Improved Assimilation of Streamflow and Satellite Soil Moisture with the Evolutionary Particle Filter and Geostatistical Modeling

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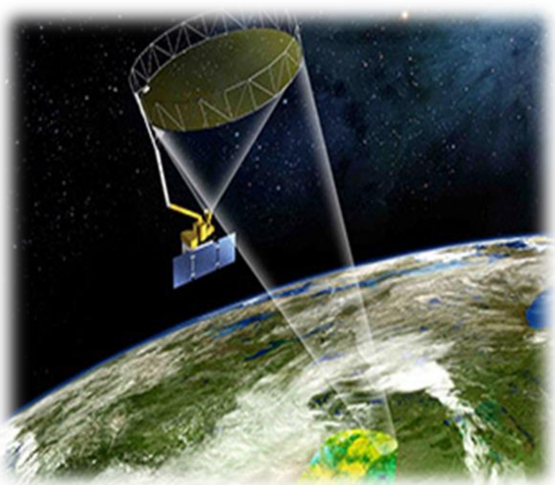
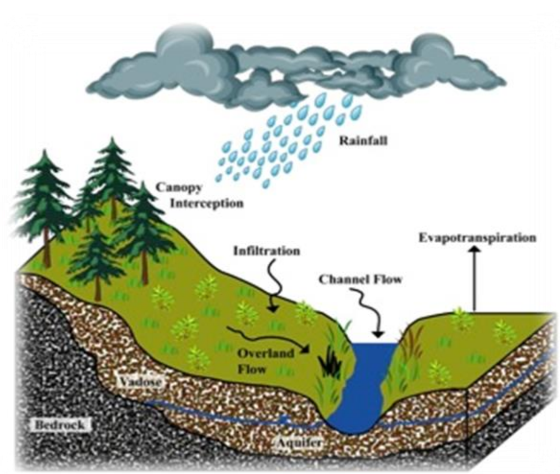




➢ Data Assimilation (an overview)

Sequential Bayesian estimation, often referred to as Data Assimilation (DA), has been recognized as one of the effective methods to improve hydrologic prediction.

❑ Kalman Filter (KF)

limited to linear dynamic systems.

❑ Extended Kalman Filter (EKF)

for nonlinear dynamic systems, which relies on linearization of model. This technique can lead to unstable results when the nonlinearity in the system is strong. To cope with this drawback, EnKF was introduced.

❑ Ensemble Kalman Filter (EnKF)

Although the successful application of the EnKF has been reported in hydrologic studies, this technique has some inherent features resulting in sub-optimal performance.

- *Gaussian assumption of errors*
- *linear updating rule within the EnKF*
- *violation of water balance.*

❑ Particle Filter (PF)

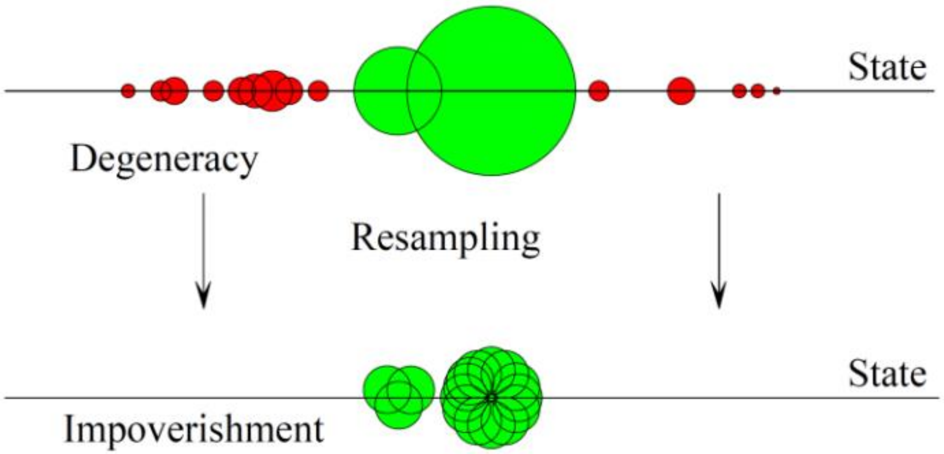
PF as a viable alternative to the EnKF.

This approach can relax the Gaussian assumption of error distributions, and therefore provide a thorough representation of the posterior distribution for a given nonlinear and non-Gaussian system.

Limitation of Particle Filter

Particle Filters (PFs) have received increasing attention by researchers from different disciplines including the hydro-geosciences, as an effective tool to improve model predictions in nonlinear and non-Gaussian dynamical systems.

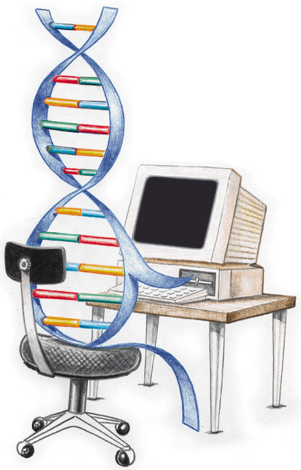
- Despite the success of the PF, one potential limitation has been the particle degeneracy.
- To address this problem, Sampling-Importance Resampling (SIR) is used to force particles to areas of high likelihood by multiplying high weighted particles while abandoning low weighted particles.
- This however may cause another problem: sample impoverishment.



How to deal with this problems!

In order to mitigate these problems, several procedures have been proposed. One of those is using Markov Chain Monte Carlo (MCMC) within the PF to reduce weight degeneracy *(Andrieu et al., 2010; Noh et al., 2011; Moradkhani et al., 2012).*

On the other hand, intelligent search and optimization methods categorized as Metaheuristic Algorithms (MAs) in computer science literature have also been used to mitigate the degeneracy problem.

