

STREAM FLOW PREDICTION AT BARTON SPRINGS USING ENSEMBLE KALMAN FILTER TECHNIQUES

Data Assimilation Workshop

August 31, 2007

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MOTIVATION

- The goal of this study is to improve prediction of discharge at Barton Springs for the purpose of preserving:
 - water resources used by the city of Austin
 - environment for the Barton Springs Salamander
- Explore the use of an Ensemble Kalman Filter (EnKF) to make real time updates of a MODFLOW model
- Investigate the possibility that EnKF methods can be used to calibrate the model

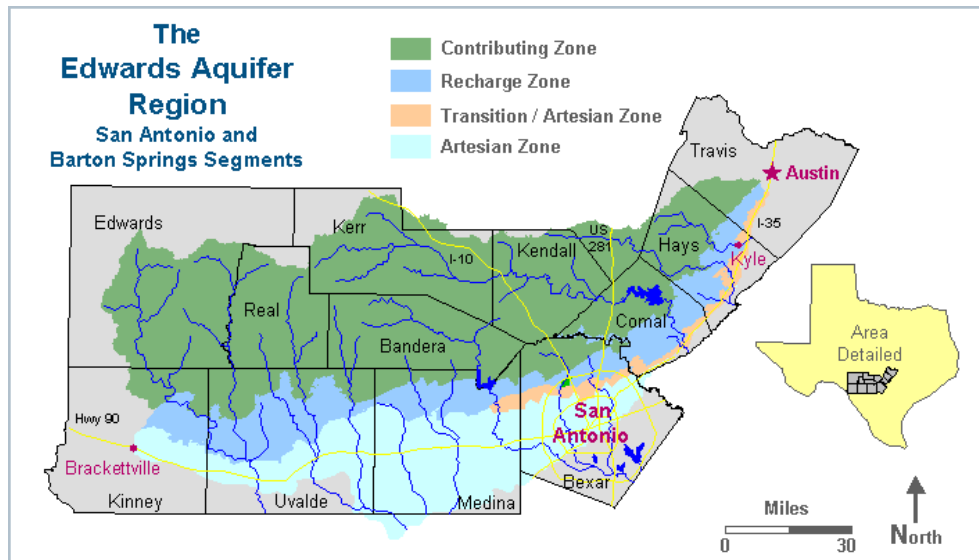


OUTLINE

1. Background on Barton Springs
2. Scanlon et al. 2001 MODFLOW model
3. Ensemble Kalman Filter (EnKF)
4. Comparison of MODFLOW and EnKF results
5. Areas for future research

BACKGROUND

- Barton Springs is fed by the Edwards Aquifer, which is used as the primary drinking water source for the city of Austin
- The Edwards Aquifer groundwater supply is challenged by recent drought and population growth in Central Texas
- Managing discharge at Barton Springs is important to ensure continued habitat for the Barton Springs Salamander, listed as an endangered species in 1997

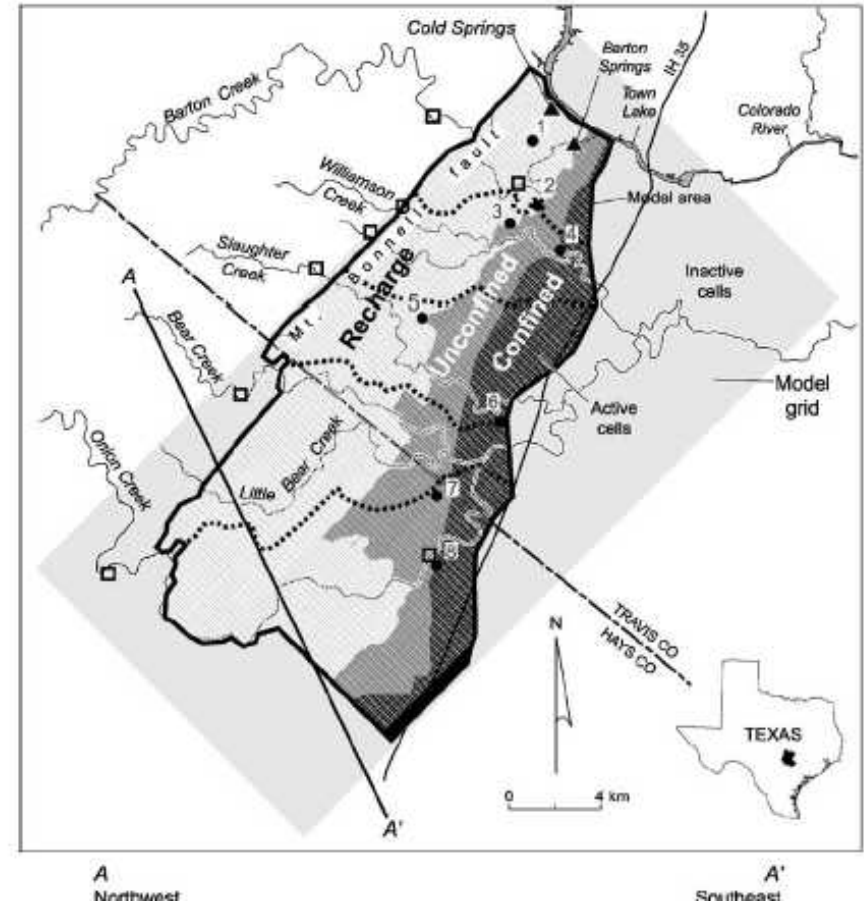


MODFLOW MODEL

- Scanlon et al., 2001

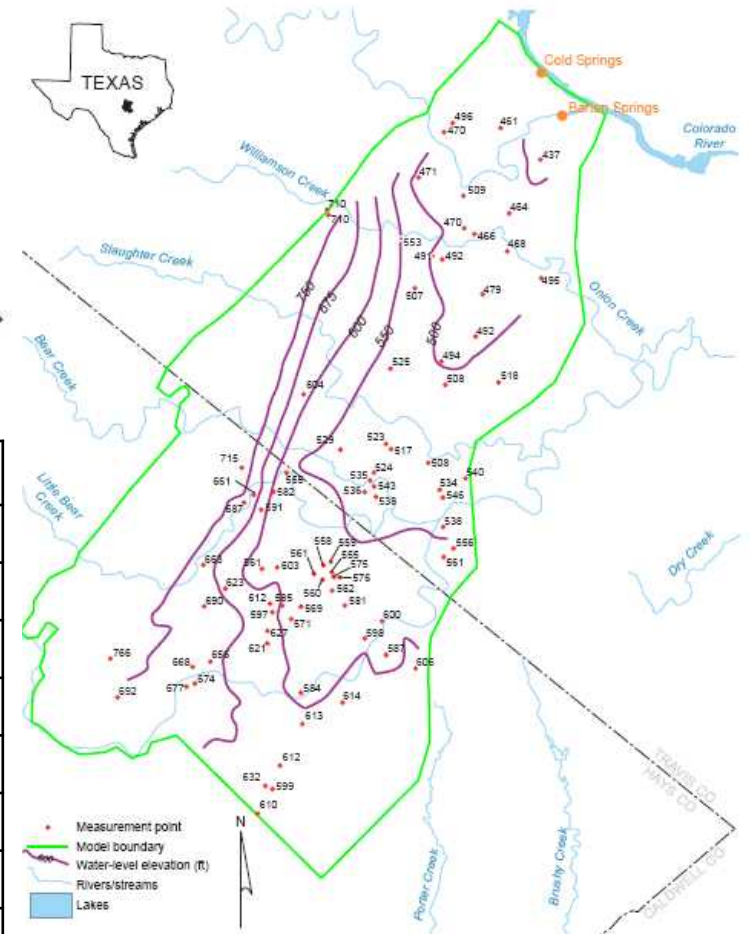
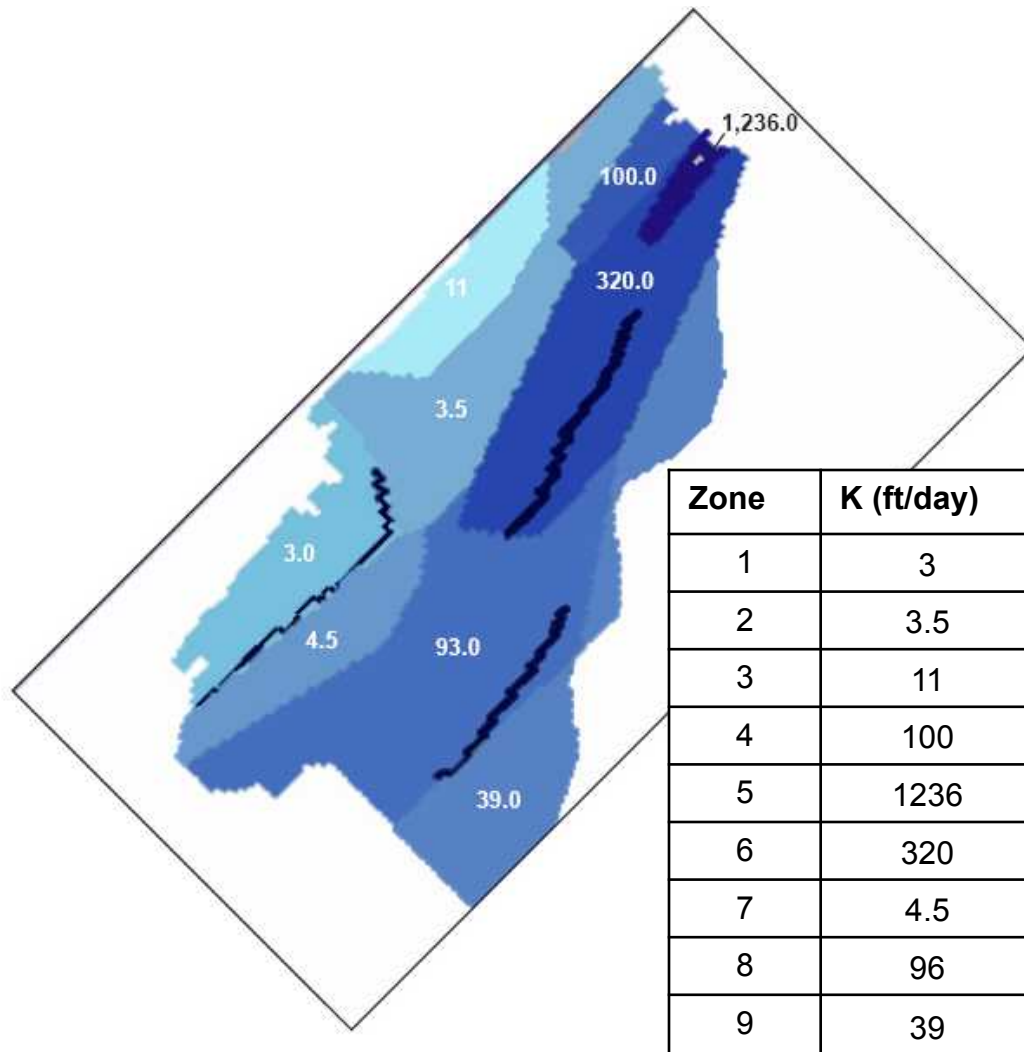
Scanlon, B. R., R.E. Mace, B. Smith, S. Hovorka, A.R. Dutton, R. Reedy, 2001, Groundwater Availability of the Barton Springs Segment of the Edwards Aquifer, Texas: Numerical Simulations Through 2050, Lower Colorado River Authority (UTA99-0)

