How well does a model reproduce hydrologic response?

Lessons from an inter-model comparison

Riddhi Singh, Basudev Biswal
Department of Civil Engineering
Indian Institute of Technology Bombay, India

2018 SWAT Conference, IIT Madras
January 10-12, 2018

Advances in Water Resources 100 (2017) 168–182

Contents lists available at ScienceDirect

Advances in Water Resources

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

Incorporating channel network information in hydrologic response modelling: Development of a model and inter-model comparison

Basudev Biswal*, Riddhi Singh

Department of Civil Engineering, Indian Institute of Technology Hyderabad, Kandi, Hyderabad, 502085, India

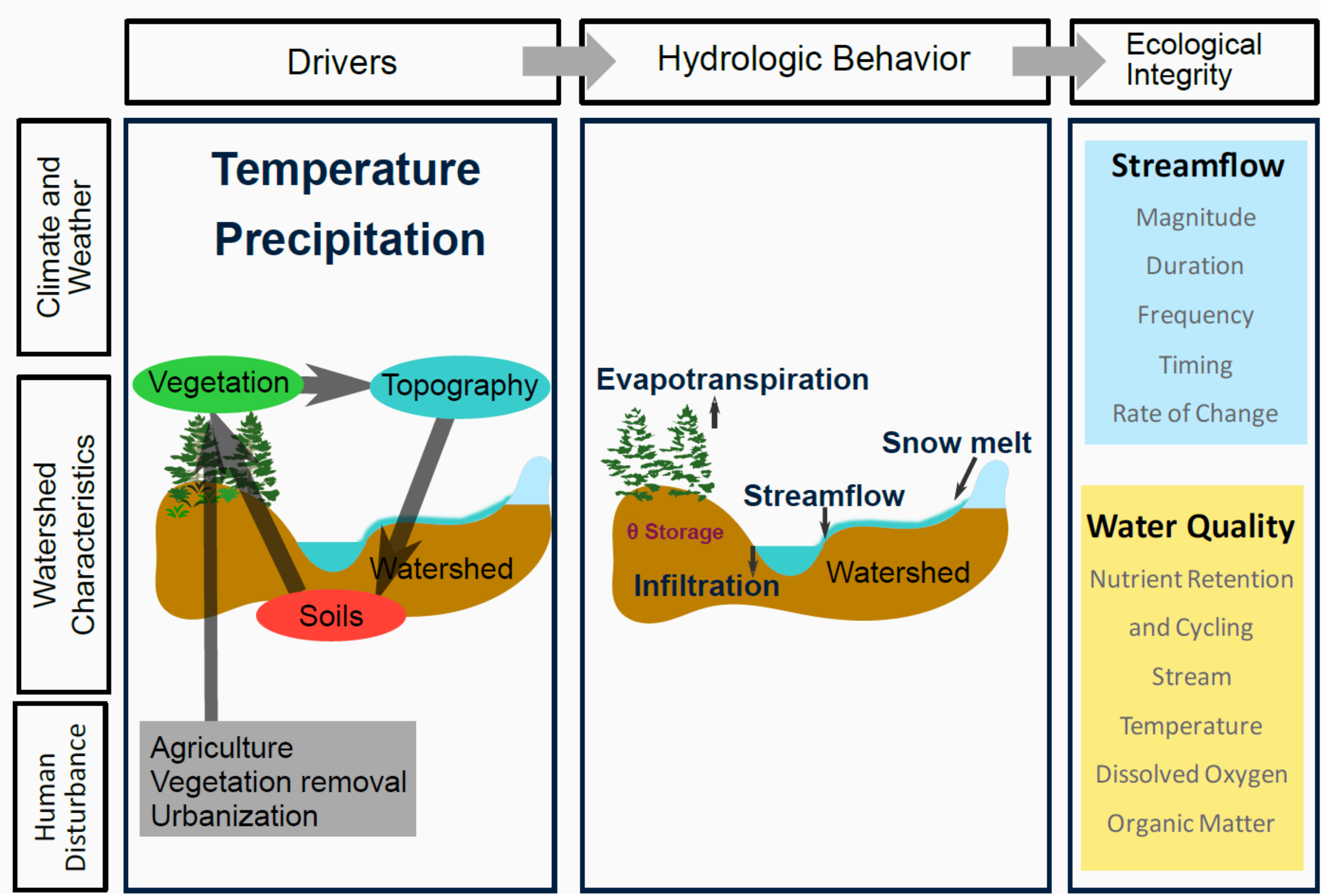
A R T I C L E I N F O

Article history:
Received 8 October 2016
Revised 28 November 2016
Accepted 12 December 2016

A B S T R A C T

Incorporation of channel network information in streamflow modelling is a well-accepted scientific practice now. In particular, channel network morphology based instantaneous unit hydrographs (IUHs) are widely used for modelling of flood response. However, very few attempts have been made so far to use

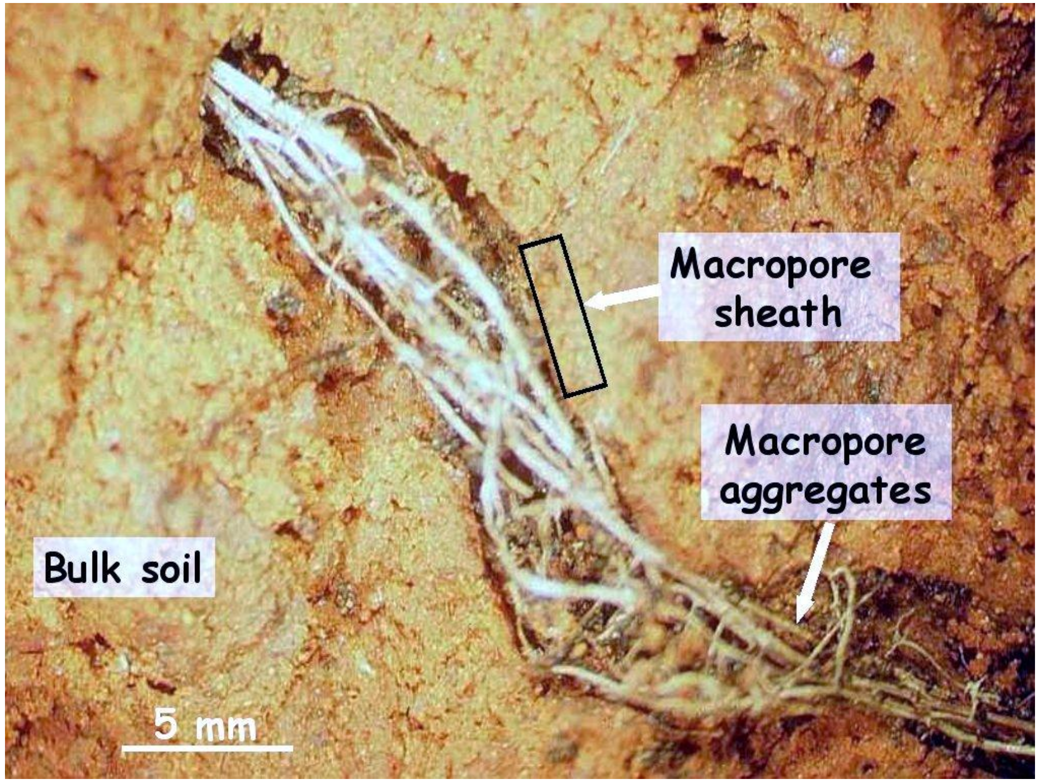
Catchments are complex systems



Kelleher et al. 2013, PhD Dissertation

The goal of modelling efforts is to abstract these complex systems to as to enable:

1. Hypothesis testing



2. Prediction: floods & droughts, climate change

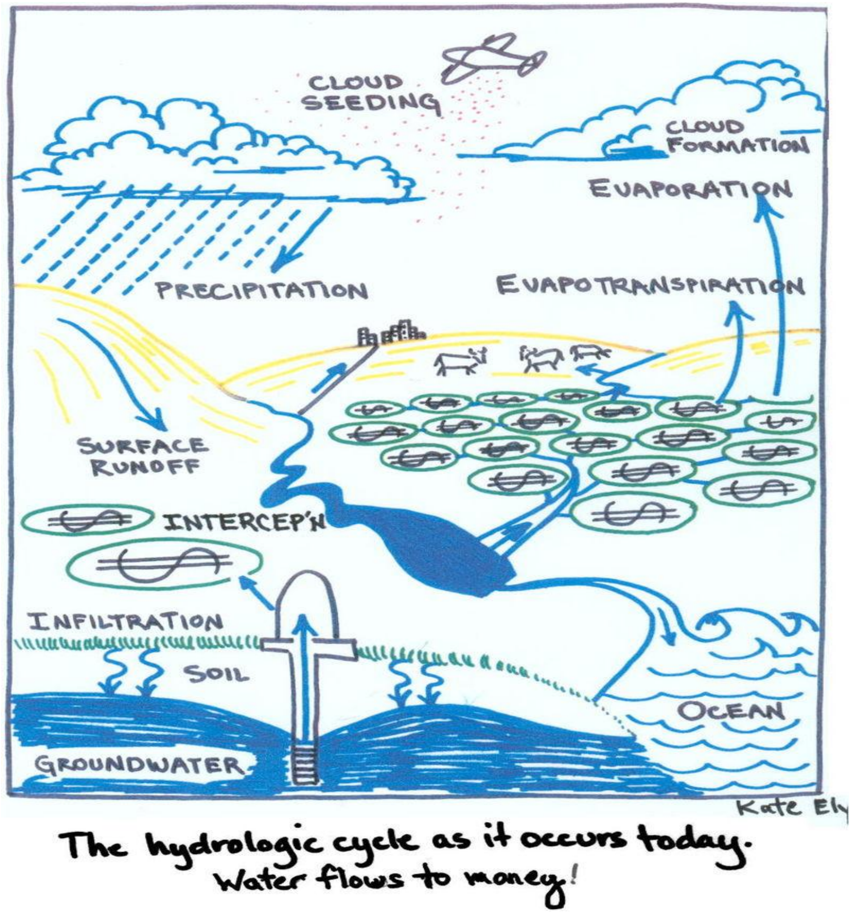


Image: http://prometheuswiki.publish.csiro.au/tiki-download_file.php?fileId=157&display (left)
http://aquadoc.typepad.com/.a/6a00d8341bf80a53ef01a3fcb83941970b-pi (right)

