Overview of WRF-Hydro Model Calibration General Strategy & Optimization

A. RafieeiNasab, A. Dugger, K. FitzGerald, D. Gochis, D., T. Enzminger, A. Mazrooei, M. McAllister, I. Srivastava, R. Cabell, P. Saylor, N. Omani

National Center for Atmospheric Research

10:15 - 11:15 am, Thursday April 7, 2022

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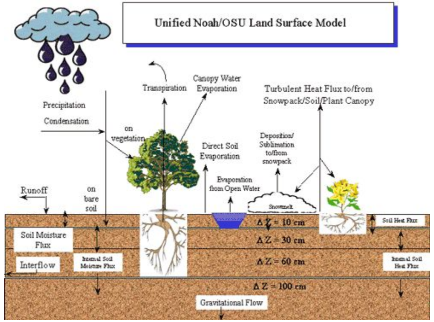
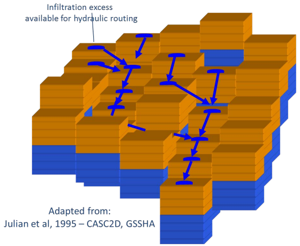
WRF-Hydro Physics Components

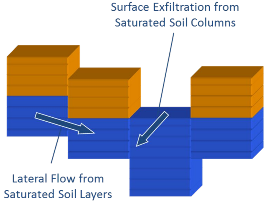
Land Surface Model



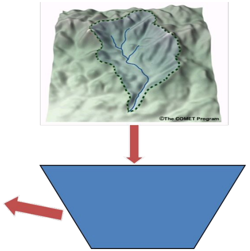
Overland Flow



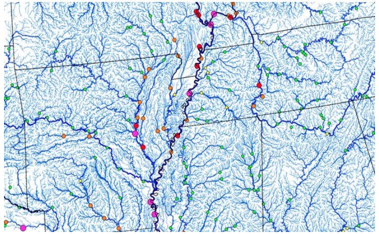
Lateral Subsurface Flow



Simplified Baseflow Parameterization



Channel Hydraulics



Simple Water Management

PyWrfHydroCalib

NCAR
UCAR

Calibration Methodology

Dynamically Dimensioned Search (DDS) algorithm

- search strategy in model parameter space is scaled to the maximum number of iterations specified by the user.
- In initial iteration the algorithm search globally and as the procedure approached the maximum user-defined number of iterations, the search transition from a global to a local search.

This transition from a global to local search is achieved by dynamically and probabilistically reducing the search dimension which is the subset of the calibration parameters that will be updated in a given iteration.

Dynamically dimensioned search algorithm for computationally efficient watershed model calibration

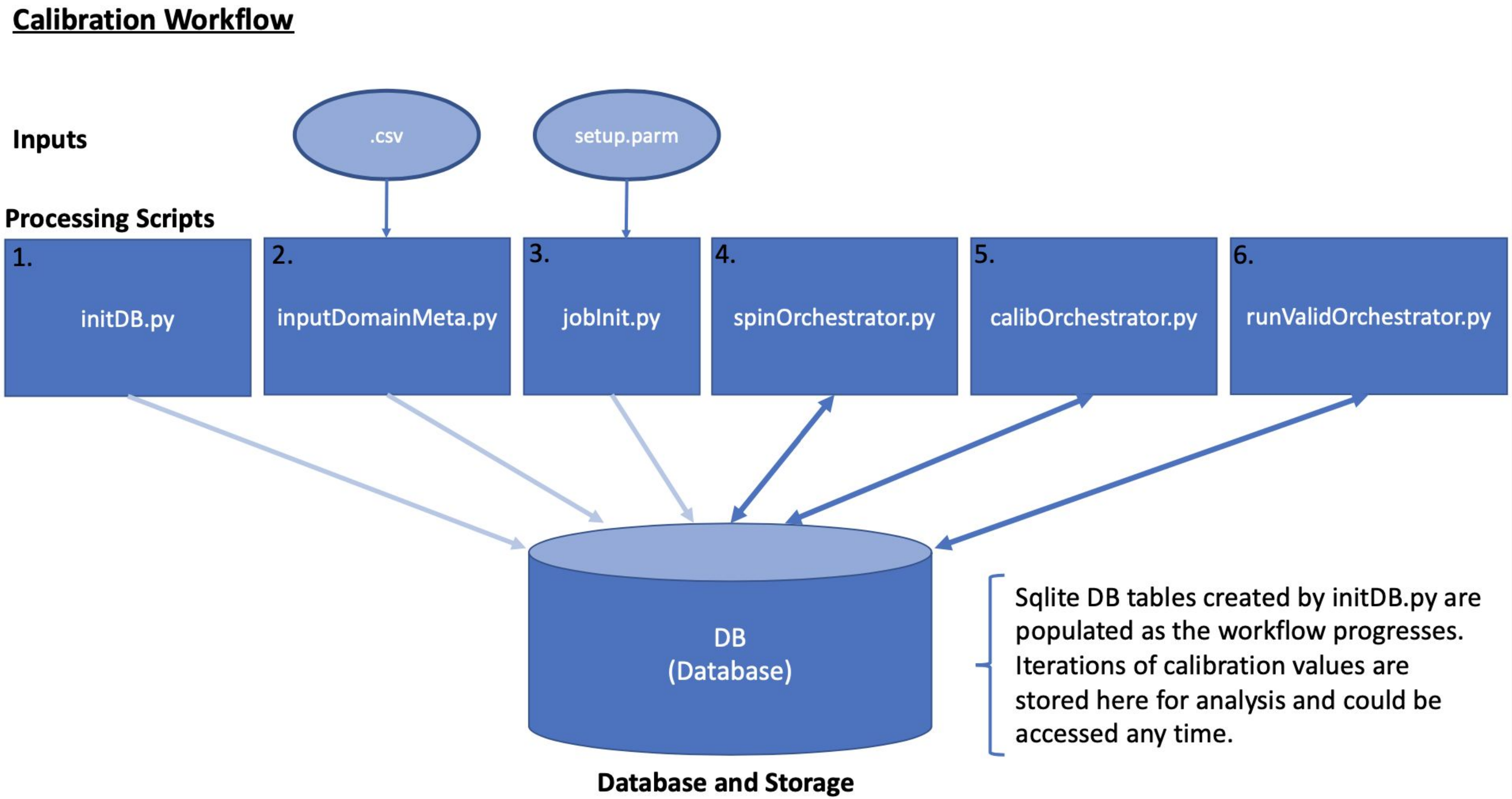
Bryan A. Tolson, Christine A. Shoemaker

First published: 17 January 2007 | https://doi.org/10.1029/2005WR004723 | Cited by: 183

Calibration Strategy (after NWM v1.2)

- Deliverables for >1100 basins demanded a more robust workflow to execute model simulations automatically on NCAR supercomputers.
- Ability to store model analysis statistics and workflow status on a database.
- Ability to restart calibrations when fatal system errors occurred.
- Proper error/message dissemination to the users running calibration.

PyWrfHydroCalib Package

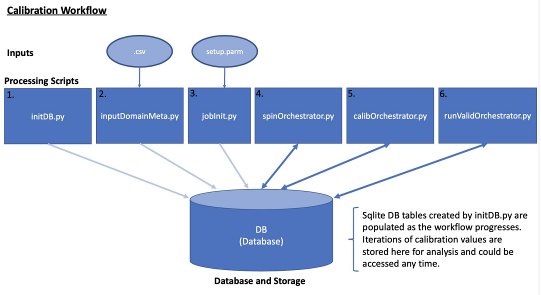


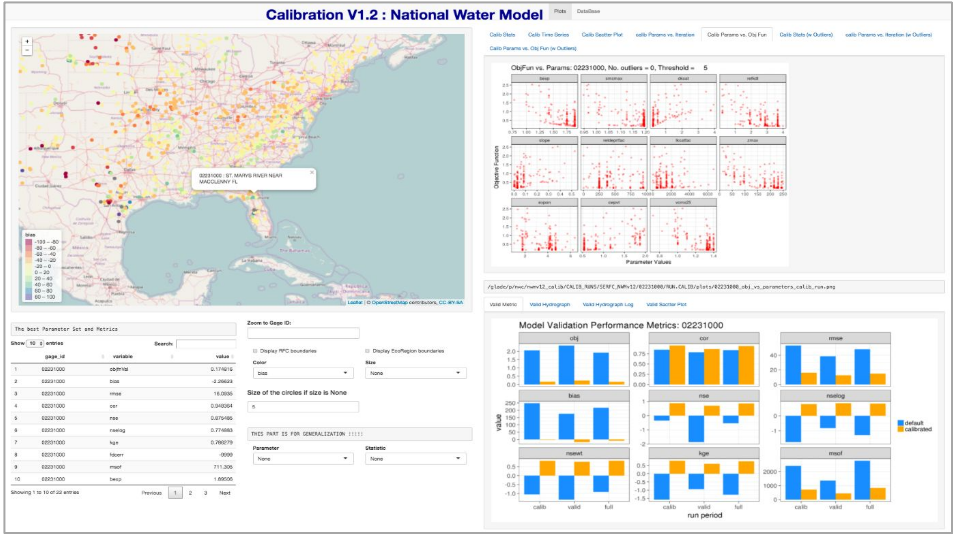
Sqlite DB tables created by initDB.py are populated as the workflow progresses. Iterations of calibration values are stored here for analysis and could be accessed any time.

