Potential of Ensemble Optimal Interpolation in Tackling Parameter Bias

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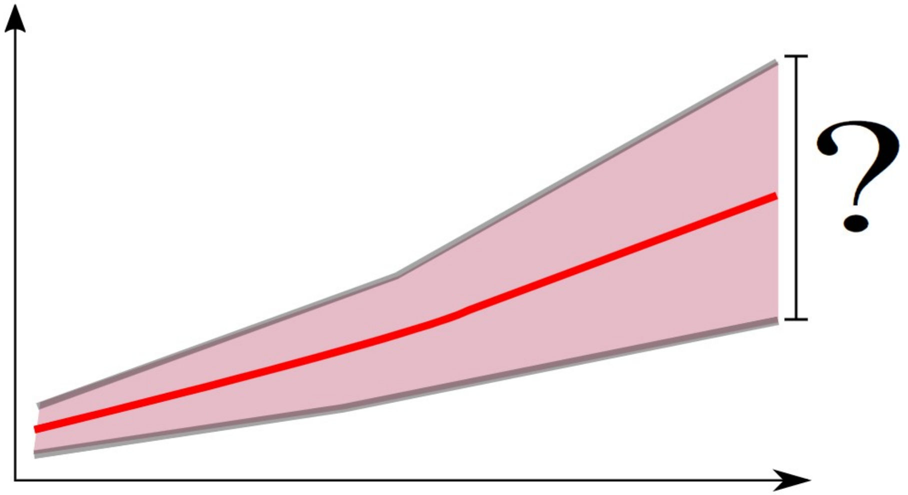
27/01/2022

Background

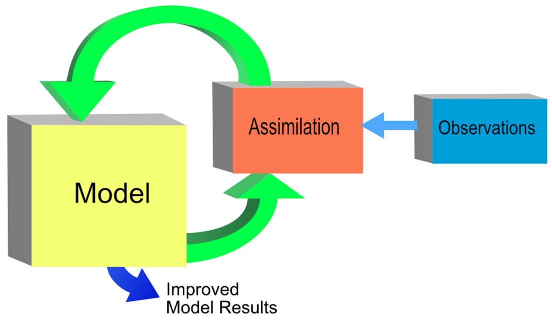


- Hydrological **modelling** is limited by various **uncertainties** (e.g. input, structure, parameter etc.)

- **Data Assimilation (DA)** has proven to be an important tool in improving the models and their forecasts by reducing the associated uncertainties

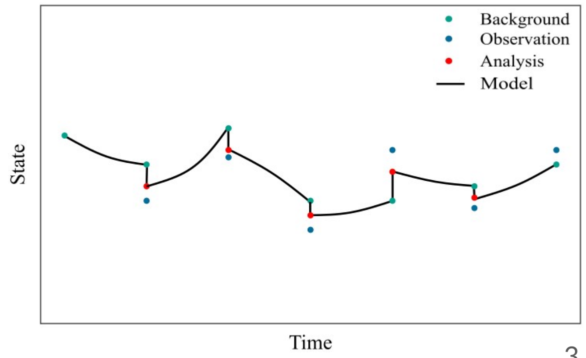
Data Assimilation

- An approach to integrate information from multiple sources in order to improve model accuracy
- provides a framework to **<u>merge model and observations</u>** based on their uncertainties
- **Data Assimilation (DA) = Model + Observation**



***Source:** http://www.cambridgeblog.org/2017/05/data-assimilation-in-every-day-life/*

- Formally, Data Assimilation involves finding the <u>best estimates of the system state</u> ***X*** given the noisy model of the system dynamics ***M*** and the noisy observations ***Z***.
- Beyond state estimation, <u>parameter identification</u> is also possible within the DA framework



***Reproduced from:** Hydrologic Data Assimilation. Walker, J.P. and Houser, P. R.*

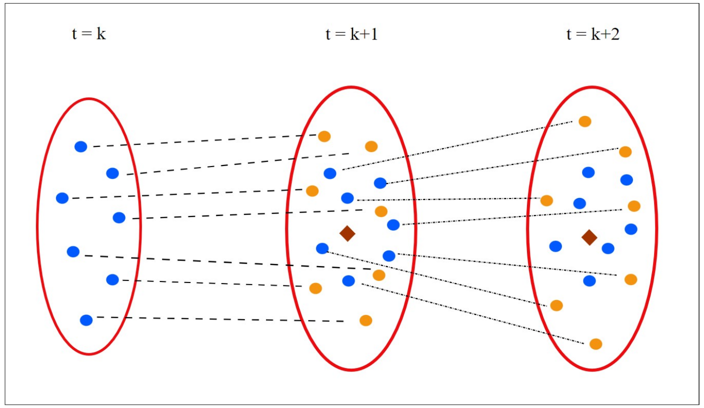
EnKF vs EnOI

Background state ensembles
Observation
Updated ensembles

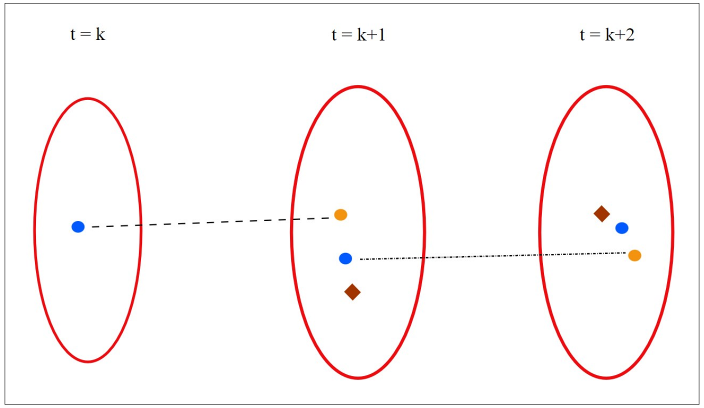
Forecast → $x_{i,t}^{b} = f(x_{i,t-1}^{a}, u_t, \theta) + \omega_i$

Update → $x_i^a = x_i^b + K(y_i - Hx_i^b)$

$K = P^b H^T (HP^bH^T + R)^{-1}$



Ensemble Kalman filter (EnKF)



Ensemble Optimal Interpolation (EnOI)

