H51E-1308: A groundwater data assimilation application study in the Heihe mid-reach

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Motivation

- Irrigated agriculture is a major socio-economic pillar in the oasis of Zhangye in the arid North-West of China.
- Irrigation is done with surface water where available and supplemented with groundwater.
- Overdraft of groundwater occurs in two districts where surface water is either in short supply or not available at all.

➡The management task is to optimize the distribution of the water resources in the oasis while maintaining a minimum environmental flow in the river.

- The basis for optimization is a groundwater model. Here a state of the art numerical groundwater flow model is presented which assimilates real-time observations and produces forecasts of groundwater levels including their uncertainty to inform decision makers.

➡Goal of this poster: How to configure the data assimilation tools to achieve optimal model performance?

- Model based formal optimization of water allocation is discussed in the related poster H23J-1811: Multi-objective optimization for conjunctive water use using coupled hydrogeological and agronomic models: a case study in Heihe mid-reach (China) by Yu Li et al.

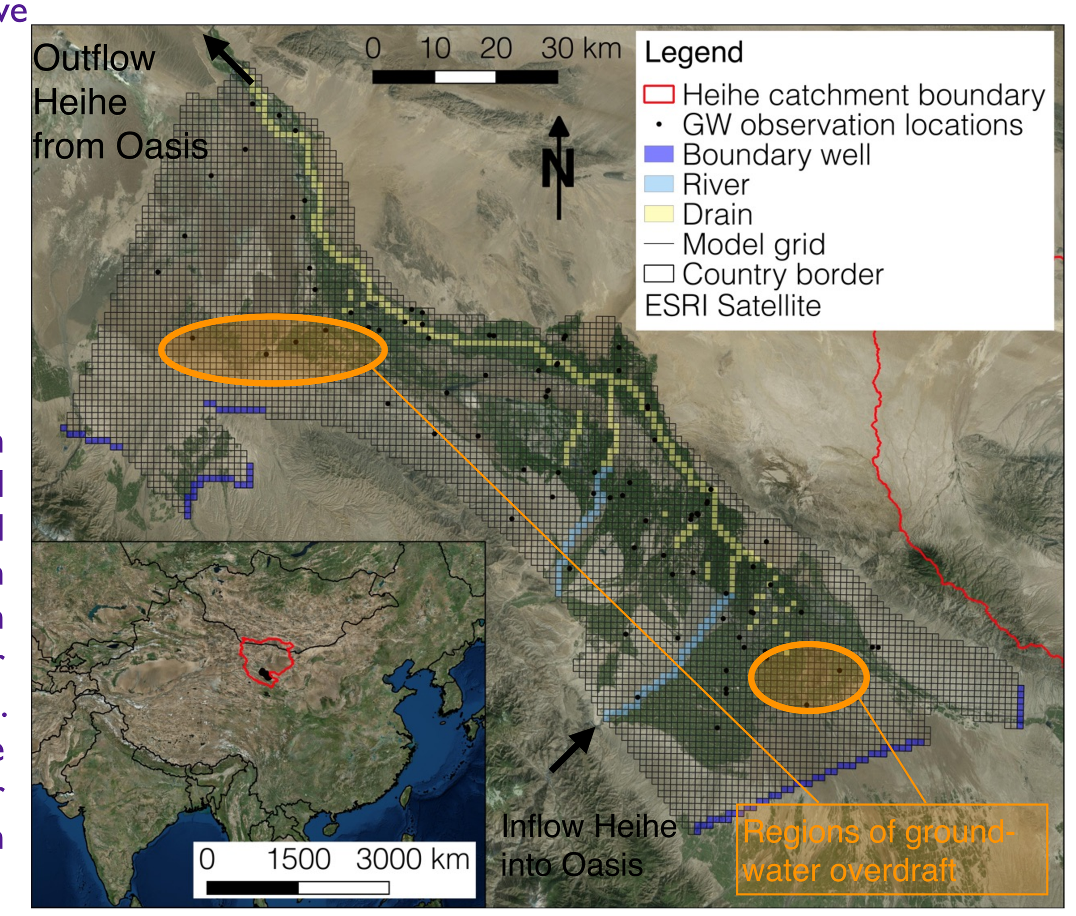

Figure 1 : Heihe river catchment in North-West China with model area. The rivers Heihe and Liyuanhe recharge the aquifer in the blue zones. In lower elevation area the river drains the aquifer and is implemented as drain. Inflows from the boundaries are estimated with a detailed water balance and implemented with boundary wells.

Data & Sources

43 monthly groundwater level observations between 1986 and 2012. Yearly groundwater abstraction rates and surface water delivery rates between 1990 and 2007. Monthly streamflow data between 1987 and 2006. Geological maps from the Chinese National Geological Survey. For data assimilation groundwater levels from 145 observation locations were available (many of them very short, recent time series).

