Development history



Product of over

45 years of

U.S. Department of

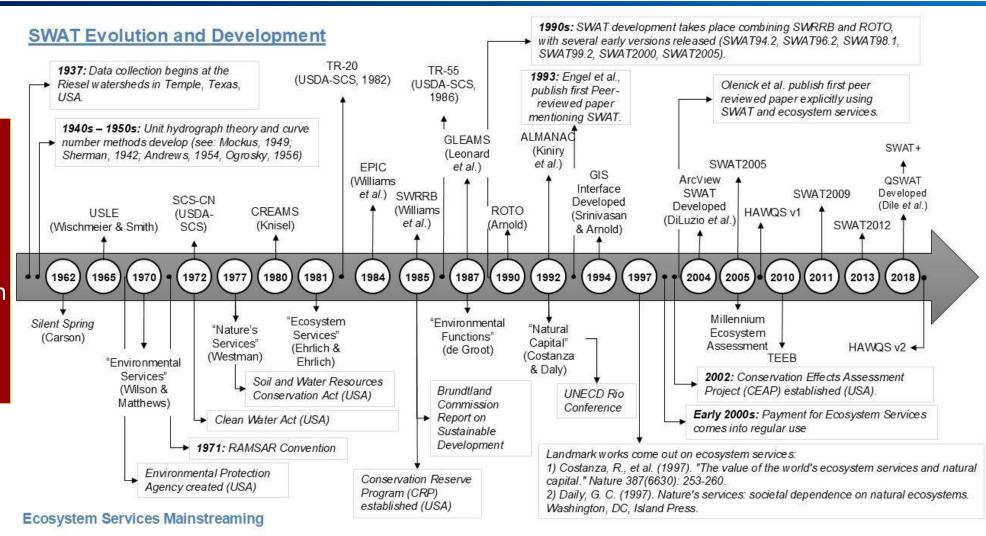
Agriculture and

Texas A&M University

model development, with

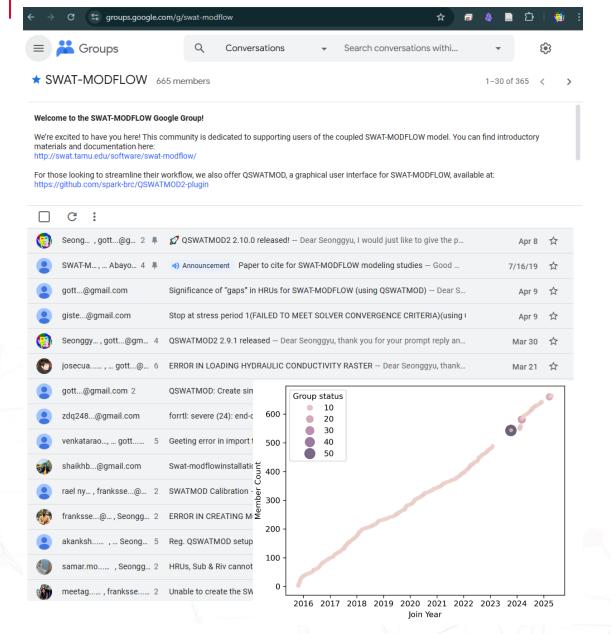
multiple additions from

the international user
community



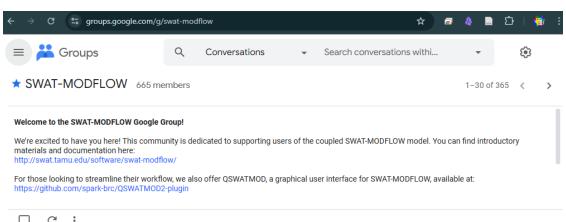
SWAT has a more than 80-year history of rigorous hydrological research and development on experimental watersheds behind it

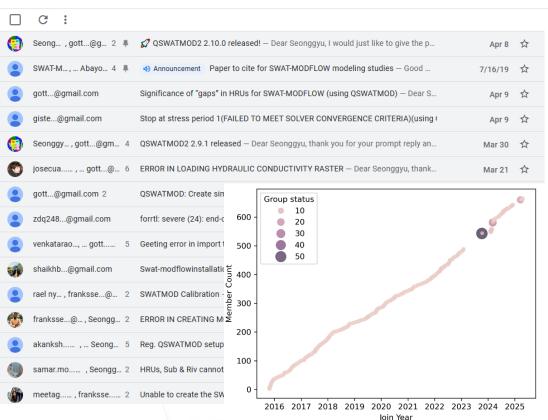
User Accessibility | Collaboration and Service