- 120 by 120 grid cells covering an area of approximately 250 square miles
- 10 year model from 1989 to 1999, monthly time step
- Model includes groundwater pumping, rainfall and creek recharge (5 creeks)
- Hydraulic conductivity (K) is divided into 9 zones based on the distribution of head gradients within the region



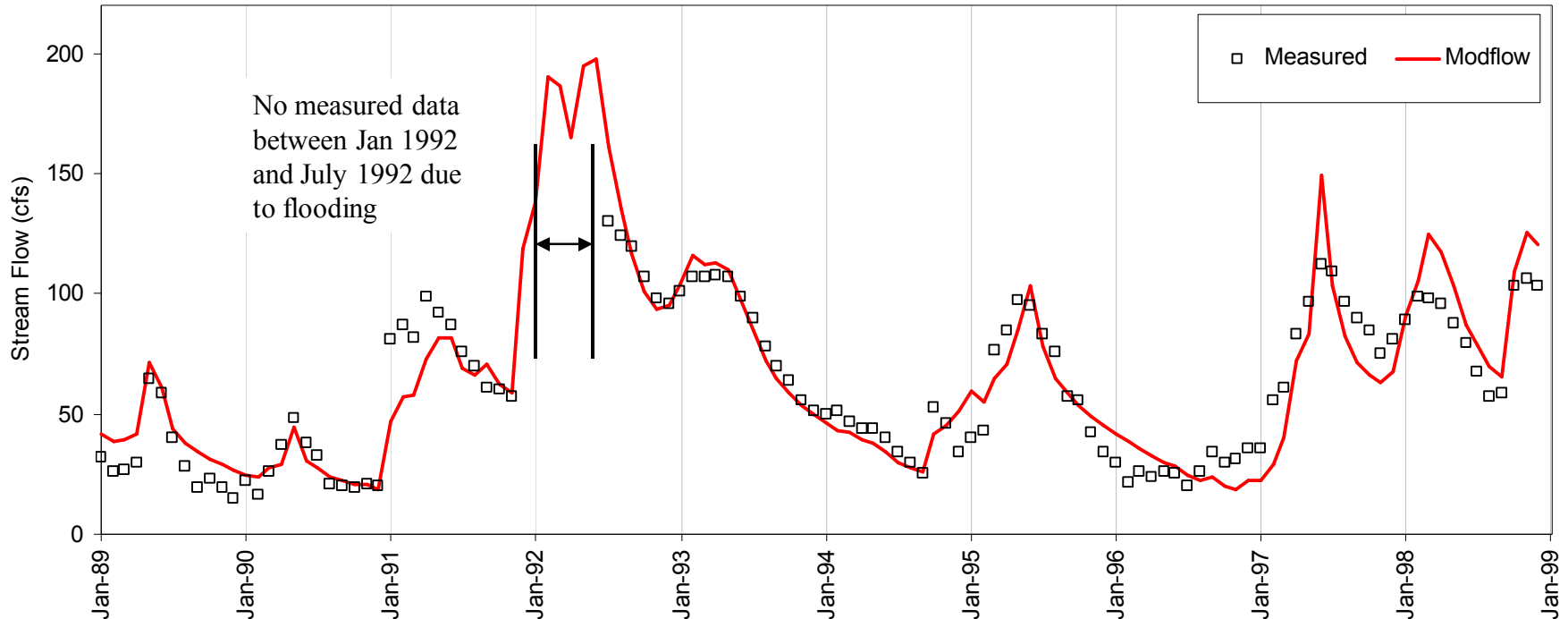
MODFLOW MODEL

- Zonal distribution of hydraulic conductivity resulting from the calibration



MODFLOW MODEL RESULTS

- Measured stream flow compared to MODFLOW results



Average difference = 9.5 cfs



ENSEMBLE KALMAN FILTER

- EnKF is a type of data assimilation that can be applied to highly nonlinear systems
- Data assimilation merges diverse data to make predictions of a dynamic system
- Data assimilation methods are used for:
 - model updating for real-time forecasting
 - model calibration
- Alternative to inverse methods for parameter estimation
 - potential time savings



ENSEMBLE KALMAN FILTER

- “Predictor-corrector” method
- An ensemble of state variables are corrected for each time step based on:
 - Kalman Gain (KG)
 - Difference between model predictions and physical observations

$$KG = \frac{COVA(K_p, SF_{mod})}{VAR(SF_{mod})} \quad K_u = K_p + KG * (SF_{mod} - SF_{meas})$$

K_p = present hydraulic conductivity = state variable

K_u = updated hydraulic conductivity

SF_{mod} = modeled stream flow = control variable

SF_{meas} = measured stream flow = observation



ENSEMBLE KALMAN FILTER

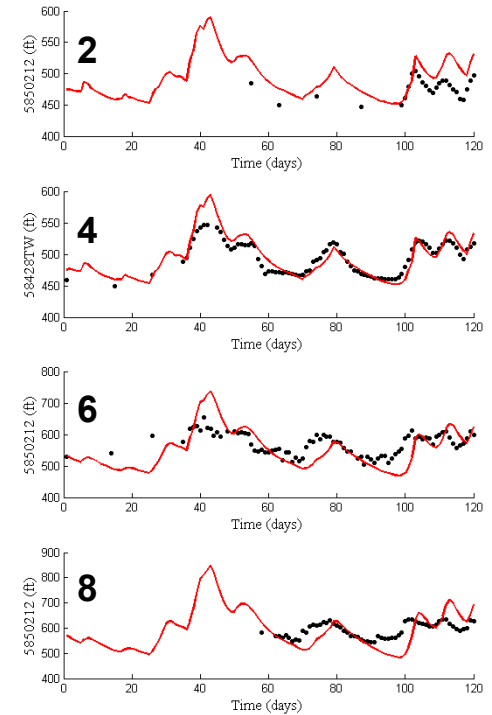
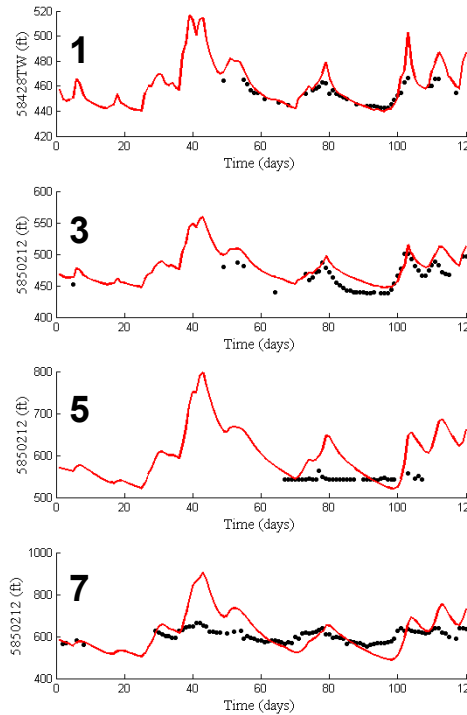
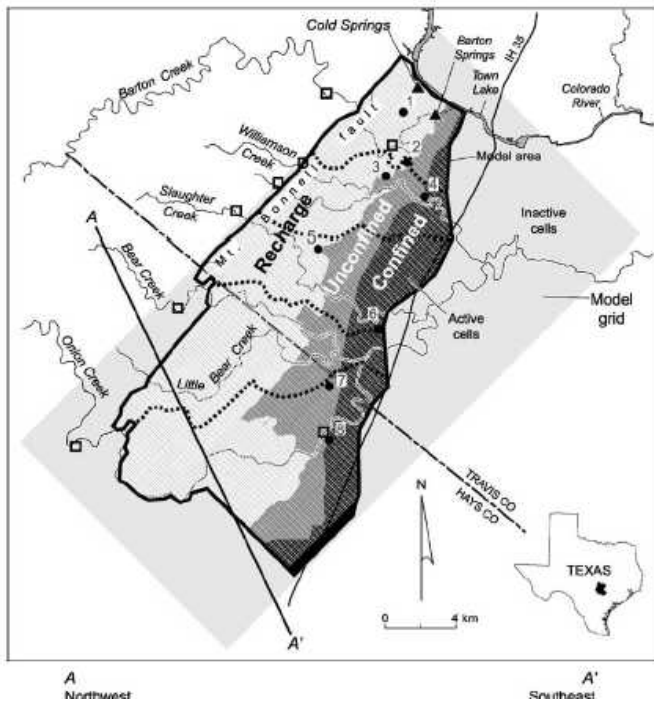
- MODFLOW = single realization of K, based on calibration
- EnKF = continuously update multiple realizations of K using current data
- EnKF updates are based on 2 methods:
 - single update per time step
 - iterative update to ensure that the state variables (K_p) approximates control data (SF_{mod}) to within a specified tolerance (5 cfs)

$$KG = \frac{COVA(K_p, SF_{mod})}{VAR(SF_{mod})} \quad K_u = K_p + KG * (SF_{mod} - SF_{meas})$$