- **Unlike the EnKF, EnOI is computationally cheap**
- **But, online estimation of error covariances is not possible in EnOI**
- **How to define the covariance matrices to address the bias present in model parameters ?**

Hydrological Model

- Distributed Hydrological Model
  - The two dimensional Rainfall-Runoff-Inundation (RRI) model (Sayama et al., 2012)
  - Separate river (1D diffusive wave) and slope components (2D diffusive wave)
  - Saturated subsurface + saturation excess overland flow module used

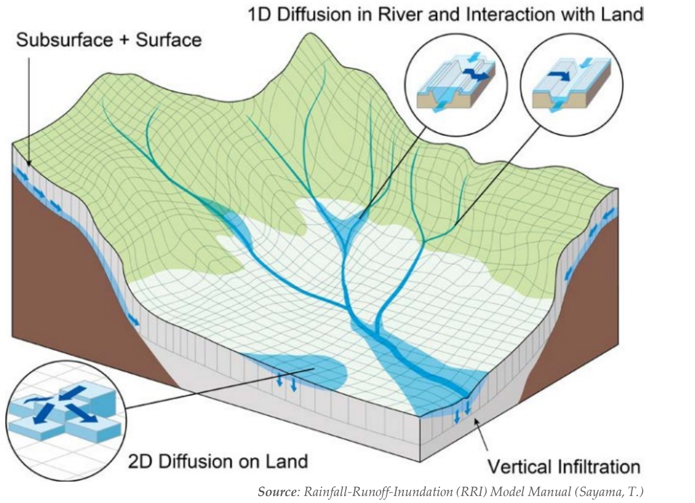


Fig. Schematic diagram of the Rainfall-Runoff-Inundation (RRI) model

hr : water level in river ←
hs : water level in slopes
qr : river discharge

- **state variable** (to be updated by DA)
- also, **assimilated variable**

Study Area and Data

Study area:

- Kamo river basin
  - 214 km^2 drainage area

Data:

- Topographical information
  - applied at 5s resolution
  - based on Japan flow direction map (Yamazaki et al., 2018)
- Rainfall data:
  - Radar raingauge analyzed product (Japan Meteorological Agency)
- River stage observations:
  - Synthetically generated

Flood events

- 2013 Typhoon 18
- 2018 July flood

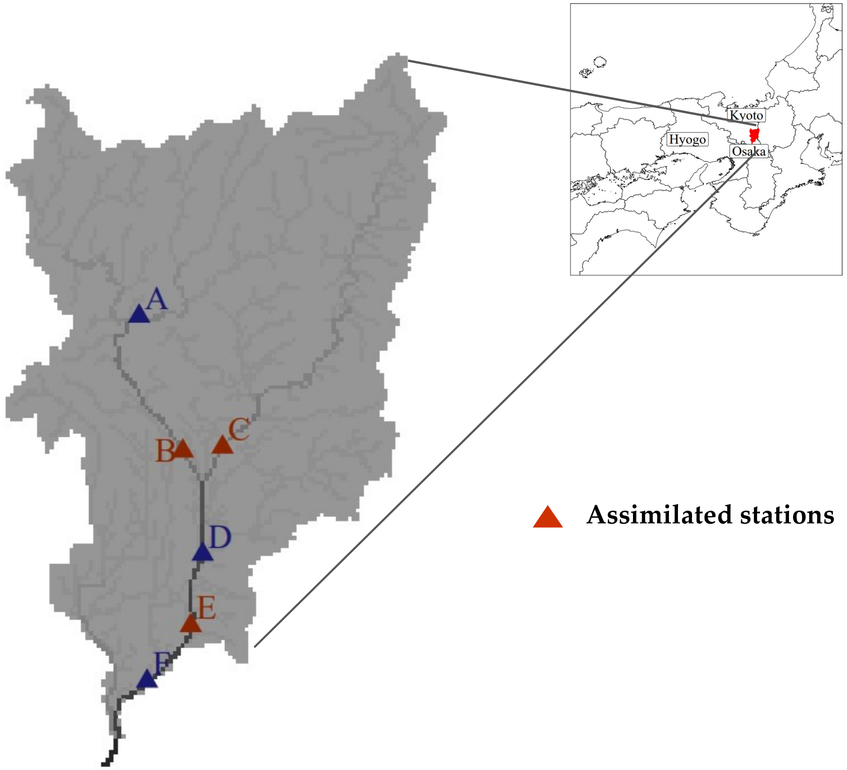
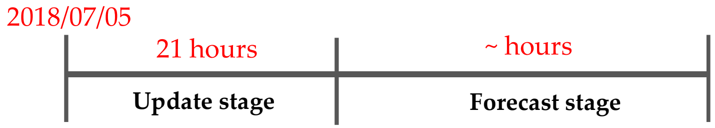
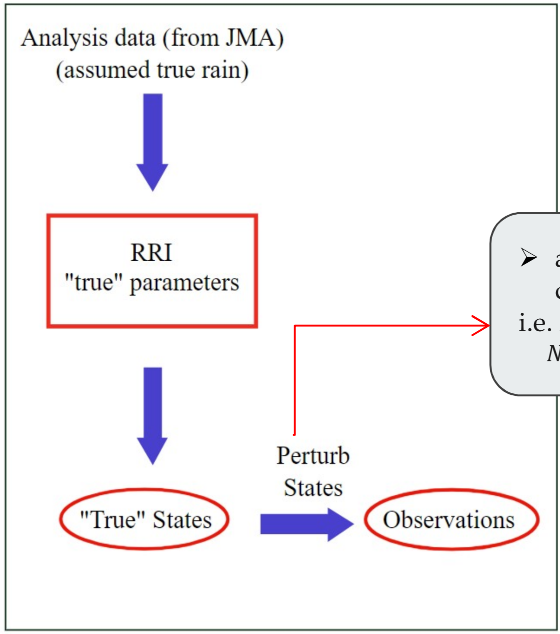