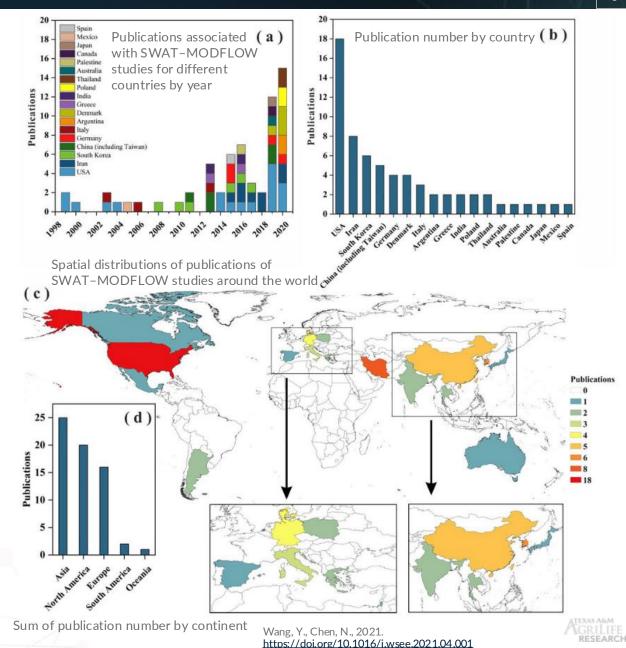




User Accessibility | Collaboration and Service



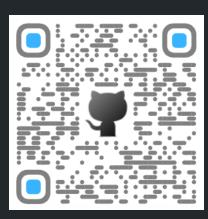




Day 2

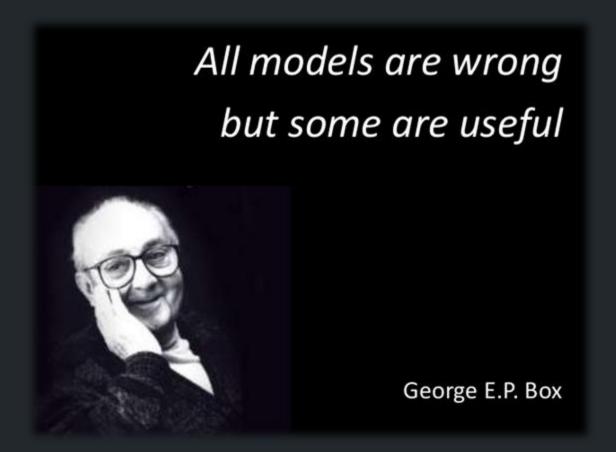
Hands-On Practice for Uncertainty Analysis

- PEST (Parameter EStimation Tool)
 - PEST official website: https://pesthomepage.org/
 - Tutorial Videos: https://pesthomepage.org/videos
 - Youtube: https://www.youtube.com/@gmdsi
 - Practice with Jupyter notebooks: https://github.com/gmdsi/GMDSI_notebooks
 - Groundwater Modeling Decision Support Initiative https://gmdsi.org/
- swatp_pst
 - Workflow: https://github.com/spark-brc/swatp_pst_wf



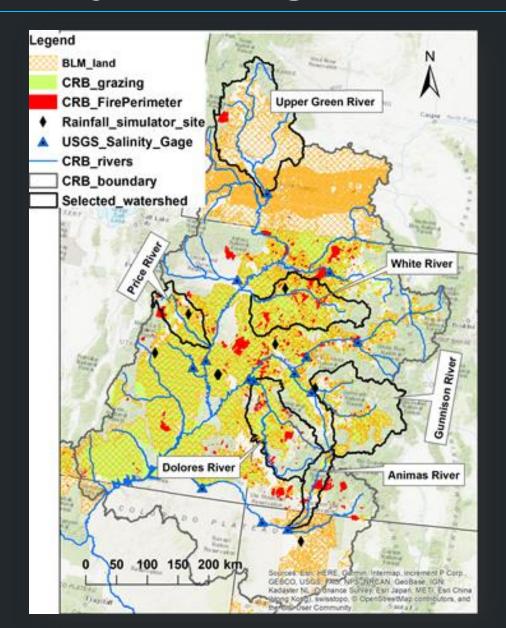


All models are wrong!