- Some fluctuation in K is reasonable, considering the karstic nature of the aquifer

ENSEMBLE KALMAN FILTER

- Well hydrographs can also be used as a control parameter

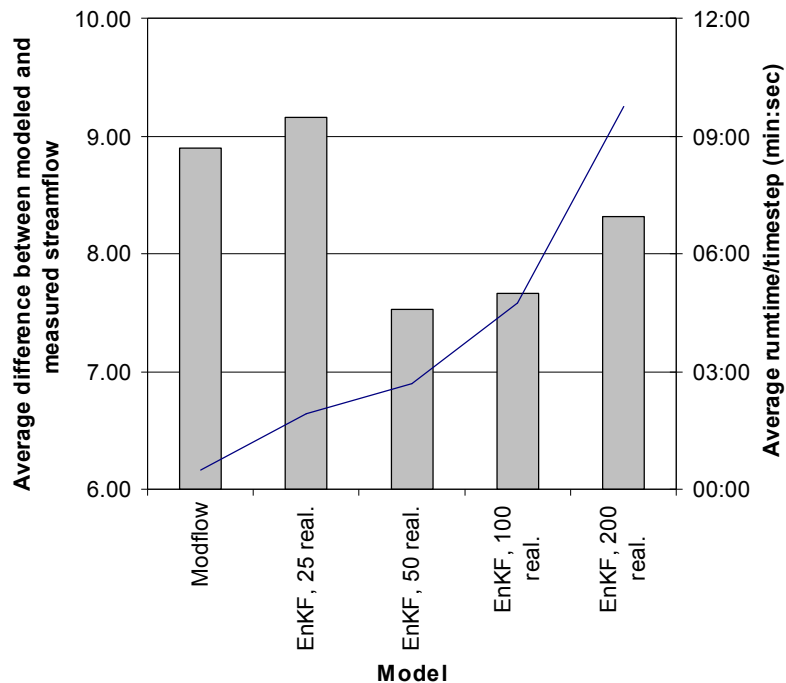
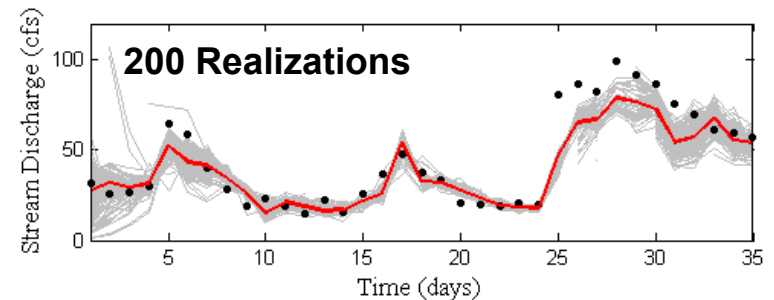
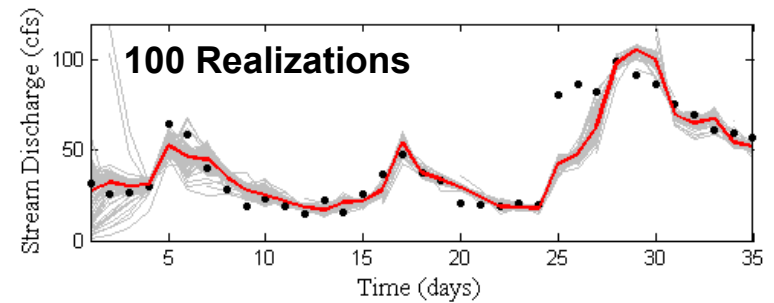
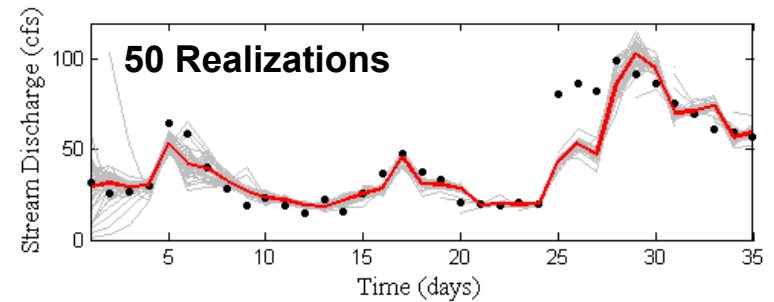
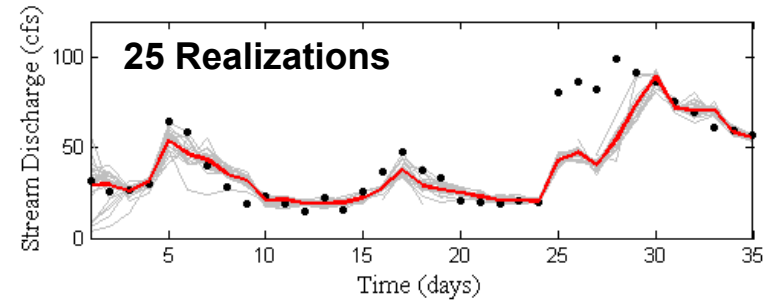
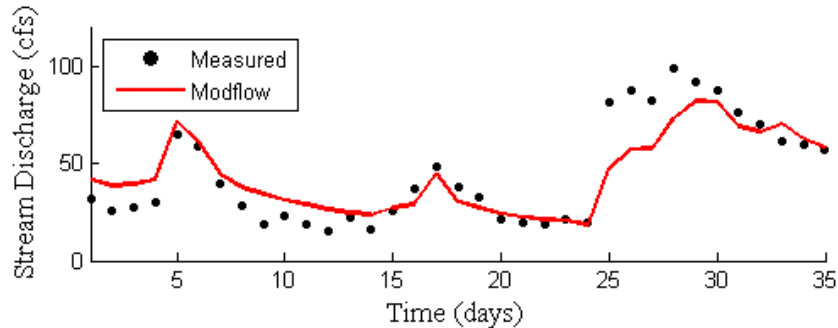


$$KG_{SF} = \frac{COVA(K_p, SF_{mod})}{VAR(SF_{mod})}, \quad KG_{WH} = \frac{COVA(K_p, WH_{mod})}{VAR(WH_{mod})}$$

$$K_u = K_p + KG_{SF} * (SF_{mod} - SF_{meas}) + KG_{WH} * (WH_{mod} - WH_{meas})$$