Fig. Kamo river basin

Experimental Setup

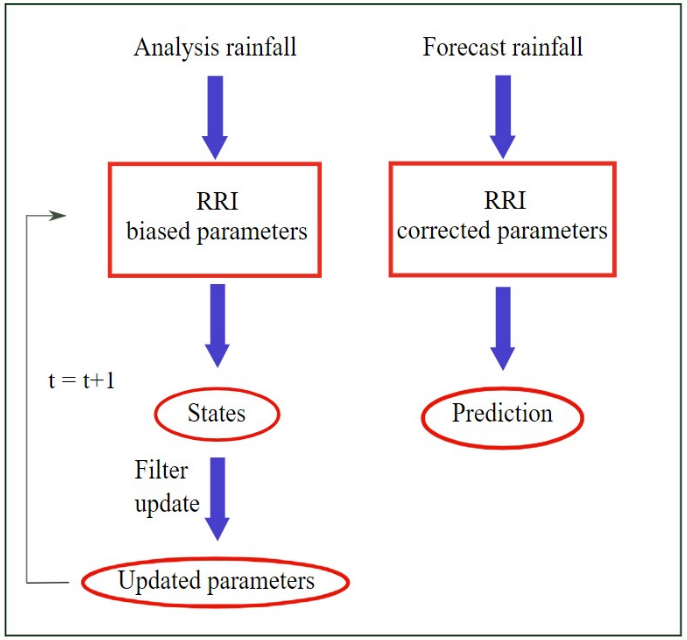




- add noise from an assumed distribution

i.e. sampled from
$N(0, (0.05 \times \mathit{true\ river\ stage})^2)$

Synthetic Truth generation

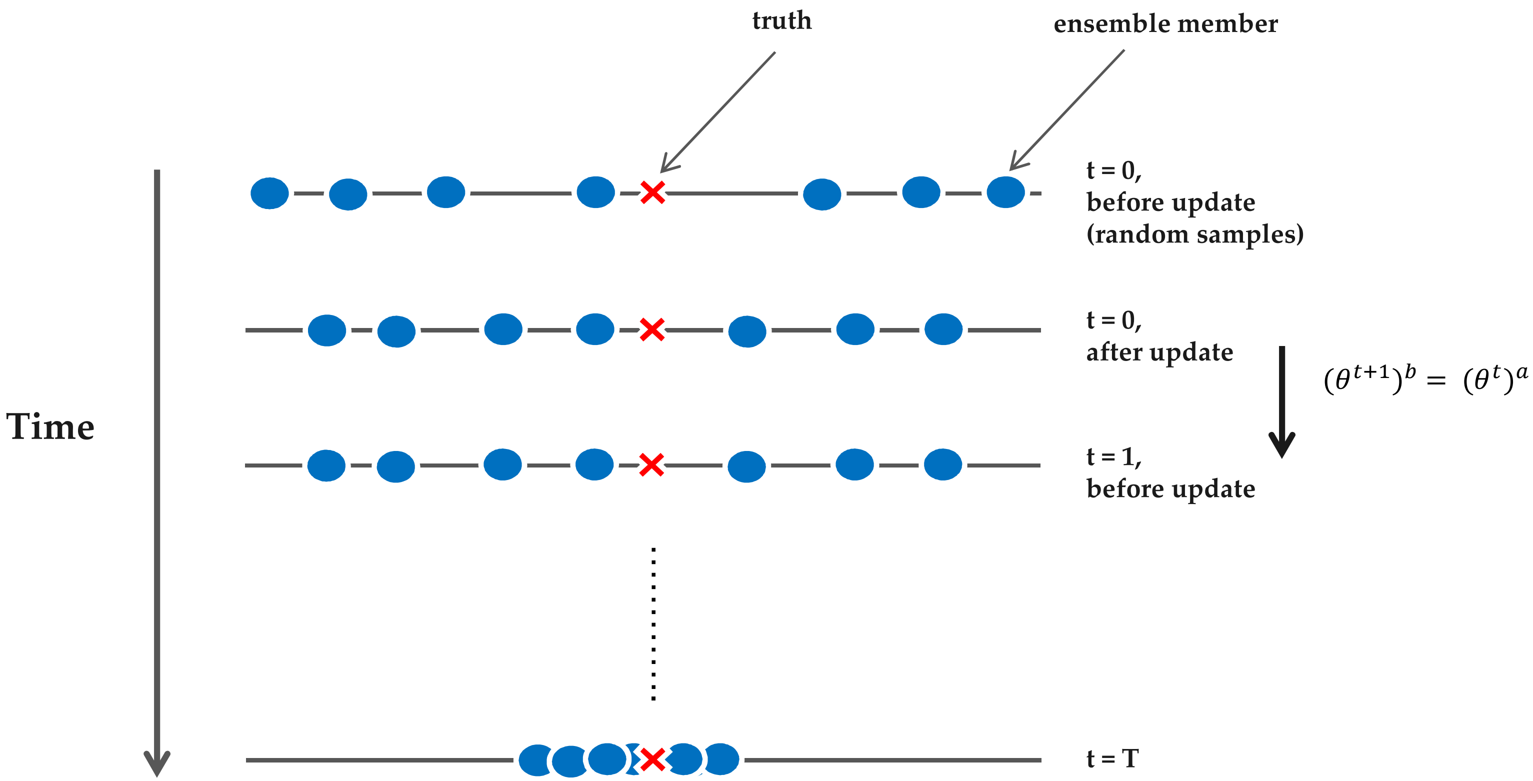


Assimilation experiment

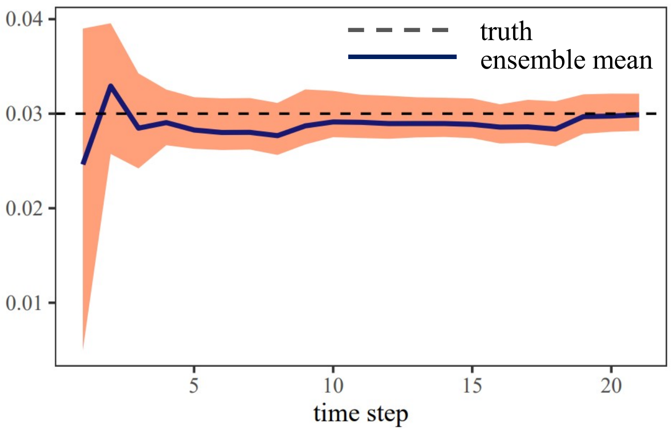
Parameter	"true" value	biased value
Manning's n (river)	0.03	0.015
Manning's n (slope)	0.3	0.5
Hydraulic conductivity (m/s)	0.075	0.04