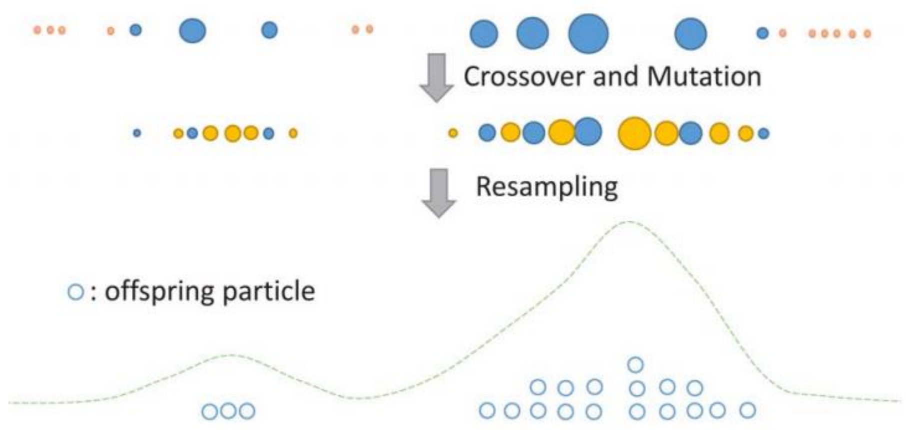


- Genetic Algorithm (GA), *(Higuchi, 1997; Kwok et al., 2005; Park et al., 2009)*
- Evolution Strategy (ES), *(Uosaki et al., 2003; Uosaki et al., 2004)*
- Particle Swarm Optimization (PSO), *(Wang et al., 2006; Li et al., 2013)*
- Ant Colony Optimization (ACO), *(Xu et al., 2009; Park et al., 2010; Zhu et al., 2010)*
- Immune Genetic Algorithm (IGA), *(Han et al., 2011)*
- Inverse Weed Optimization, *(Ahmadi et al., 2012)*

Among these attempts, Genetic Algorithm (GA) has received more attention and is known as a more effective method to combine with the PF to prevent the particle degeneracy.

➢ How to deal with this problems!

An Illustration of GA-PF algorithm: *(Yin et al., 2015)*



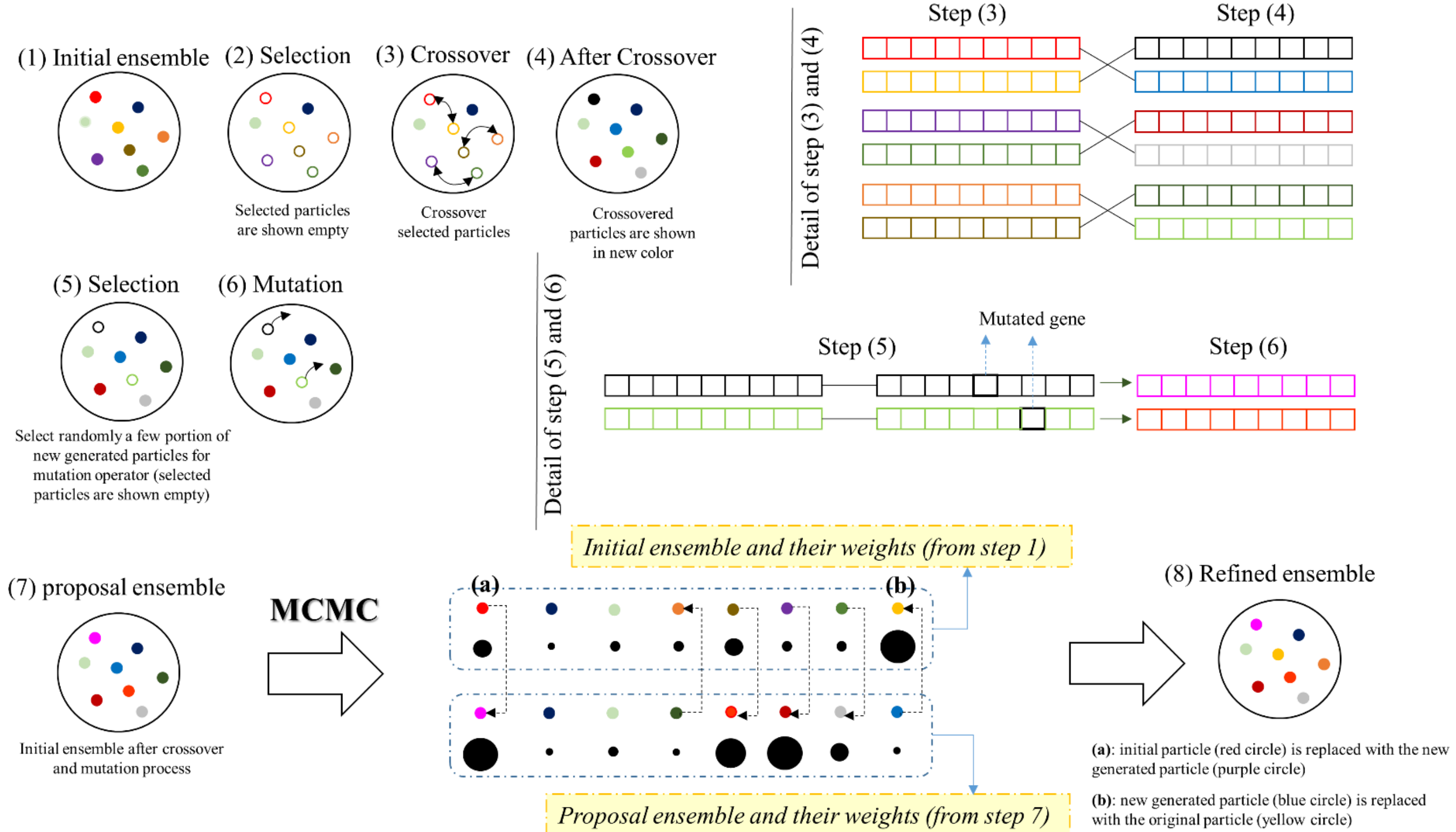
Limitation of using a single evolutionary algorithm with the PF:

- ❑ This approach reduces the weights of large-weight particles and may lead to sub-optimal performance. It is entirely possible that the shuffled particles after the GA operators move outside the posterior distribution and lead to a degraded performance.

A new approach (GA-MCMC)

In this study, we expand the GA approach suitable for applications to hydrologic models. In particular, we use a MCMC move inside the GA to guide the PF performance.

- This procedure is introduced as a GA-MCMC process.