A goodness-of-fit statistic or objective functions quantifies the distance between model output and observations

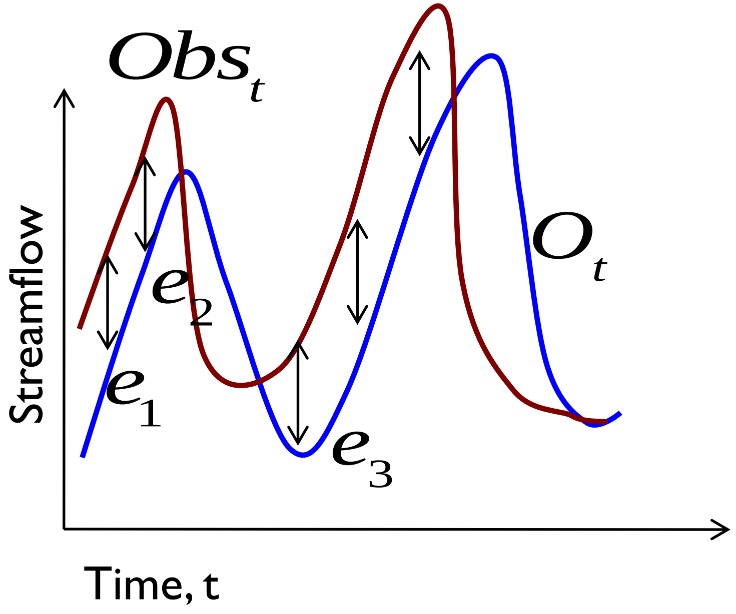
$$X_t = M_f(\Theta, X_{t-1}, I_{t-1})$$

$$O_t = M_g(\Theta, X_{t-1}, I_{t-1})$$

$$Obs_t$$

I_t → MODEL (M) → O_t → $e_t = Obs_t - O_t$ →

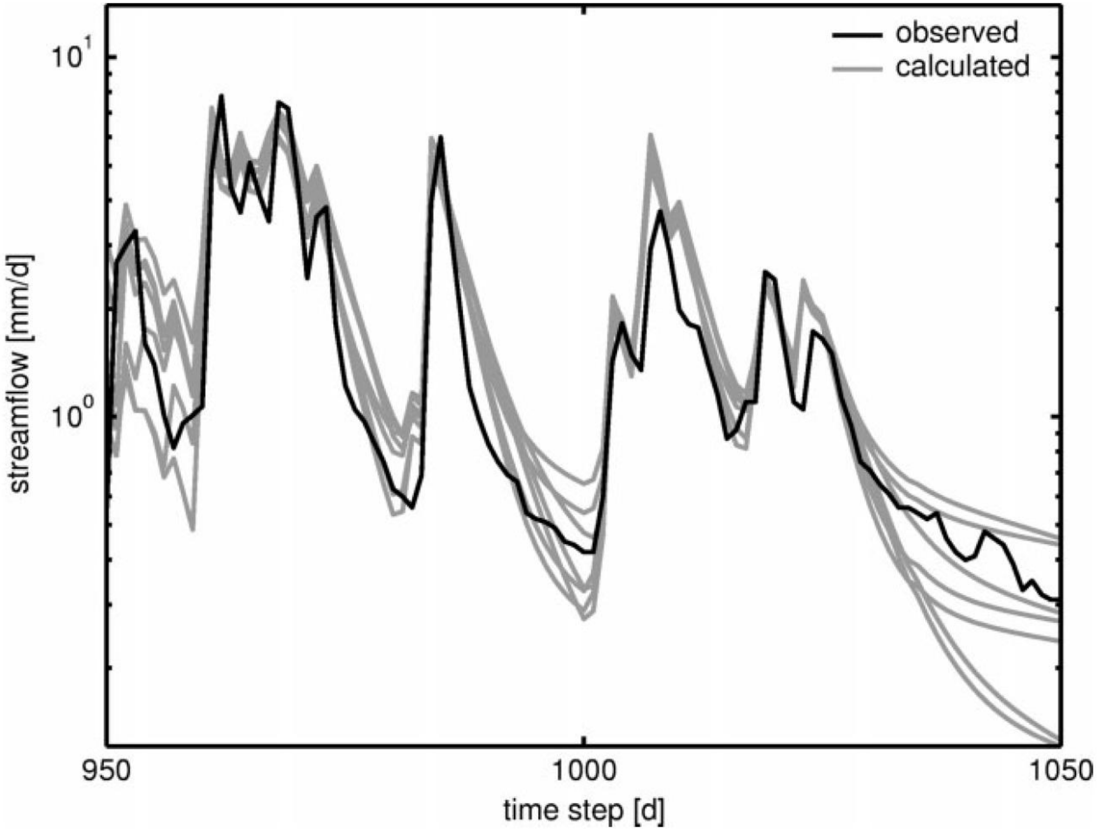
State update (X_t)



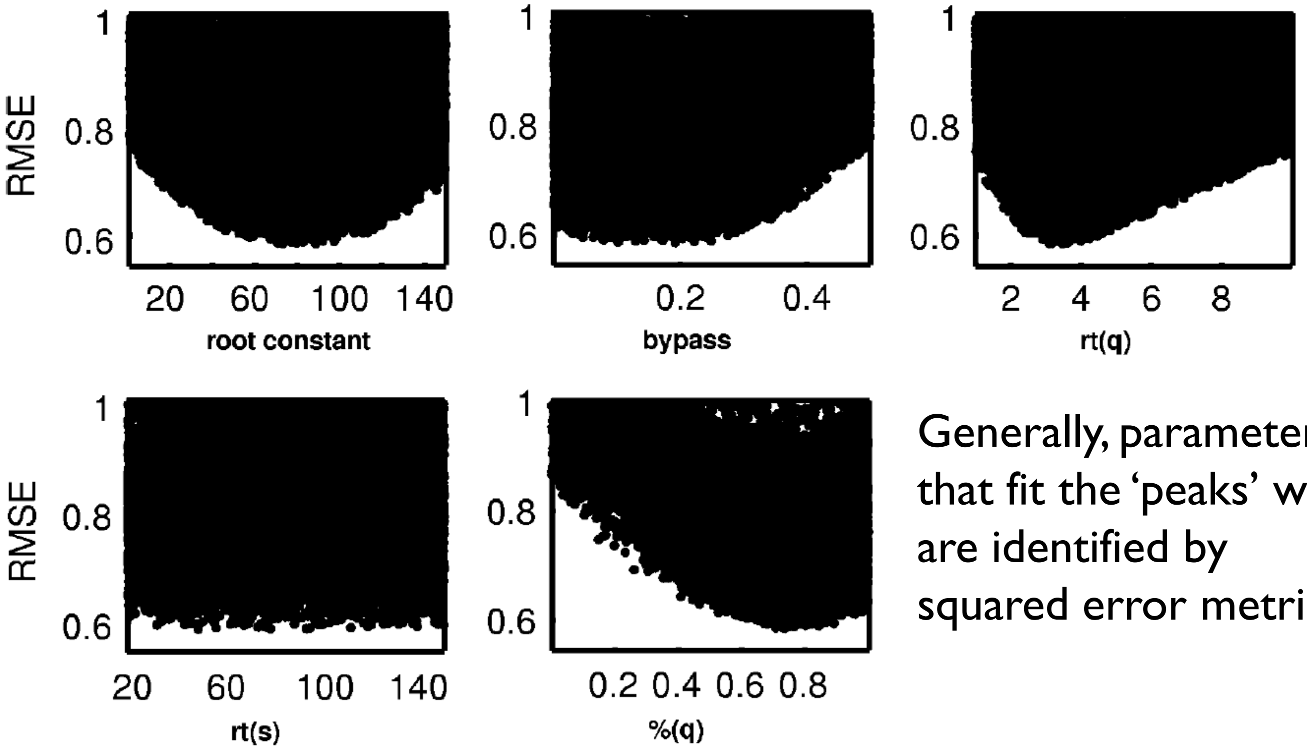
$$Total\ error\ \ E(\theta, Obs, X_o) = f(e_1, e_2, ..., e_t, ...)$$

Common objective functions such as the NSE, RMSE, or percentage bias collapse this information into a single value

Most common objective function lead to un-identifiability of one or more model parameters



All simulations yield an RMSE value of 0.60!