*JMA: Japan Meteorological Agency

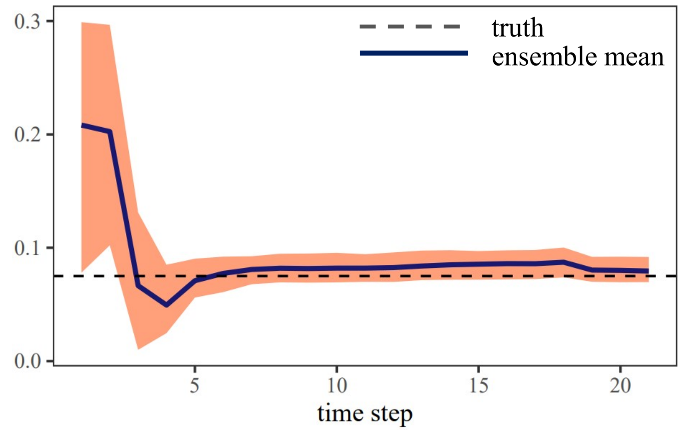
Parameter Estimation with the EnKF



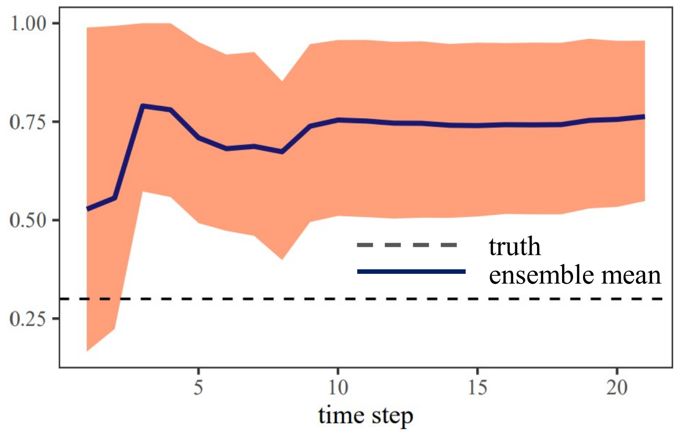
Manning's n (river)



Hydraulic conductivity



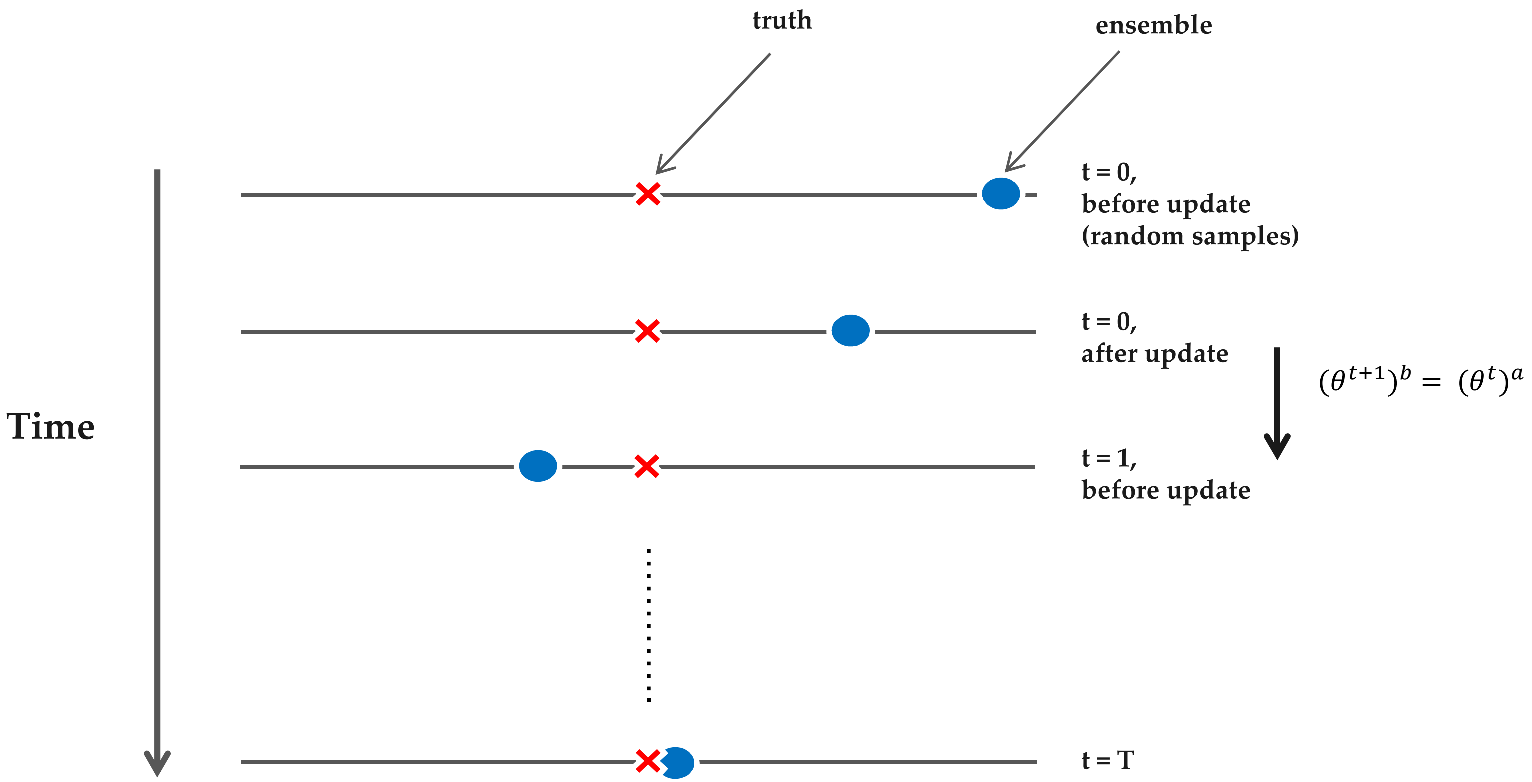
Manning's n (slope)



