Assessing sensitivity and persistence of updated initial conditions through Particle filter and EnKF for streamflow forecasting

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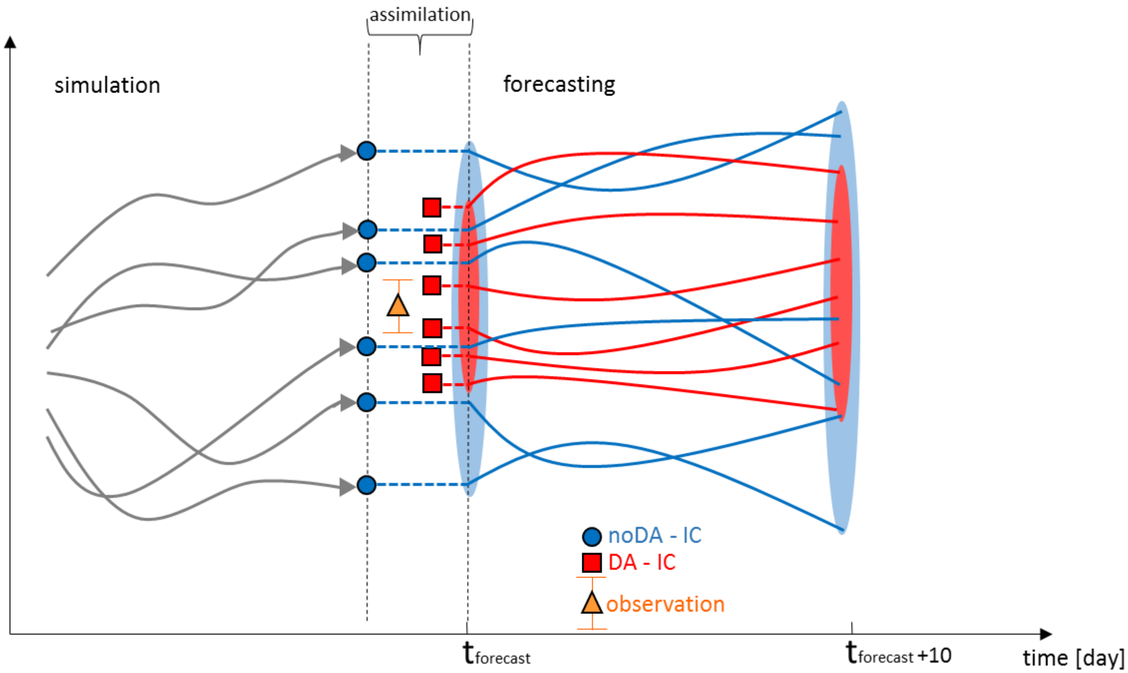
Table of contents

Table of contents

Main goals

Skillful streamflow forecasts provide key support to several water-related applications. Because of the critical impact of initial conditions (ICs) on forecast accuracy, data assimilation (DA) can be performed to improve their estimation.



Assessment of DA-based forecast ICs

- sensitivity to several sources of uncertainty
- efficiency of the update of different model states and parameters

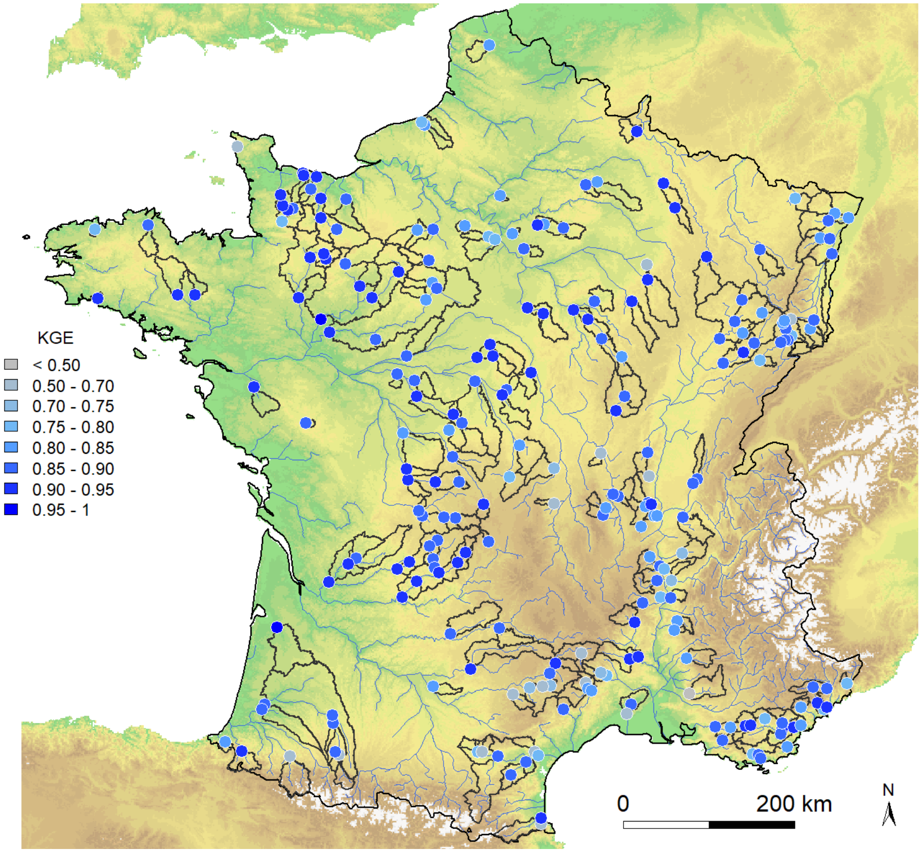
Comparison between EnKF and Particle filter