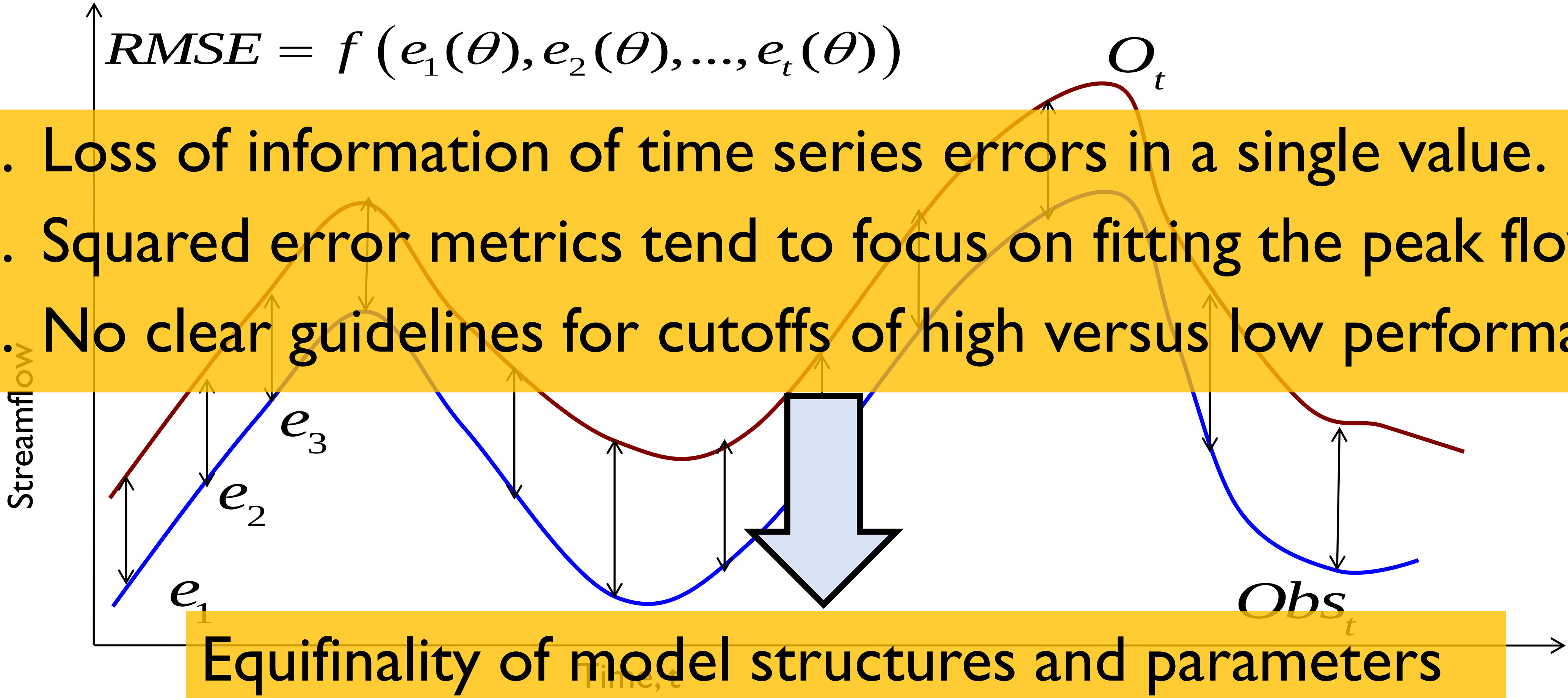
Generally, parameters that fit the 'peaks' well are identified by squared error metrics.

Only some parameters are identifiable using RMSE.

Wagener et al. 2003, DYNIA, *Hydrological Processes*

Challenges in model structure and parameter identification

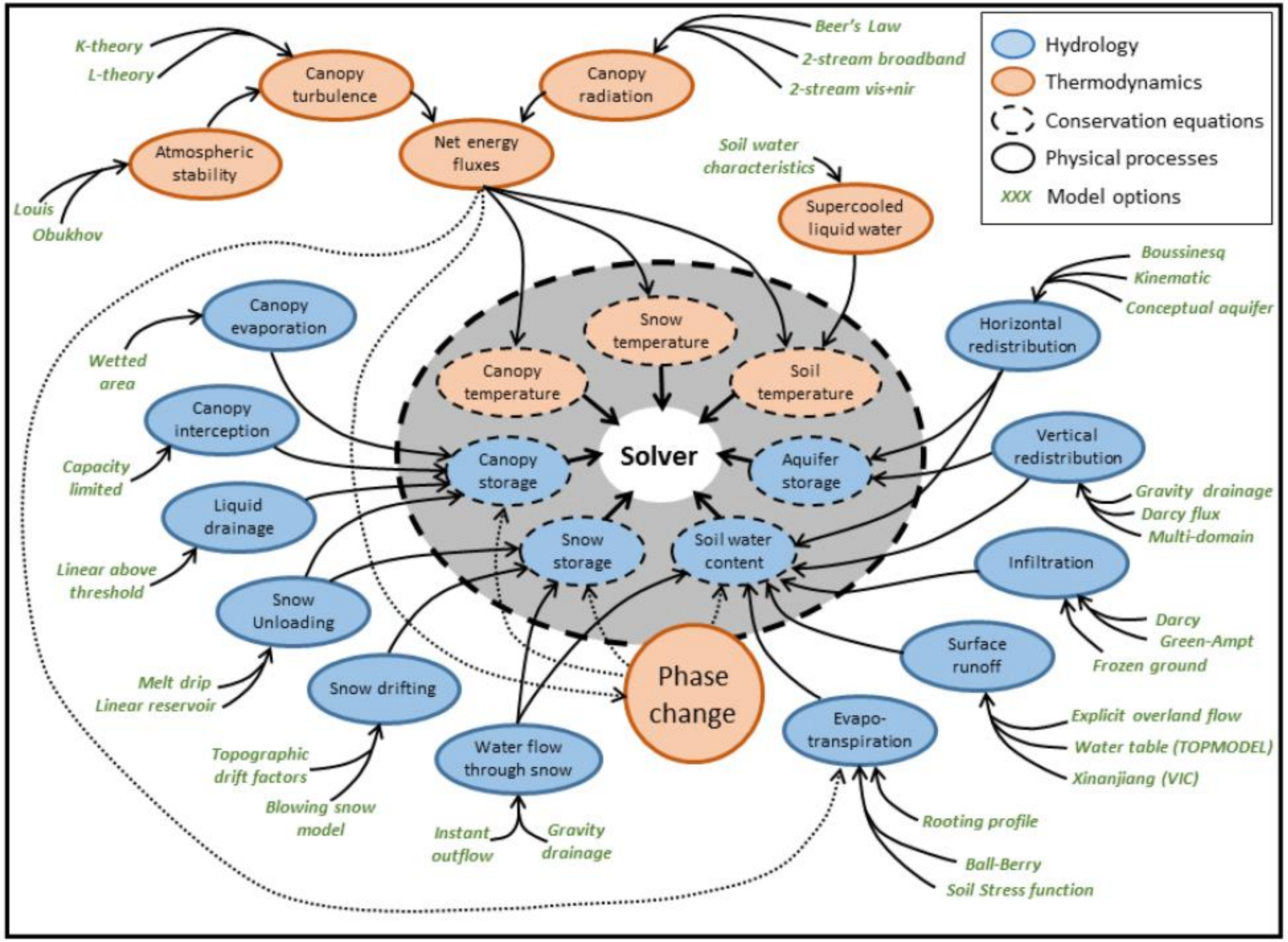
$$RMSE = f\left(e_1(\theta), e_2(\theta), \ldots, e_t(\theta)\right)$$



1. Loss of information of time series errors in a single value.
2. Squared error metrics tend to focus on fitting the peak flows
3. No clear guidelines for cutoffs of high versus low performance

