# 2017 AGU: H51E-1304

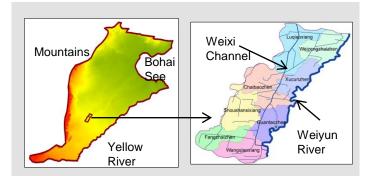
## Data assimilation for groundwater flow modelling using Unbiased Ensemble Square Root Filter: Case study in Guantao, North China Plain

**Ning Li**<sup>1</sup>, Wolfgang Kinzelbach<sup>1</sup>, Haitao Li<sup>2</sup>, Wenpeng Li<sup>2</sup>, Fei Chen<sup>3</sup>, Wang Lu<sup>1</sup> <sup>1</sup> ETH Zurich, **Email: ning.li@ifu.baug.ethz.ch**; <sup>2</sup>CIGEM; <sup>3</sup>GIWP

#### **1** Introduction

This study builds and evaluates a data assimilation system for the Guantao groundwater flow model coupled with a onedimensional soil column simulation (Hydrus 1D). It uses an Unbiased Ensemble Square Root Filter (UnEnSRF) based on the Ensemble Kalman Filter (EnKF) to update parameters and states, separately or simultaneously. In order to assure the continued functioning of the ensemble filter during the data assimilation, two factors are introduced in the study. One is a damping factor damping the update amplitude of the posterior ensemble mean to avoid nonrealistic values. The other is an inflation factor to relax the posterior ensemble distribution close to prior to avoid filter inbreeding problems.

#### 2 Study area



- Guantao County, located in the southern North China Plain, has an area of 456 km<sup>2</sup>
- Precipitation: 555 mm/yr
- Pan Evaporation: 1515.6 mm/yr
- Weiyun River: runoff volume 397 · 10<sup>6</sup> m<sup>3</sup>/yr (80% between July and October)
- ✤ Weixi Channel: 3.1 · 10<sup>6</sup> m<sup>3</sup>/yr
- ✤ Main crops: winter wheat, summer maize
- Environmental problems: groundwater depletion and land subsidence due to overpumping

#### 3 Method overview

#### ✓ Numerical models:

**1. Modflow:** groundwater flow simulation from 2003 to 2012, discretized into 210 rows and 190 columns with a grid size of 200 m by 200 m. Boundary conditions are specified by measured heads.

2. Hydrus 1D: soil water movement in the unsaturated soil column of 20 m discretized into 20 cm layers. A simplified linear relationship between inputs and outputs was established and is applied in the data assimilation. ✓ EnSRF:

$$\begin{aligned} X^{a} &= \overline{X^{a}} + X'^{a} \\ \overline{X^{a}} &= \overline{X^{f}} + \gamma K(Y^{obs} - \overline{Y^{f}}) & 0 \leq \gamma \leq 1 \\ X'^{a} &= X'^{f}T \\ X'^{a} &= (1 - \beta)X'^{a} + \beta X'^{f} & 0 \leq \beta \leq 1 \end{aligned}$$

X: Parameters (n x N) : 4 hk+ 4 SY + 2 Recharge Ratios; K: Kalman gain (n x m); Y: Calculations (m x N); Y<sup>obs</sup>: Real measurements (m x N); T: Transformation matrix;  $\beta$ : Covariance inflation factor;  $\gamma$ : Damping factor.

Typical parameter probability distributions (Log

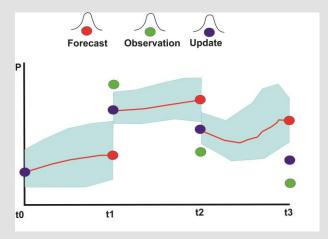
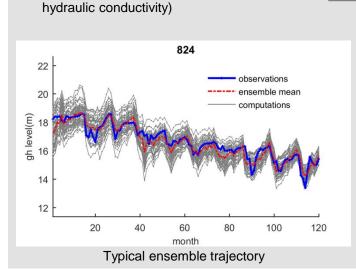


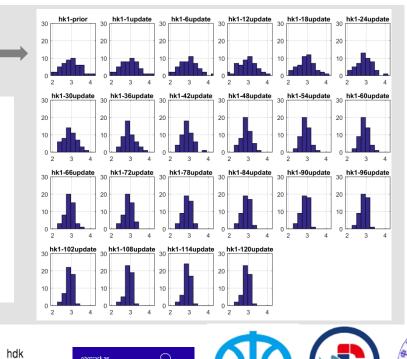
Fig.1 Parameters'/states' evolution with assimilation of observations (x-axis represents the assimilation time step; y-axis represents the parameters/states)

#### 4 Results



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### **5** Conclusion

- The simplified version of Hydrus 1d obtained from the best linear relationship to fit the output from Hydrus 1d works very well in data assimilation.
- The Ensemble Square Root filter is adopted for data assimilation. When parameters and states are updated simultaneously, filter inbreeding occurs. This is not observed when only states are updated.
- The filter inbreeding problems could be mitigated by covariance inflation. The combination of covariance inflation with a damping factor works very well in this study.
- The distributions of parameters become narrower and narrower while assimilating observations. This also means that the uncertainty of parameters can be significantly improved by incorporating observations.
- With updating, the ensemble mean fits the observations quite well. This indicates that the data assimilation has improved the model accuracy. Simultaneously the model uncertainty is reduced.

#### **6** References

- Hunt, B.R., Kostelich, E.J., Szunyogh, I. (2007). Efficient data assimilation for spatiotemporal chaos: A local ensemble transform Kalman filter. Physica D: Nonlinear Phenomena. 230(1), 112-126.
- Hendricks Franssen, H.J., Kinzelbach, W. (2008). Real-time groundwater flow modeling with the ensemble Kalman filter: Joint estimation of states and parameters and the filter inbreeding problem. Water Resources Research, 44(9).
- Zhang, F., Snyder, C., Sun, J. (2004). Impacts of initial estimate and observation availability on convective-scale data assimilation with an ensemble Kalman filter. Monthly Weather Review, 132(5), 1238-1253.

