Data Assimilation with the Ensemble Kalman Filter using Integrated Subsurface Flow Models

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Abstract

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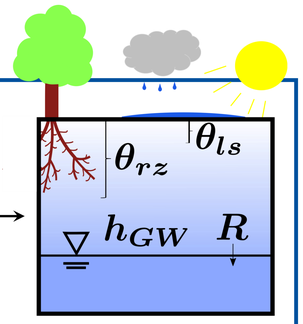
Outstanding Student & PhD candidate Presentation contest

FOR 2131

DFG

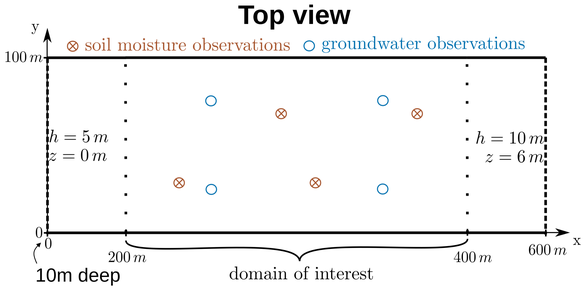
Motivation and Aim

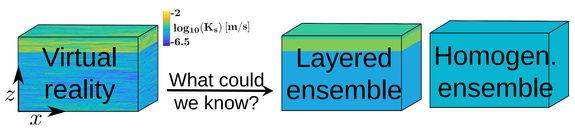
- Data assimilation (DA): estimate the most likely model state *given* the observations
- Integrated subsurface flow: vadose zone and groundwater →
- **Which** observations should be used?
- **How** should they be used?



Setup

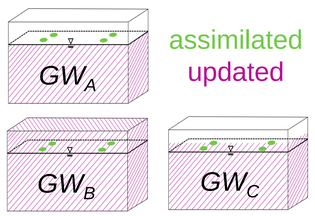
Top view





DA experiments

- Soil moisture DA (*SM*)
  bias correction *(bias)*
- Groundwater table DA
  three different update variants:



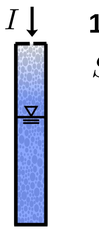
- Multivariate DA (*SMGW*)
  assimilating both soil moisture and groundwater tables

- 100 ensemble members
- Updating parameters (α,n,K_s,ϕ)
- t_{max} = 200 *d*, DA turned off at 150 *d*
- Estimating spatial averages (small domain)

Conclusions

- Largest errors furthest away from the observations (bias correction can tackle this)
- Updating the deep vadose zone along with the groundwater gave best estimates
- Groundwater recharge predictions improved after parameters were updated by DA
- For root zone soil moisture estimates
  - knowledge of soil layering matters
  - assimilating observations from both compartments is beneficial

Methodology

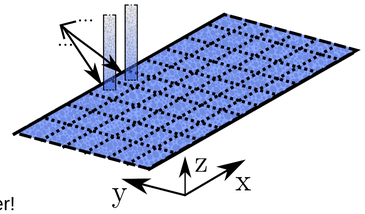


1D model contains groundwater!

1D variably saturated flow [1]

$$S_s\, S_w(\psi)\, \frac{\partial \psi}{\partial t} + \phi\, \frac{\partial S_w(\psi)}{\partial t} = \nabla \cdot [K(\psi) \nabla h] + Q_s$$

coupled [2] iteratively



2D groundwater flow

$$S_y \frac{\partial h}{\partial t} = \nabla \cdot \left[\overline{K}_s (h - z_0) \nabla h\right] + R$$

estimated by the model

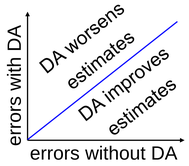
Ensemble Kalman Filter [3]

$$X_k^a = X_k^f + K_k \left(Y_k^{obs} - Y_k^f\right)$$

Bias correction [4]