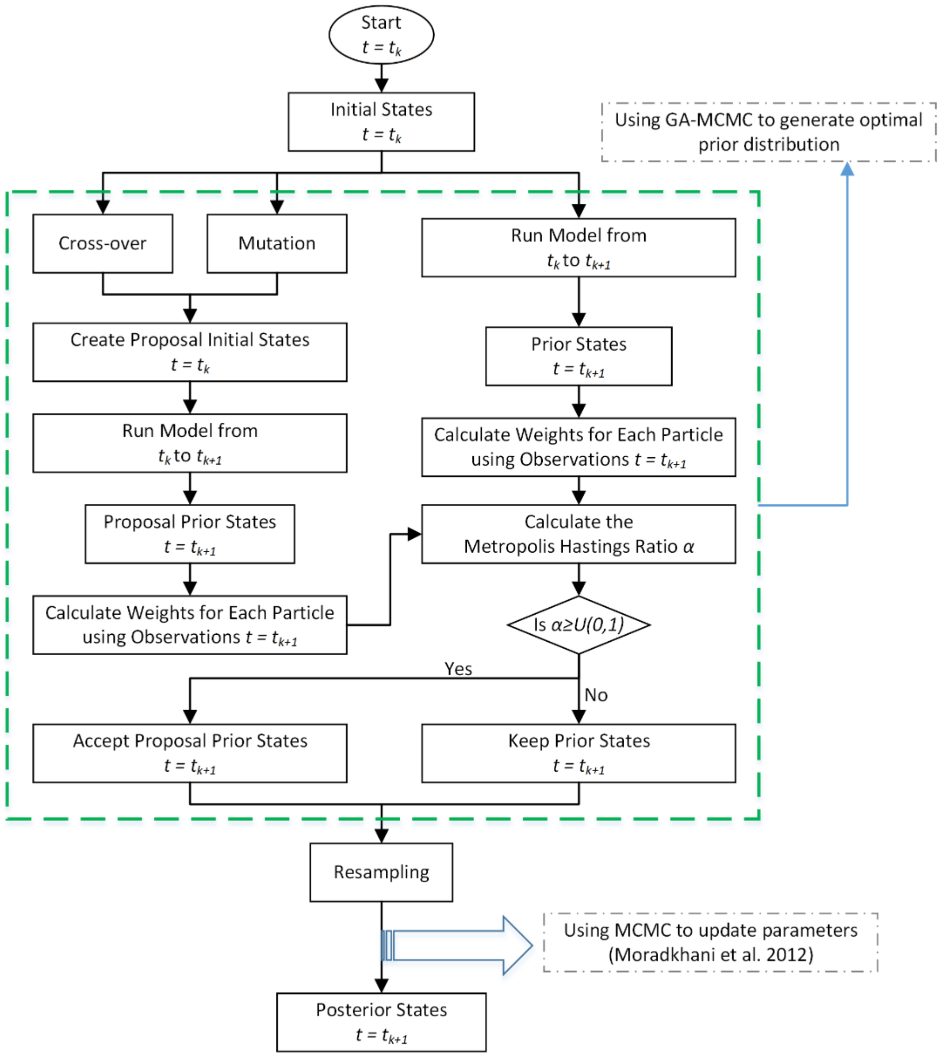


Evolutionary Particle Filter with MCMC

- The proposed model employs the recently developed PF-MCMC algorithm (Moradkhani et al., 2012) as a benchmark to further improve the assimilation results.

- Therefore, the presented hybrid PF approach, the so-called Evolutionary Particle Filter with MCMC (EPFM), joins the strengths of GA-MCMC and PF-MCMC algorithms.

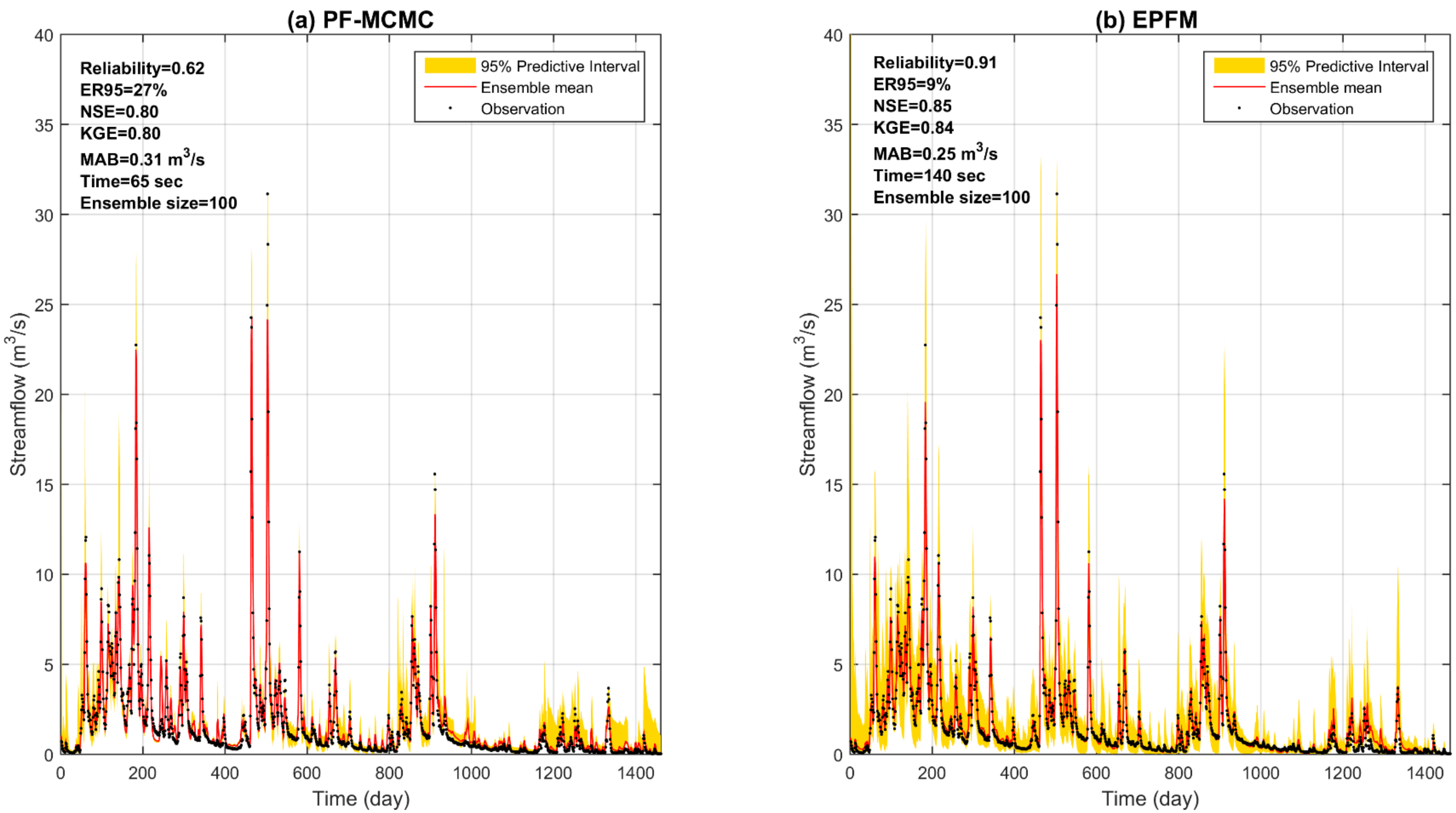
- In this methodology, MCMC is used twice, before resampling step in order to accept or reject the new generated state variable which leads to an optimal state prior distribution, after resampling step during updating the parameters of model.