Method

Numerical groundwater flow model : Detailed water balance study and numerical groundwater flow model using Modflow. Steady-state and transient calibration with 11 hydraulic conductivity zones and 7 specific yield zones.

Data assimilation : Correction of known constant bias between modelled and observed groundwater levels prior to data assimilation. Ensemble Kalman filter (EnKF) for joint state and parameter update (Hendricks-Franssen & Kinzelbach, 2008) and asynchronous data assimilation (Sakov et al., 2010):

$$x_t^+ = x_t + \alpha K_t\left(y_t - Hx_t\right) \quad \text{with} \quad x_t = \left[h_t; p_t; \ldots; p_{t-T}\right]$$

where t: current time step, h: groundwater levels in each model cell for each replicate, p: parameters [hydraulic conductivity zone values; specific yield zone values; ....], H: transformation matrix maps simulation results to observation locations, α: damping factor $\in [0,1]$, K: Kalman gain matrix, y: observations.

Against filter inbreeding following measures where implemented: Covariance inflation around the mean of the simulated heads $\overline{h_t^*}$ with factor λ (Anderson, 2007)

$$h_t = \lambda\left(h_t^* - \overline{h_t^*}\right) + \overline{h_t^*}$$

Spatial localization (Houtekamer & Mitchell, 2001) using a compactly supported fifth-order piecewise rational function ρ with a similar shape as a bell curve to weight the covariance matrix (values farther away than r_c are 0).

$$K_t = \frac{\rho \circ \left(C_t H\right)}{\rho \circ \left(H C_t H^T\right) + R}$$

with C: Model state ensemble covariance matrix and R: observation error covariance matrix. Red symbols represent filter parameters which need tuning.

Preliminary Results

Bias correction : Although EnKF can compensate for biased observations, model results become better if known constant biases are corrected prior to data assimilation.