PyWrfHydroCalib: Python + R package for model calibration

- Domain subsetting tools
- Parameter sensitivity analysis
  - Distributed Evaluation of Local Sensitivity Analysis (DELSA) methodology (Rakovec et al. 2014)
- Calibration:
  - Dynamically Dimension Search (DDS) algorithm (Tolson, B. A., and C. A. Shoemaker: 2007)
  - Split sample calibration/validation
  - Multiple criteria monitoring (NSE, RMSE, % bias, correlation, KGE, MSOF, …)

Automated workflow using Python and R interacting with a database (PyWrfHydroCalib)





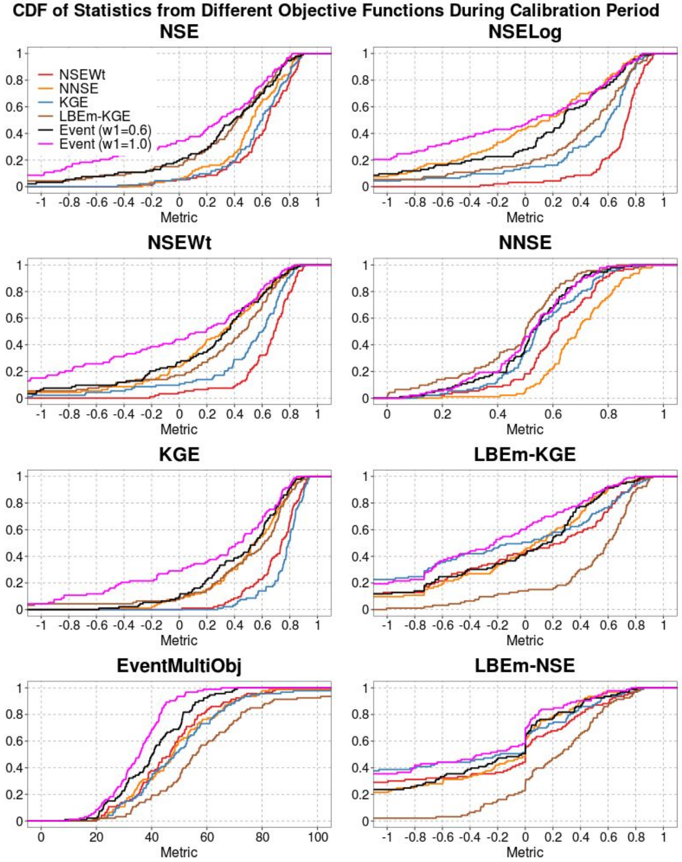
Calibration: Metrics

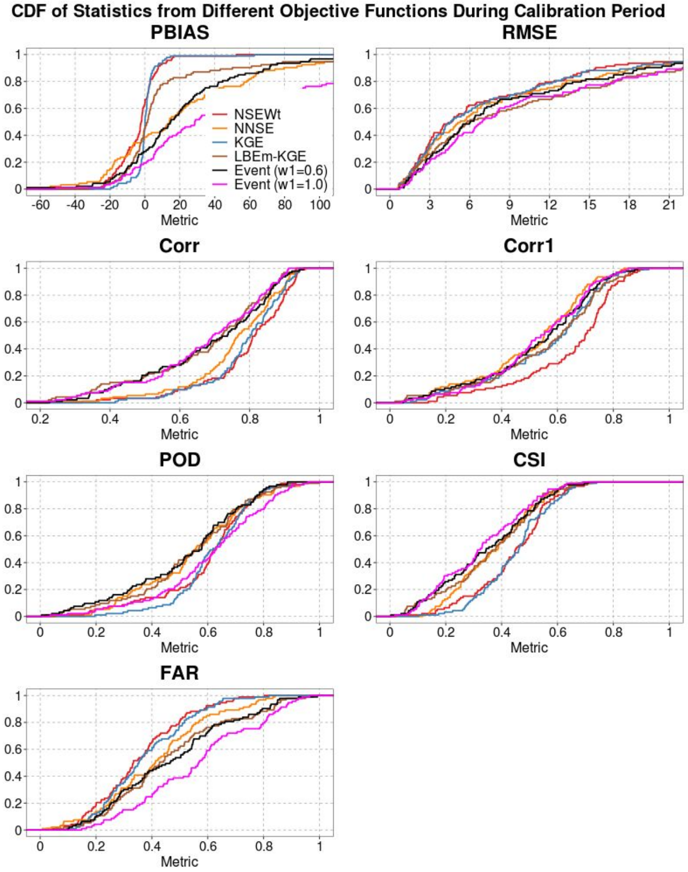
Metric	Equation	Optimal Value	Reference	Purpose
Nash-Sutcliffe Efficiency (NSE)	NSE = 1 - (sum((obs - sim)^2) / sum((obs - mean(obs))^2)	1	See:Nash & Stucliffe 1970	Single metric combining timing and magnitude errors.
Log-transformed NSE (NSELog)	NSELog =1 - (sum((log10(obs) - log10(sim))^2) / sum((log10(obs) - mean(log10(obs)))^2)	1		Same as above but applied to log-transformed flowrates.
Weighted NSE (NSEWt)	(NSE + NSELog)/2	1		Capture flow timing and magnitude errors jointly via the NSE metric and somewhat reduce the peak flow emphasis of NSE by including the log-transformed metric.
Pearson correlation (Cor)		1		Flow timing
Root mean squared error (RMSE)	RMSE = sqrt(sum((sim - obs)^2)/n))	0		Flow magnitude
Percent bias (Bias)	Bias = sum(sim - obs) / sum(obs)	0		Flow magnitude
Kling-Gupta Efficiency (KGE)	KGE = sqrt((s.r*(1-r))^2 + (s.alpha*(1-alpha))^2 + (s.beta*(1-beta))^2); r = cor(sim, obs, use=use); alpha = sd(sim, na.rm=na.rm) / sd(obs, na.rm=na.rm); beta = mean(sim, na.rm=na.rm) / mean(obs, na.rm=na.rm)	1	See:Gupta et al 2009	Single metric combining timing and magnitude errors.
Multi-Scale Objective Function (MSOF)	MSOF=sqrt(sum((sd0/sd(k))^2*sum((obs-sim)^2))) where: sd0=standard deviation at native scale (e.g., hourly); sd(k)=standard deviation at the aggregated scale k (e.g., 6 hourly) obs, sim=aggregated observation or simulation at the kth aggregation scale first sum is over the n specified aggregation scales (k=1,n) second sum is over the m ordinates at the kth aggregation scale	0	See: Kuzmin et al. 2008	The MSOF was adopted as an optimization criterion for calibrating the HL-RDHM using the Stepwise Linear Search (SLS) algorithm. The rationale behind MSOF is to simultaneously consider contributions from a wide range of time scales of aggregation during the calibration process (i.e., mimicking manual calibration), and to reduce the likelihood of the search getting stuck in small ‘pits’, by smoothing the objective function surface