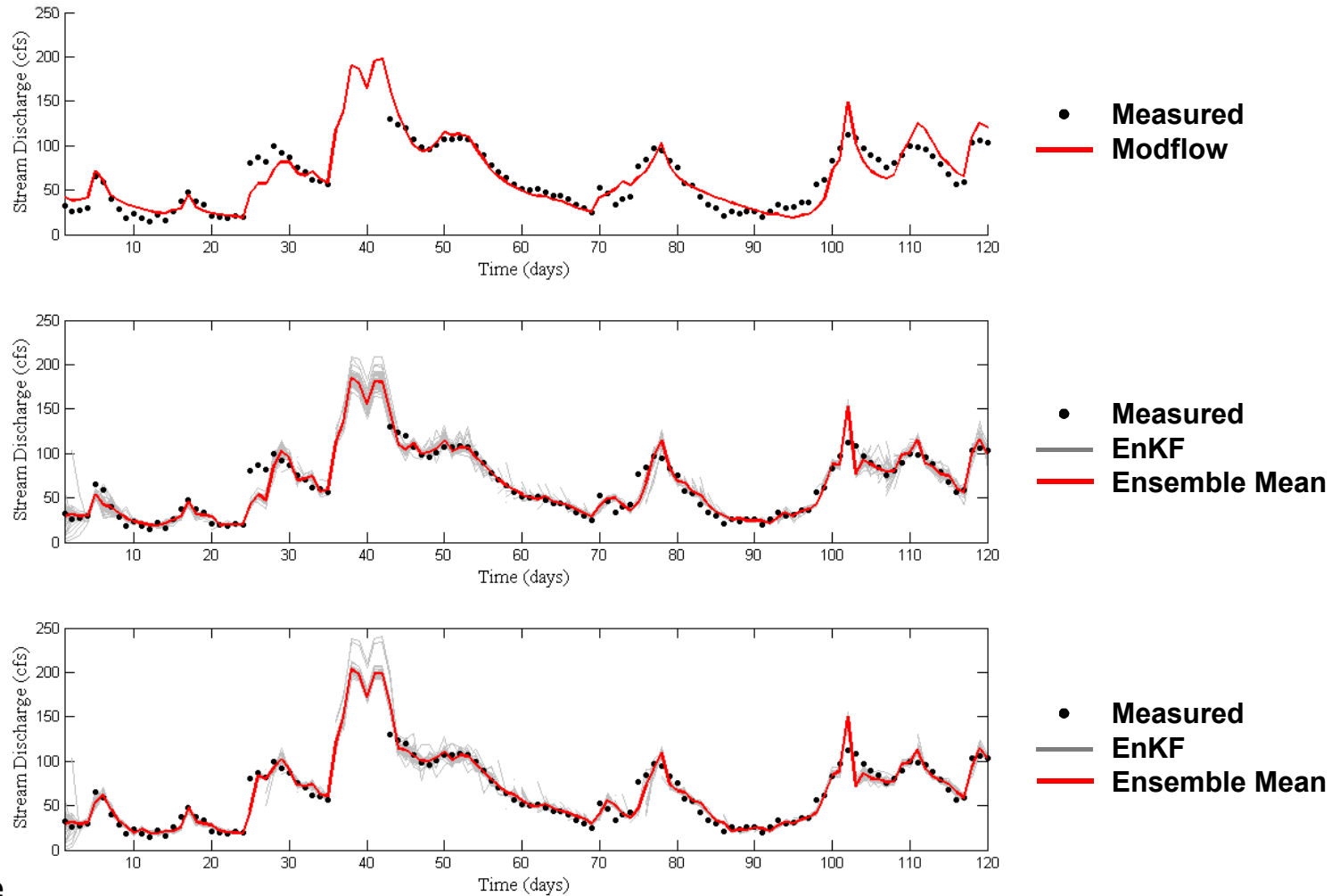
NUMBER OF REALIZATIONS

- Analysis using first 35 days
- Single update, SF only



EnKF RESULTS

- Control Data = SF only



Average difference

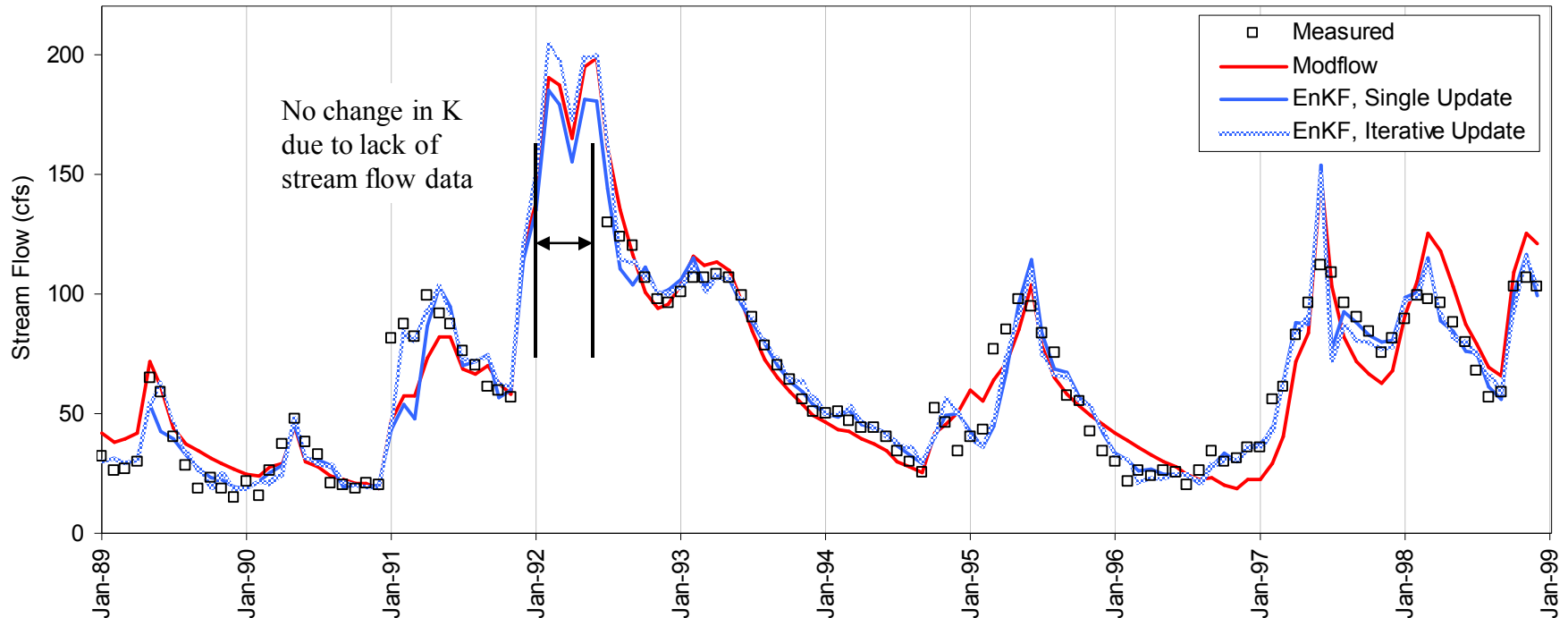
MODFLOW = 9.5 cfs

EnKF, Single Update = 7.0 cfs, 26.3% improvement

EnKF, Iterative Update = 6.1 cfs, 35.3% improvement

EnKF RESULTS using SF

- Measured stream flow compared to MODFLOW and EnKF results



Average difference

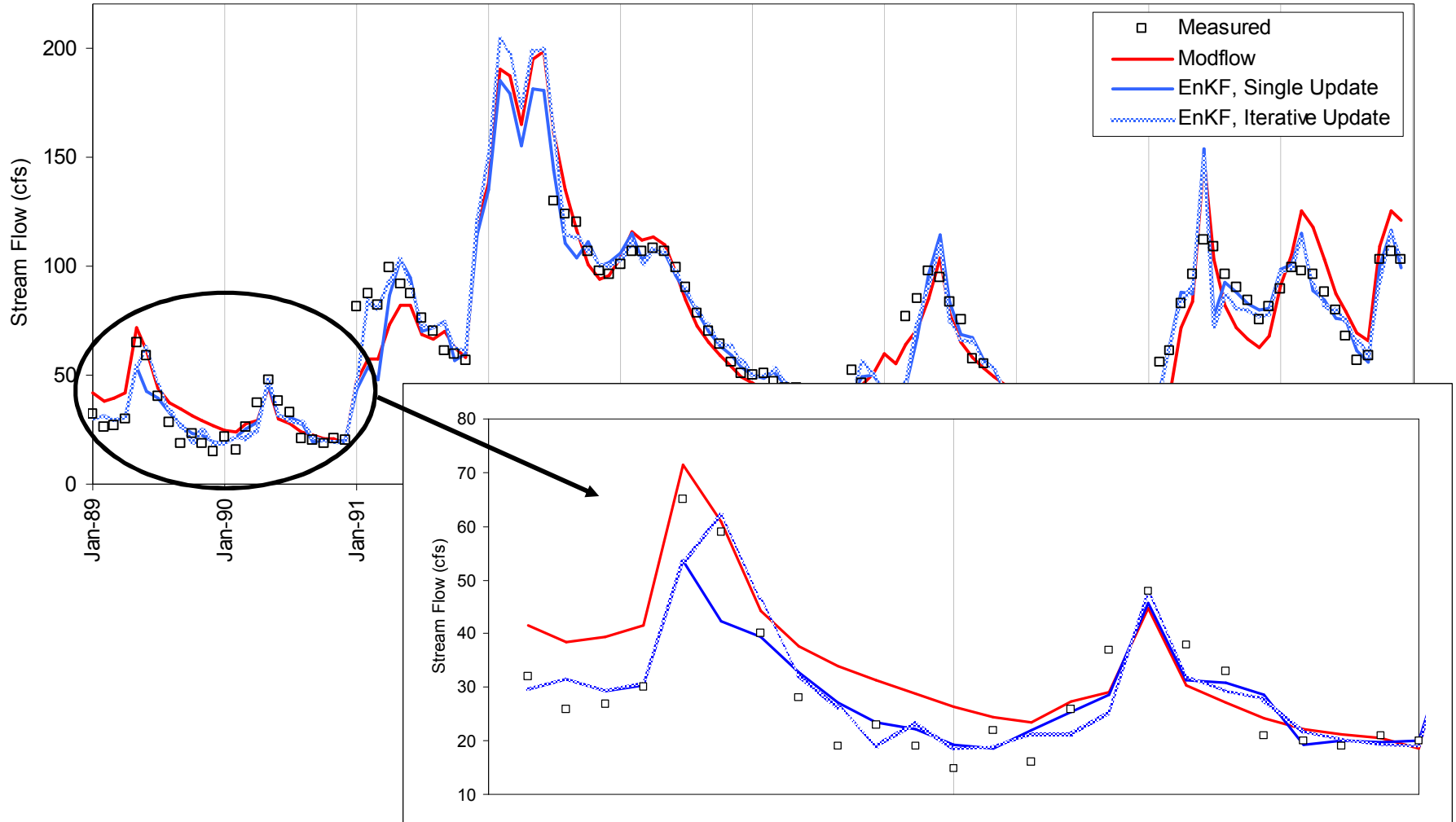
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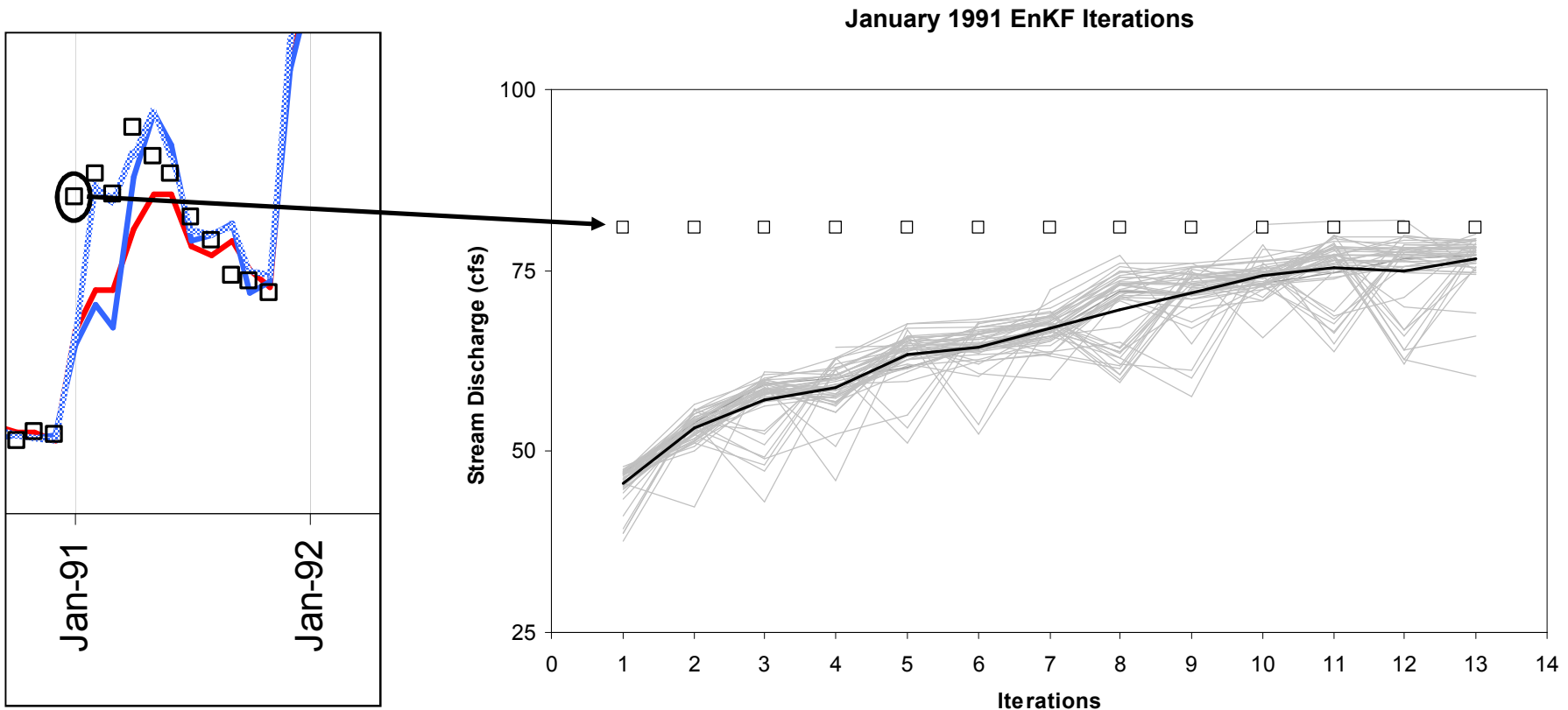
EnKF RESULTS, compare single and iterative update

