Sugarawa, 1979) |
| K | 8 | 3 | WAGENINGEN (Warmerdam et al., 1997) |
| L | 8 | 4 | XINANJIANG (Zhao et al., 1980) |

# Phase 2 – Isolate their functional components



# Phase 2 – Isolate their functional components



# Phase 2 – Isolate their functional components

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

| Name | Sf | So | Gw | Rof | Rif | Rbf | Rtf |
|---|---|---|---|---|---|---|---|
| A | | | | | | | |
| H | | | | | | | |
| E | | | | | | | |
| B | | | | | | | |
| C | | | | | | | |
| J | | | | | | | |
| K | | | | | | | |
| L | | | | | | | |
| D | | | | | | | |
| F | | | | | | | |
| G | | | | | | | |
| I | | | | | | | |
| | 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 $km^2$, 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 $RMSE$

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

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

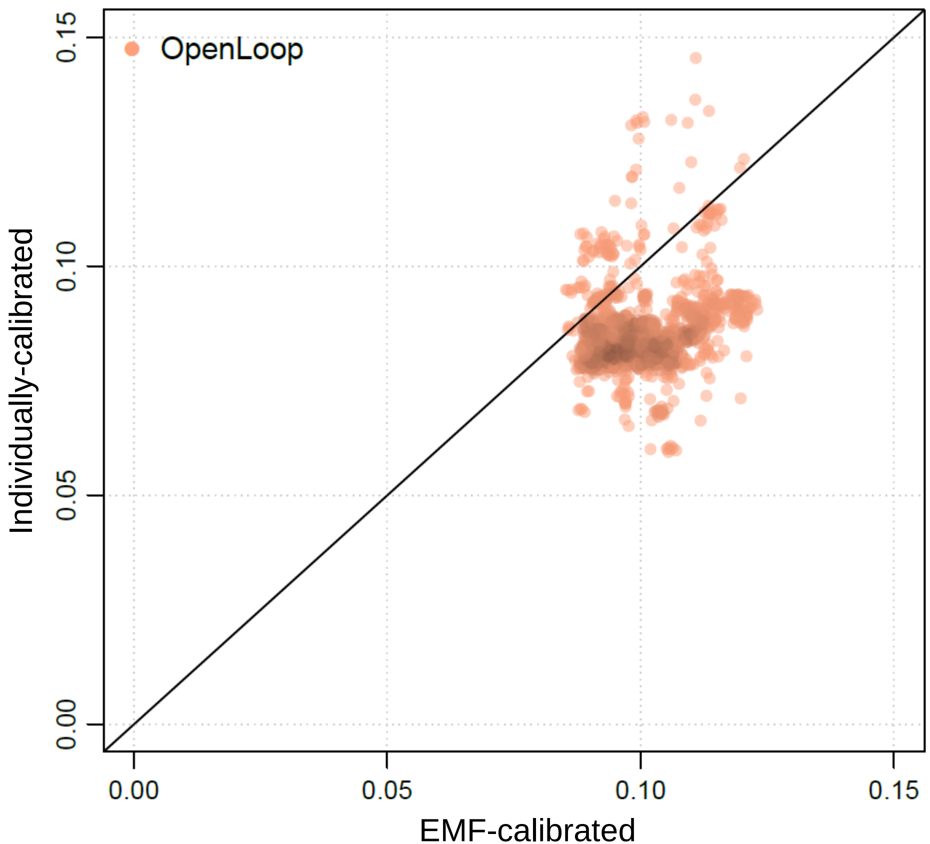
So, we are seeking a $NRD'$ value close to 0 %