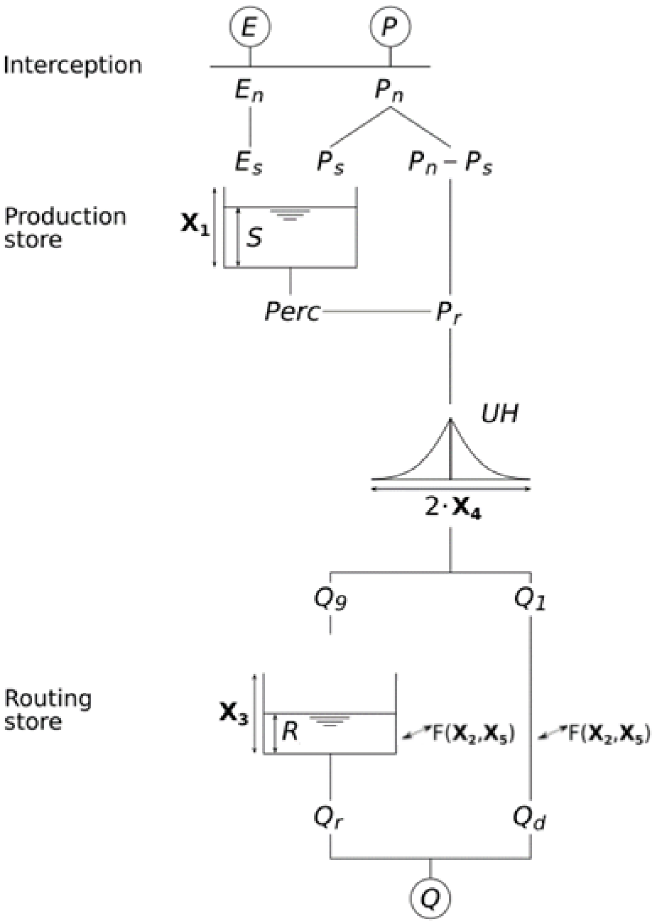
- forecasting accuracy
- temporal persistence of the updating effect (up to 10 days)

Table of contents

Hydrological model

GR5J is a daily lumped conceptual model relying on 5 free parameters (X_1, …, X_5) (Le Moine, 2008).





GR5J was calibrated at 232 watersheds in France over the analysis period 2006–2011.

➡ KGE > 0.85 for 65% of watersheds

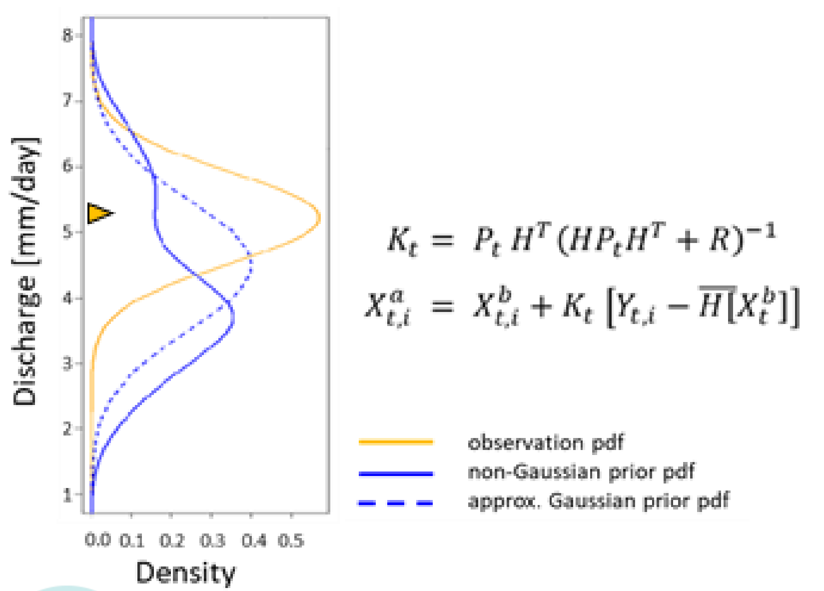
DA schemes

Two sequential ensemble-based DA techniques are tested:

1. Ensemble Kalman filter (EnKF)
2. Sequential importance resampling particle filter (SIR-PF).

Daily discharge measurements at watershed outlets (Y_t) are assimilated.
The uncertainty in observations is assessed as a function of the streamflow rate (Weerts and El Serafy, 2006; Thirel et al., 2010).

