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

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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)
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**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.

$\text{KGE} > 0.85$ for 65% of watersheds
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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

\[
K_t = P_t H^T (HP_t H^T + R)^{-1}
\]

\[
x_{t,i}^a = x_{t,i}^b + K_t [Y_{t,i} - H[x_t^b]]
\]

SIR-PF

Importance weights using
likelihood function
Resampling

\[
Y_t
\]
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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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Methodology

Uncertainty in meteorological forcings

Meteorological forcings

- Potential evapotranspiration (E)
- Precipitation (P)

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

Model state variables

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

Parameters

- Capacity of production store (X₁)
- Capacity of routing store (X₃)
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Methodology

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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Methodology

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)

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

Parameters
- Capacity of production store (X₁)
- Capacity of routing store (X₃)
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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
- A1 $\rightarrow$ all the 3 state variables
- A2 $\rightarrow$ production store level ($S$)
- A3 $\rightarrow$ routing store level ($R$)
- A4 $\rightarrow$ unit hydrograph (UH)

Experiments B: uncertainty in model inputs & parameters
- B1 $\rightarrow$ capacity of production store ($X_1$)
- B2 $\rightarrow$ capacity of routing store ($X_3$)
- B3 $\rightarrow$ store capacities ($X_1$ and $X_3$)

Experiments C: uncertainty in model inputs & states
- C1 $\rightarrow$ all the 3 state variables
- C2 $\rightarrow$ production store level ($S$)
- C3 $\rightarrow$ routing store level ($R$)
- C4 $\rightarrow$ unit hydrograph (UH)
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Results

Experiments A

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)
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Results

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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Results

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)
  - C3 → routing store level (R)
  - C4 → unit hydrograph (UH)
Results

Joint DA-based estimation of forecast initial states and parameters

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

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

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:
  - 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

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

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

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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## 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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