Equifinality of model structures and parameters

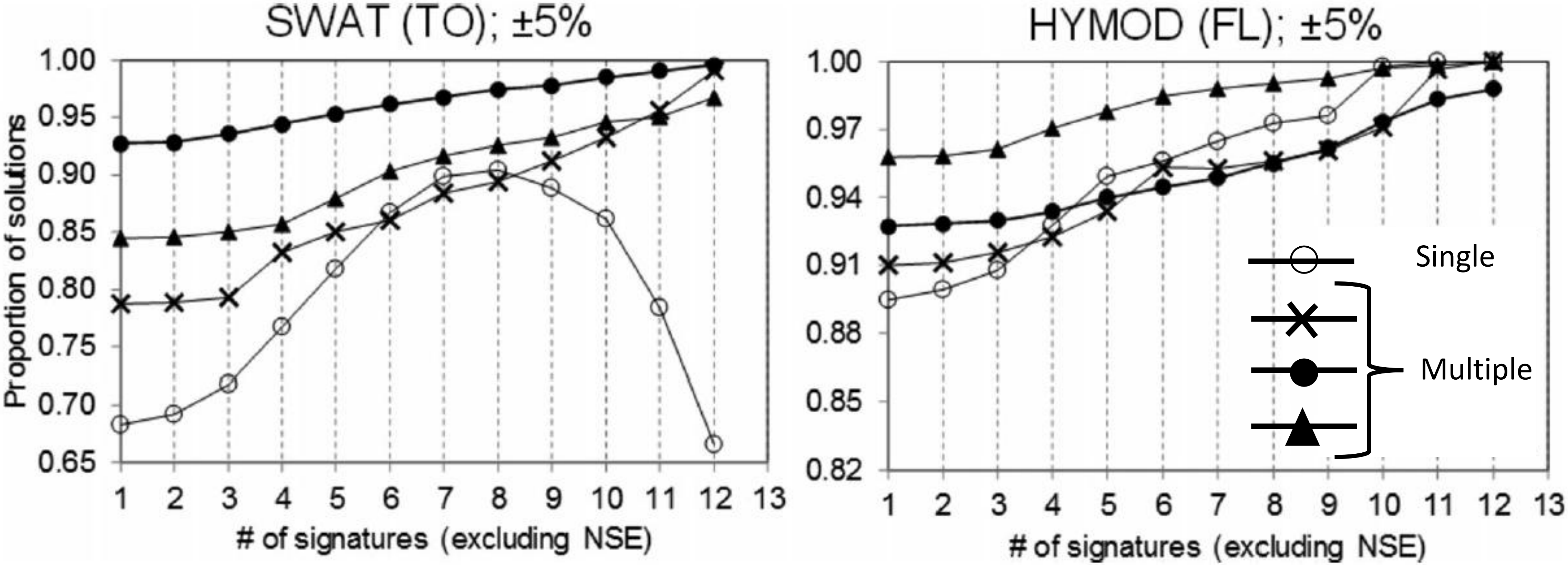
Recent studies suggest a modular approach to model building



Clark et al., 2015, SUMMA, *WRR*

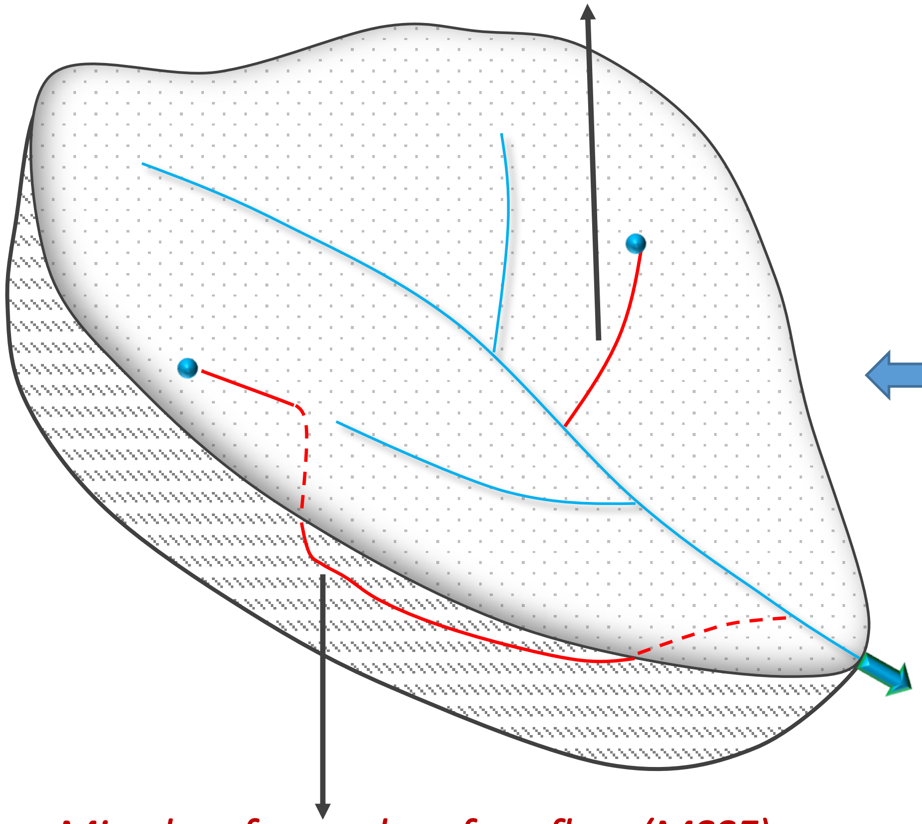
Beyond NSE: including hydrologic signatures in model assessment

"Pareto dominance based multiobjective optimization yields the highest level of consistency among all formulations."



Shafi and Tolson, 2015, Optimizing hydrological consistency by incorporating hydrological signatures into model calibration objectives, *WRR*

Our study: compare model performance for a proposed routing structure



Reality

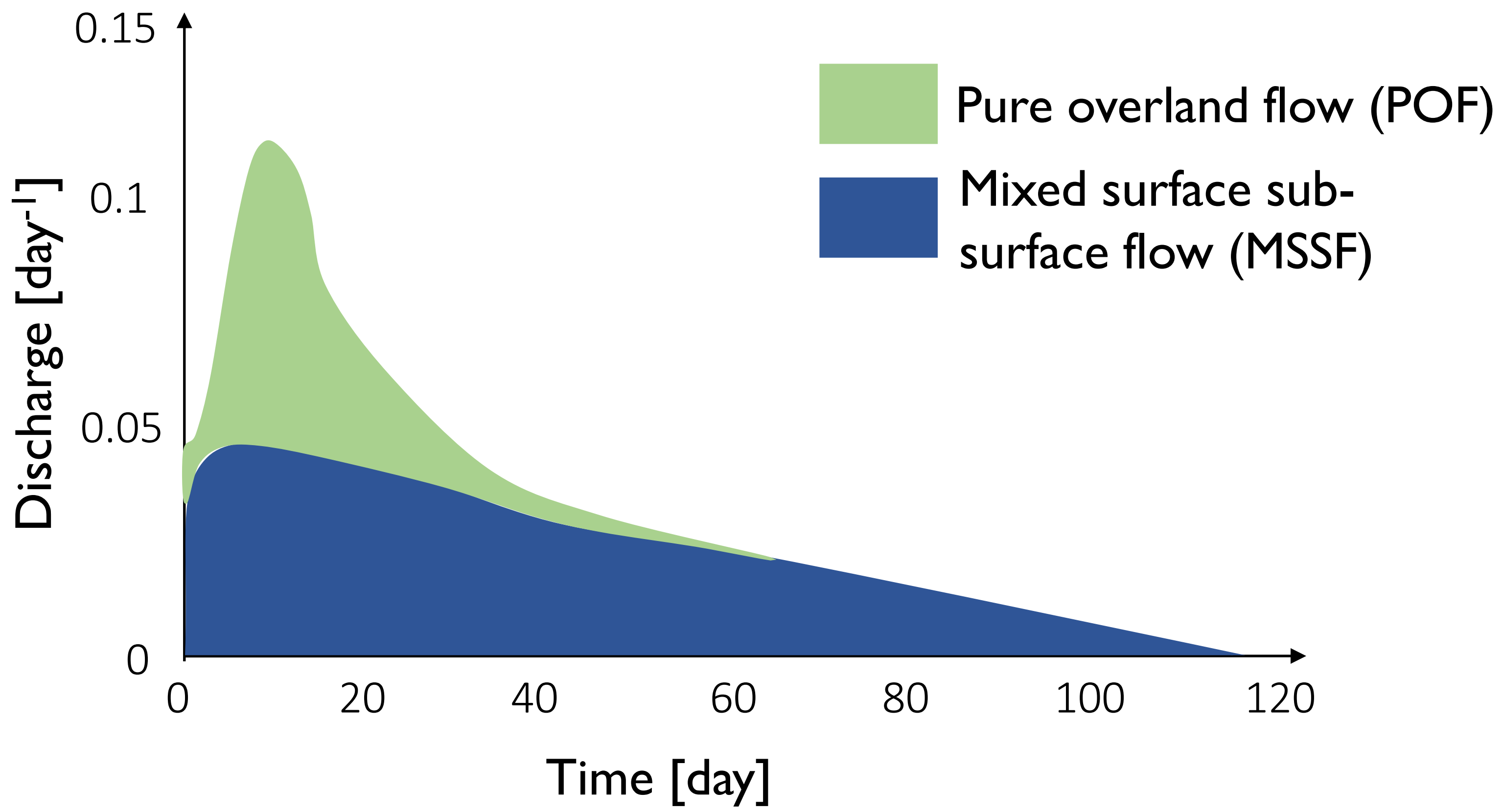
Image source: http://www.krisweb.com/hydrol/Salmon_River.jpg)

The two flow components can then be modelled separately.