- Improvement using EnKF



EnKF RESULTS

- Main advantage in using iterative approach

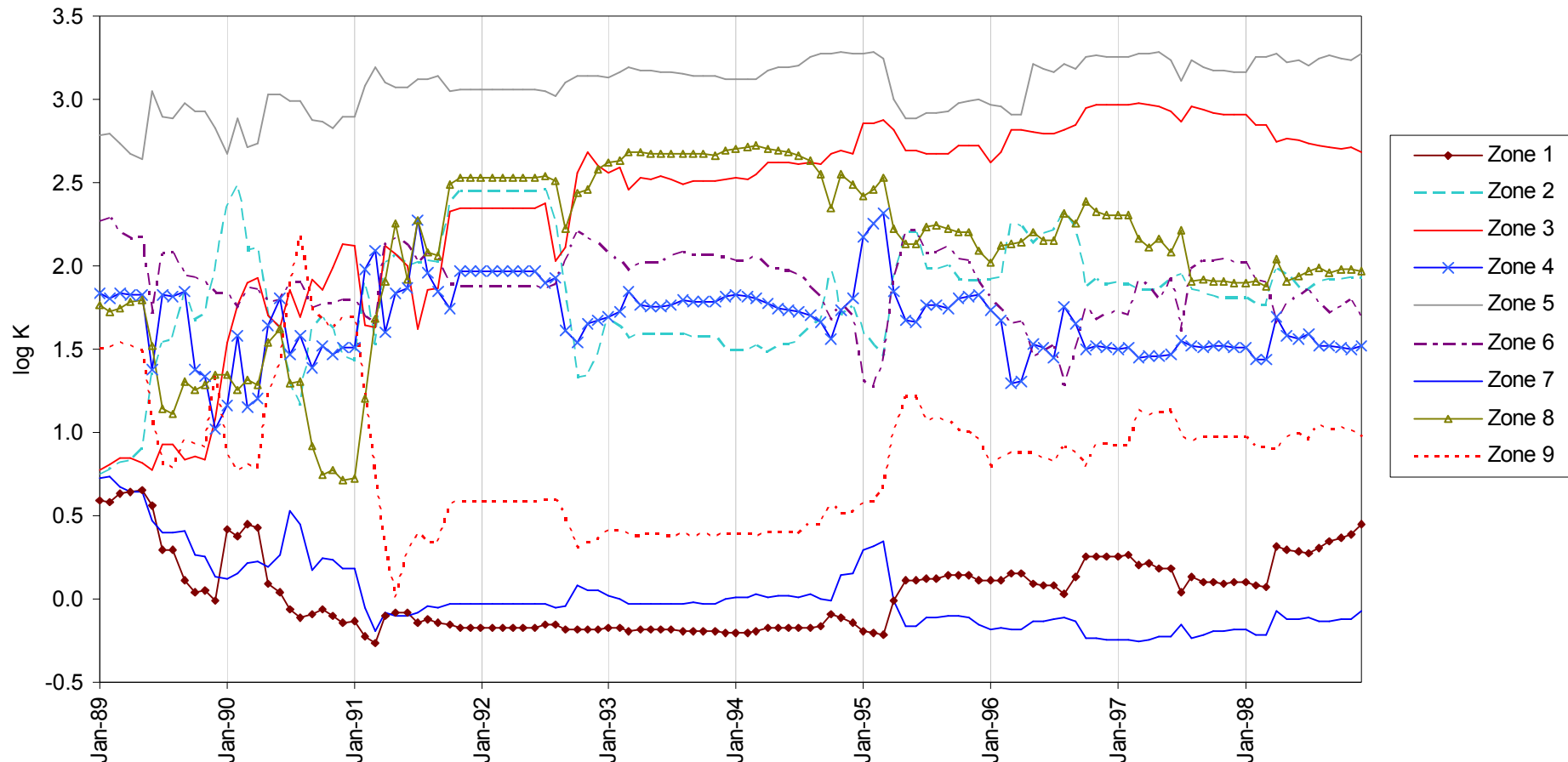


13 iterations to achieve a tolerance of 5 cfs

In general, the number of iterations remains between 1 to 3 for most time steps

EnKF RESULTS

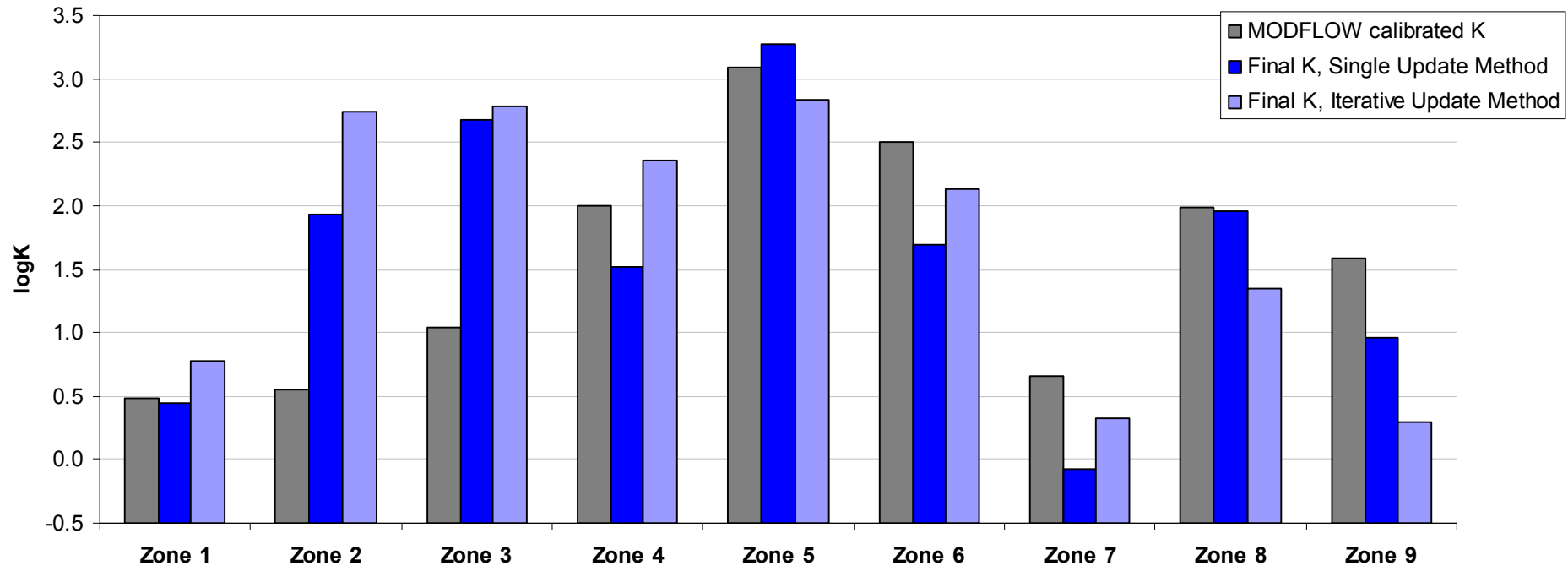
- Change in K, single update method
- Similar variation using iterative update method