Calibration: Metrics (NEW)

peak_bias	$Peak\_bias = \frac{\overline{\lvert P_m - P_o \rvert}}{P_o} * 100)$ $Where:$ $p_m = model peaks for matched events$ $P_o = observation peaks for matched events$	0	Quantifies the overall peak bias in matched events between the model and observation throughout the calibration window.
event_volume_bias	$Event\ Volume\ bias = \frac{\overline{\lvert V_m - V_o \rvert}}{V_o} * 100$ $where:$ $V_m = volume\ model$ $V_o = volume\ observed$	0	Quantifies the overall volume bias in matched events between the model and observation throughout the calibration window.
eventmultiobj	$W1 * abs(Pbiaspeak) + W2 * abs(VEFlow)$	0	Account for peak error and volume error.
peak_tm_err_hr	$peak\_tm\_err\_hr = (\overline{\lvert T_m - T_o \rvert})$ $where:$ $T_m = model\ time\ (hours)$ $T_o = observation\ time\ (hrs)$	0	Quantifies the central value of time offset between observed and modeled peak events in hours
Probability of Detection (POD)	$POD = \frac{a}{a+c}$	1	Probability that a flood was observed when it was forecasted; where 1 is a perfect score and 0 is the worst.
False Alarm Ratio (FAR)	$FAR = \frac{b}{a+b}$	0	Probability that a flood was forecasted, but not observed; where 0 is perfect and 1 is the worst
Critical Success Index (CSI)	$CSI = \frac{a}{a+b+c}$	0	The proportion of correctly forecast floods over all floods, either forecast or observed
Stedinger's (1981) lognormal estimator of correlation (corr1)	$r1 = \frac{e^{\sigma^{2}UV} - 1}{\sqrt{e^{\sigma^{2}U} e^{\sigma^{2}V}}}$	1	Stedinger's (1981) lognormal estimator of correlation (corr1) Purpose: Improved estimator of correlation when hydrologic data is skewed (non-normal), which is often the case for daily and subdaily streamflow https://doi.org/10.1080/02626667.2019.1686639
Lamontagne-Barber Efficiency Mixture Model (lbem)	See Ref.	1	Improved theoretical estimator of efficiency based on NSE for when hydrologic data is skewed (non-normal) and exhibits periodicity (e.g., seasonality), which is often the case for daily and subdaily streamflow.
Lamontagne-Barber Efficiency Estimators (lbemprime)	See Ref.	1	Improved theoretical estimator of efficiency based on KGE for when hydrologic data is skewed (non-normal) and exhibits periodicity (e.g., seasonality), which is often the case for daily and subdaily streamflow. (Lamontagne 2020 https://doi.org/10.1029/2020WR027101)

Objective Function Selection



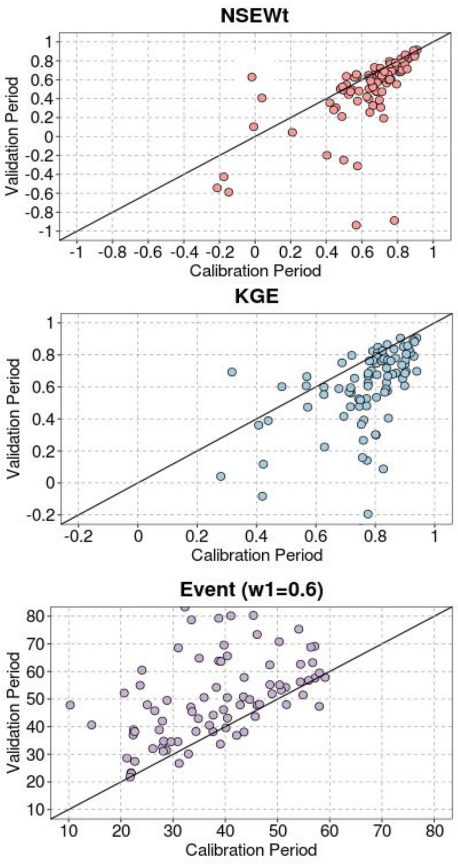


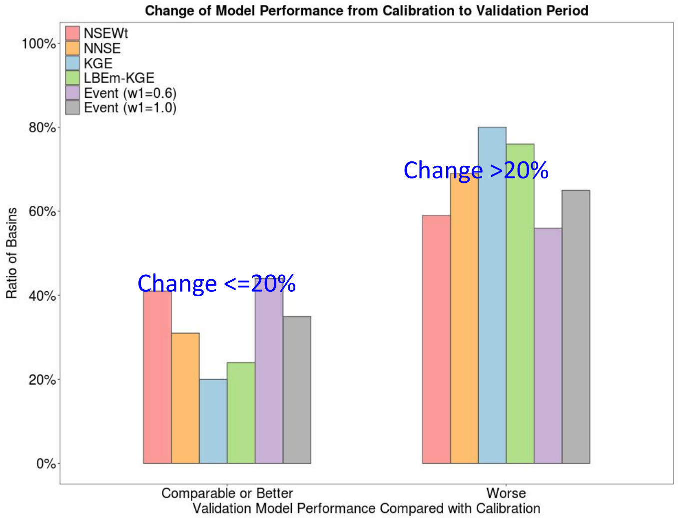
Tested Objective Functions

Summary Results

- Among five objective functions, NSEWt and KGE perform better in terms of all evaluation measures.
- Models optimized with the event based objective functions show advantage in representing the magnitude of peak flow but biased in representing other portions of streamflow regimes.

Objective Function Selection





Summary Results

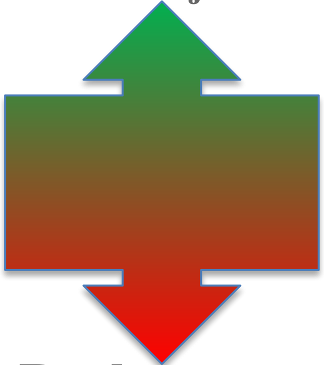
- Among five objective functions, NSEWt and KGE perform better in terms of all evaluation measures.
- Models optimized with the event based objective functions show advantage in representing the magnitude of peak flow but biased in representing other portions of streamflow regimes.
- **Final Decision → KGE is selected as objective function.**

Calibration: Parameters

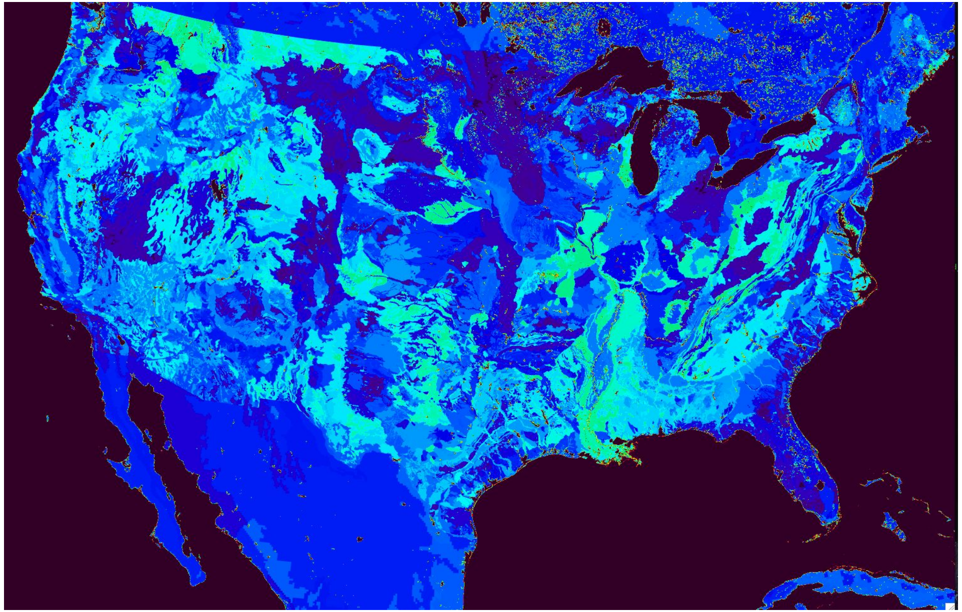
Name	Description	Units
SOIL PARAMS		
bexp	Pore size distribution index	dimensionless
smcmax	Saturation soil moisture content (i.e., porosity)	volumetric fraction
dksat	Saturated hydraulic conductivity	m/s
rsurfexp	Exponent in the resistance equation for soil evaporation	dimensionless
RUNOFF PARAMS		
refkdt	Surface runoff parameter; REFKDT is a tuneable parameter that significantly impacts surface infiltration and hence the partitioning of total runoff into surface and subsurface runoff. Increasing REFKDT decreases surface runoff	unitless
slope	Linear scaling of "openness" of bottom drainage boundary	0-1
RETDEPRTFAC	Multiplier on retention depth limit	unitless
LKSATFAC	Multiplier on lateral hydraulic conductivity (controls anisotropy between vertical and lateral conductivity)	unitless
GROUNDWATER PARAMS		
Zmax	Maximum groundwater bucket depth	mm
Expon	Exponent controlling rate of bucket drainage as a function of depth	dimensionless
VEG PARAMS		
CWPVT	Canopy wind parameter for canopy wind profile formulation	1/m
VCMX25	Maximum carboxylation at 25C	umol/m2/s
MP	Slope of Ball-Berry conductance relationship	unitless
SNOW PARAMS		
MFSNO	Melt factor for snow depletion curve; larger value yields a smaller snow cover fraction for the same snow height	Dimensionless
CHANNEL PARAMETERS		
Bw	Parameterized width of the bottom of the stream network	m
HLINK	Initial channel depth	m
ChSSlp	Channel side slope	m/m
MannN	Manning's roughness coefficient	Dimension