Biswal and Singh, 2017, *AWR*

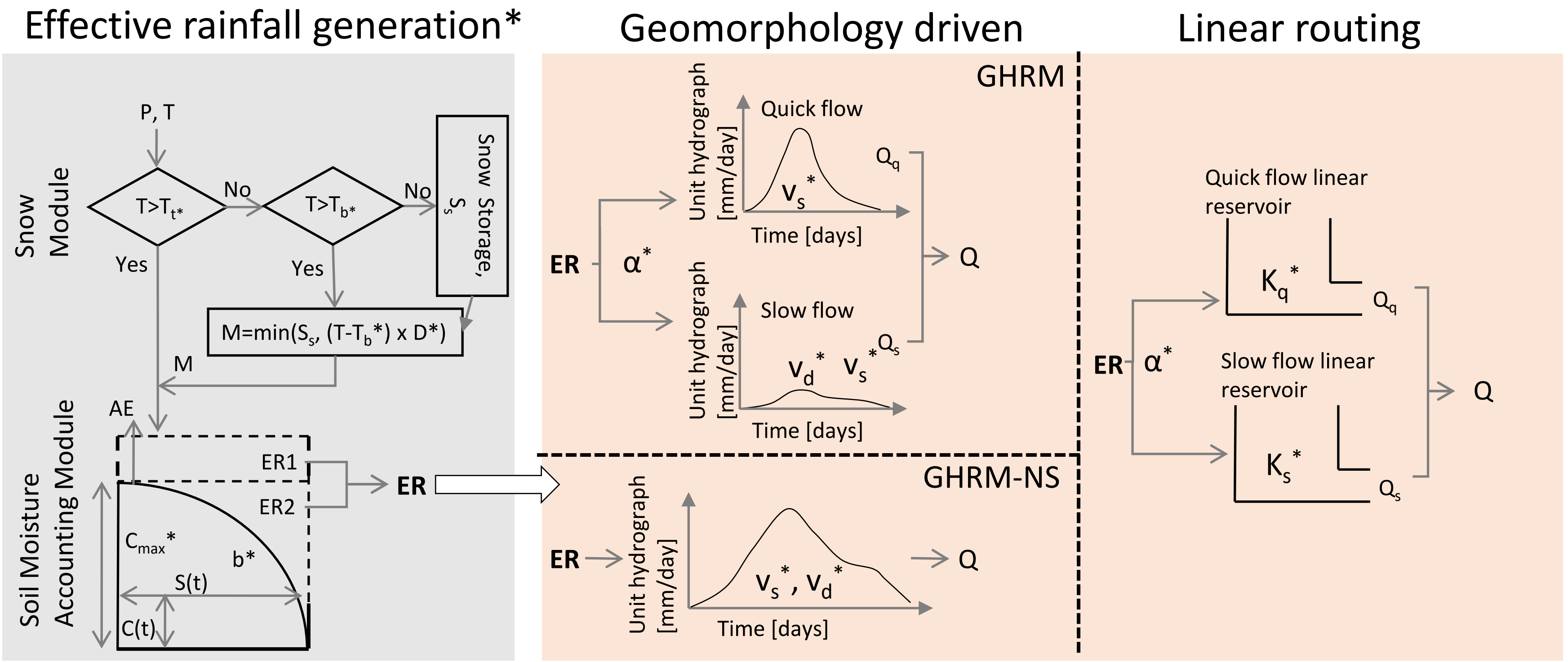
The geomorphic hydrological response model (GHRM)

CFIUH: $u_c(t) = \alpha \cdot u_o(t) + (1 - \alpha) \cdot u_m(t)$ (α the splitting parameter)



Biswal and Singh, 2017, *AWR*

We create two model structures based on GHRM and compare it against a liner reservoir type routing