Greatest change = Zone 2 and 3. Least change = Zone 1 and 8

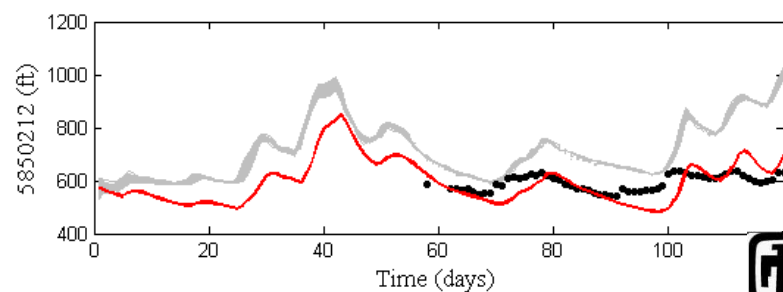
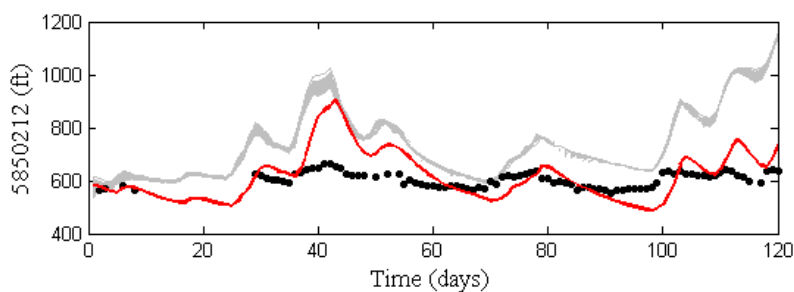
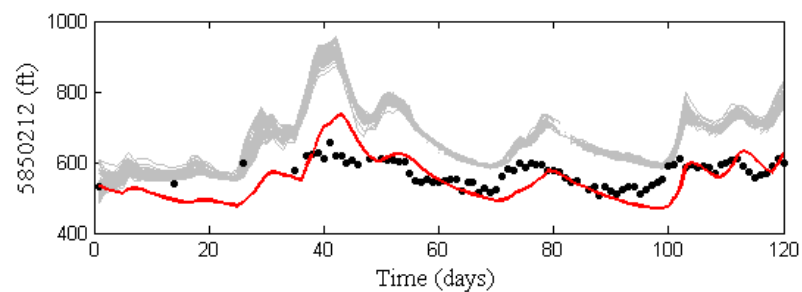
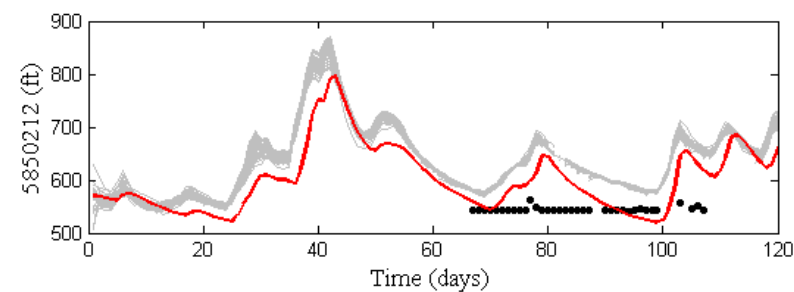
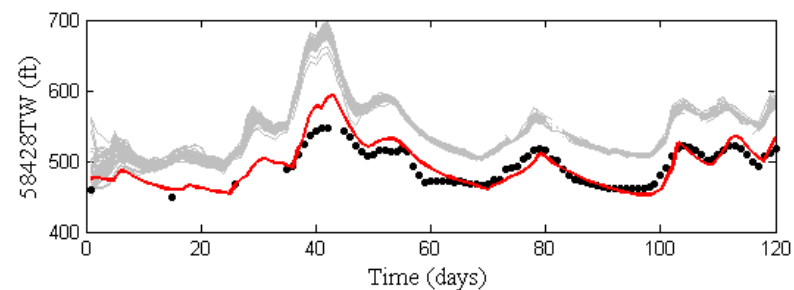
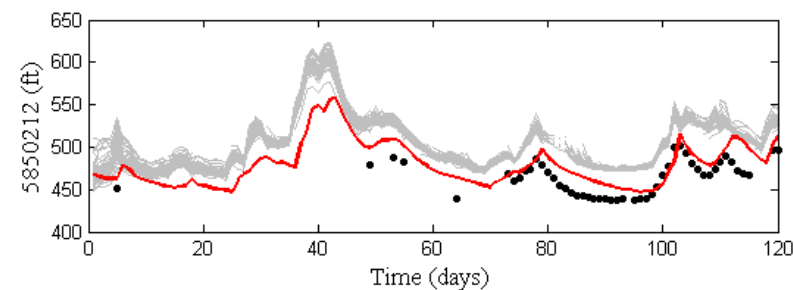
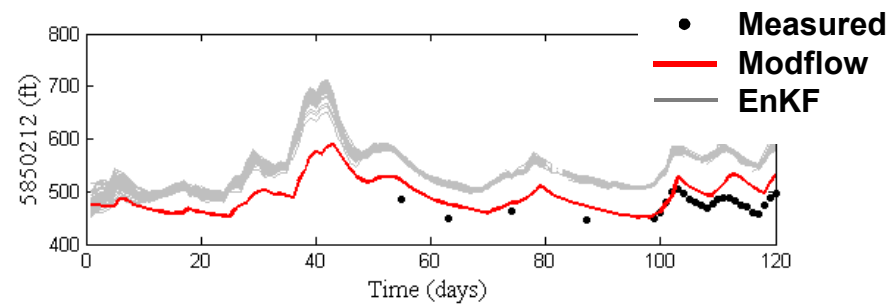
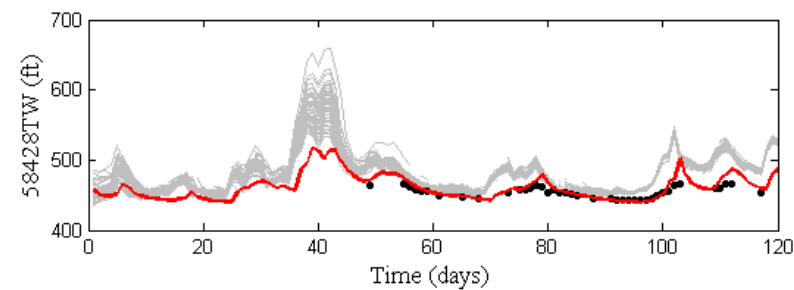
EnKF RESULTS

- Final EnKF K values compared to MODFLOW calibrated K



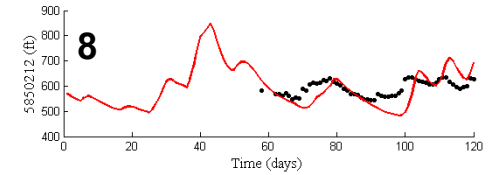
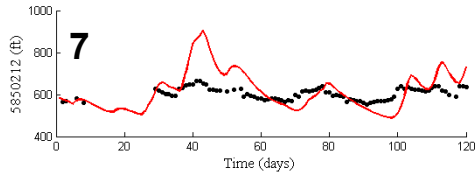
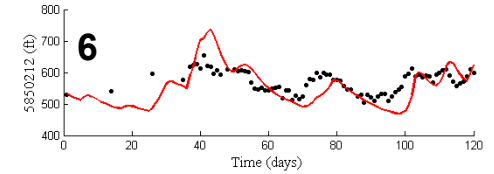
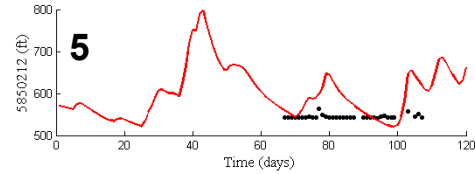
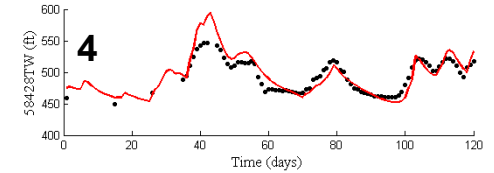
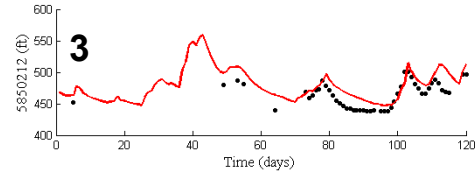
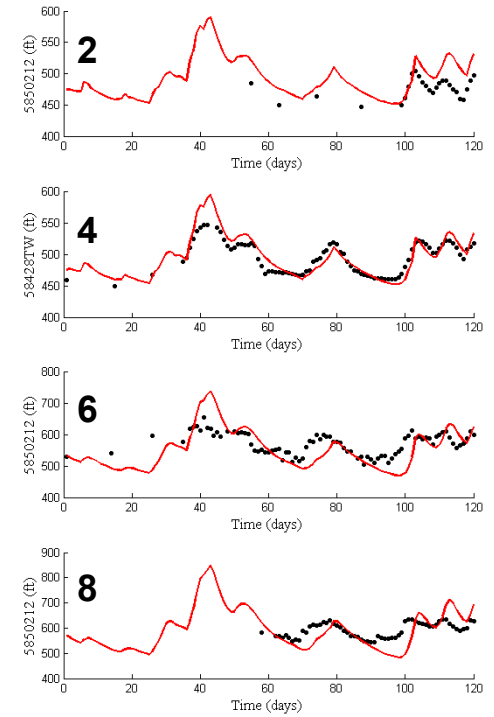
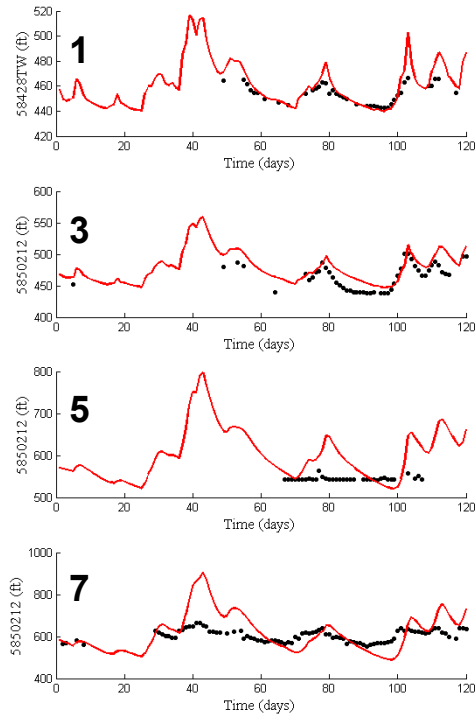
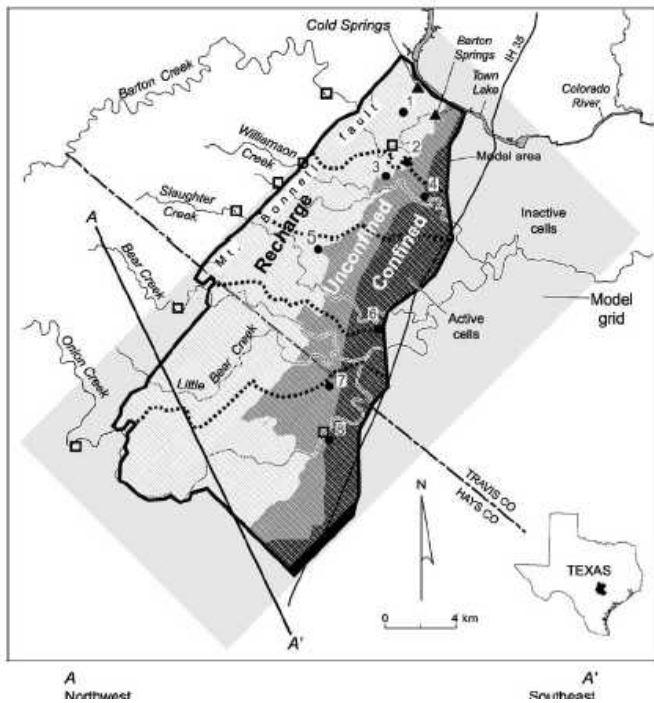
Do the final values of K constitute an alternate calibration?