Selection procedure

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

# Results

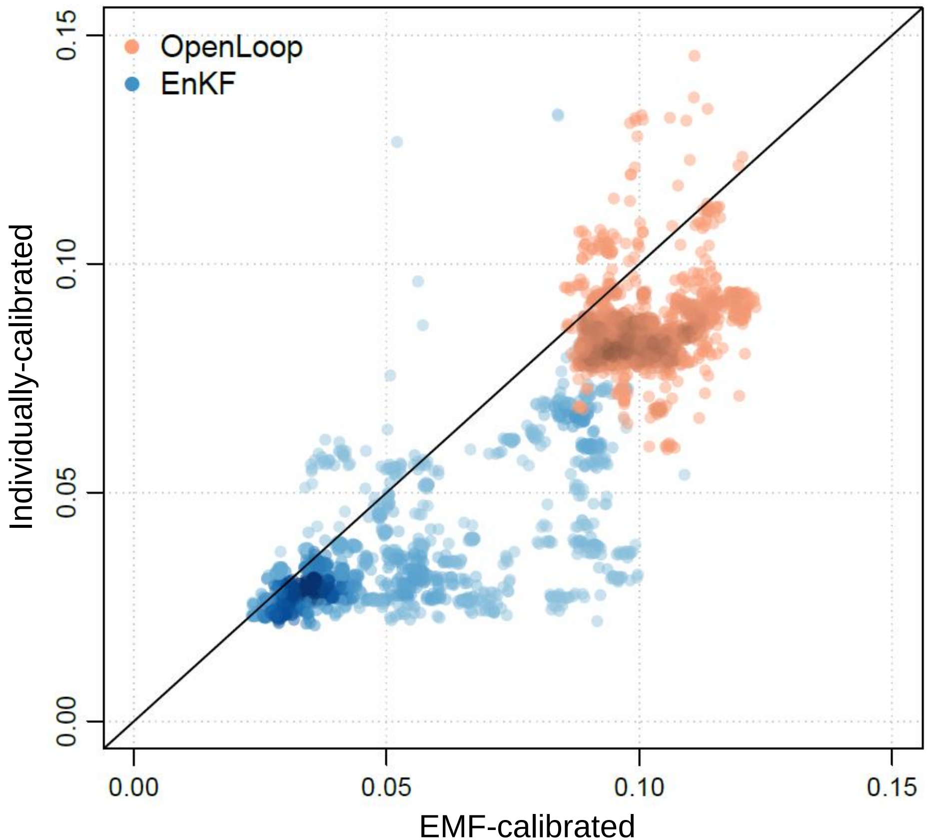
# EMF- vs individually-calibrated MCRPS




OpenLoop

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

# EnKF impact on MCRPS



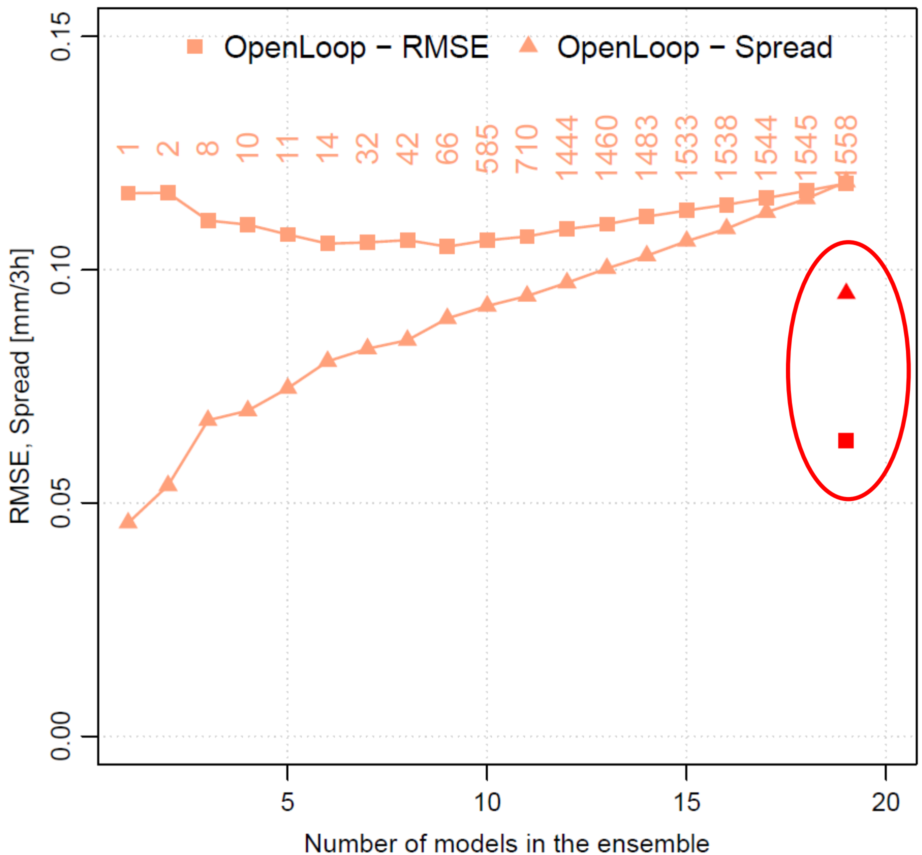

OpenLoop

- 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



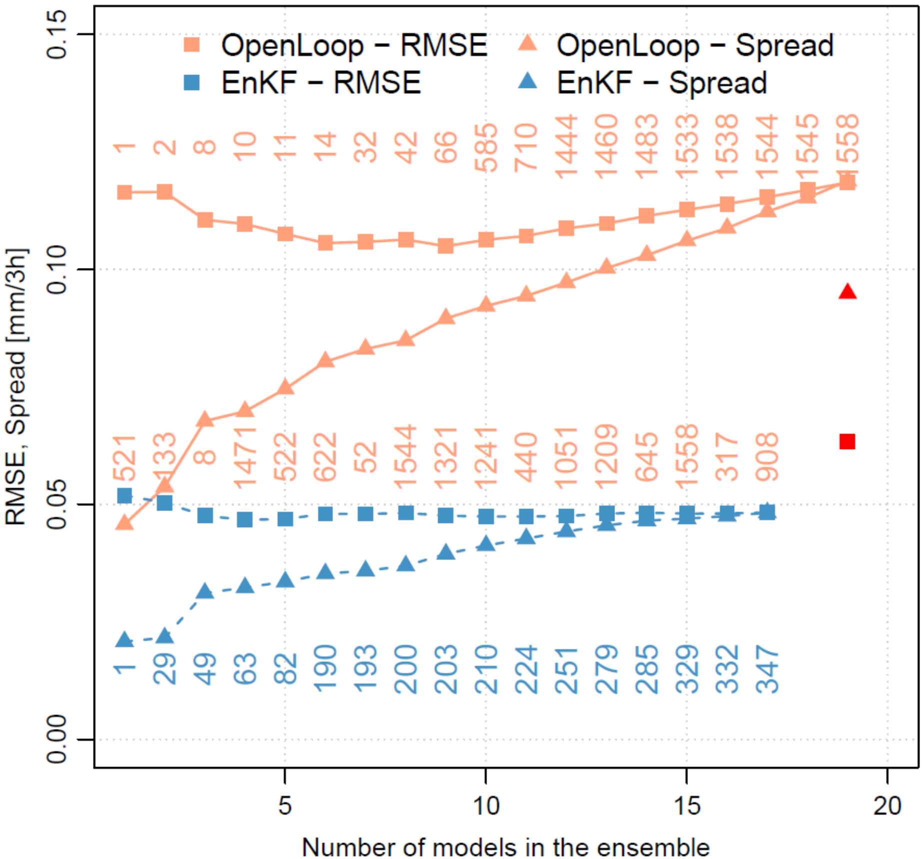

OpenLoop selection

- 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




EnKF selection

- Individual models are better
  - A lower spread is needed
- OpenLoop ordering offers no clue how to optimally select models
- Perfoms better than when EnKF is applied after the OpenLoop selection (in red)

# Highlight

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

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