Calibration: Parameters

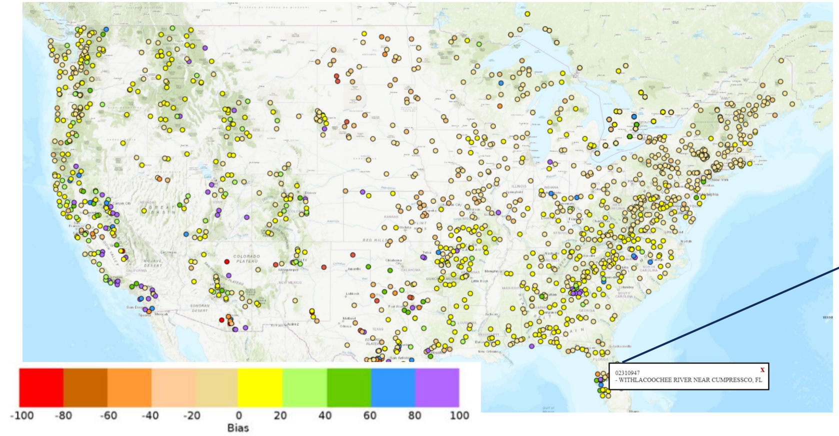
- **Parameter adjustment:**
  - Scalar adjustment

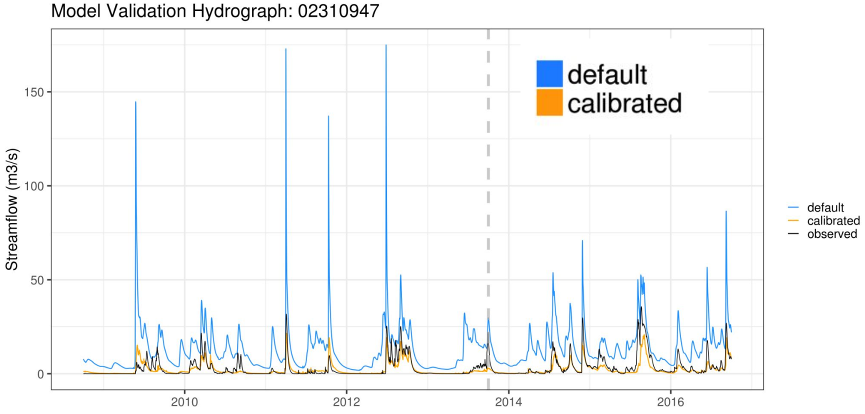


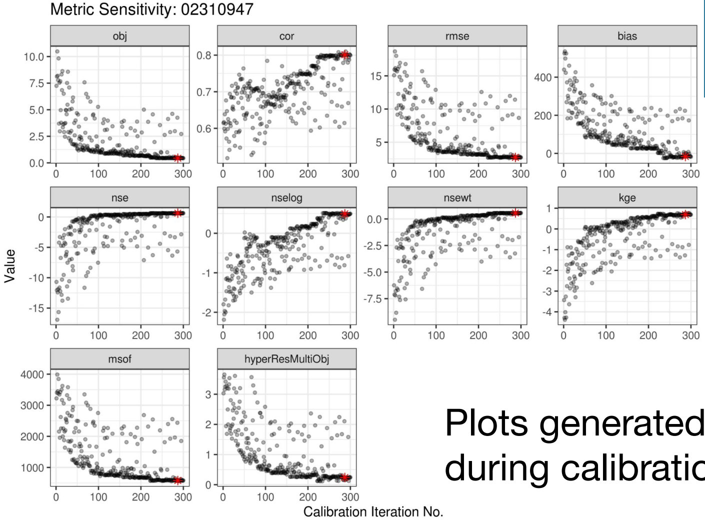
  - Replacement
    - Table values
    - Parameters with uniform values across domain



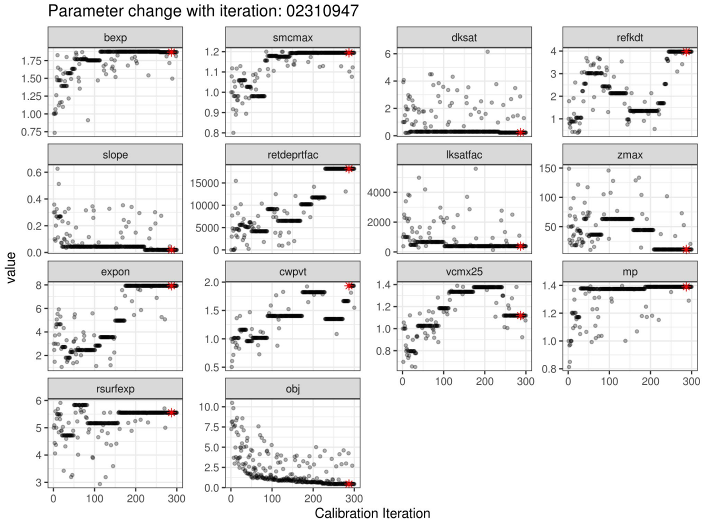
Model Calibration







Plots generated during calibration



Sensitivity Analysis

Sensitivity Analysis

Distributed Evaluation of Local Sensitivity Analysis (DELSA), a hybrid local-global sensitivity analysis (SA) method, for extracting useful information on the importance of each parameter, with the added advantage of being relatively low computational cost compared to other common SA methods such as Sobol.

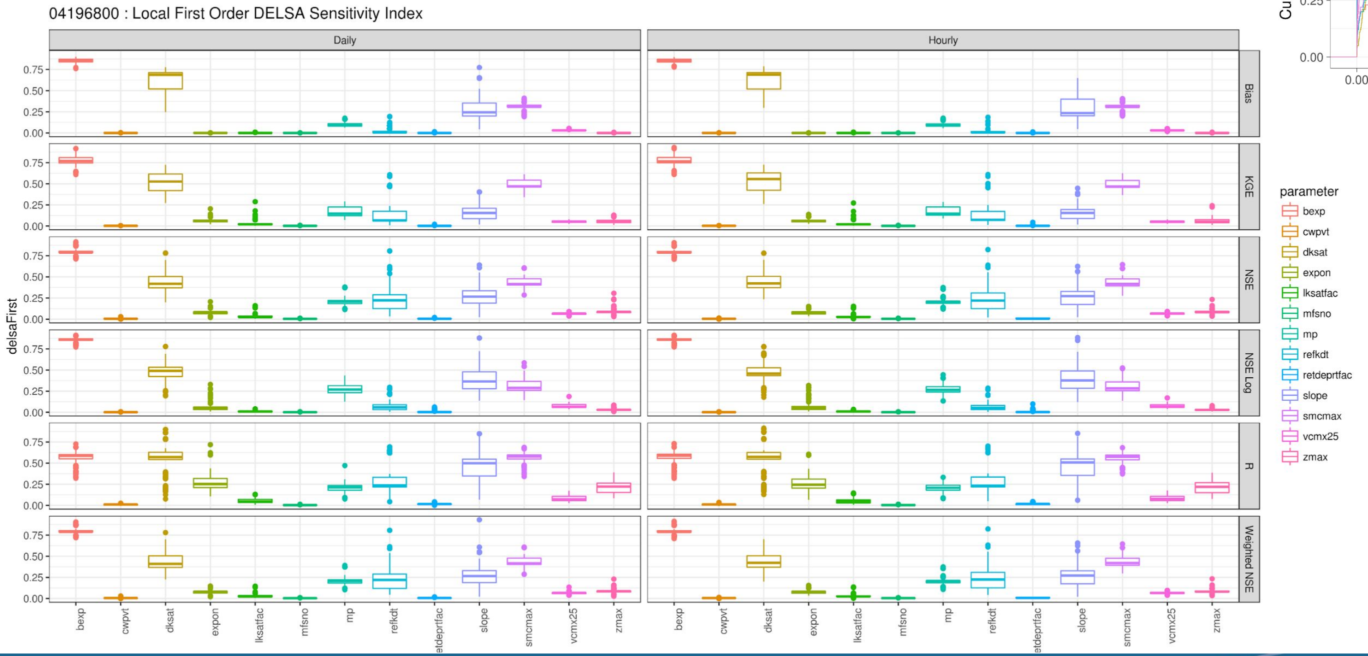
Name	Description	Units	Default value	Min Value	Max Value
SOIL PARAMS					
bexp	Pore size distribution index	dimensionless	x1	x0.4	x1.9
smcmax	Saturation soil moisture content (i.e., porosity)	volumetric fraction	x1	x0.8	x1.2
dksat	Saturated hydraulic conductivity	m/s	x1	x0.2	x10
RUNOFF PARAMS					
refkdt	Surface runoff parameter; REFKDT is a tuneable parameter that significantly impacts surface infiltration and hence the partitioning of total runoff into surface and subsurface runoff. Increasing REFKDT decreases surface runoff	unitless	0.6	0.1	4
slope	Linear scaling of "openness" of bottom drainage boundary	0-1	0.1	0	1
RETDEPRTFAC	Multiplier on retention depth limit	unitless	1	0.1	10
LKSATFAC	Multiplier on lateral hydraulic conductivity (controls anisotropy between vertical and lateral conductivity)	unitless	1000	10	10000
GROUNDWATER PARAMS					
Zmax	Maximum groundwater bucket depth	mm?	25	10	250
Expon	Exponent controlling rate of bucket drainage as a function of depth	dimensionless	1.75	1	8
VEG PARAMS					
CWPVT	Canopy wind parameter for canopy wind profile formulation	1/m	x1	x0.5	x2
VCMX25	Maximum carboxylation at 25C	umol/m2/s	x1	x0.6	x1.4
MP	Slope of Ball-Berry conductance relationship	unitless	x1	x0.6	x1.4
SNOW PARAMS					
MFSNO	Melt factor for snow depletion curve; larger value yields a smaller snow cover fraction for the same snow height	dimensionless	2	0.5	3