➢ A Synthetic Case

The Sacramento Soil Moisture Accounting Model (SAC-SMA) was used to simulate the streamflow at four different basins (a synthetic and three real data experiments).

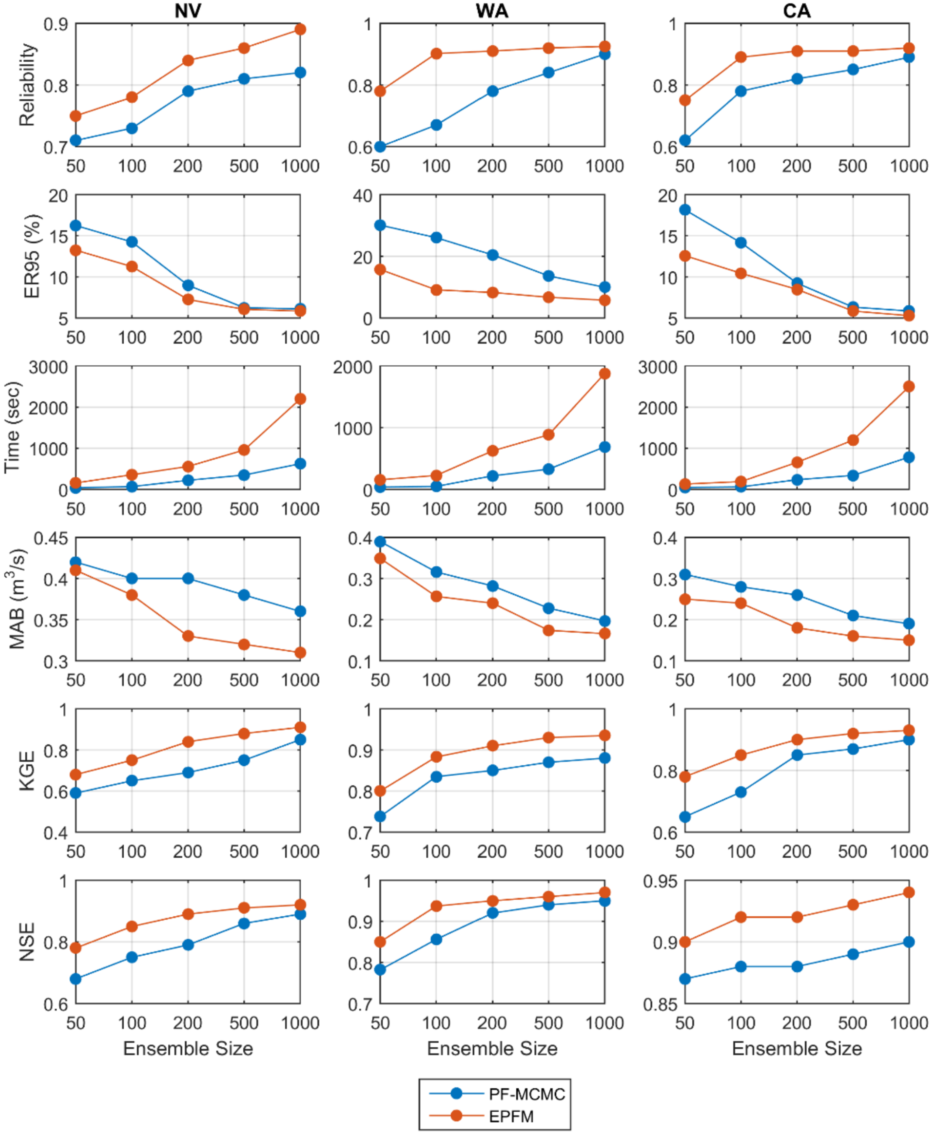
❑ Leaf River Basin located in the southern Mississippi was considered for a synthetic study.



➢ Three real case studies

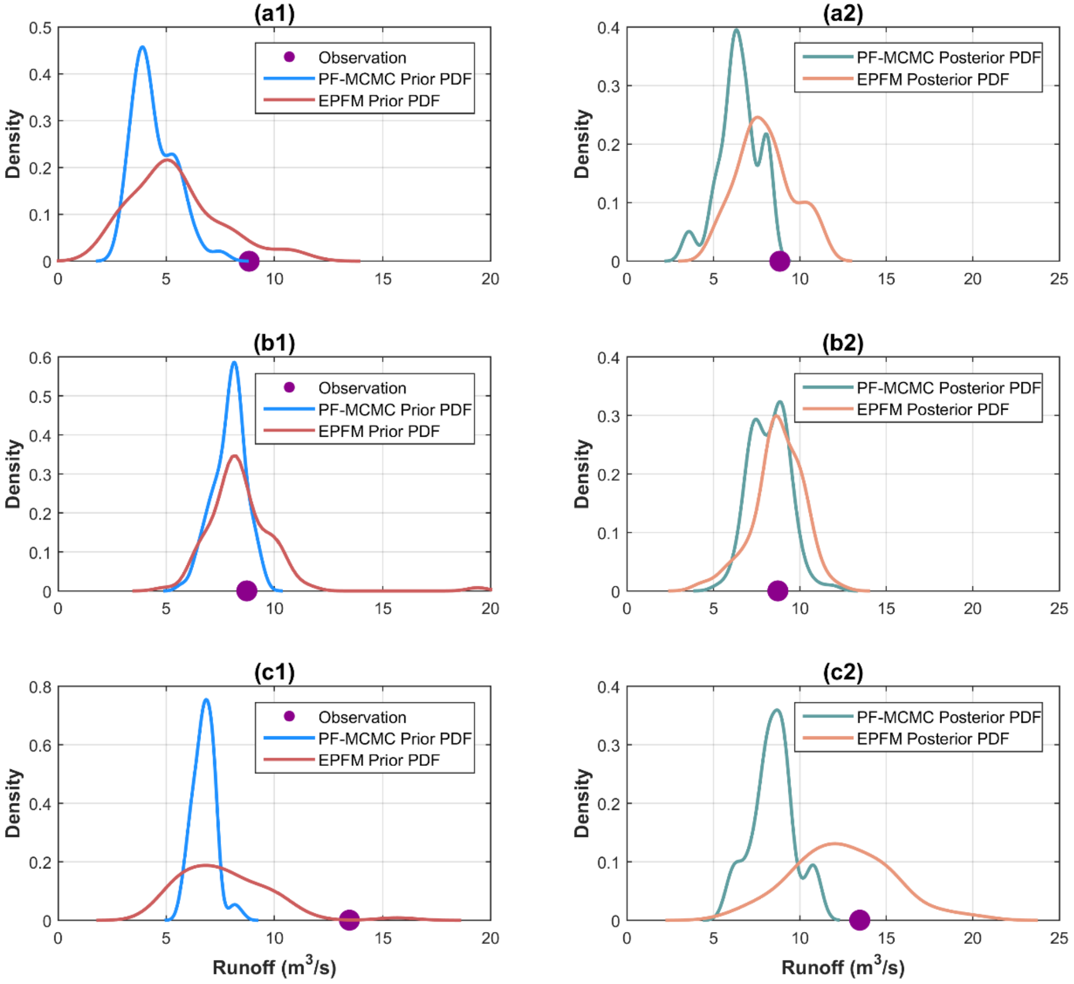
In addition to the synthetic study, three real data experiments are also performed in three basins located in different climate and geographical conditions, to fully examine the performance of the proposed EPFM.