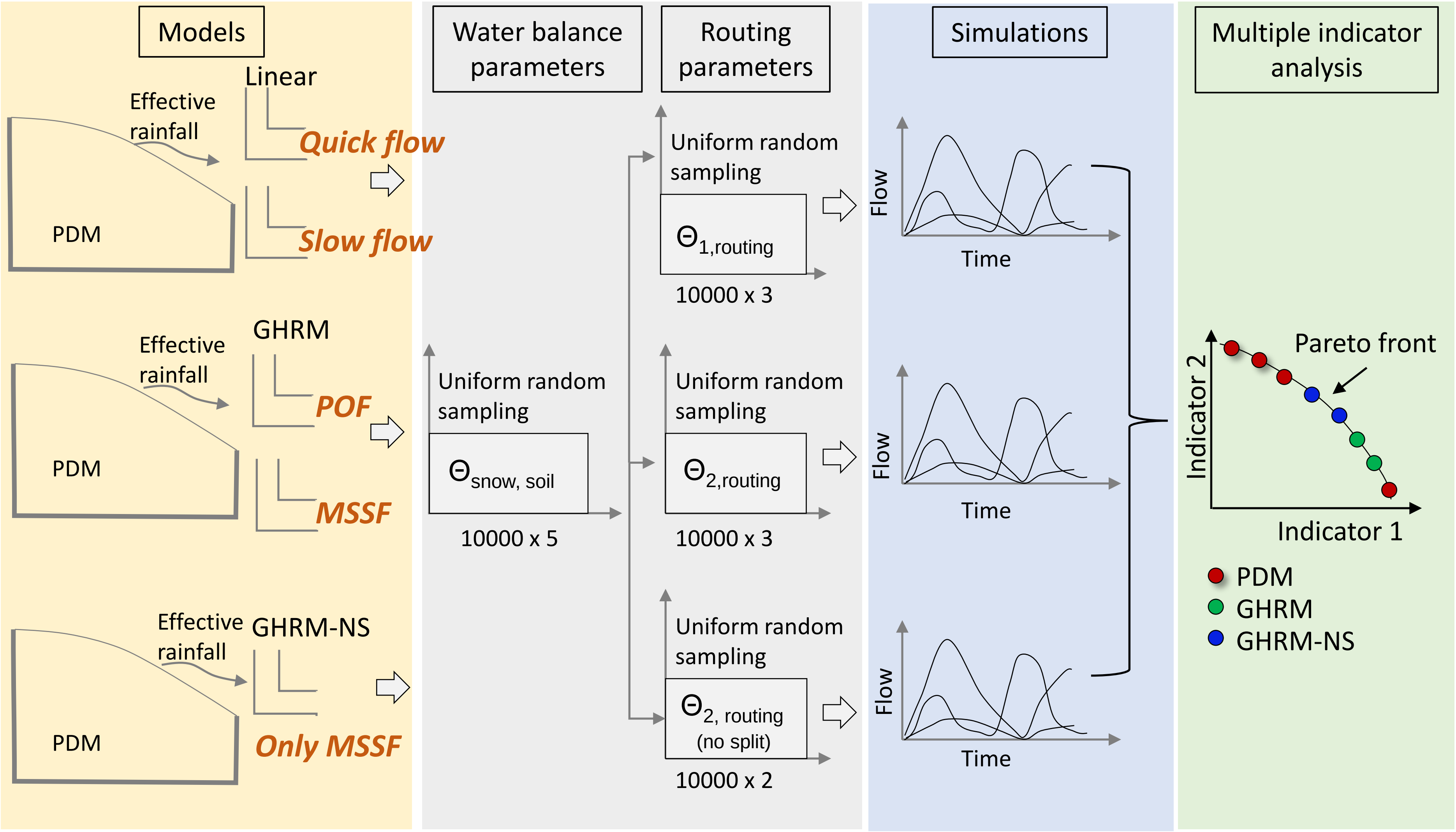


*The probability distributed model

Routing

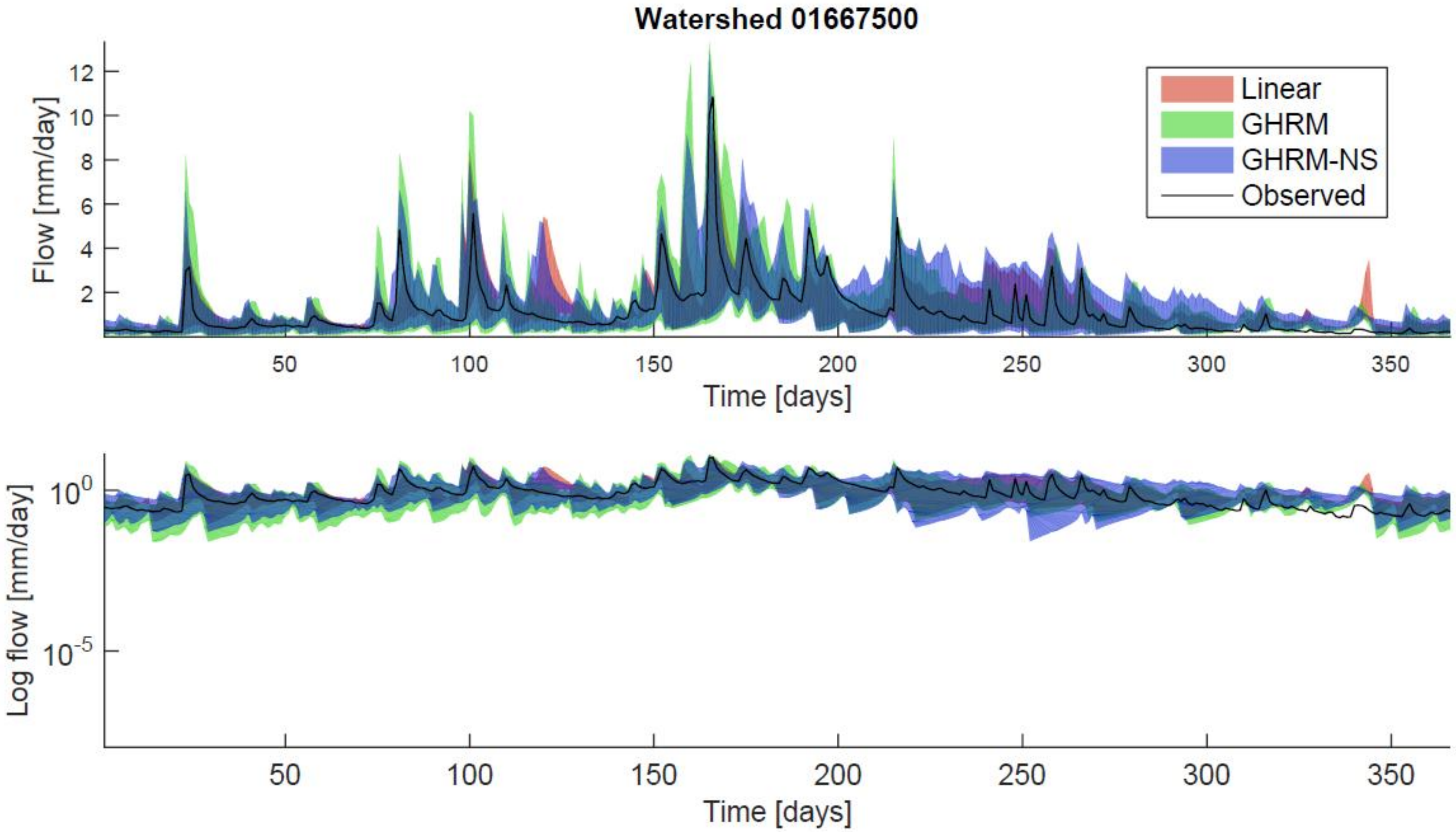
Biswal and Singh, 2017, *AWR*

Identifying the behavioral parameter space using multiple ecologically relevant indicators



Biswal and Singh, 2017, *AWR*

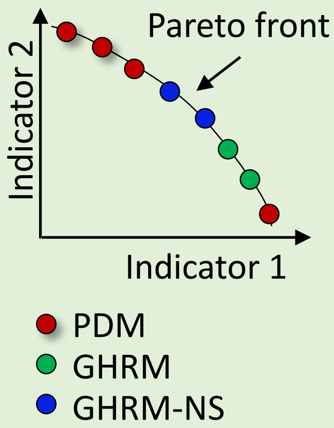
Using multiple objectives allows us to obtain envelopes of streamflow for each model

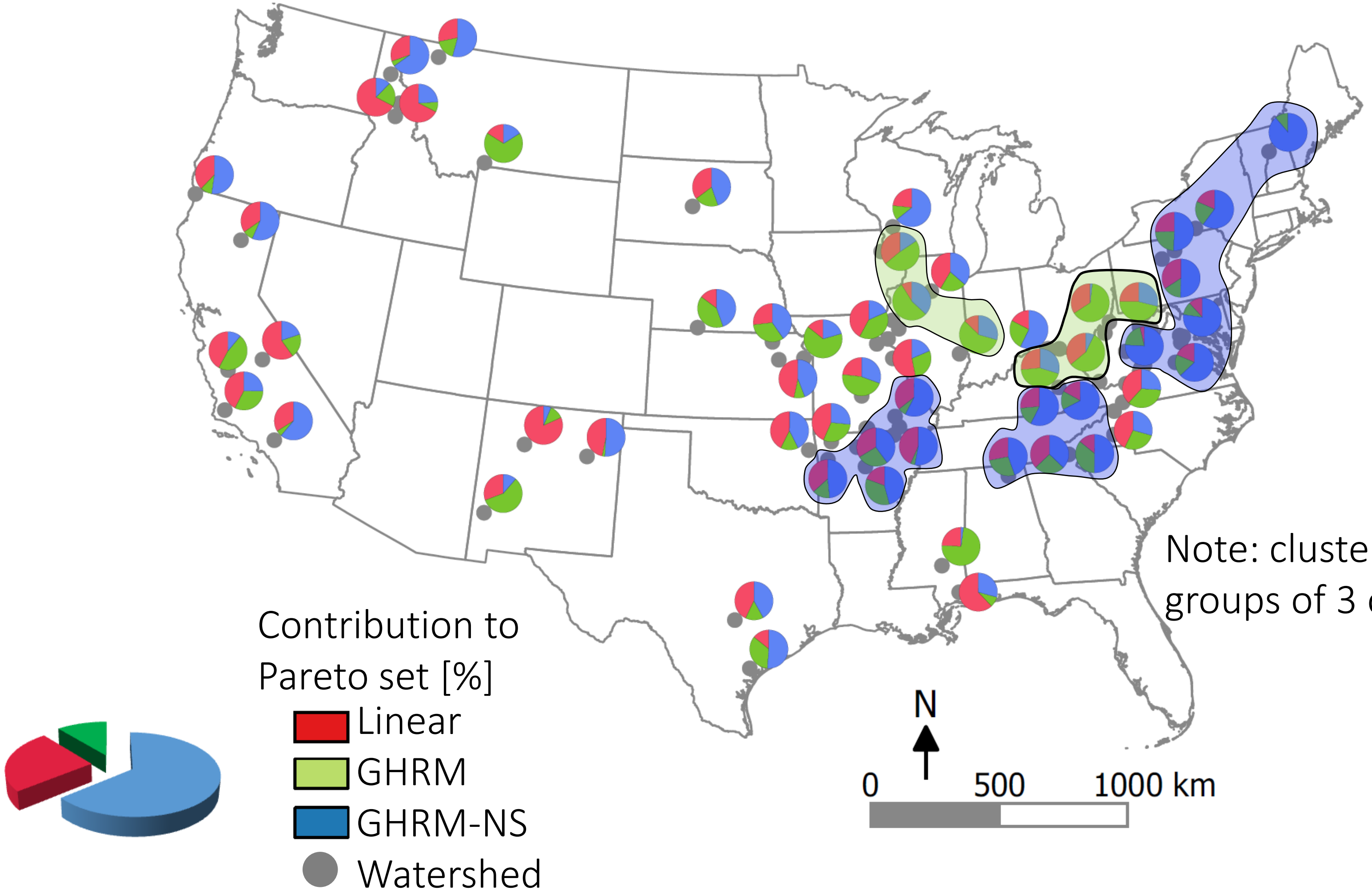


Biswal and Singh, 2017, *AWR*

We find significant spatial variation in the contribution of each model to the Pareto optimal set