All models are approximations.
Essentially, all models are wrong, but some are useful. However, the approximate nature of the model must always be borne in mind.

Project Background



- Colorado river transports 7-9 million tons of salt annually to the Gulf of California.
- Irrigated agricultural districts causes highly saline conditions.
- Salinity contributes to more than \$300 million dollars
 per year in economic damage.
 - Assess the sources of salinity and its transportation in the Colorado River Basin and
 - Develop effective management strategies.

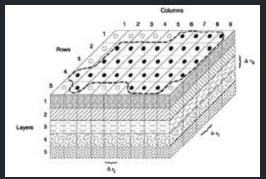
Approaches | Model Integration & Development



developed and maintained by



- The Agricultural Policy / Environmental eXtender (APEX) model was developed and included
 - crop growth algorithms
 - nutrient cycling in the soil profile
 - nutrient transport and
 - loading to streams in surface runoff, soil lateral flow, and groundwater flow, and in-stream transport.



developed and maintained by

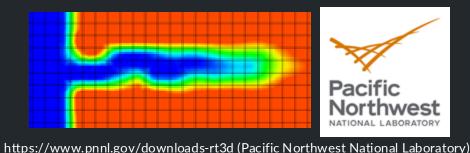


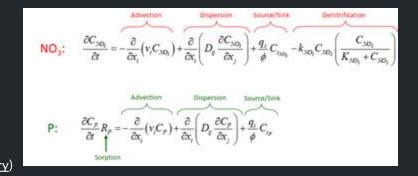
Partial Differential Equation: develop water balance for each point (cell) in the aquifer

$$\frac{\partial}{\partial x} \left(hK_x \frac{\partial h}{\partial x} \right) + \frac{\partial}{\partial y} \left(hK_y \frac{\partial h}{\partial y} \right) + Q_{rech} - Q_{pump} - Q_{ET} = S_y \frac{\partial h}{\partial t}$$

- MODFLOW is the U.S. Geological Survey modular finitedifference flow model
 - solve the groundwater flow equation,
 - simulate the flow of groundwater through aquifers.

Reactive Transport in 3 Dimensions





Salinity Module 8 major ions (SO₄, Ca, Mg, Na, Cl, K, CO₃, HCO₃)

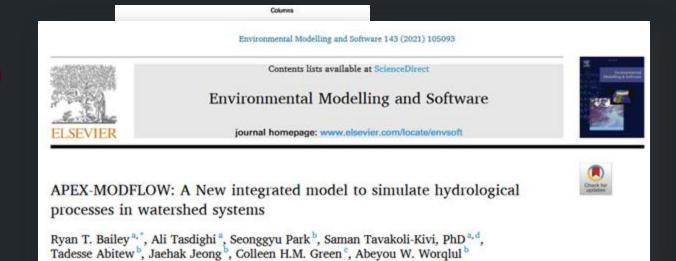
Approaches Model Integration & Development



developed and maintained by



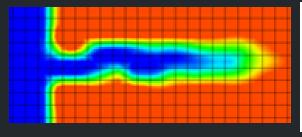
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difference flow model

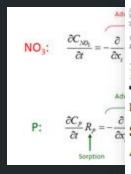
- solve the groundwater flow equation,
- simulate the flow of groundwater through aguifers.

Reactive Transport in 3 Dimensions





https://www.pnnl.gov/downloads-rt3d (Pacific Northwest National Laboratory)





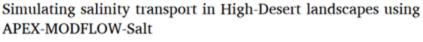
Journal of Hydrology

Journal of Hydrology 610 (2022) 127873

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journal homepage: www.elsevier.com/locate/jhydrol

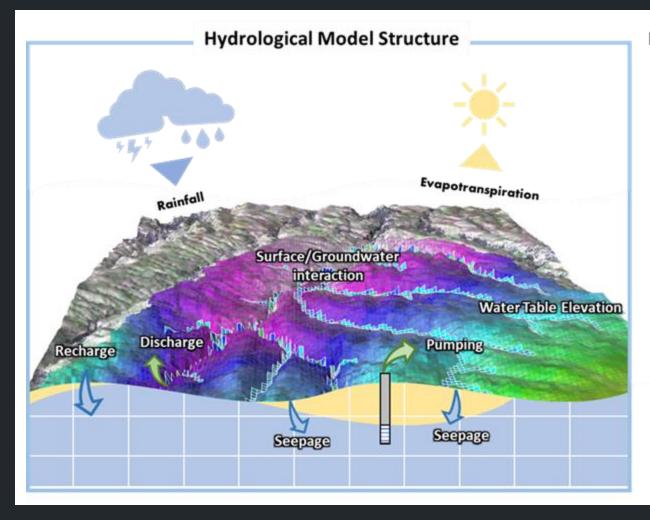






Ryan T. Bailey a, , Jaehak Jeong b, Seonggyu Park b, Colleen H.M. Green c

Challenges | Source of uncertainty



Parameters for APEX-MODFLOW-RT3D-Salt (Source of Uncertainty)