- The Chehalis River Basin with an area of 895 square miles is the second largest basin in Washington State.
- The Indian Creek Watershed is located in the Klamath National Forest, and drains into the Klamath River in California State.
- The Carson River Watershed originates from the Alpine County in California with an area of nearly 3,966 square miles, 85% of which lies in Nevada State.



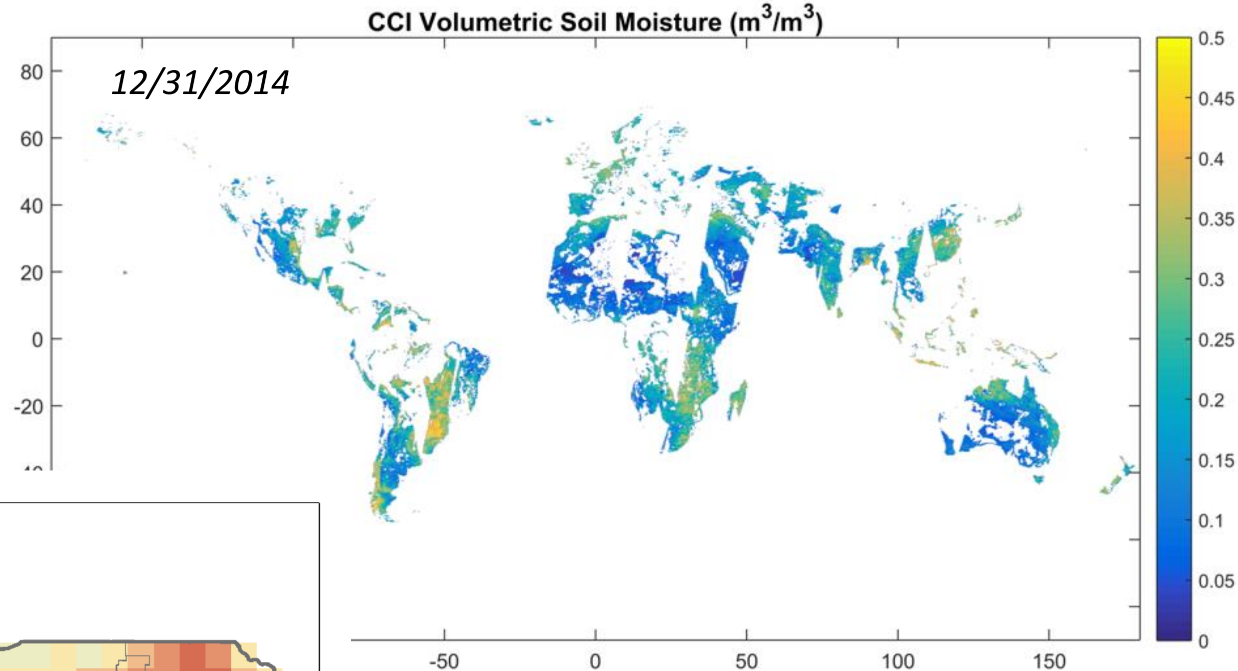
➢ Why EPFM?

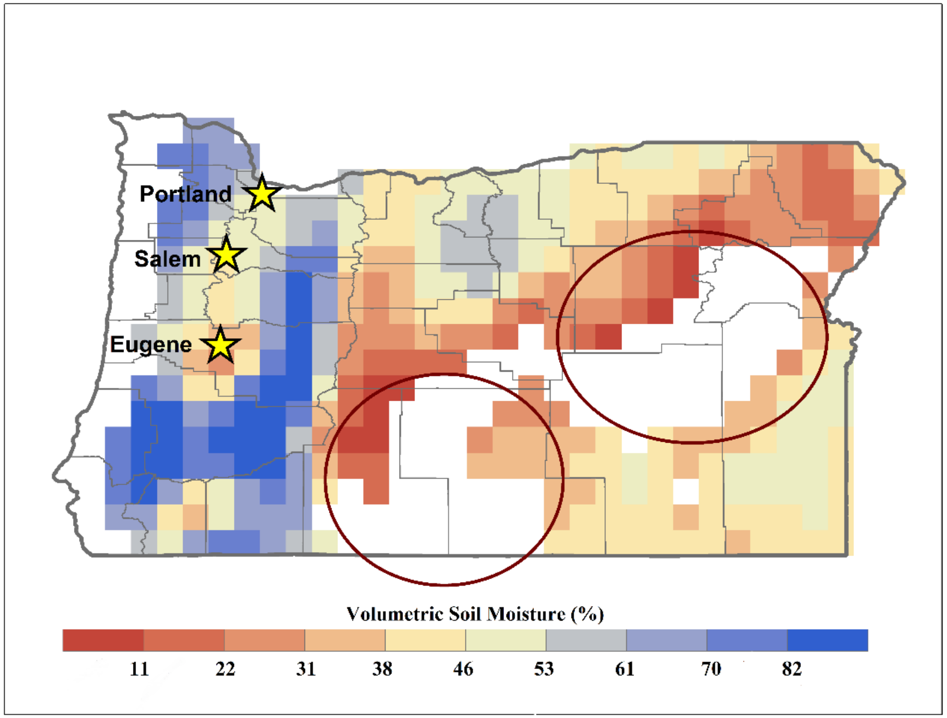
- The prior and posterior distributions for PF-MCMC and EPFM for three days: (a) day = 50, (b) day = 431, (c) day = 761. These results are reported for the Chehalis River Basin in WA.
- For PF-MCMC, a large percentage of particles ends up far from the observations and has negligible weight, leading to an over-confident posterior distribution.
- For EPFM, through the mutation and crossover process, the optimal prior distribution is drawn towards to the observation, leading to a more robust posterior distribution.