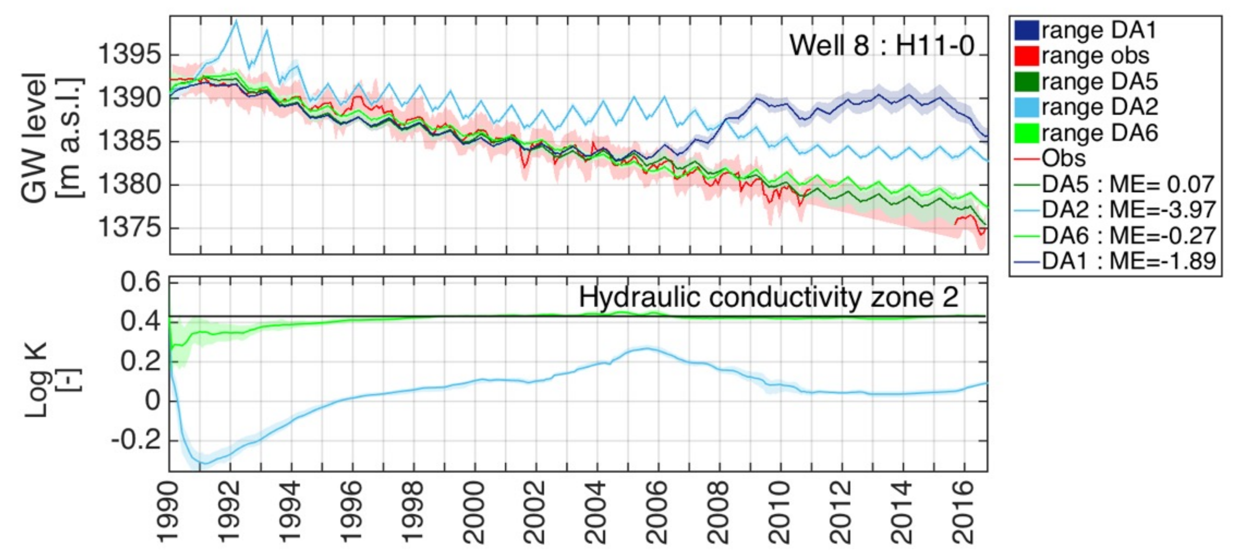

Figure 2 : Bias correction (green lines: DA5, DA6) vs. no bias correc-tion (blue lines, DA1 & DA2) & update of only states (light lines, DA1, DA5) vs. joint update of states and parameters (dark lines, DA2, DA6). Red: observed groundwater level.

Ensemble size : The present model is not sensitive to ensemble size. This might be due to a choice of replicates which are well balanced around the ensemble mean and many groundwater levels are not sensitive to initial conditions because they are determined by drains.

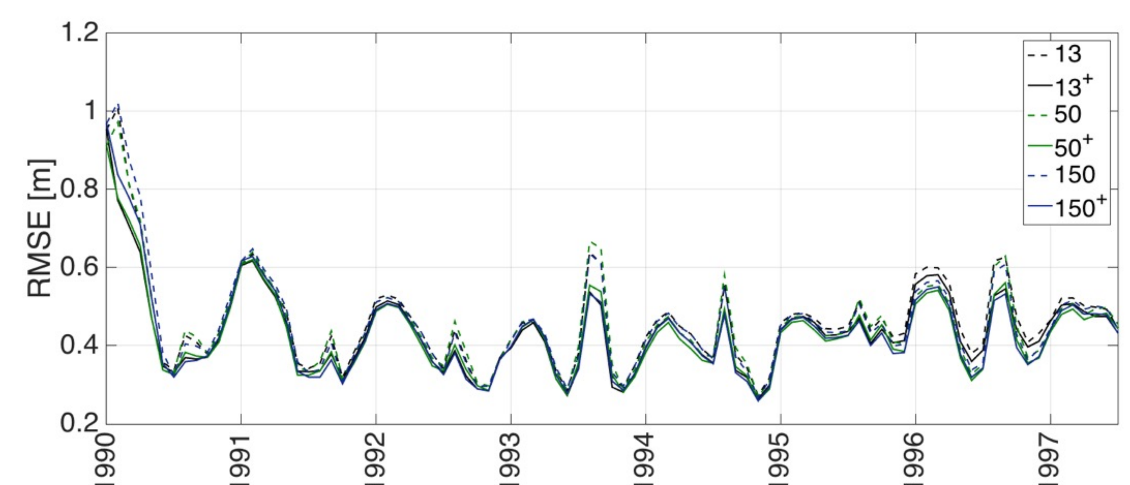

Figure 3 : Model results for ensemble sizes of 13, 50, and 150 replicates. Simulation results prior to the model update are shown in dashed lines, simulation results after updating are marked with + shown in solid lines.

Parameter update frequency : Different frequencies for asynchronous parameter updates have been compared. Very high update frequency for parameters is not recommended for this model which shows a strong seasonality in the model errors (see also Figure 3) because the EnKF will try to compensate for the model error by seasonally changing the parameters.