EnKF



SIR-PF

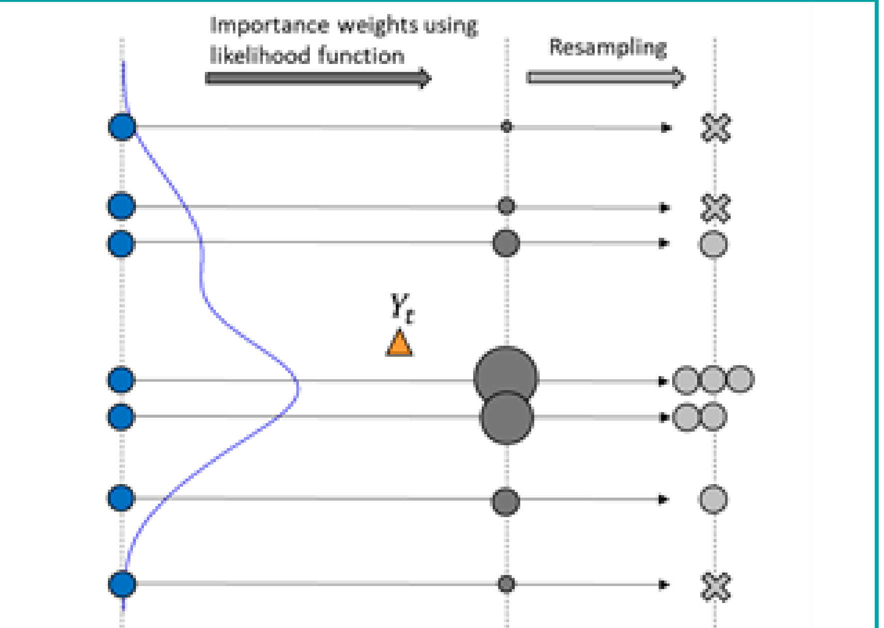


Table of contents

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Sources of uncertainty

Meteorological forcings

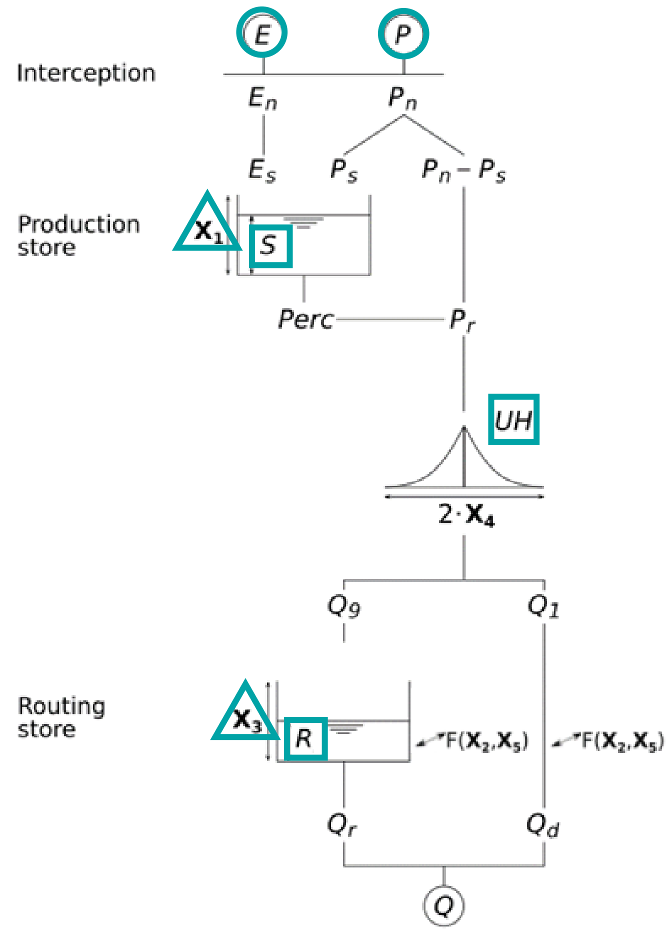
- Potential evapotranspiration (E)
- Precipitation (P)

Model state variables

- Production store level (S)
- Routing store level (R)
- Unit hydrograph (UH)

Parameters

- Capacity of production store (X_1)
- Capacity of routing store (X_3)



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Uncertainty in meteorological forcings

Meteorological forcings

- Potential evapotranspiration (E)
- Precipitation (P)