Field Parameters: Available water capacity of the soil layer,
Runoff curve number
Soil evaporation coefficient
Transmissivity (T)

Hydraulic Conductivity (K)

Specific Storage (Ss) Specific Yield (Sy)

Boundary Parameters: Initial Head Boundary

Riverbed Conductance, Thickness

Decision Parameters: Rainfall, Recharge, Evapotranspiration,

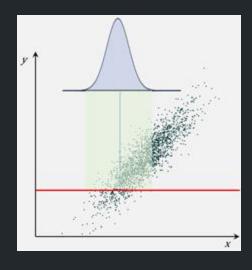
Pumping and Injection Rates

Numerical Algorithm: Spatio-Temporal Variation

Salinity: Initial Salt Ion Concentrations / fractions

Uncertainty Analysis | Bayes Theorem





$$P(\theta|X) = P(X|\theta)P(\theta)$$

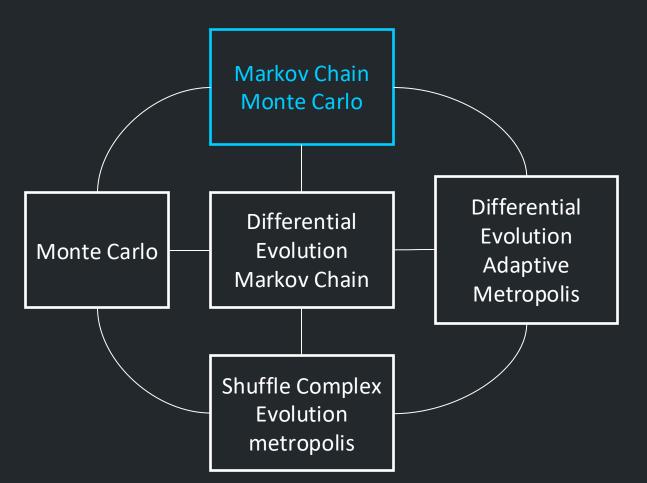
- Conditional Probability
- Prior
- Posterior
- Likelihood

Uncertainty Analysis | Sampling the posterior parameter probability distribution

- Populate a model with realizations of parameter fields
- Filter realizations based a metric of likelihood function

Uncertainty Analysis | Sampling the posterior parameter probability distribution

- Populate a model with realizations of parameter fields
- Filter realizations based a metric of likelihood function



- Less than 1000 parameters
- Short model run time
- Long convergence time

Uncertainty Analysis | Ensemble Method

Fundamental Concept:

approximate model-based relations with ensembles

 Ensemble methods: optimization (minimization) algorithms that use ensembles to approximate first-order (partial first derivatives) between parameters and outputs to enable (very) highdimensional data assimilation (White et al, 2018)

Ensembles: a collection of randomly-sampled model inputs and the corresponding collection of model outputs

Ensemble Methods: Monte Carlo + Linear Algebra

Uncertainty Analysis | Ensemble Method

- Model-based relations of interest:
 - Covariance between measured and unmeasured model outputs
 - State estimation
 - Cross-covariance (e.g. gradient) between model inputs and outputs
 - Parameter estimation
- What's Great: uncertainty analysis and history matching in a single algorithmic workflow
- What's Great: forces you to think about model input uncertainty from the very beginning!