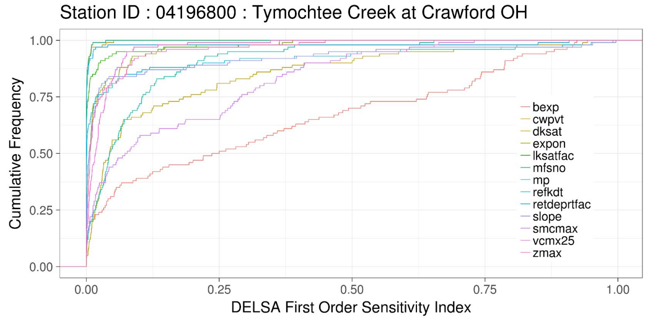
DELSA sensitivity index

Higher values DELSA sensitivity index indicates the model performance (for this example NSE) is more sensitive to the change in the parameter.

CDFs of the SA index for all the parameters are displayed for the NSE metric.

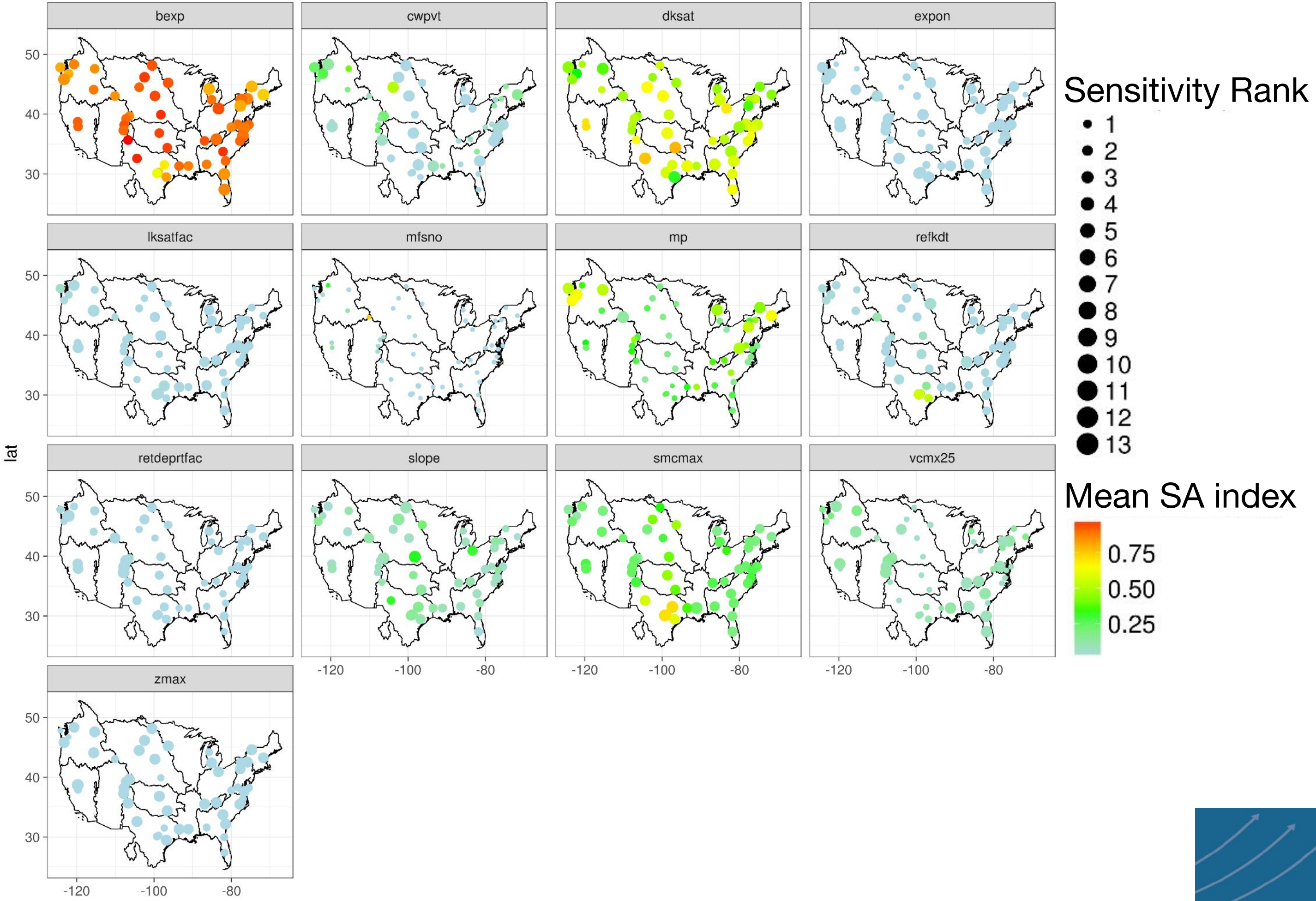
For the selected basin located in Idaho, bexp is the most sensitive parameter and the mfsno is the least sensitive parameter.





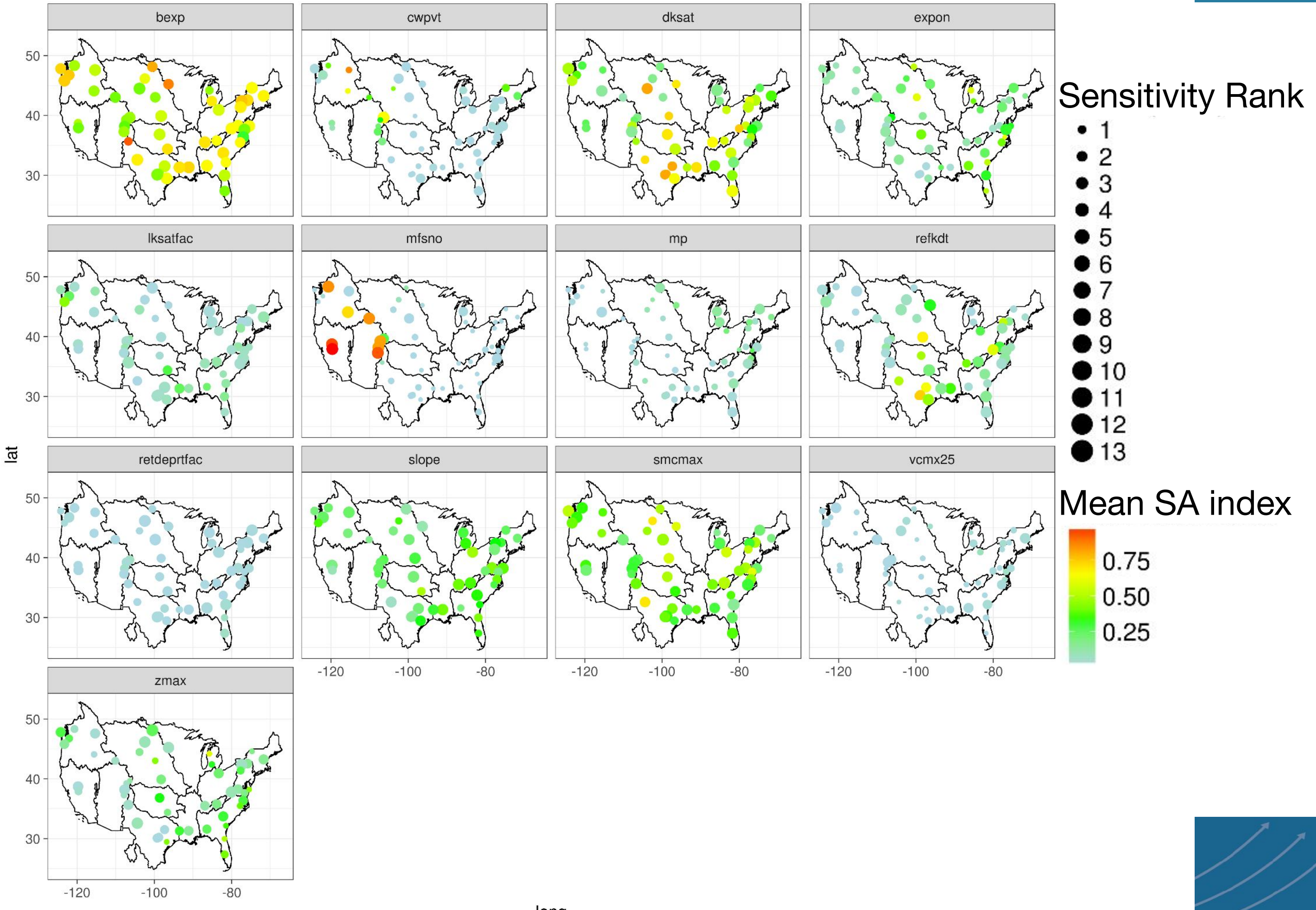
Mean of DELSA sensitivity index for streamflow bias

Bias is most sensitive to bexp parameter across US, followed by dksat, smcmax, mp.