Update bias terms within the filter

Results

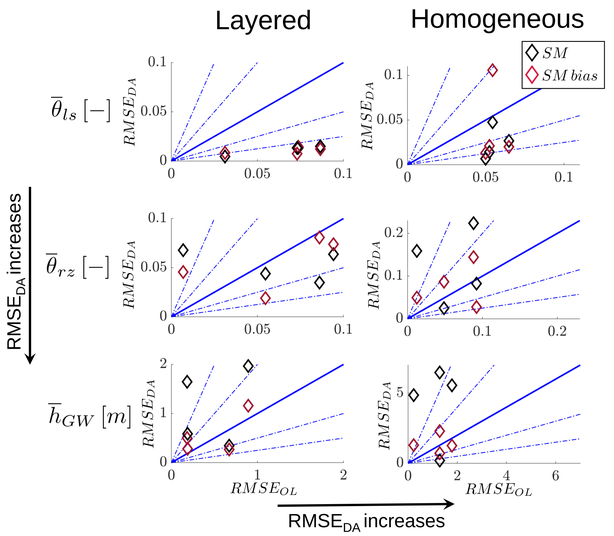


$$RMSE = \sqrt{\frac{\sum_{i=1}^{N_t} \left(\overline{x_i} - x_i^{VR}\right)^2}{N_t}}$$

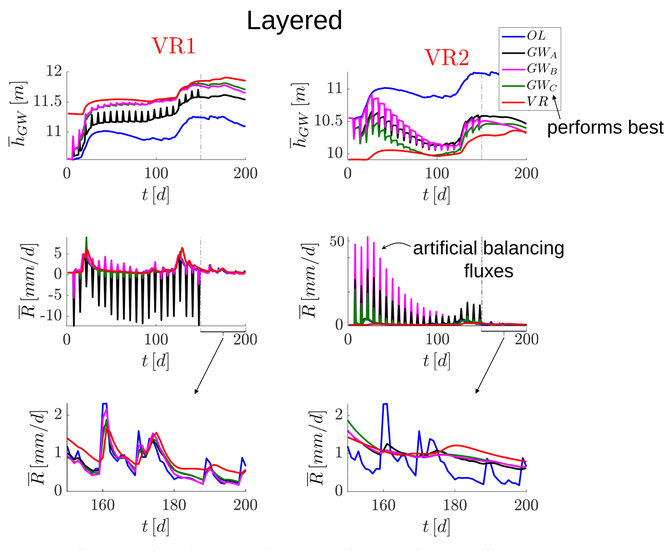
estimated ensemble mean

estimate from virtual reality

Soil moisture DA

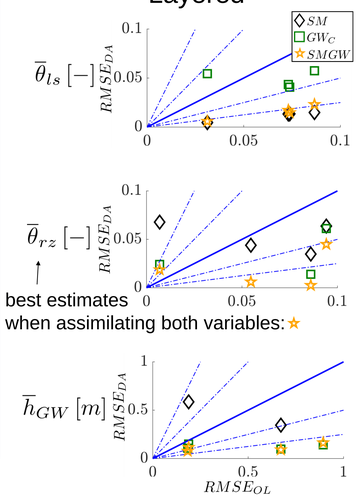


Groundwater table DA



Multivariate DA

Layered



best estimates when assimilating both variables: ☆

References

[1] Richards, L. A. (1931). Capillary conduction of liquids through porous mediums. Physics,1(5):318–333.
[2] Brandhorst, Natascha, Daniel Erdal, and Insa Neuweiler. "Coupling saturated and unsaturated flow: comparing the iterative and the non-iterative approach." *Hydrology and Earth System Sciences* 25.7 (2021): 4041-4059.
[3] Evensen, G. (1994). Sequential data assimilation with a nonlinear quasi-geostrophic model using Monte Carlo methods to forecast error statistics. Journal of Geophysical Research: Oceans, 99(C5):10143–10162.
[4] Madsen, H. and Canizares, R. (1999). Comparison of extended and ensemble Kalman filters for data assimilation in coastal area modelling. International Journal for Numerical Methods in Fluids, 31(6):961–981.