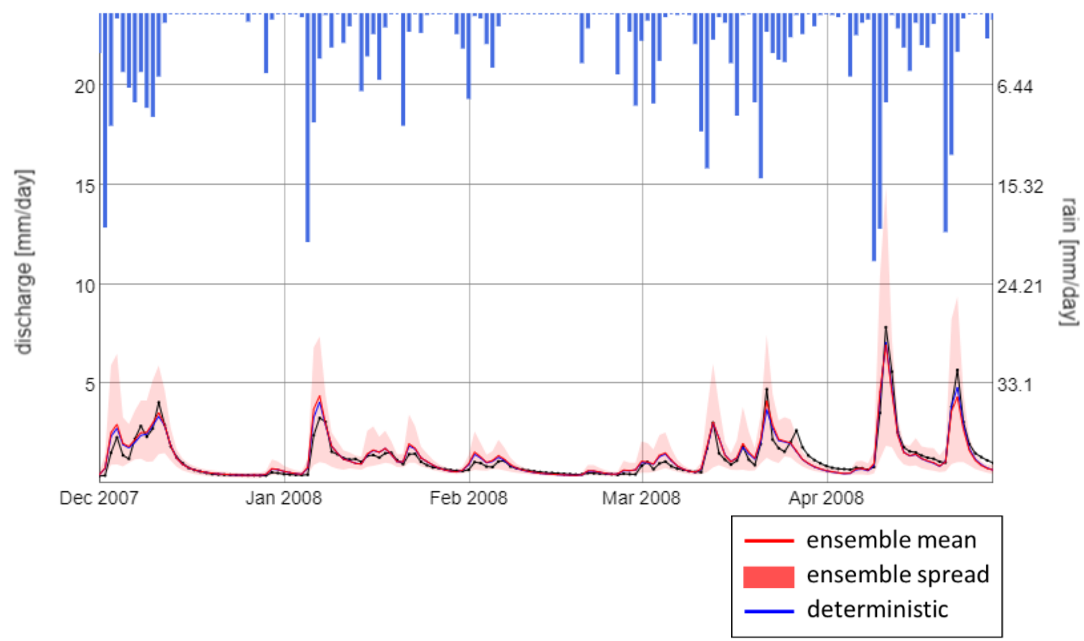
Model state variables

- Production store level (S)
- Routing store level (R)
- Unit hydrograph (UH)

Parameters

- Capacity of production store (X_1)
- Capacity of routing store (X_3)

Probabilistic meteorological forecasts are generated by stochastically perturbing the SAFRAN meteorological reanalysis with multiplicative stochastic noise (Clark et al., 2008).



Uncertainty in model states

Meteorological forcings

- Potential evapotranspiration (E)
- Precipitation (P)

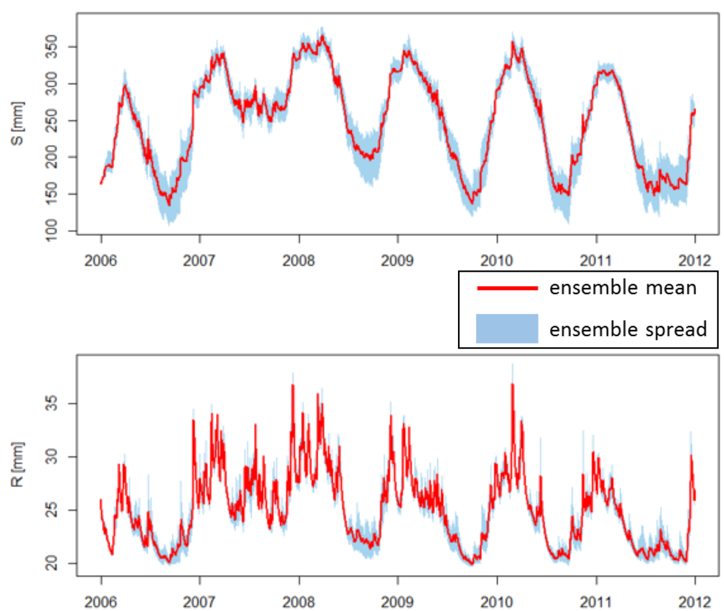
Model state variables

- Production store level (S)
- Routing store level (R)
- Unit hydrograph (UH)

Parameters

- Capacity of production store (X_1)
- Capacity of routing store (X_3)

After the analysis procedure, model states are perturbed through normally distributed null-mean noise (Salamon and Feyen, 2009).



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Uncertainty in model parameters

Meteorological forcings

- Potential evapotranspiration (E)
- Precipitation (P)

Model state variables

- Production store level (S)
- Routing store level (R)
- Unit hydrograph (UH)

Parameters

- Capacity of production store (X_1)
- Capacity of routing store (X_3)

Model parameters are jointly updated with state variables, according to the augmented state vector approach, and perturbed (Moradkhani et al., 2005).