Uncertainty Analysis I Iterative Ensemble Smoother (IES)

P (ne x npar)

	hk	mineral fraction	Initial sconc
real1	0.123	0.9	12.3
real2	0.321	0.0001	32.1
real3	0.987	0.2	69.0
real N	0.789	0.2345	54.1

model runs = ne (number reals) (e.g. Monte Carlo)











	nead	instream	sconc inaqufier
real1	1.11	0.0001	3.21
real2	2.22	0.003	1.23
real3	3.33	0.0003	9.6
realN	4.44	0.001	1.45

D_{sim} (ne x nobs)

Uncertainty Analysis Iterative Ensemble Smoother (IES)

$$\Delta_P \propto (P - \bar{P})$$

P (ne x npar)

	hk	mineral fraction	Initial sconc
real1	0.123	0.9	12.3
real2	0.321	0.0001	32.1
real3	0.987	0.2	69.0
real N	0.789	0.2345	54.1

 $J \propto \Delta_{D_{sim}}^T \Delta_P^{-1}$

model runs = ne (number reals) (e.g. Monte Carlo)













D_{sim} (ne x nobs)

		head	sload instream	sconc inaqufier
	real1	1.11	0.0001	3.21
>	real2	2.22	0.003	1.23
	real3	3.33	0.0003	9.6
	realN	4.44	0.001	1.45

Uncertainty Analysis Iterative Ensemble Smoother (IES)

$$P_{\Delta} = -((I^{T}\Sigma_{\varepsilon}^{-1}I) + (1+\lambda)\Sigma_{P}^{-1})^{-1}(\Sigma_{P}^{-1}(P - P_{0}) + I^{T}\Sigma_{\varepsilon}^{-1}(D_{sim} - D_{obs}))$$

upgraded parameter matrix

Approx Hessian

dampening

parameter change matrix

residual vector

D_{sim} (ne x nobs)

$$\Delta_P \propto (P - \bar{P})$$

$J \propto \Delta_{D_{cim}}^T \Delta_P^{-1}$

$$\Delta_{D_{sim}} \propto (D_{sim} - \overline{D}_{sim})$$

P (ne x npar)

	hk	mineral fraction	Initial sconc
real1	0.123	0.9	12.3
real2	0.321	0.0001	32.1
real3	0.987	0.2	69.0
real N	0.789	0.2345	54.1

update via GLM (e.g. maths)

model runs = ne (number reals) (e.g. Monte Carlo)











	head	sload instream	sconc inaqufier
real1	1.11	0.0001	3.21
real2	2.22	0.003	1.23
real3	3.33	0.0003	9.6
realN	4.44	0.001	1.45

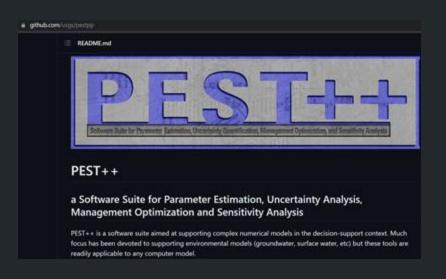
Uncertainty Analysis | Iterative Ensemble Smoother (IES)

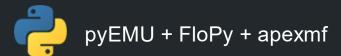
 Number of forward model runs required is controlled by the number of realizations.

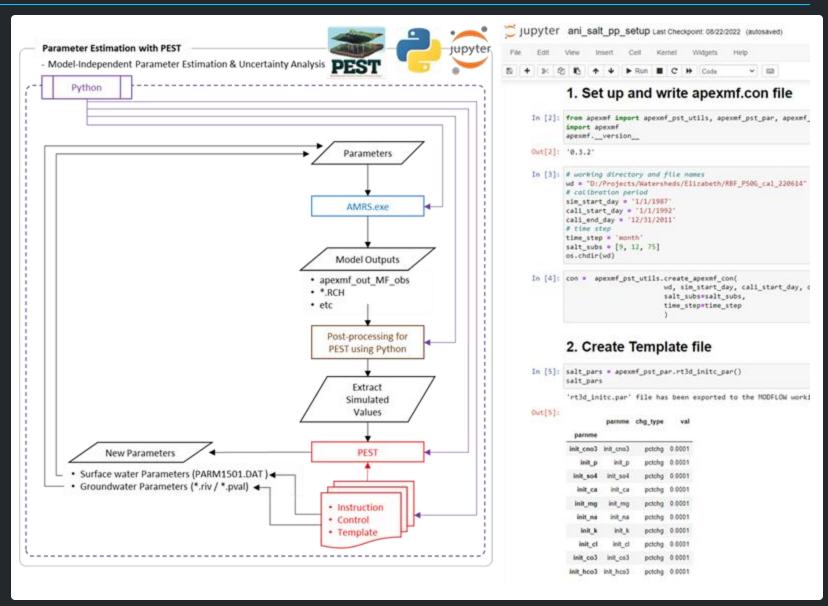
Uncertainty Analysis I Iterative Ensemble Smoother (IES)