Satellite Soil Moisture Discontinuity

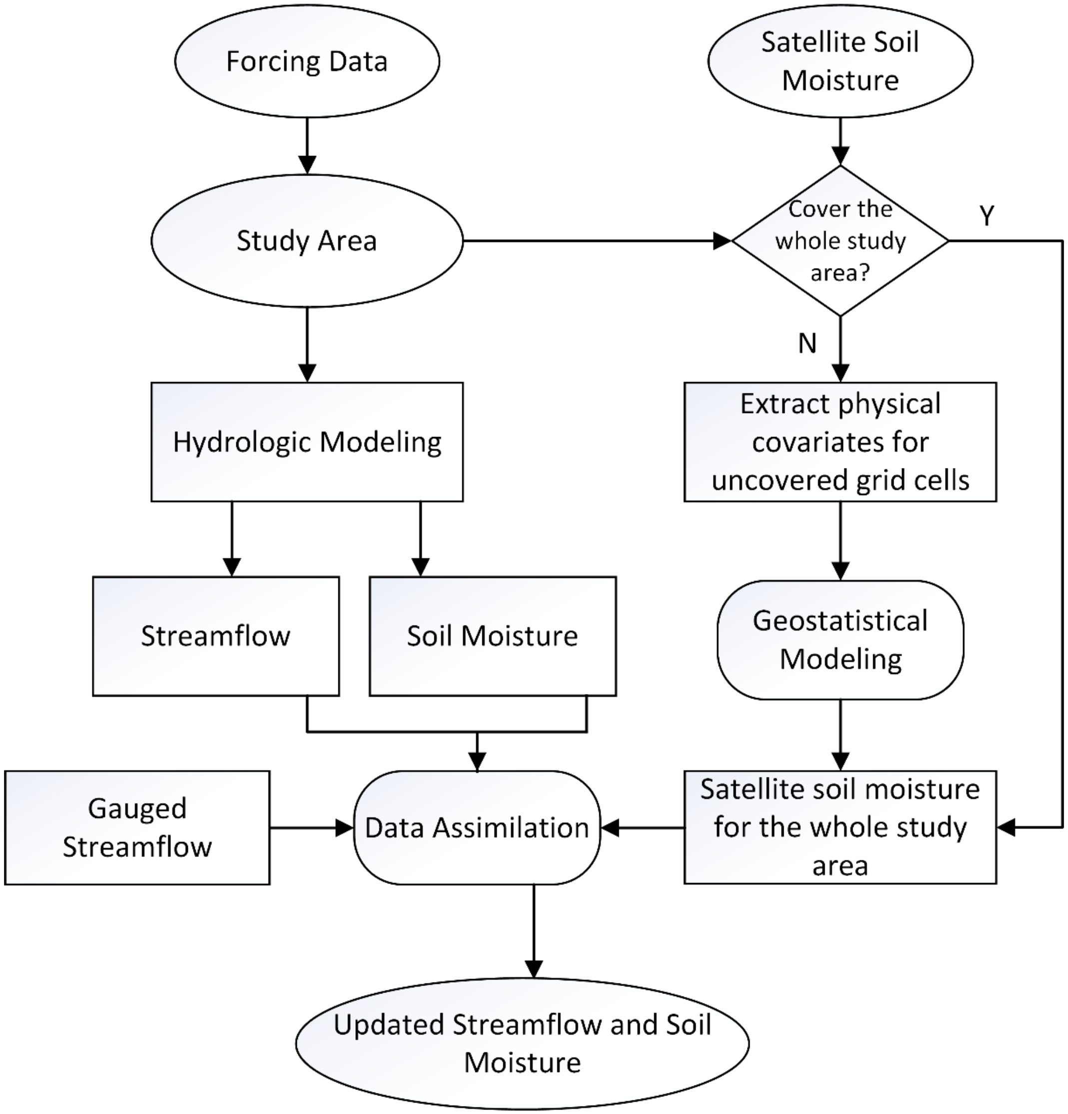
Due to the temporal and spatial limitations of satellite instruments, it is common that not all the watershed grid cells can be measured at the same time.





AMSR-E soil moisture for Oregon State on January 02, 2006. Uncovered areas are shown in the red ellipses due to the sensor limitation, however, the satellite soil moisture is critical for these areas since they are especial vulnerable to droughts.