EnKF RESULTS



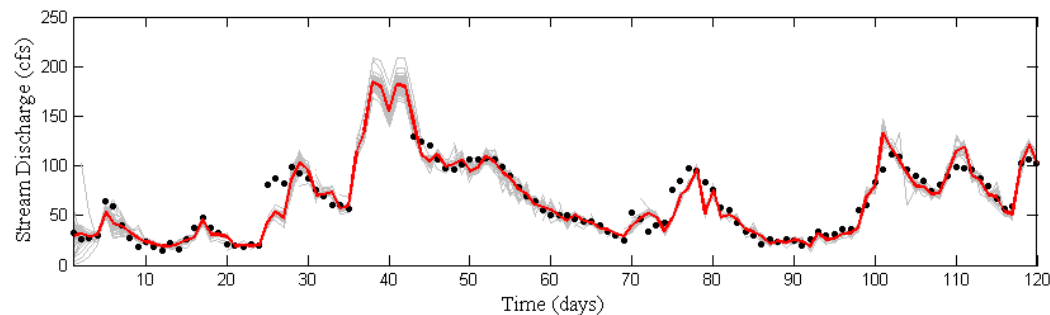
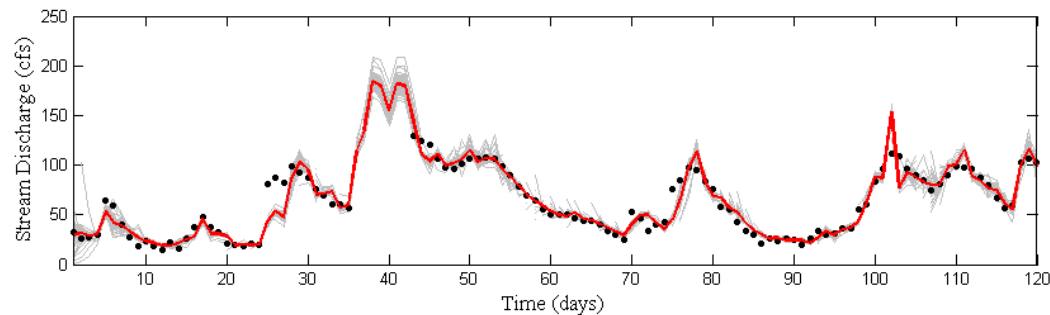
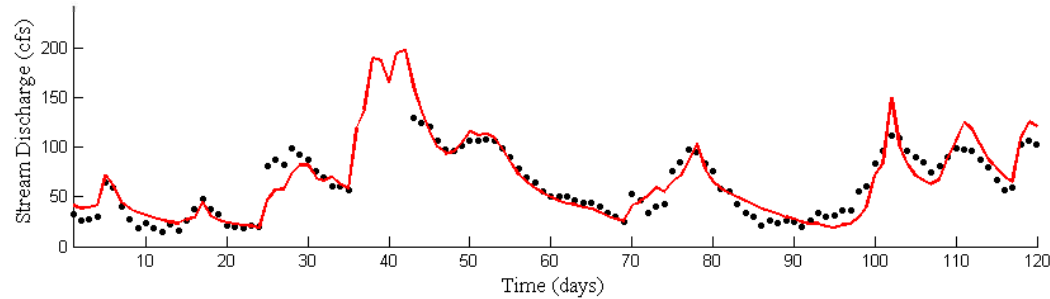
EnKF RESULTS

- Control Data = SF and WH



EnKF RESULTS

- Control Data = SF and WH (58428TW), Single update EnKF



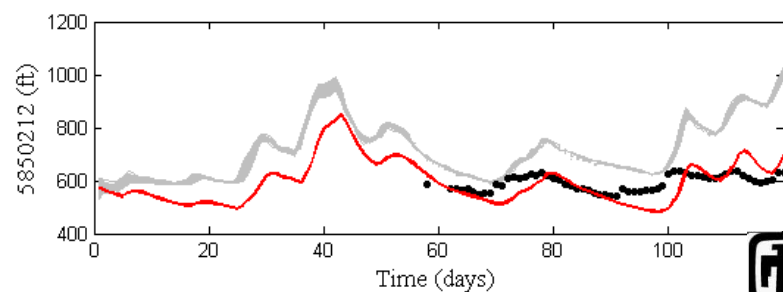
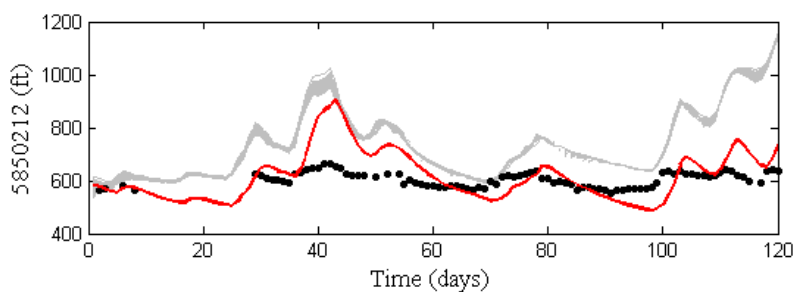
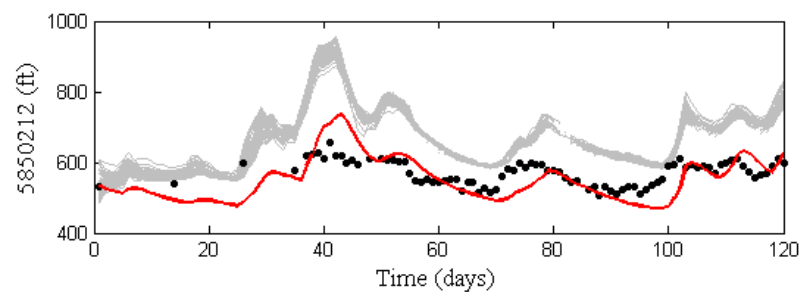
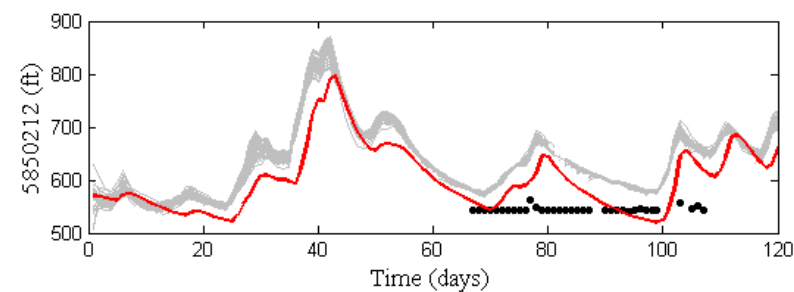
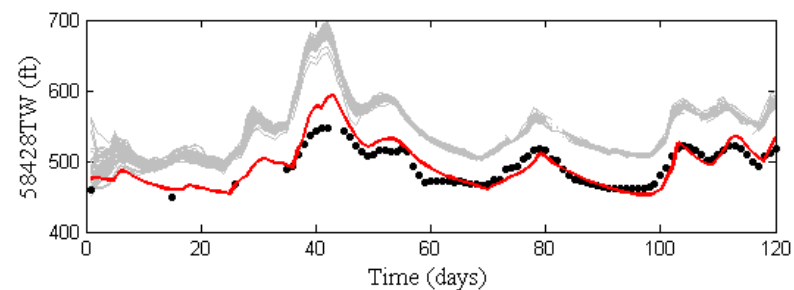
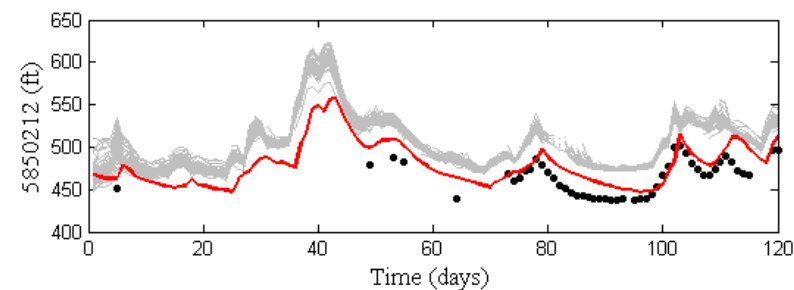
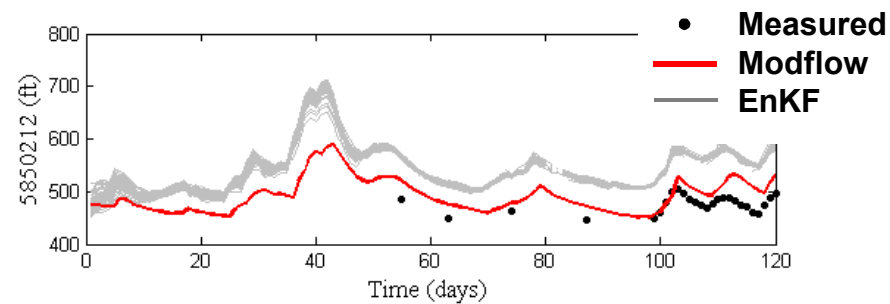
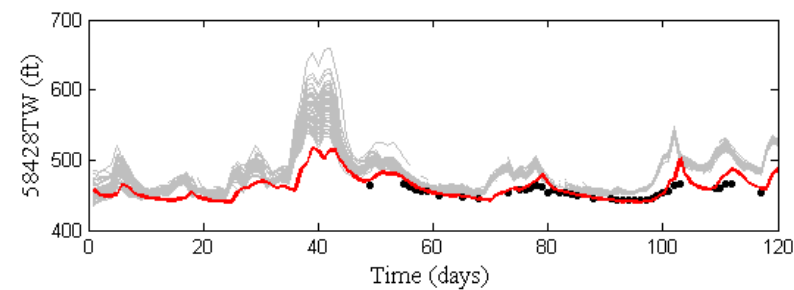
Average difference