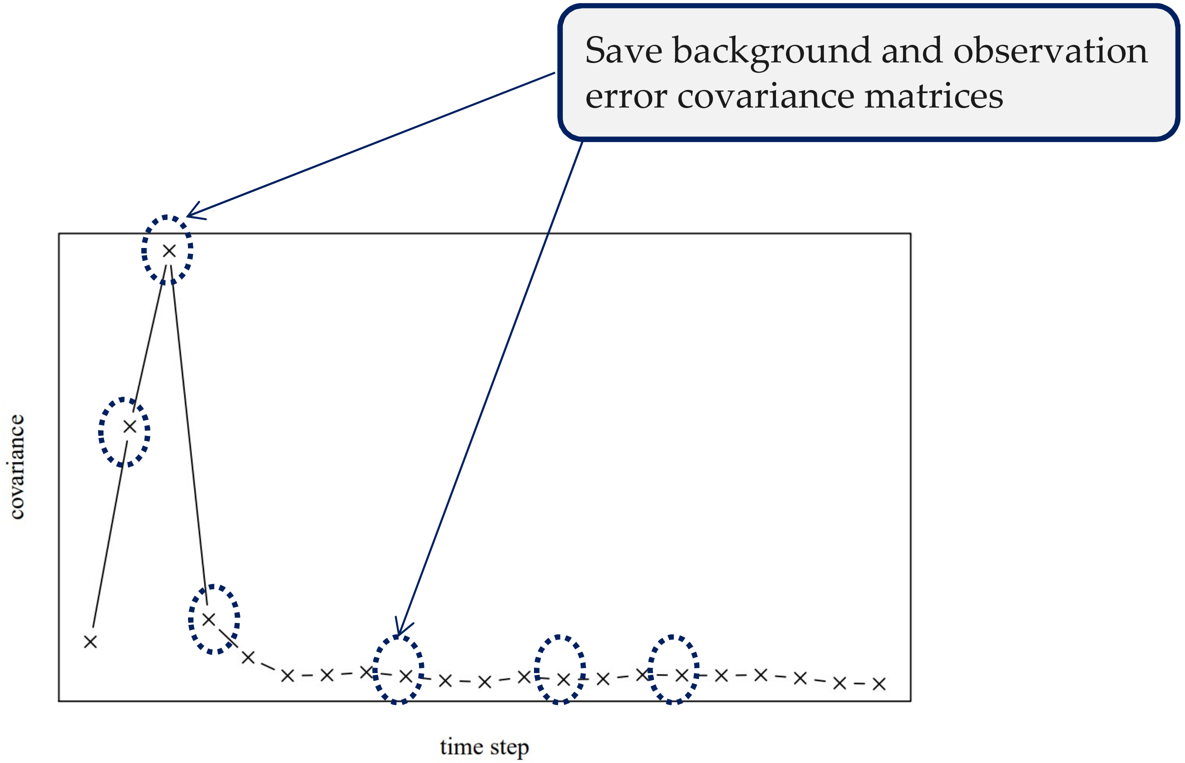
- EnKF was able to correctly approximate the two sensitive parameters

Fig. Parameter ensemble evolution (EnKF)