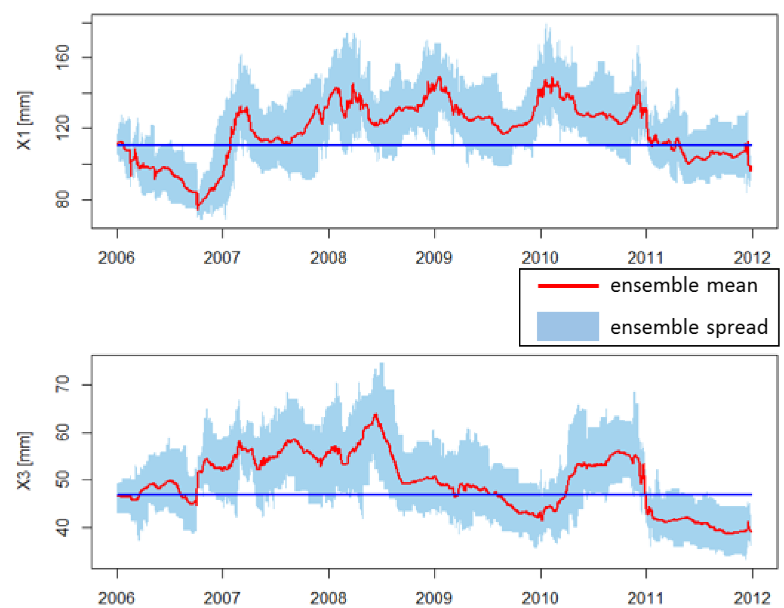

Table of contents

Experimental setup

All the experiments rely on an ensemble of 100 members.

To compare the performance of the EnKF and PF schemes, they are assessed against the open-loop (OL) probabilistic predictions (i.e., no DA).

Experiments A: uncertainty in model inputs

DA-based update of :

A1 → all the 3 state variables

A2 → production store level (S)

A3 → routing store level (R)

A4 → unit hydrograph (UH)

Experiments B: uncertainty in model inputs & parameters

DA-based update of all the 3 state variables <u>and</u> :

B1 → capacity of production store (X_1)

B2 → capacity of routing store (X_3)

B3 → store capacities (X_1 and X_3)

Experiments C: uncertainty in model inputs & states

DA-based update of :

C1 → all the 3 state variables

C2 → production store level (S)

C3 → routing store level (R)

C4 → unit hydrograph (UH)

Experiments A

Experiments A: uncertainty in model inputs

DA-based update of :

A1 → all the 3 state variables

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A3 → routing store level (R)

A4 → unit hydrograph (UH)

Experiments B: uncertainty in model inputs & parameters

DA-based update of all the 3 state variables and :

B1 → capacity of production store (X_1)

B2 → capacity of routing store (X_3)

B3 → store capacities (X_1 and X_3)

Experiments C: uncertainty in model inputs & states

DA-based update of :

C1 → all the 3 state variables

C2 → production store level (S)

C3 → routing store level (R)

C4 → unit hydrograph (UH)

Experiments A: uncertainty in model inputs

DA-based update of :
A1 → all the 3 state variables
A2 → production store level (S)
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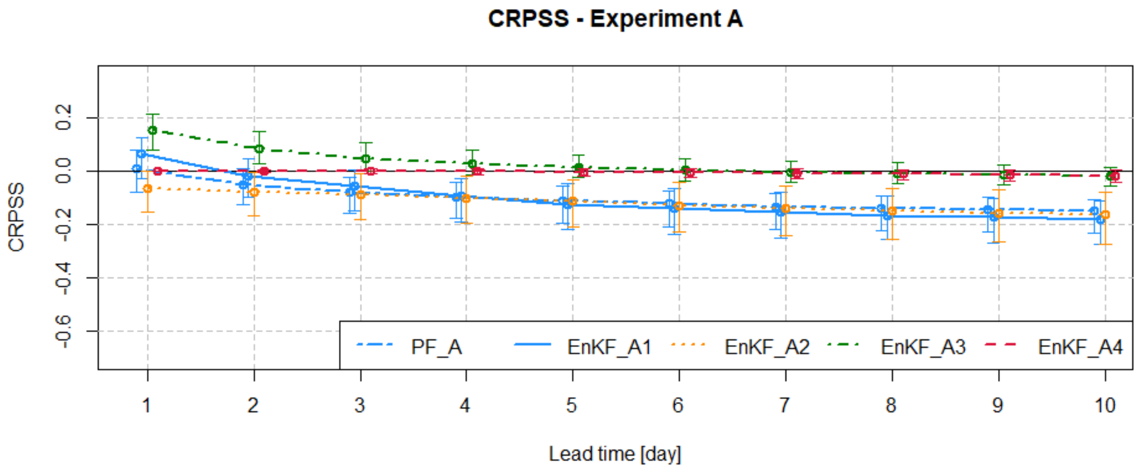
Impact of meteorological uncertainty on DA-based forecasts