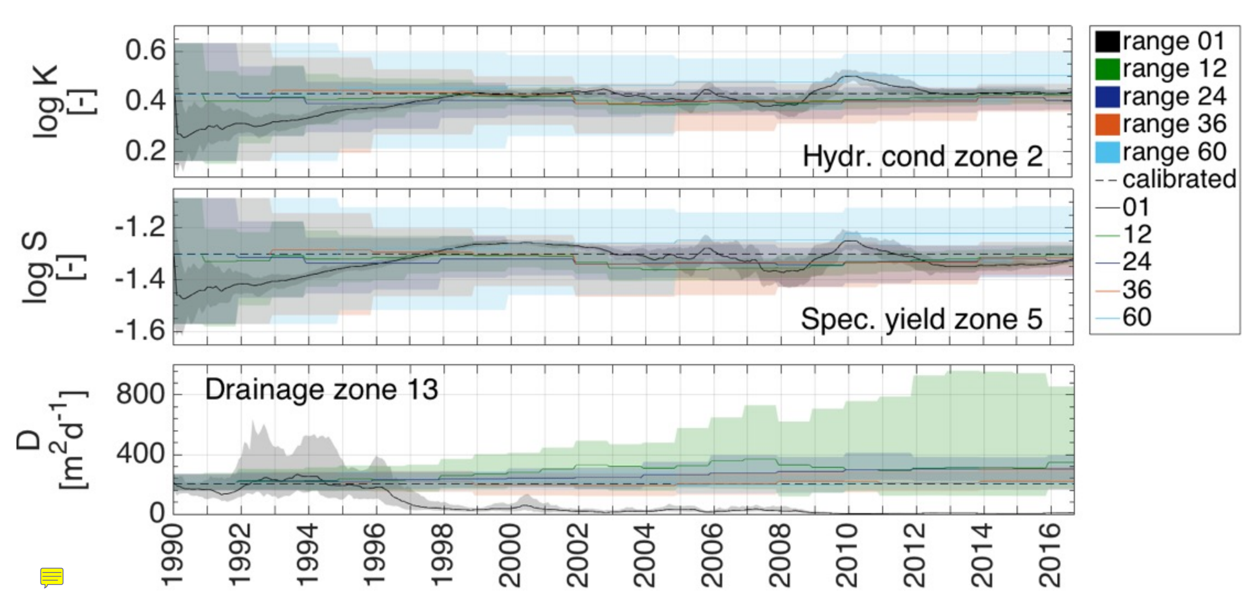

Figure 4 : Parameter update intervals from 1 to 60 months. Heads are updated every time step and parameters are updated asynchronously every 1, 12, 24, 36, or 60 time steps.

Filter inbreeding counter measures : Damping of parameter updates (α=0.1) does not improve the results. An inappropriate choice of EnKF parameters, e.g. the range of influence for the spacial localization r_c, can lead to worse Filter performance than leaving out filter inbreeding countermeasures altogether.