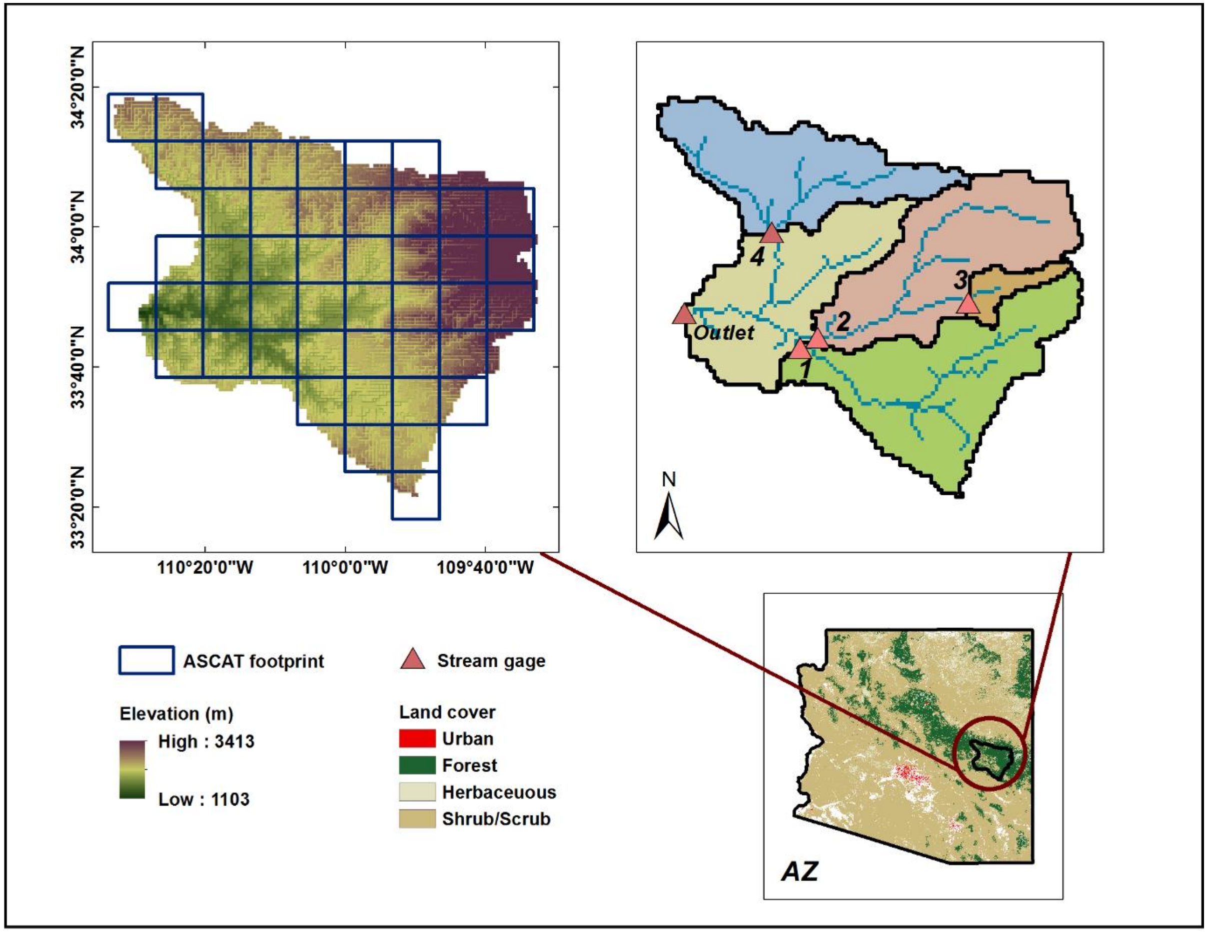
➢ Solution: Geostatistical Modeling



- ❑ Soil moisture is related to the physical covariates, such as slope, elevation, and aspect.
- ❑ In this study, the general Gaussian approach (Leung and Cooley, 2014) is introduced instead of the traditional geostatistical variogram model
- ❑ The predicted soil moisture from general Gaussian approach are assimilated into the hydrologic model to further improve soil moisture filed

➢ Case Study

- A sub-watershed of Salt River basin (HUC 150601), located in the west of Arizona. The size is 7,379 km^2
- The studied watershed is one of the selected watersheds in the Model Parameter Estimation Experiment (MOPEX), therefore the effects of water management can be ignored.
- Synthetic ASCAT soil moisture (12.5 x 12.5 km^2) is generated using the fully distributed SAC-SMA model



General Gaussian Geostatistical Modeling

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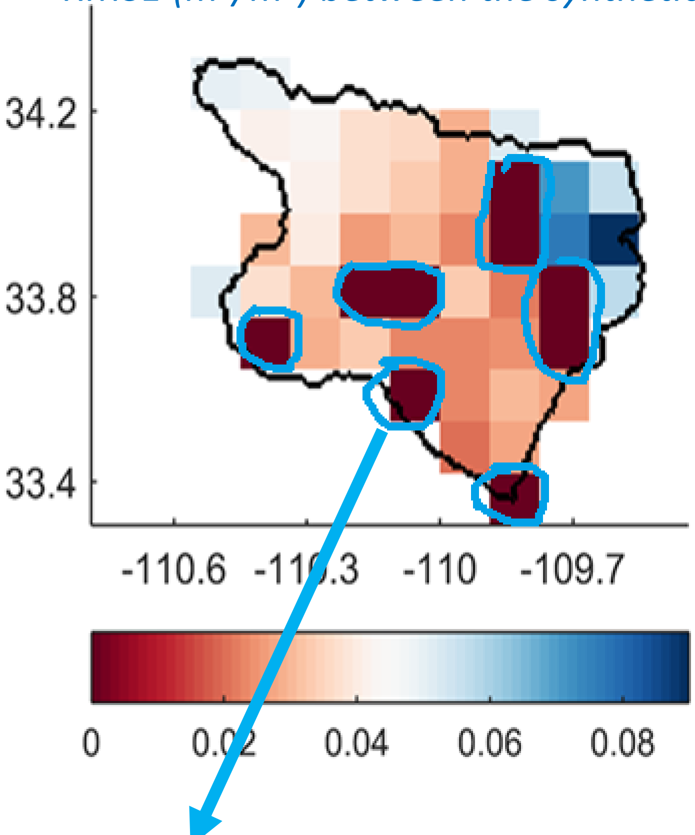
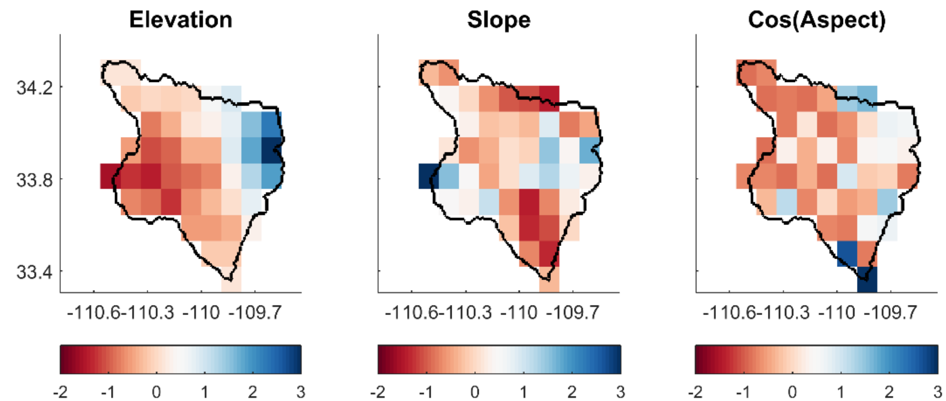
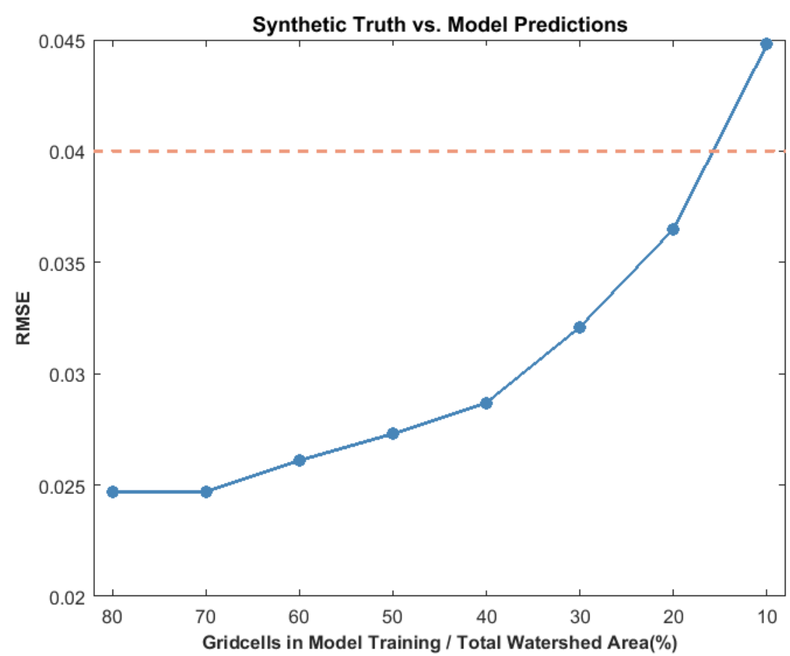
RMSE (m^3/m^3) between the synthetic truth