Parameter Estimation with the EnOI



Covariance Matrices for EnOI Implementation



Results

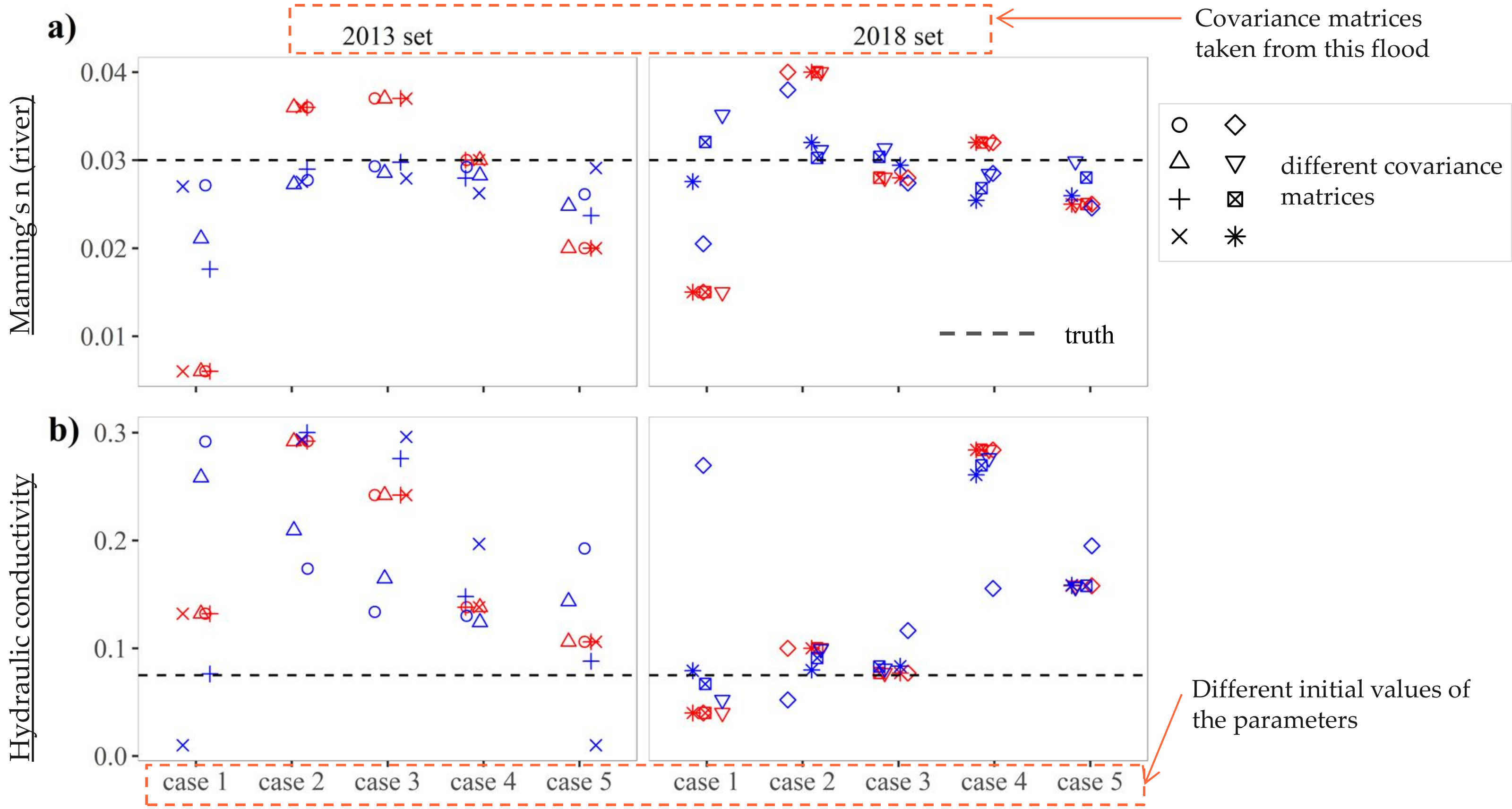
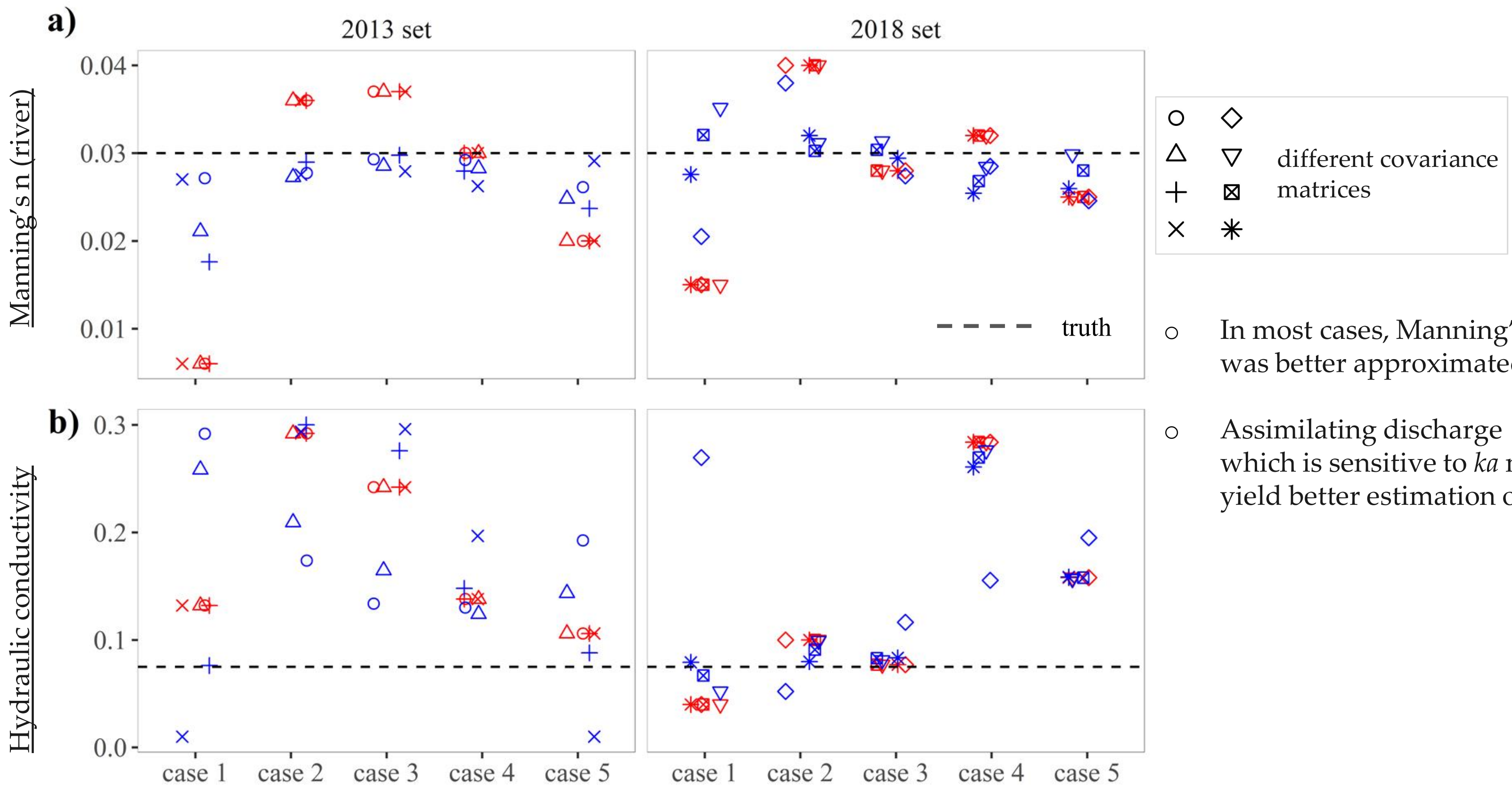