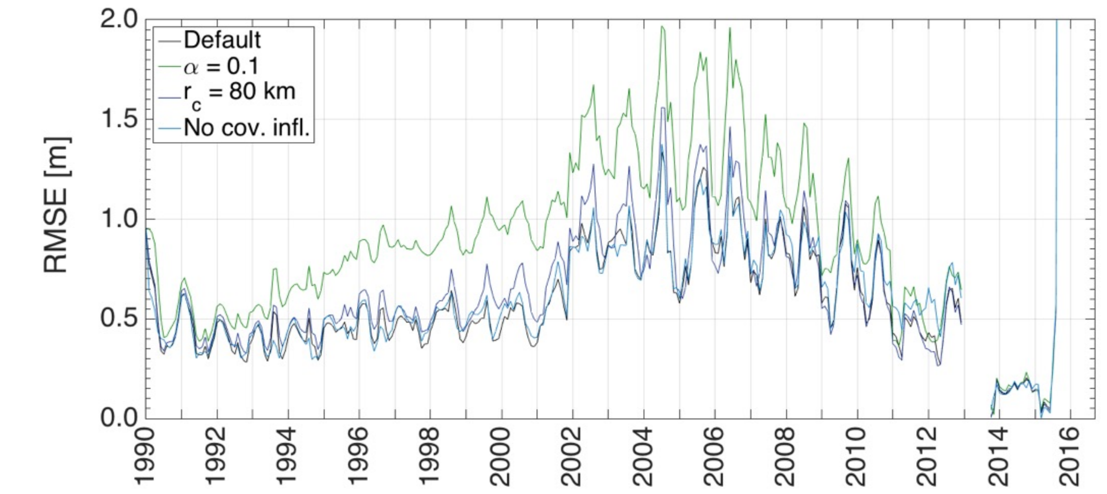

Figure 5 : Parameter update intervals from 1 to 60 months. Heads are updated every time step and parameters are updated asynchronously every 1, 12, 24, 36, or 60 time steps.

Choice of observations and variances : The choice of observations and their variance has a big impact on the performance of the EnKF. In the present example, model performance is better if also observations are included. Overestimation of the observation errors leads to model deterioration.

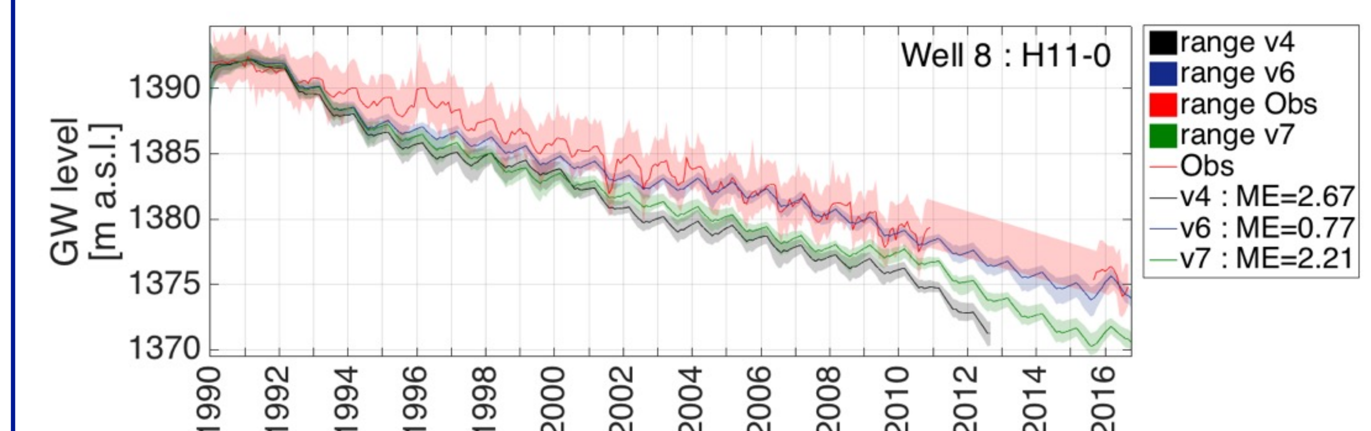

Figure 6 : v4: exclude observations influenced by drains, v6: all observations, small variances, v7: all observations, large variances.

Conclusions

- All known biases should be corrected. The better the model, the better the real-time model
- Filter tuning is not sensitive to ensemble size in this study
- Asynchronous parameter updates are especially useful for slow changing parameters and for models with seasonality in errors.
- Covariance inflation and spatial localization are very useful tools to counter filter inbreeding. Damping of parameter updates did not have the same desired effect on model performance
- Model performance improved the more observations were included in the data assimilation. Great care has to be given to the estimation of the observation variances.

References, Acknowledgements, Funding

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