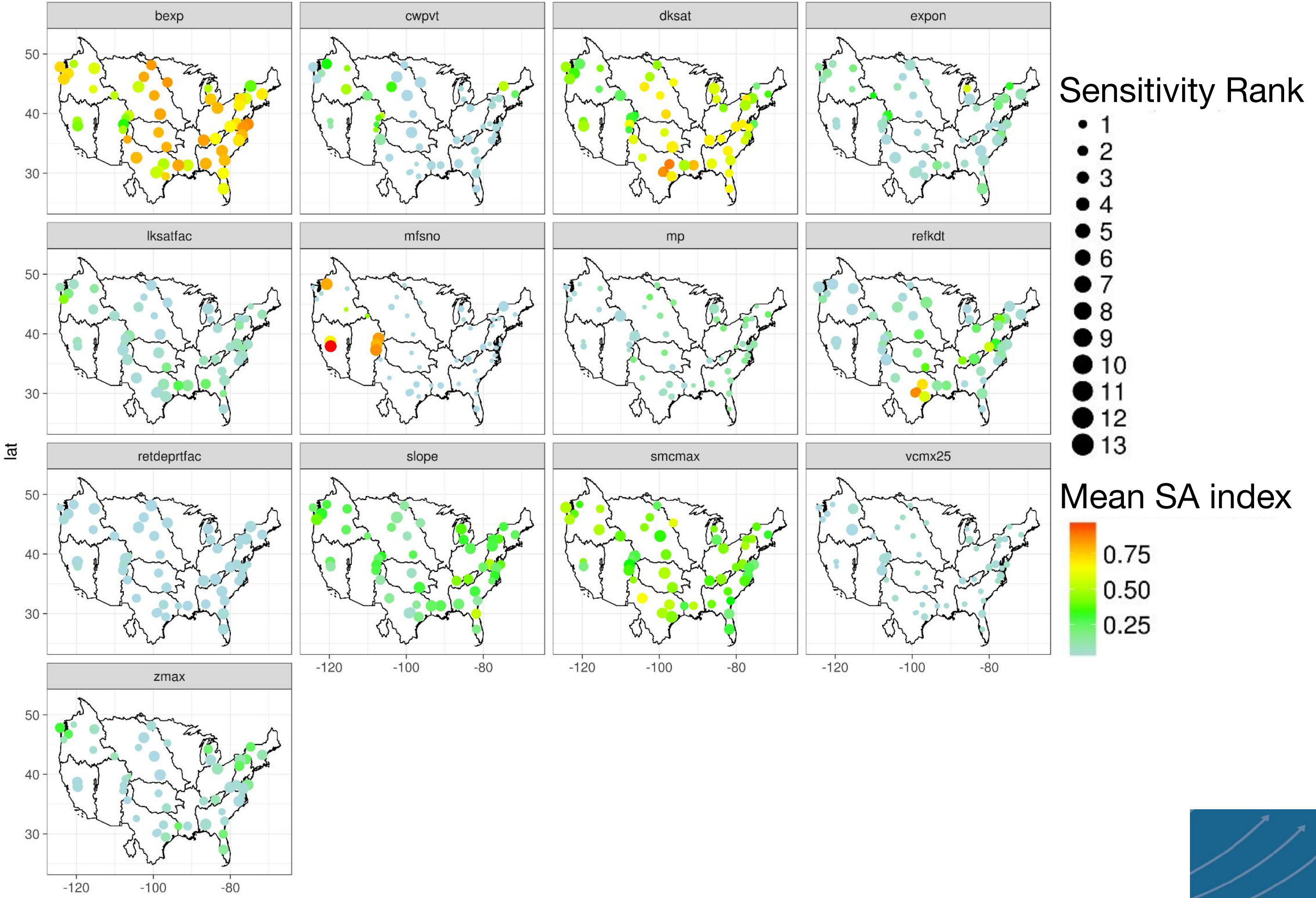
Mean of DELSA sensitivity index for streamflow Correlation Coefficient (hourly time step)

Hourly Correlation Coefficient across US is most sensitive to bexp, dksat, smcmax, slope and mfsno in the snow deriven regions.



Mean of DELSA sensitivity index for streamflow NSE (hourly time step)

Hourly NSE across US is most sensitive to bexp, dksat, smcmax, slope and mfsno in the snow deriven regions.

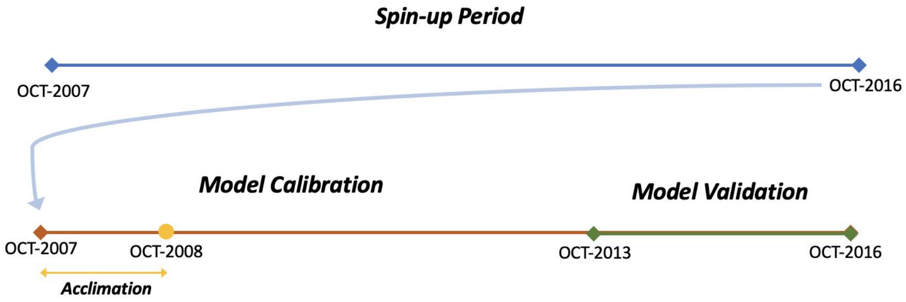


Calibration Strategy and NWM calibration specifics

Calibration Period and Forcing

- Spin up with the default parameters: (2007-10 to 2016-10)

- Iteration 1 to n (max number of iterations)
  - Spin up: 1 year (2007-10 to 2008-10)
  - Calibration: 5 years (2008-10 to 2013-10)



- Final Parameters
  - Validation: 3 years (2013-10 to 2016-10)

- What to use as forcing data?
  - Ideally, it is preferred to calibrated using the same forcing as what is used in for the final application.
  - Downscaled NLDAS-2 in NWMv1.1 and NWMv1.2.
  - A mountain-mapper adjustment to the precipitation data of downscaled NLDAS-2 in NWMv2.0.
  - Analysis of Record for Calibration (AORC) introduced by Kitzmiller et al. 2019 in NWMv2.1.

Basin Selection Criteria For Calibration

- **Size of the basins:** 10,000 km^2 as an upper bound for the basin size

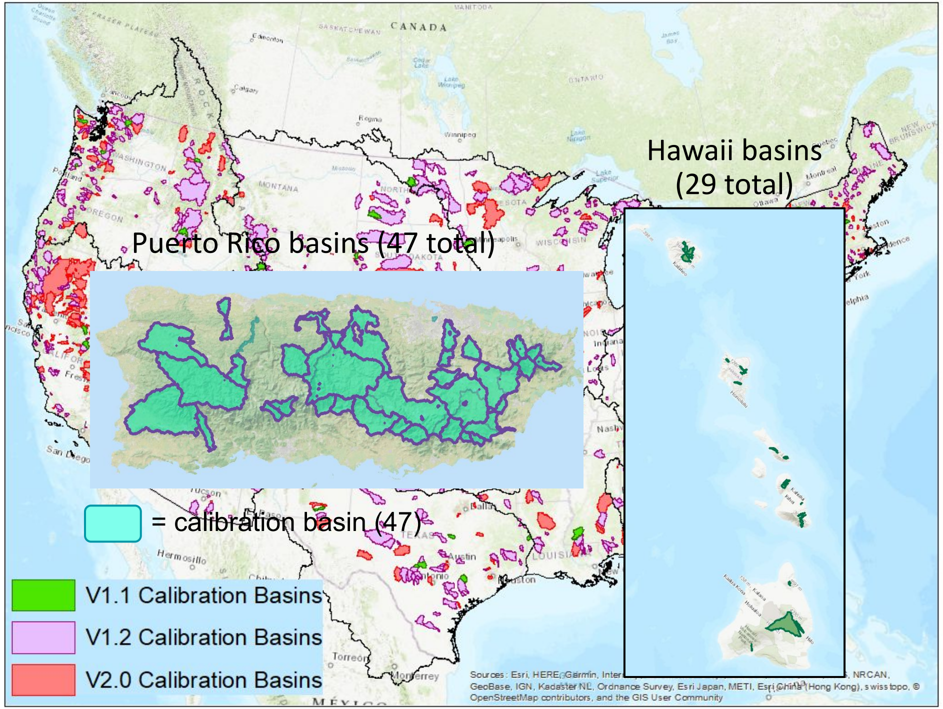
- **Completeness of the streamflow observation:** 50% completeness in calibration period in order to include some of the seasonal gages also. When criteria was not met, we checked the daily time step.