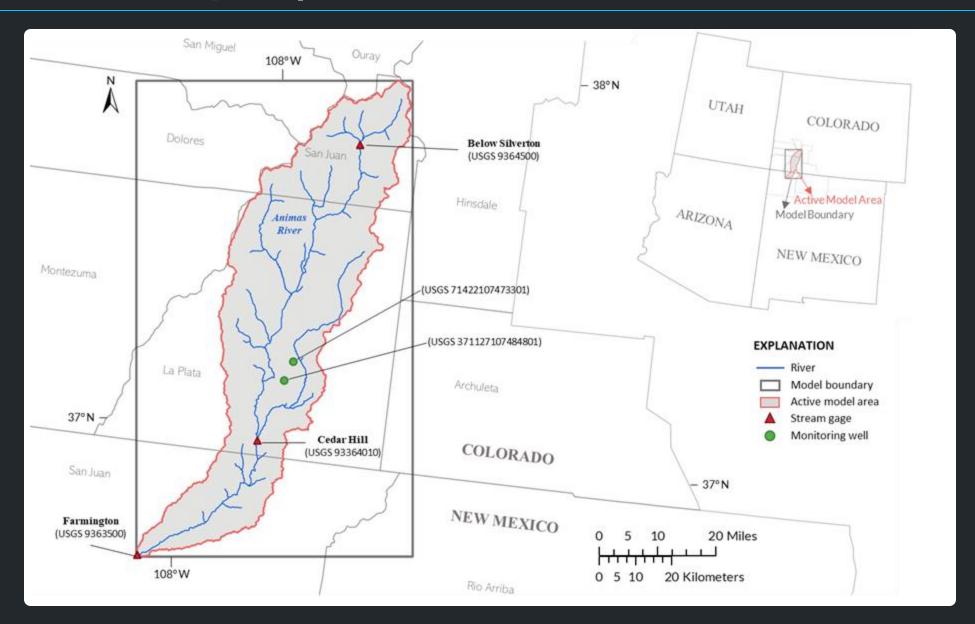
- Number of forward model runs required is controlled by the number of realizations.
- The parameter ensemble is a sample of the posterior parameter distribution which we can use for uncertainty analysis.