Fig. Parameters at the beginning and end of the update stage

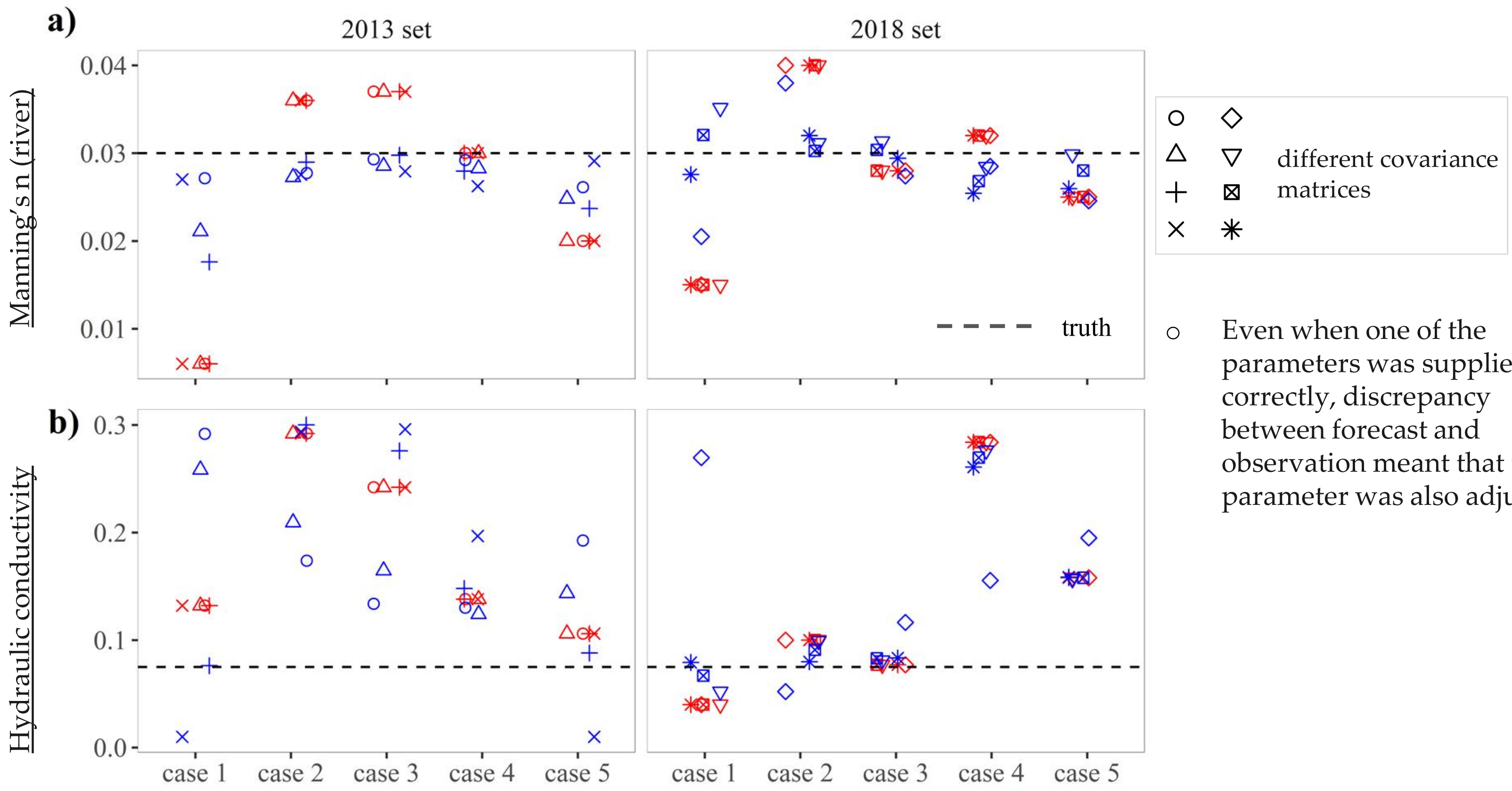
Results



- In most cases, Manning's n was better approximated
- Assimilating discharge which is sensitive to *ka* may yield better estimation of *ka*

Fig. Parameters at the beginning and end of the update stage

Results



- Even when one of the parameters was supplied correctly, discrepancy between forecast and observation meant that this parameter was also adjusted

Fig. Parameters at the beginning and end of the update stage

Issues

- high cross-covariance may introduce instabilities
- gain should be limited

Manning's n (river)

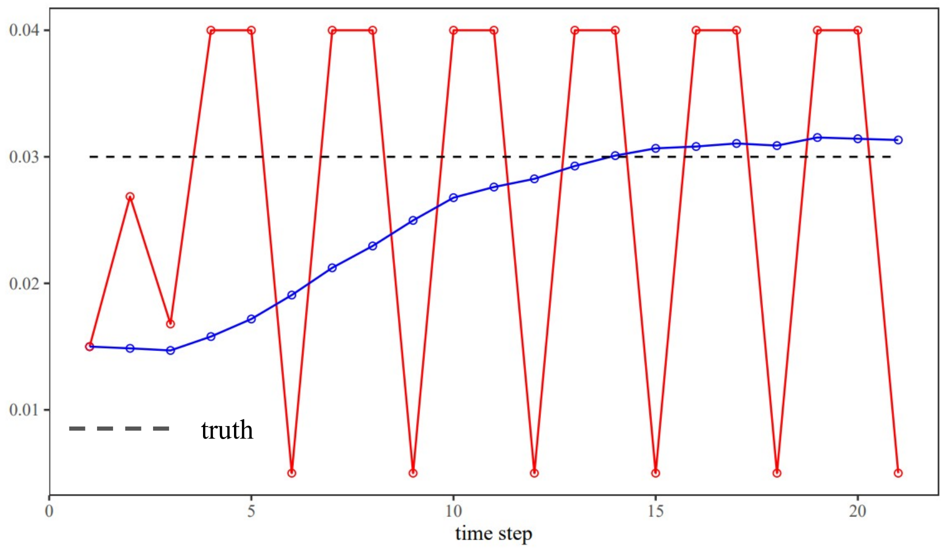


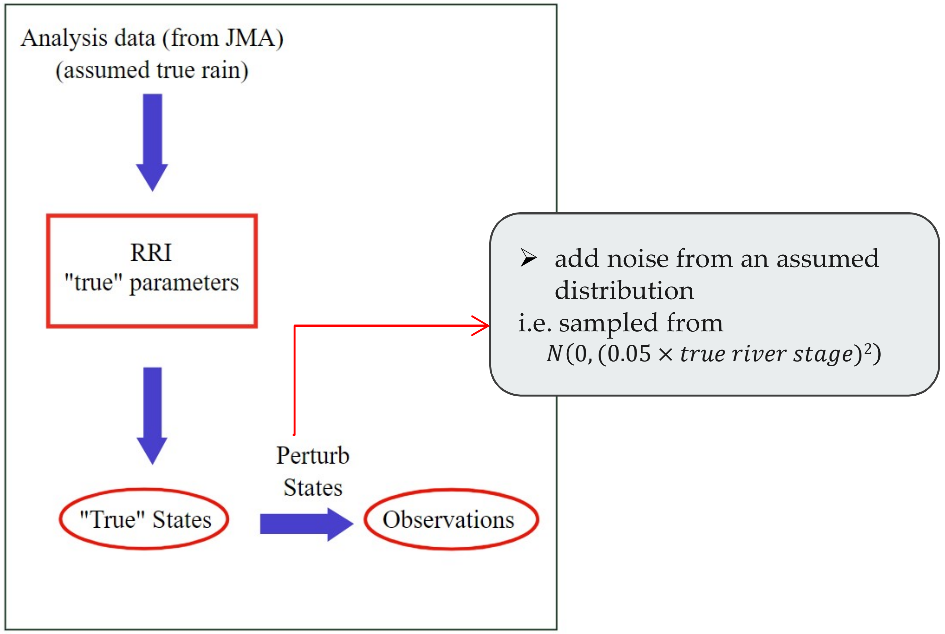
Fig. Parameter evolution for two different covariance matrices