Multiple indicator analysis

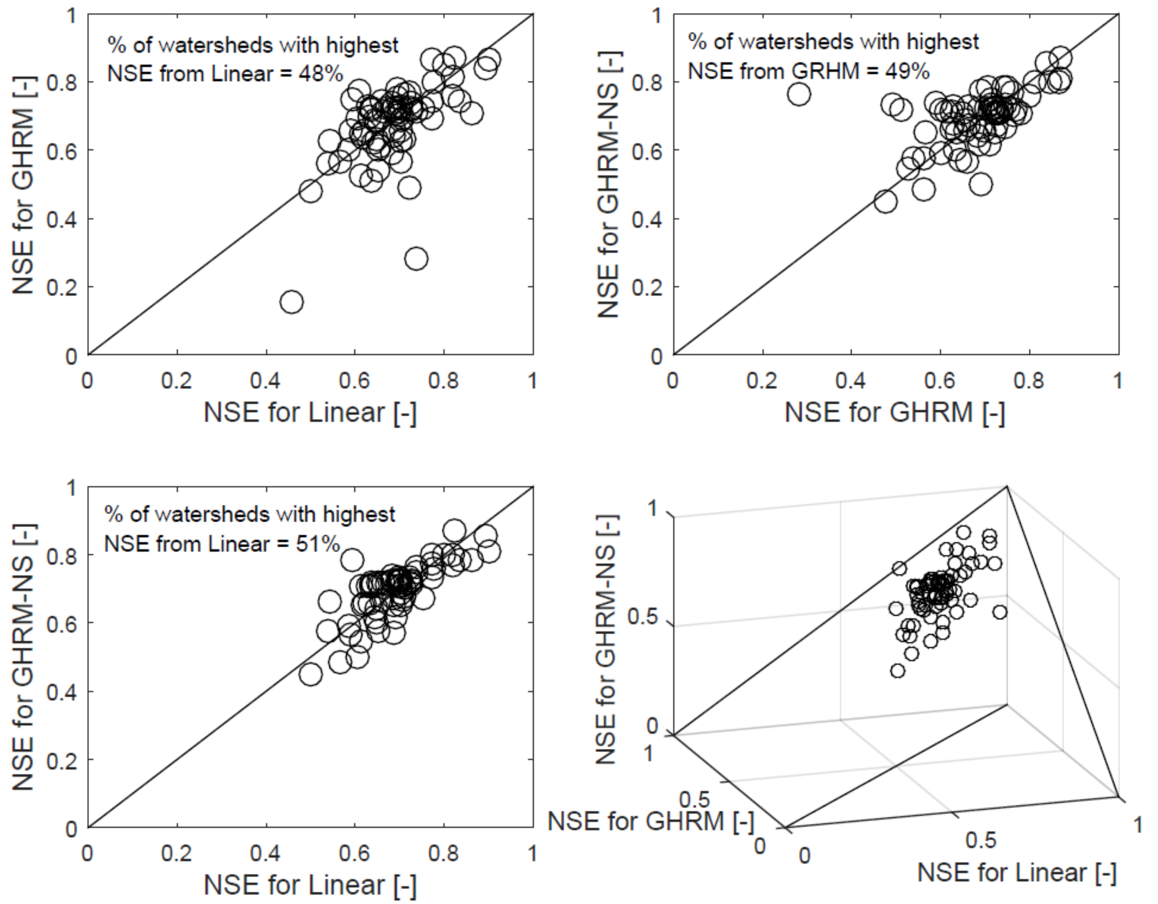




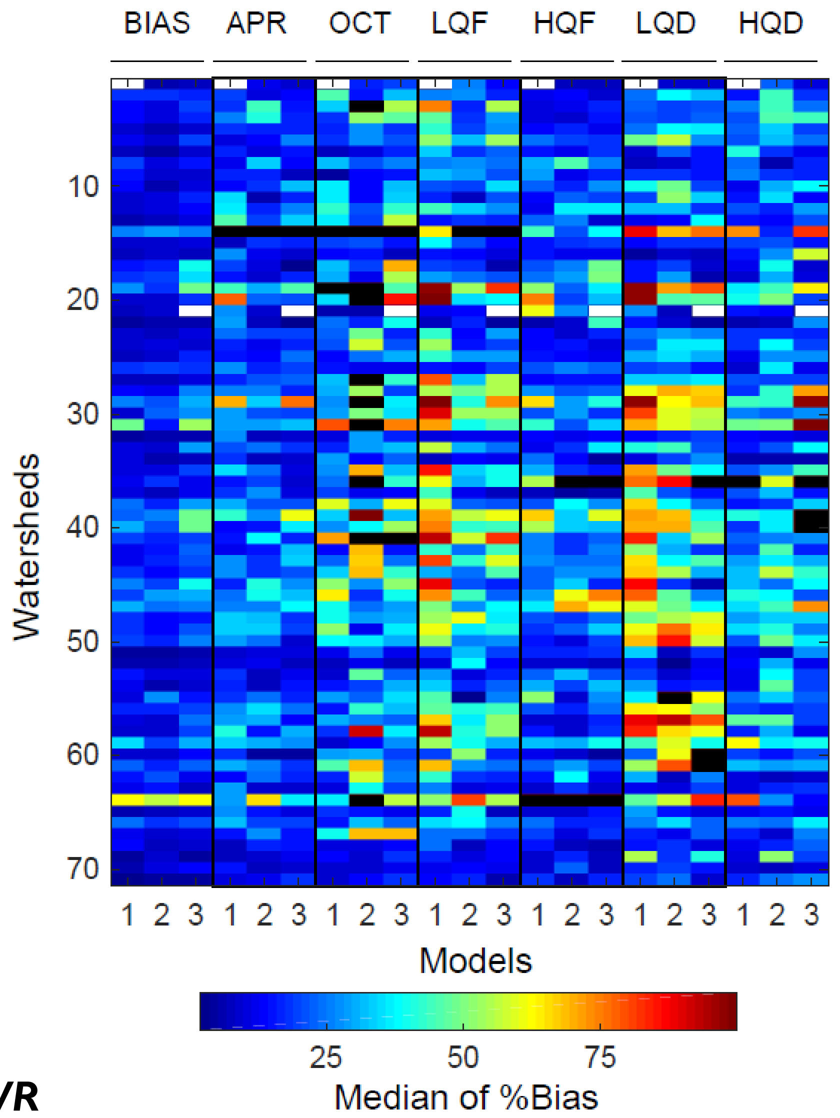
Note: clusters are delineated for groups of 3 or more watersheds

Biswal and Singh, 2017, *AWR*

NSE performance of the three model structures was comparable



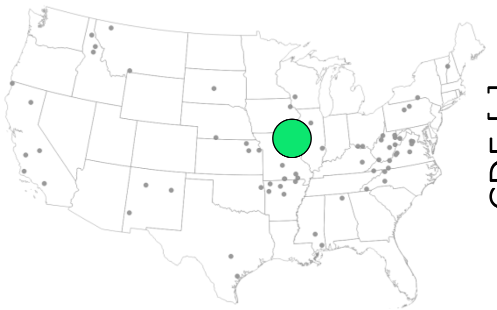
A multi-dimensional assessment of model performance

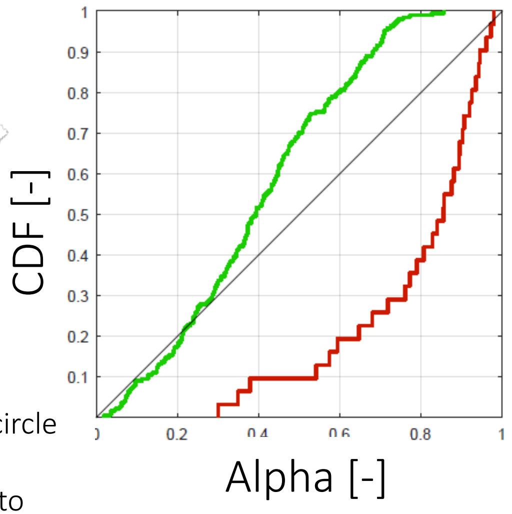


1 Linear
2 GHRM
3 GHRM-NS

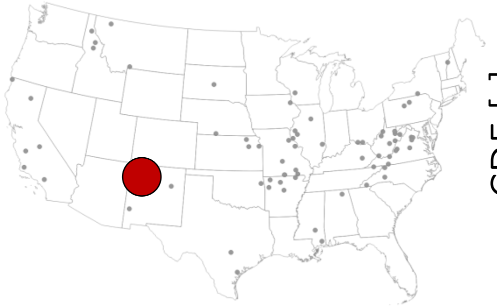
Biswal and Singh, 2017, *AWR*

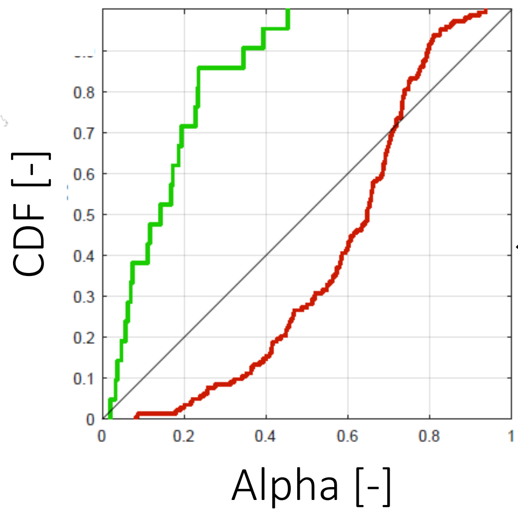
Partitioning of flow varies significantly between linear routing and geomorphological routing

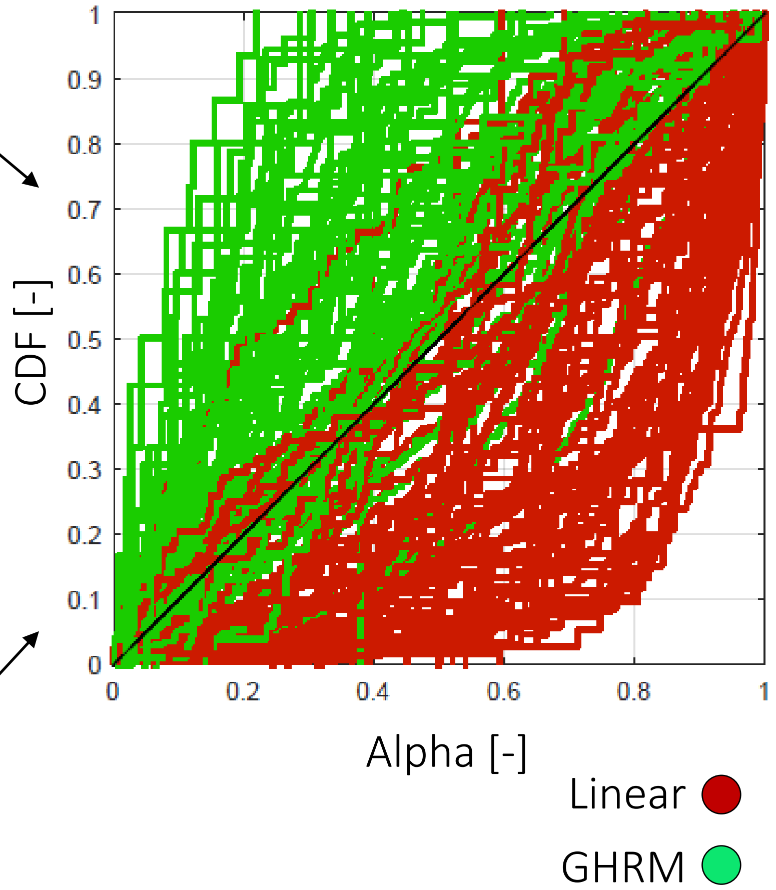




Watershed location is shown by a circle and color denotes the model with maximum contribution to the Pareto sets