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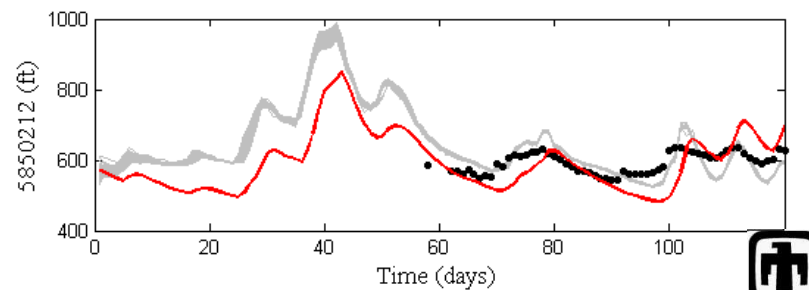
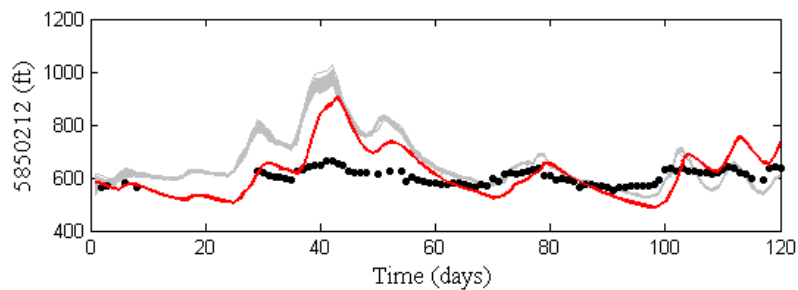
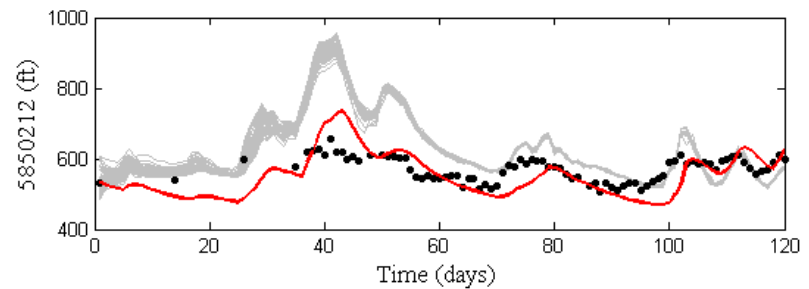
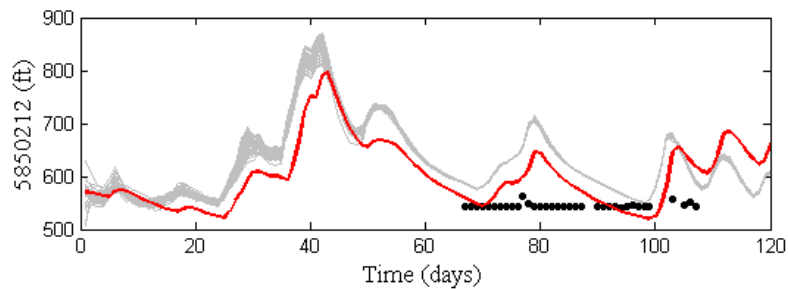
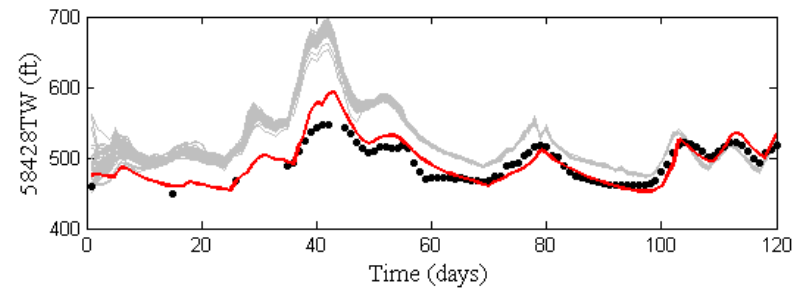
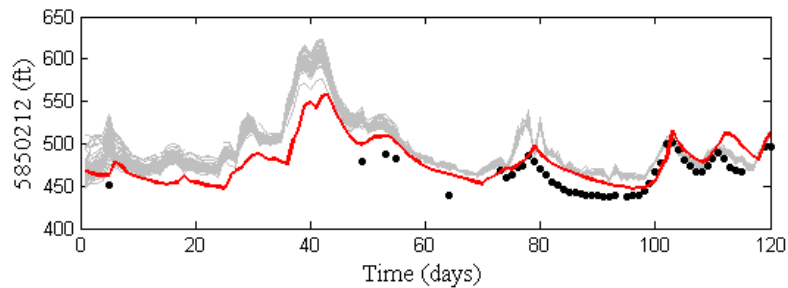
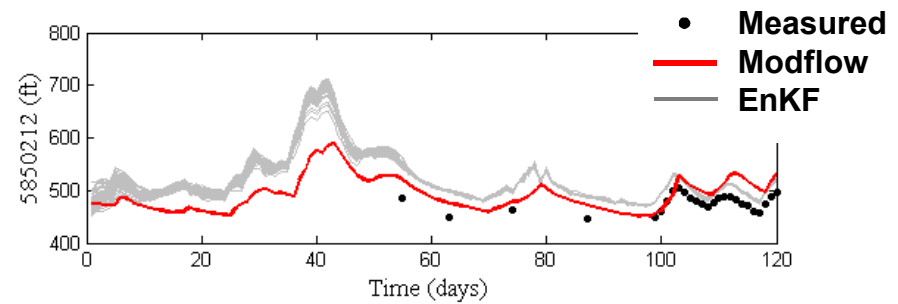
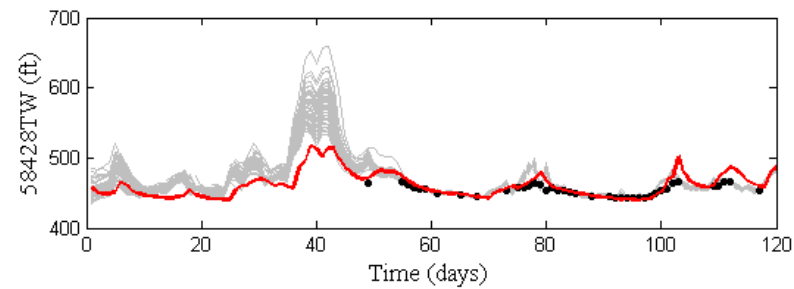
EnKF, Single Update, SF only = 7.0 cfs, 26.3% improvement

EnKF, Single Update, SF and WH = 7.2 cfs, 24.6% improvement

EnKF RESULTS



EnKF RESULTS





CONCLUSION

Stream Flow	MODFLOW Scanlon et al. (2001)	EnKF Single Update, SF only	EnKF Single Update, SF and WH	EnKF Iterative Update, SF only	EnKF Iterative Update, SF and WH
1989	9.4	5.0	5.0	4.6	
1990	3.8	3.3	3.3	4.0	
1991	13.9	14.8	14.8	7.6	
1992	9.6	9.2	9.2	9.2	
1993	4.3	2.8	4.4	2.8	
1994	5.7	4.3	4.6	5.3	
1995	9.7	12.0	11.1	9.6	
1996	9	4.0	3.9	3.4	
1997	17.1	9.2	9.5	10.9	
1998	12.7	7.3	7.5	5.6	
10 year average	9.5	7.0	7.2	6.1	

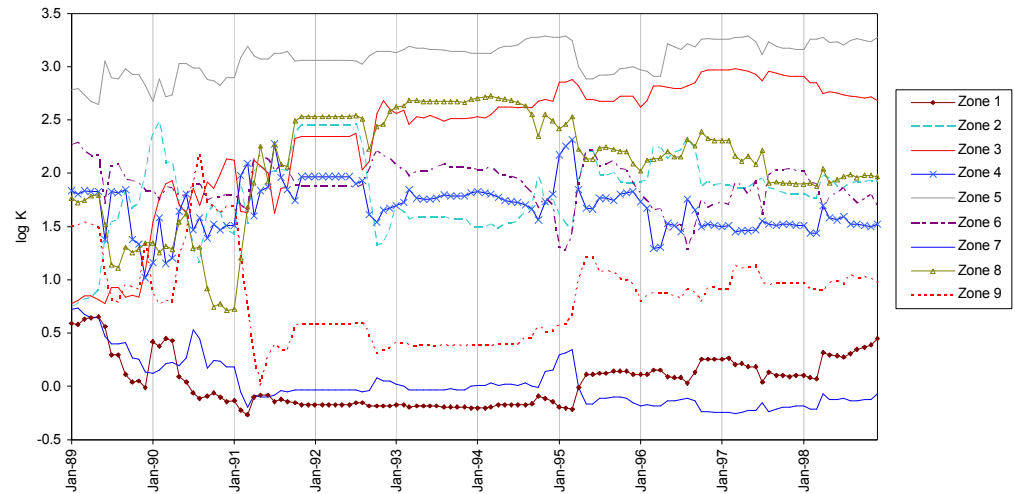


CHALLENGES RUNNING ENKF

- MODFLOW convergence using various combinations of K.
- Local gradient based calibration (PEST)
- Methods for keeping K within a reasonable range.
- Optimal number of realizations?
- Trade off between adding control data and estimating the parameter in question

AREAS FOR FUTURE RESEARCH

- Explore the ability of EnKF methods to calibrate the K model



- Based on drought and pumping forecasts, predict the future state of Barton Springs



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