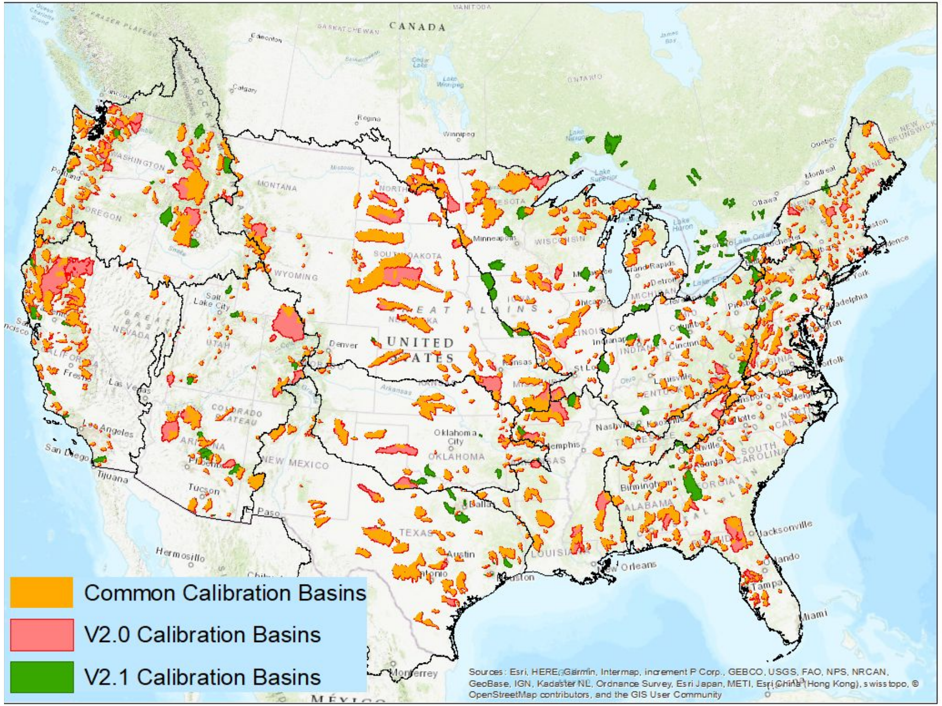
- **Disturbance index:** Considering 7 variables, including major density, reservoir storage, fresh water withdrawal, road density, landscape fragmentation, percentage of streamline coded as canals/ditches/pipelines, and distance to the nearest major National Pollutant Discharge Elimination System site.

- **Basins containing lakes:** Even though the calibration basins were investigated to have minimal regulation through disturbance index, we further investigated the calibration basins containing water bodies.
  - Number of lakes in a basin
  - Distance of the lake outlet to the basin outlet
  - Percentage of the total lake drainage area to the basin drainage area
  - Percentage of the regulated flow (outflow from lakes in the basins) to basin outflow
  - Ratio of the lake storage volume to the basin mean annual flow volume

- Consider having enough basins available for regionalization

NWM Calibration: Version-to-Version Changes



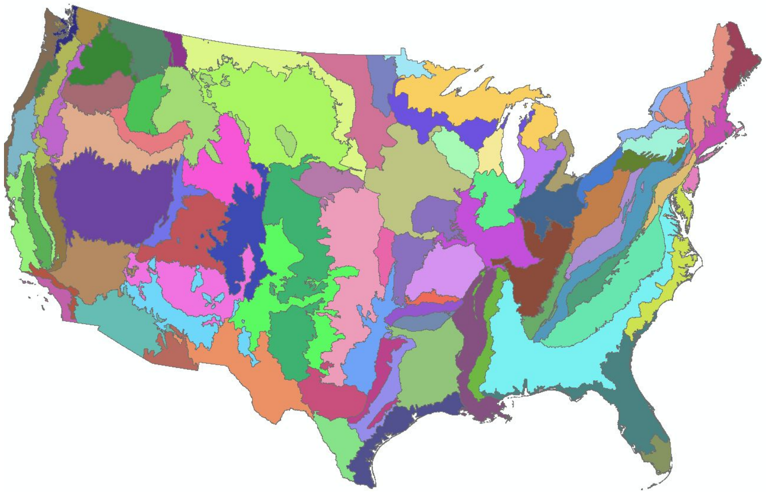


Regionalization

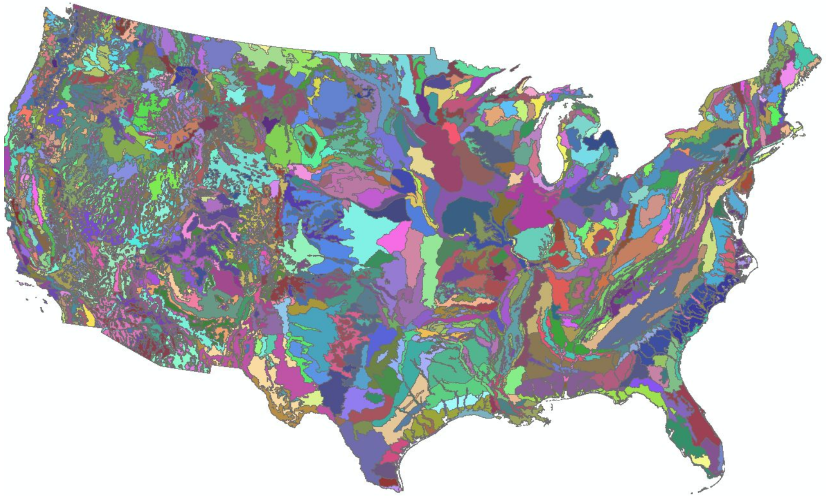
Regionalization

Ecoregions are based on perceived patterns of a combination of causal and integrative factors including land use, land surface form, potential natural vegetation, and soil ([Omernik J.M., 1987]) and are mapped into different levels based on the degree of classification details.

Ecoregion Level III

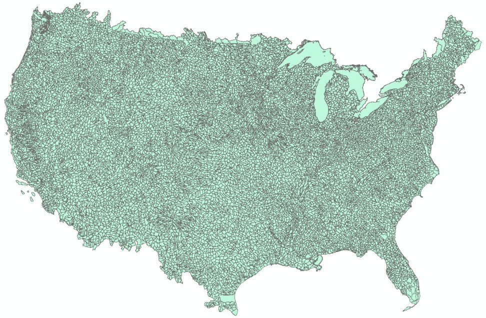


Ecoregion Level IV



Hydrologic Landscape Regions (HLR) Clustering

- **Collect/compute HLR parameters**
  - Climate (P-PET), land surface form (total %flatland, %flatland in upland, %flatland in lowland, relief)
  - Soil & geology (% sand, % clay, bedrock permeability), land cover (% forest cover)
- **Perform principal component analysis (PCA)**
  - Removes correlation among parameters
  - Identify principal components with each explaining at least 5% of the total variance
- **Perform clustering analysis**
  - Determine the number of clusters to use (tricky!)
  - Classify the HUC10 and calibration basins into clusters (K-means clustering)
- **Perform parameter regionalization**
  - Identify a donor calibration basin for each HLR (HUC10)
  - Map back to NWM grid