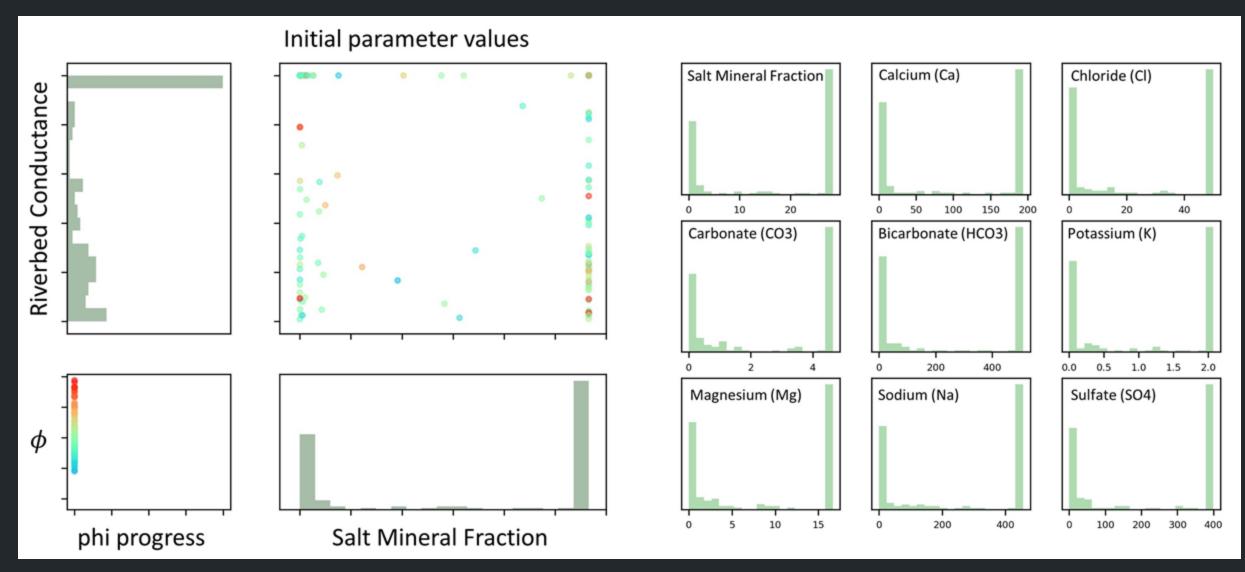
Uncertainty Analysis | Framework

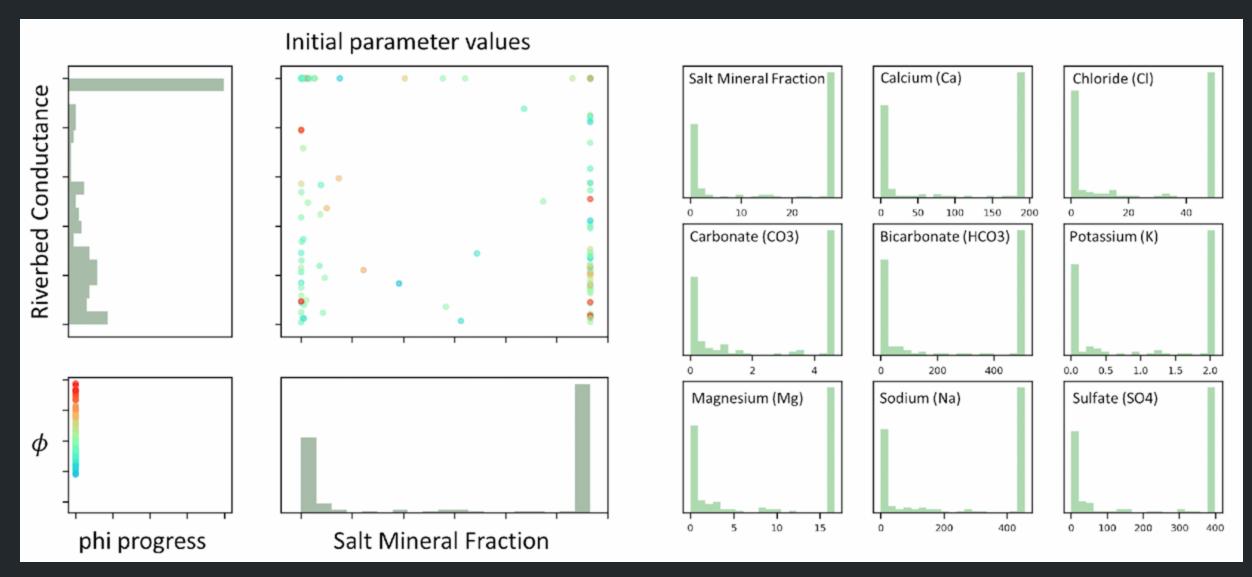


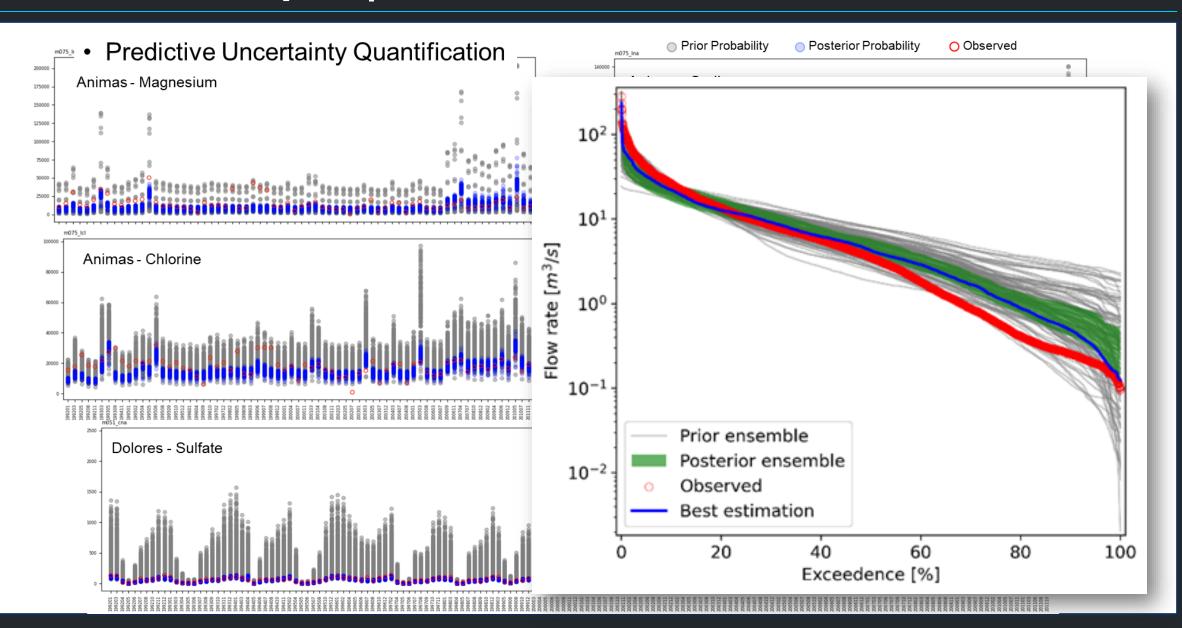




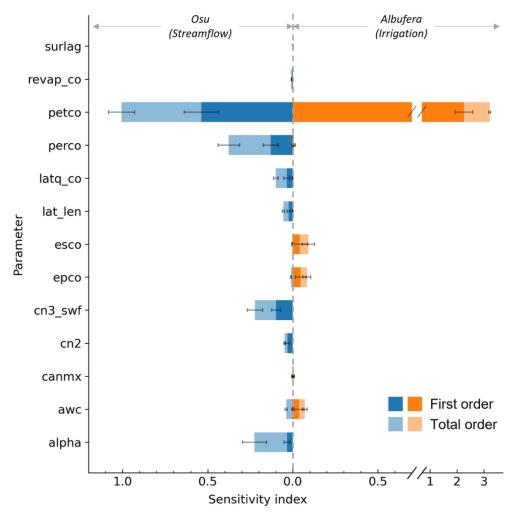




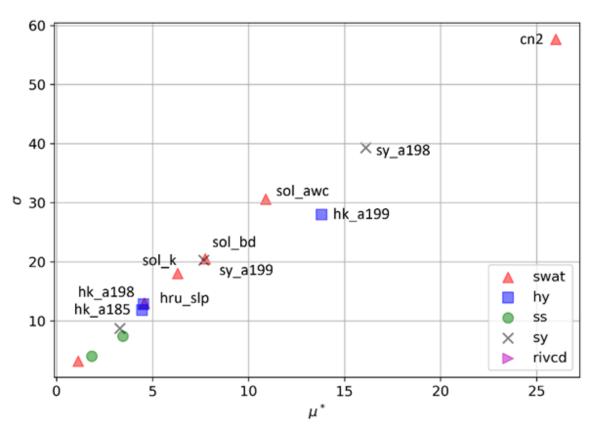




A Worked Example | Sensitivity Analysis



Sobol's first-order and total-order sensitivity indices were estimated for the selected 13 parameters. Error bars correspond to a 95% confidence interval.



Morris Screening Result:

Only the most sensitive parameters are labeled for clarity. The σ values indicate the degree of nonlinearity or factor interaction, while μ^* represents the sensitivity measure.

References

- Algorithm Guide:
 - SPOTPY: https://spotpy.readthedocs.io/en/latest/Algorithm_guide/
- Bayesian Theorem:
 - Probabilistic-Programming-and-Bayesian-Methods-for-Hackers: https://github.com/CamDavidsonPilon/Probabilistic-Programming-and-Bayesian-Methods-for-Hackers
 - Bayesian Modeling and Computation in Python: https://bayesiancomputationbook.com/welcome.html
 - PyMC: https://www.pymc.io/welcome.html
- DREAM:
 - Vrugt, J.A., 2016. Markov chain Monte Carlo simulation using the DREAM software package: Theory, concepts, and MATLAB implementation. Environmental Modelling & Software 75, 273–316. https://doi.org/10.1016/j.envsoft.2015.08.013

References

• DREAM:

- Tasdighi, A., Arabi, M., Harmel, D., Line, D., 2018. A Bayesian total uncertainty analysis framework for assessment of management practices using watershed models. Environmental Modelling & Software 108, 240–252. https://doi.org/10.1016/j.envsoft.2018.08.006
- Sadegh, M., Vrugt, J.A., 2014. Approximate Bayesian Computation using Markov Chain Monte Carlo simulation: DREAM(ABC). Water Resources Research 50, 6767–6787. https://doi.org/10.1002/2014WR015386
- Laloy, E., Vrugt, J.A., 2012. High-dimensional posterior exploration of hydrologic models using multiple-try DREAM _(ZS) and high-performance computing: EFFICIENT MCMC FOR HIGH-DIMENSIONAL PROBLEMS. Water Resour. Res. 48.

https://doi.org/10.1029/2011WR010608