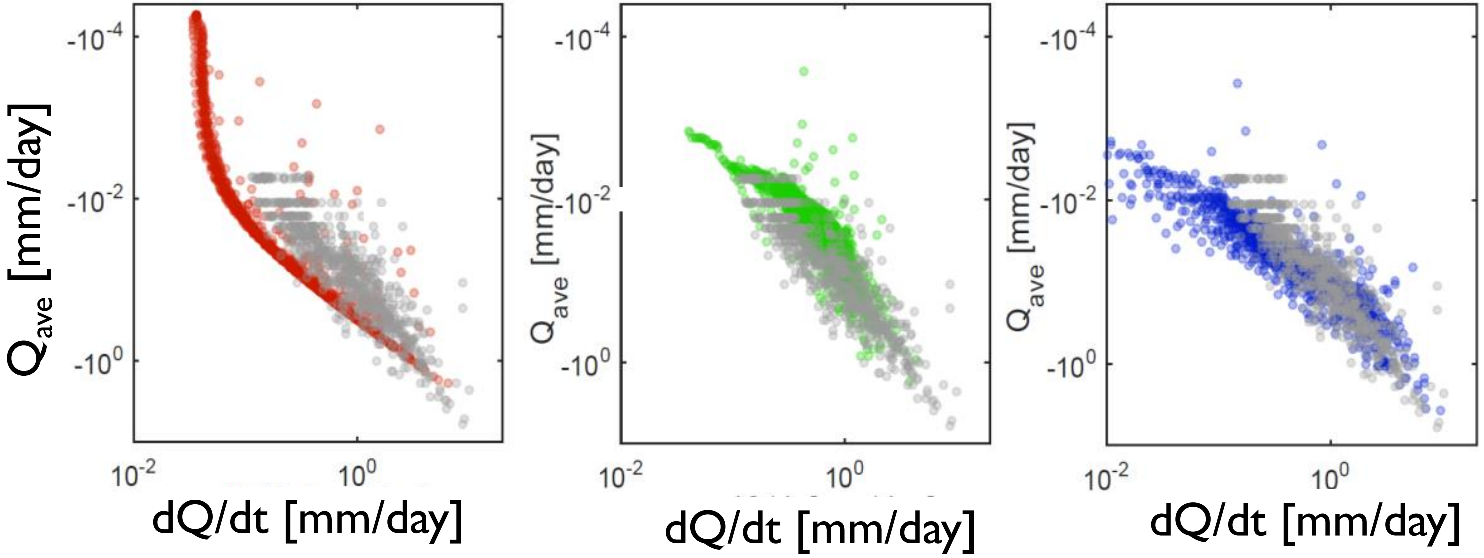


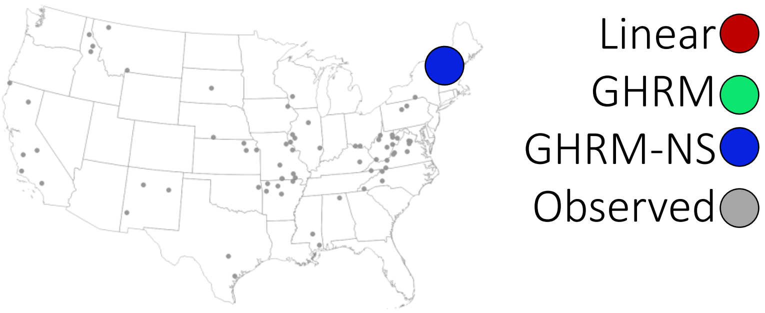
Biswal and Singh, 2017, *AWR*

Cumulative distribution of split parameter across the Pareto optimal sets shows very different behavioral ranges for the linear and geomorphic models.

The recession behavior changes considerably between linear and geomorphology based models

Simulations for the Pareto optimal set
with the best NSE value for each model



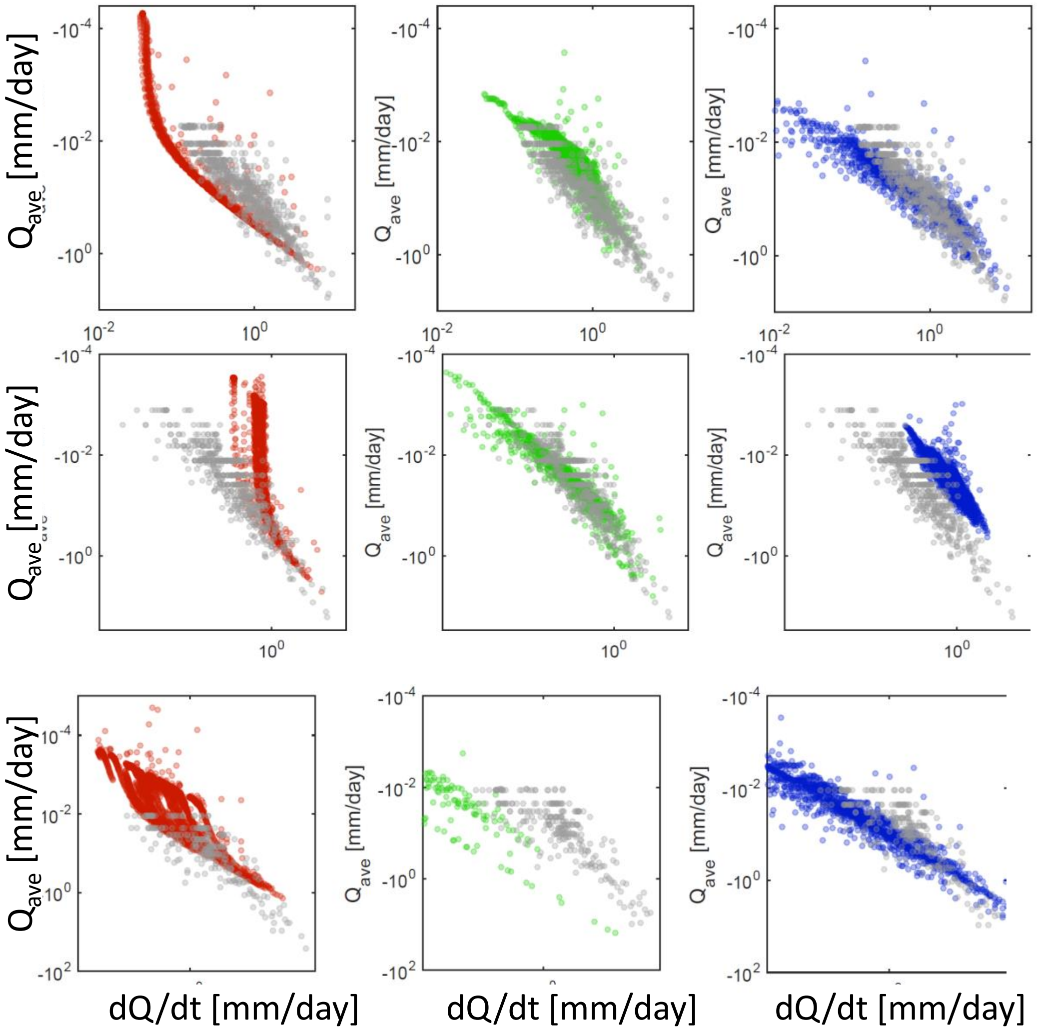


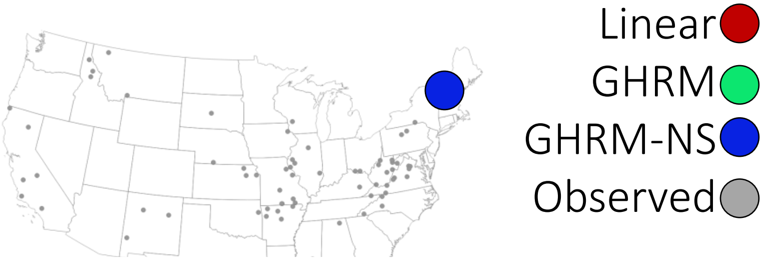
Watershed location is shown by a circle and color denotes the model with maximum contribution to the Pareto sets

Biswal and Singh, 2017, *AWR*

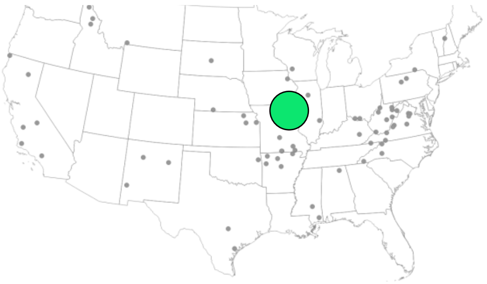
The recession behavior changes considerably between linear and geomorphology based models

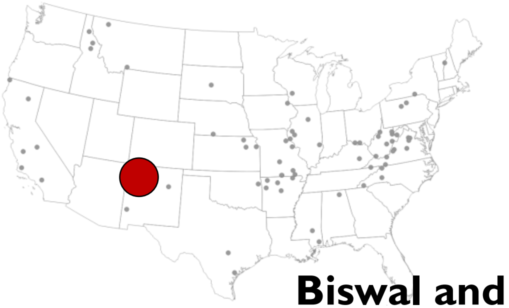
Simulations for the Pareto optimal set with the best NSE value for each model





Watershed location is shown by a circle and color denotes the model with maximum contribution to the Pareto sets





Thank you!

Biswal and Singh, 2017, *AWR*