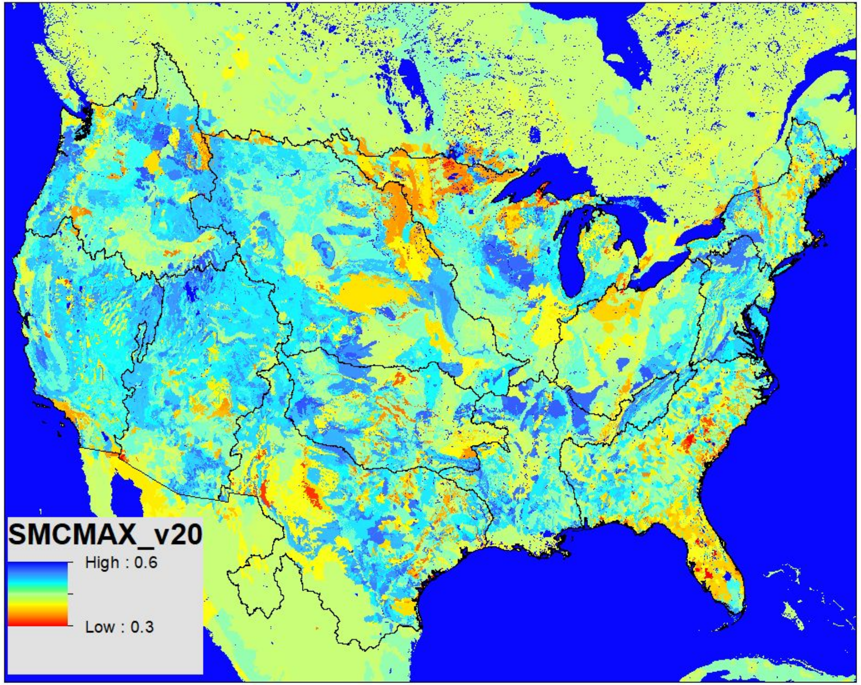


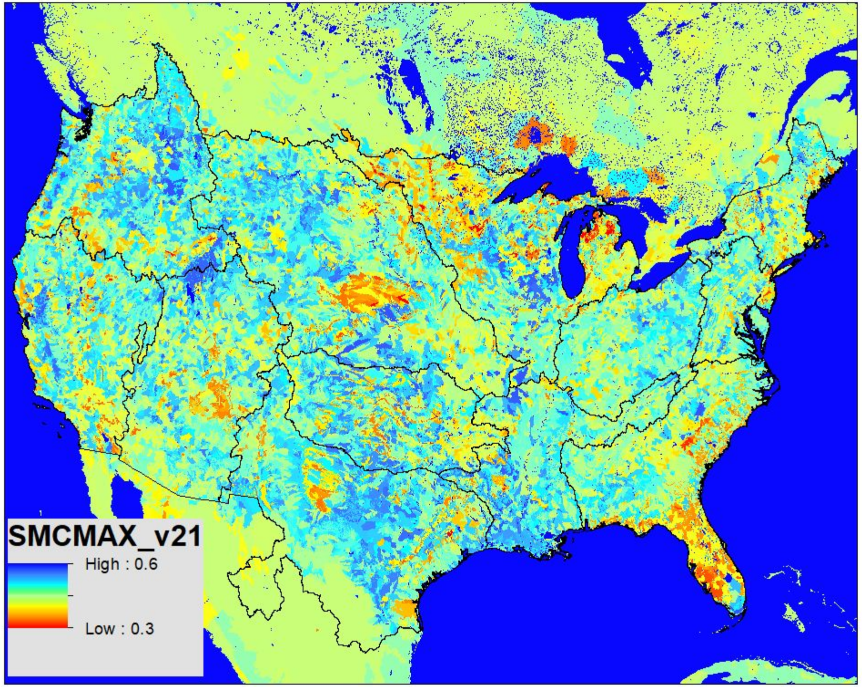
Gower Distance

1. Calculate all the attributes for the basins and HUC10s
2. Perform Principal Analysis to remove potential correlation among attribute values
3. The PCA reduces the raw dataset from 12 attributes to 4-5 principal components.
4. Calculate Gower's distance (distance or dissimilarity between two objects characterized by multiple variables) based on the scores of the principal components from PCA analysis and percentages of the total variance explained by individual principal components.
5. Identify the donors that has a Gower's distance smaller than the minimum distance
6. From the donors identified in Step 5), choose the donor that has the minimum spatial distance from the HUC10 basin.

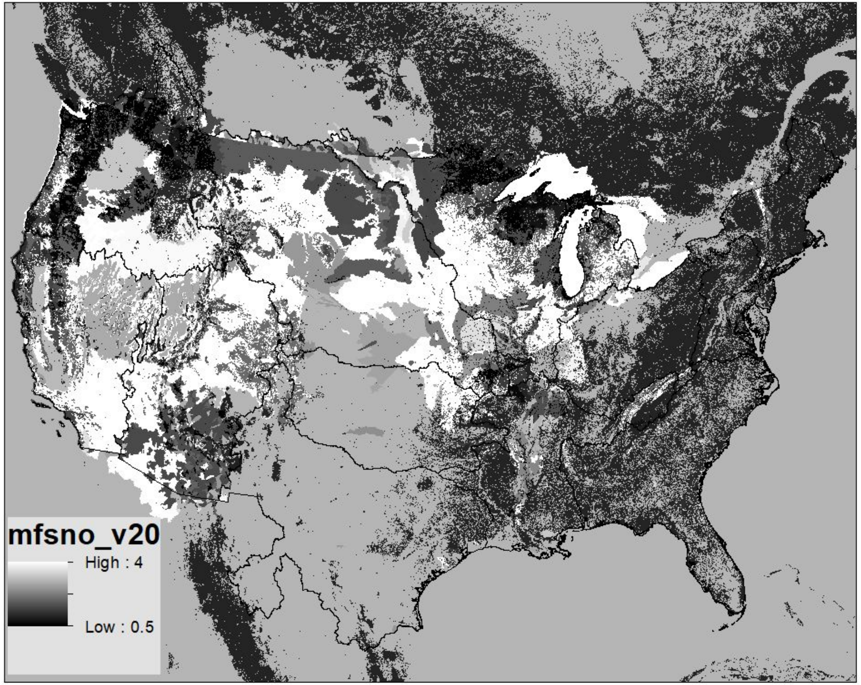
Category	Attribute	Notes
Landform	% flatland (total)	Total percent cover of flatland in the basin; flatland refers to areas with a slope of less than 0.01
	% flatland (upland)	Upland refers to areas above the middle elevation of the basin
	% flatland (lowland)	Lowland refers to areas below the middle elevation of the basin
	Relief	Difference between the highest and lowest elevations
	Circularity index	The ratio of the basin's area over the area of a circle with the same length of perimeter as the basin
Soil & geology	% sand	Mean percentage of sand in the soil column (upper 2m)
	% clay	Mean percentage of clay in the soil column (upper 2m)
	Depth to bedrock	Average thickness of soil
Land cover	% forest	Percent cover of forest (all types) in the basin
	% cropland	Percent cover of cropland (all types) in the basin
	% urban	Percent cover of urban areas in the basin
Climate	Feddema moisture index (FMI)	1-(PET/P) (if P>=PET) or (P/PET)-1 (if P<PET), where P & PET are annual mean precipitation and potential evapotranspiration, respectively. See Feddema (2005) & Leibowitz et al. (2016)

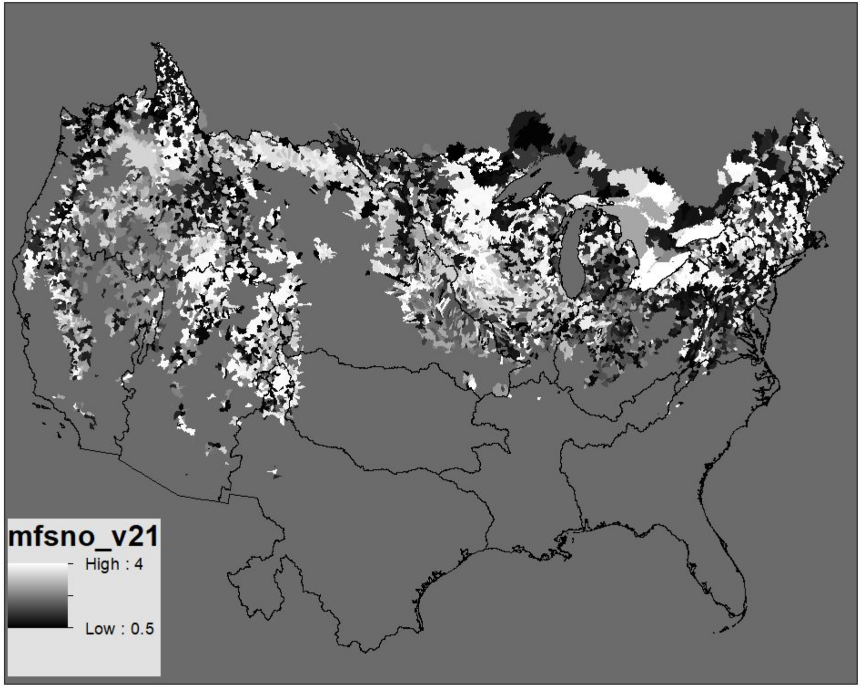
Sample Regionalized Parameter





Sample Regionalized Parameter





It should be noted that the MFSNO was allowed to go up to 6 in V20 and was a function of vegetation but it was the same everywhere in V21 and was allowed to max at 4.

What else?

- New components in PyWrfHydroCalib
  - Step wise snow calibration
  - Soil moisture calibration

- Continuous effort for calibration with PEST++
  - Stay tuned …

For more information contact:

arezoo@ucar.edu

adugger@ucar.edu

THANK YOU!