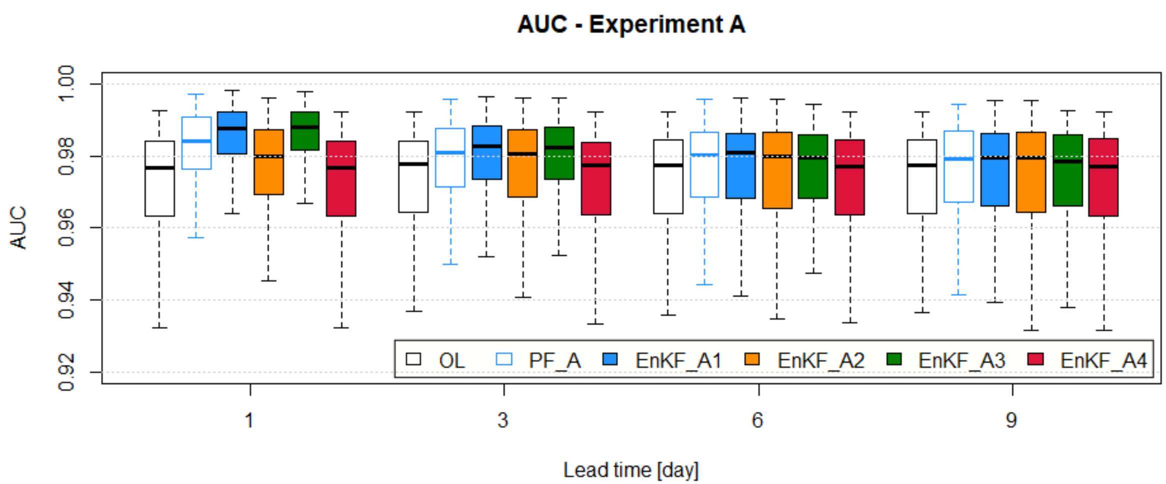


EnKF (**EnKF_A1**) outperforms the PF (**PF_A**) → poor usefulness even for the very short lead time.

Update of R (**EnKF_A3**) → most benefit, improvement up to 5 days.

Low sensitivity to the UH (**EnKF_A4**)

Both the DA-based estimates of ICs (**EnKF_A1**, **PF_A**) improve the event discrimination capability up to a 6-day lead time.



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Experiments B

Experiments A: uncertainty in model inputs

DA-based update of :

A1 → all the 3 state variables

A2 → production store level (S)

A3 → routing store level (R)

A4 → unit hydrograph (UH)

Experiments B: uncertainty in model inputs & parameters

DA-based update of all the 3 state variables and :

B1 → capacity of production store (X_1)

B2 → capacity of routing store (X_3)

B3 → store capacities (X_1 and X_3)

Experiments C: uncertainty in model inputs & states

DA-based update of :

C1 → all the 3 state variables

C2 → production store level (S)

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Experiments B: uncertainty in model inputs & parameters

DA-based update of all the 3 state variables and :
B1 → capacity of production store (X_1)
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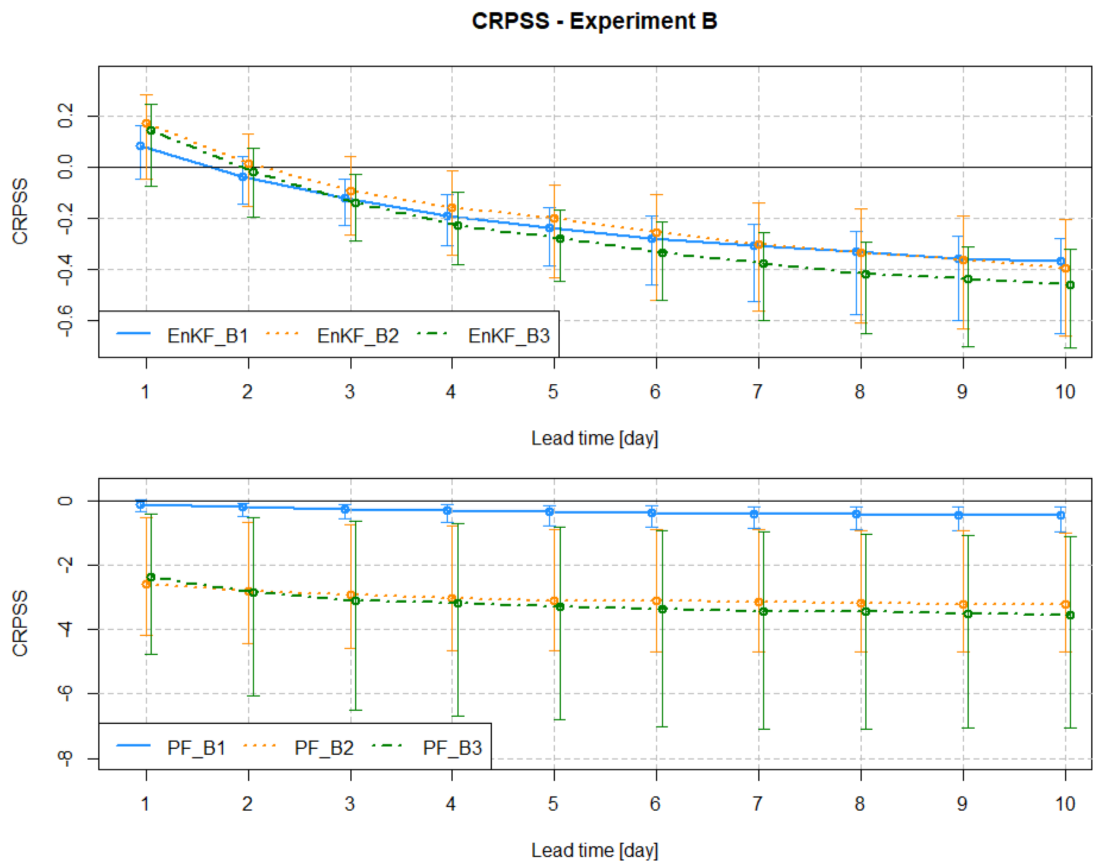
B3 → store capacities (X_1 and X_3)