20% gridcell (9) for training, and 80% for testing

The quality of soil moisture estimated from geostatistical model within the expected satellite data quality threshold (RMSE<0.04)



Data Assimilation of Soil Moisture estimated from Geostatistical Modeling

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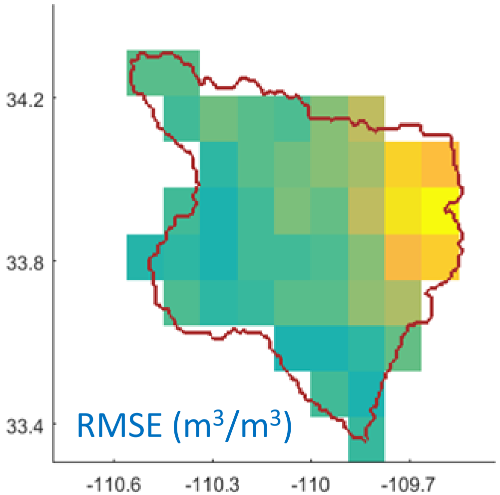
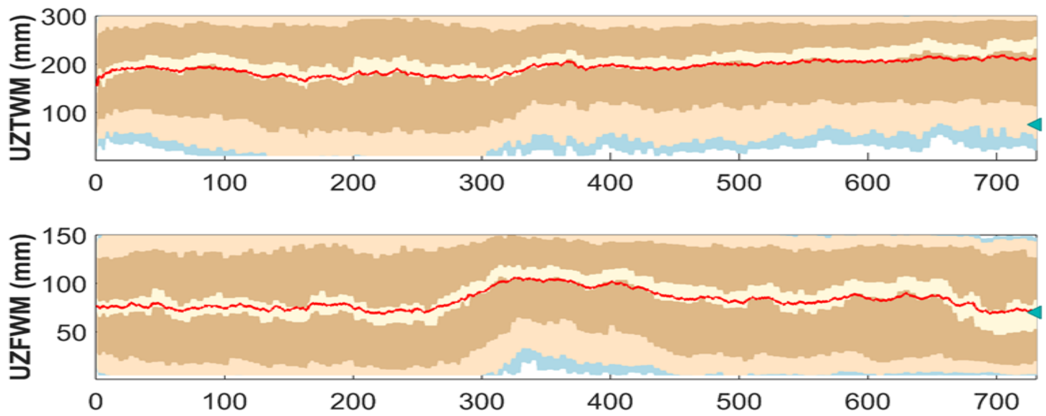
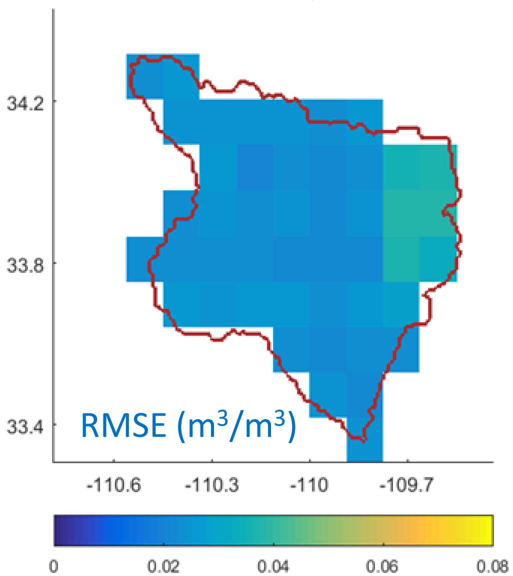
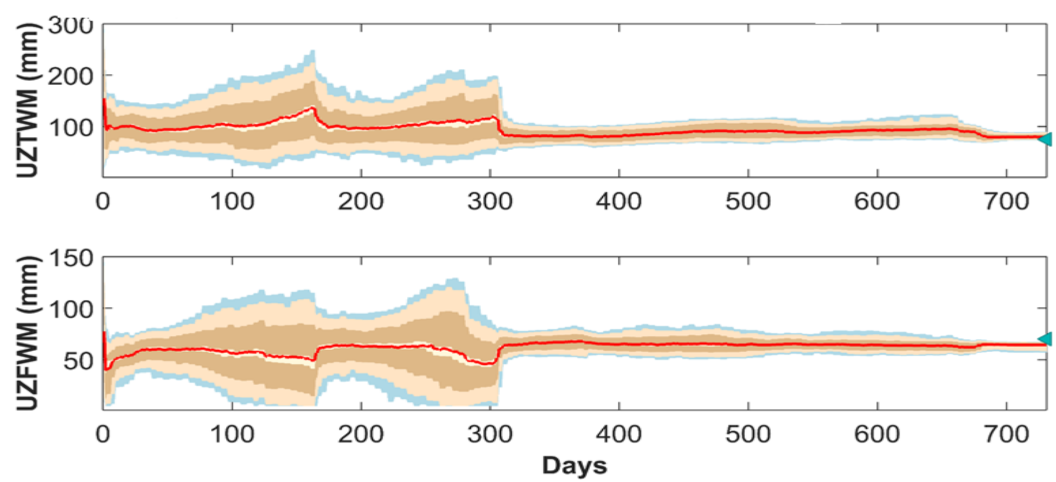
Assimilation of outlet streamflow





Assimilation of outlet streamflow and geostatistical soil moisture





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