Summary

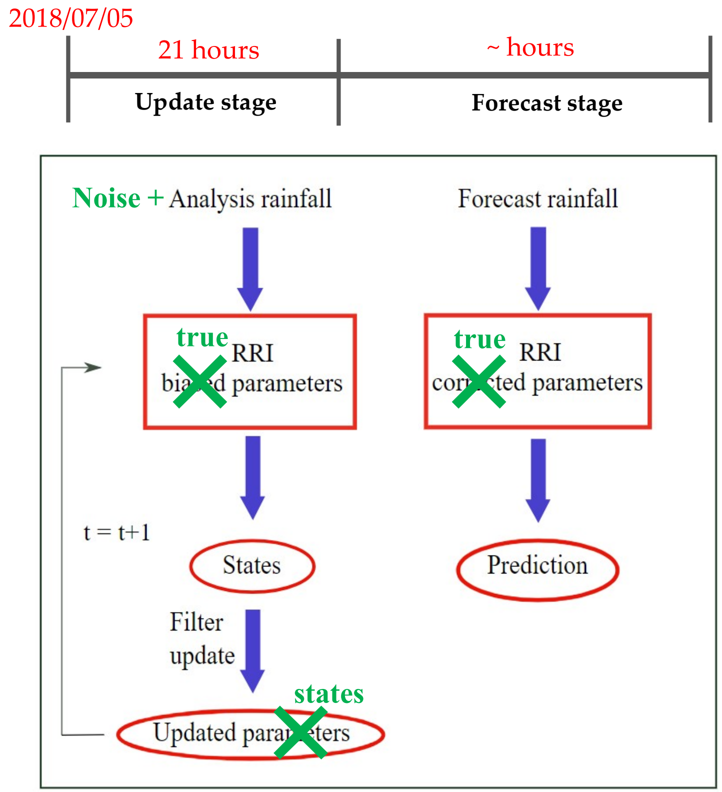
- This study investigated the efficacy of a computationally inexpensive assimilation algorithm i.e. the ensemble optimal interpolation in reducing the biases in the model parameters by using synthetic river stage observations for assimilation
- Ensemble Kalman filter was first applied to two flood events to yield a set of covariance matrices (both background and observation error) which were then utilized to update the model parameters of the deterministic model runs
- While large magnitudes of covariances led to oscillations in the parameters, gradual nudging through small gains led the parameters - especially the manning's n for river - to be close to the truth at the end of the assimilation period

State Estimation with EnOI

Experimental Setup



Synthetic Truth generation



Assimilation experiment

*JMA: Japan Meteorological Agency

Input uncertainty

- following Nijssen and Lettenmaier, 2004

Relative bias(=0)

Standard normal error

Corrupted precipitation

$$P_c = \frac{(1+\beta)}{\sqrt{E^2+1}} \exp\left(\sqrt{\ln[E^2+1]}\,\varepsilon(0,1)\right)P$$

True precipitation

Relative error (= 0.75)

Results

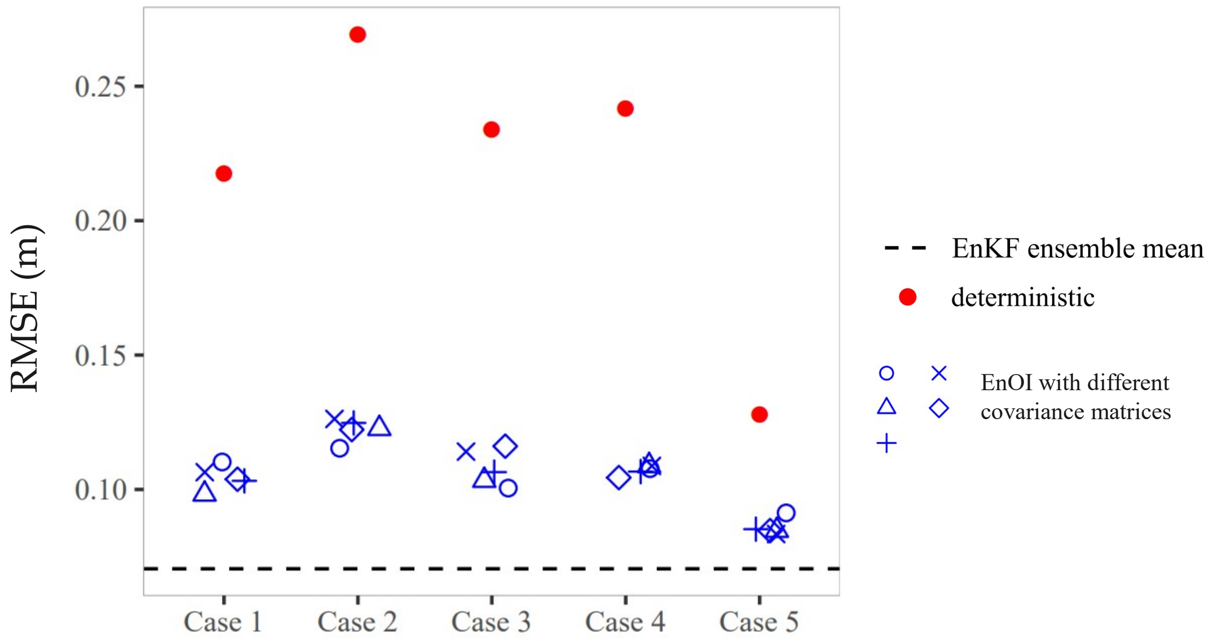


Fig. Average water level RMSE (m) at the three validation locations

Summary

- State estimation with EnOI led to better performance compared to the deterministic model run during the update stage

Future Steps

- ❑ Can the covariance matrices be adaptively changed within the EnOI framework?
- ❑ If so, does that yield better performances?
- ❑ Extend the study to other events and model uncertainties including experiments with real data

Thank you very much for your kind attention !!