Joint DA-based estimation of forecast initial states and parameters



Compared to Exps. A, the DA-based estimation of :

- X_1 (**Exp. B1**) → no significant improvement
- X_3 via EnKF (**EnKF_B2**) → higher predictive accuracy in the very short term
- X_3 via PF (**PF_B2**) →undermined forecast reliability

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Experiments C

Experiments A: uncertainty in model inputs

DA-based update of :

A1 → all the 3 state variables

A2 → production store level (S)

A3 → routing store level (R)

A4 → unit hydrograph (UH)

Experiments B: uncertainty in model inputs & parameters

DA-based update of all the 3 state variables and :

B1 → capacity of production store (X_1)

B2 → capacity of routing store (X_3)

B3 → store capacities (X_1 and X_3)

Experiments C: uncertainty in model inputs & states

DA-based update of :

C1 → all the 3 state variables

C2 → production store level (S)

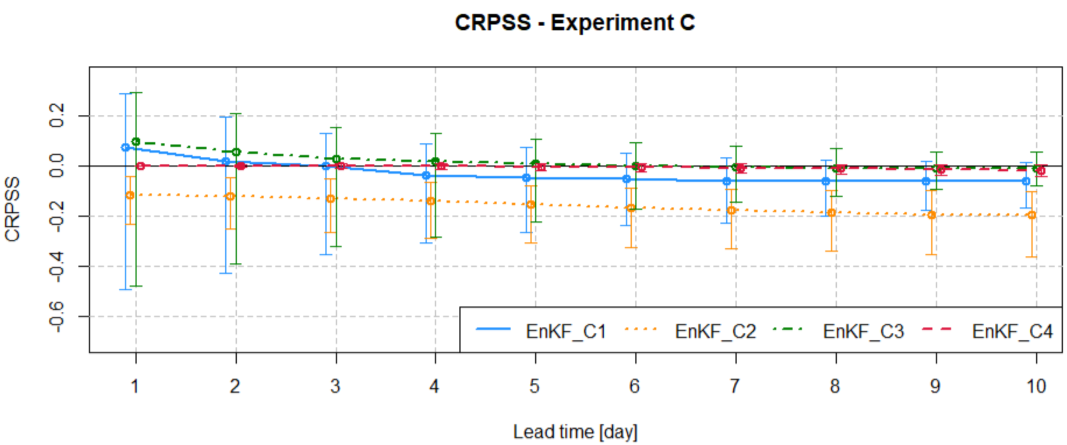
C3 → routing store level (R)

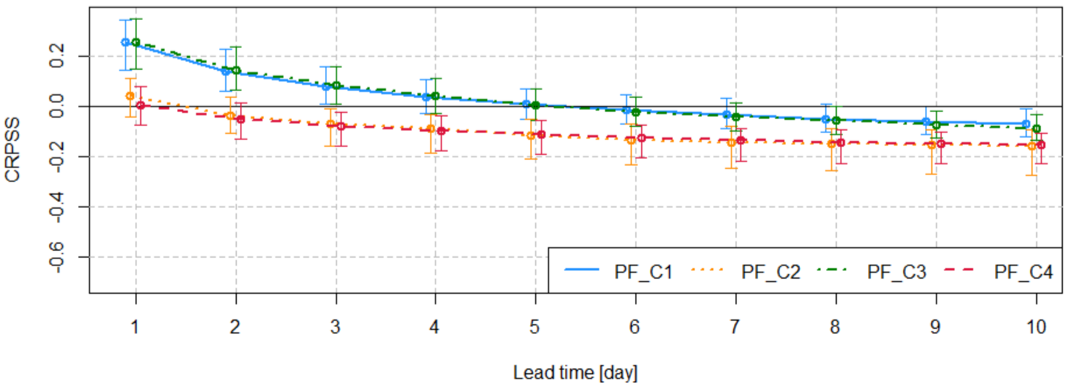
C4 → unit hydrograph (UH)

Impact of state uncertainty on DA-based forecasts

Experiments C: uncertainty in model inputs & states

DA-based update of :
C1 → all the 3 state variables
C2 → production store level (S)
C3 → routing store level (R)
C4 → unit hydrograph (UH)





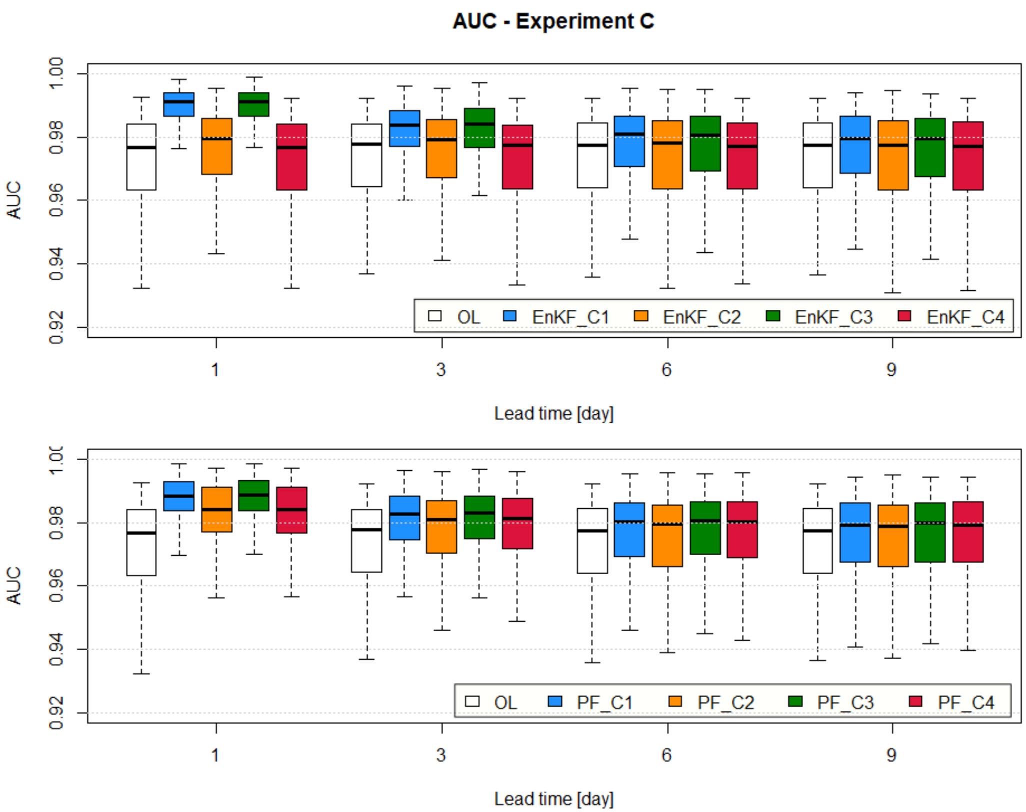
Compared to Exps. A, the DA-based estimation of :

- all the state variables → PF (**PF_C1**) outperforms EnKF (**EnKF_C1**)
- S (**EnKF_C2**, **PF_C2**) → less accurate estimation due to low correlation with observed discharges
- R via EnKF (**EnKF_C3**) → larger improvement of ICs, but the accuracy decreases more sharply
- R via PF (**PF_C3**) → most efficient improvement of IC accuracy up to a 5-day lead time

Impact of state uncertainty on DA-based forecasts

Experiments C: uncertainty in model inputs & states

DA-based update of :
C1 → all the 3 state variables
C2 → production store level (S)
C3 → routing store level (R)
C4 → unit hydrograph (UH)



Compared to Exps. A, the event discrimination capability is significantly enhanced when accounting for the uncertainty in R (**PF_C3**, **EnKF_C3**), especially in the short term.

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Table of contents

Main conclusions

- Both the EnKF and the PF schemes reveal an effective usefulness to improve predictive accuracy by the assimilation of observed discharges.
- When dealing with a conceptual hydrological model, the main interest is on the **routing dynamics** to derive the most benefit from the DA-based ICs.

Compared to PF, EnKF-based ICs guarantee a greater improvement in predictive accuracy (PF affected by ensemble shrinkage during no-rain periods).

A comprehensive representation of both meteorological and state uncertainties allows for a more efficient improvement of predictive skill.

→ PF-based ICs are greatly enhanced thanks to a larger spread of the ensemble simulations.
→ While the PF-based updating effect is longer lasting, the benefit of larger corrective terms for the EnKF rapidly decreases within a short lead time.

High sensitivity to the parameter estimation, as store capacities define the simulated hydrological responsiveness of the basin.

→ Parameter values estimated at the forecast time may not be the optimal ones to represent the model response over the forecast horizon.
→ The equifinality issue can affect the parameter estimates, especially in PF.

Ongoing and future perspectives

This study has been recently submitted to the Water Resources Research journal:
Piazzi, G., Thirel, G., Perrin, C., Delaigue, O. Sequential data assimilation for streamflow forecasting: assessing the sensitivity to uncertainties and updated variables of a conceptual hydrological model.

➡ An R package providing the DA schemes will be soon available.

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Table of contents

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