Parameter values for ungauged catchments:

Comparing regionalization approaches using large-sample hydrology

Welcome to our presentation!

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Motivation

1. The parameterization of hydrological models in ungauged catchments is one of the oldest tasks in hydrology and still remains challenging.

2. The increased availability of large-sample data sets in recent years provides new opportunities for regionalization.

Using a large-sample data set, we systematically test and compare a large number of regionalization approaches to understand where and why models succeed or fail in predicting discharge in ungauged catchments.

The 600+ study catchments

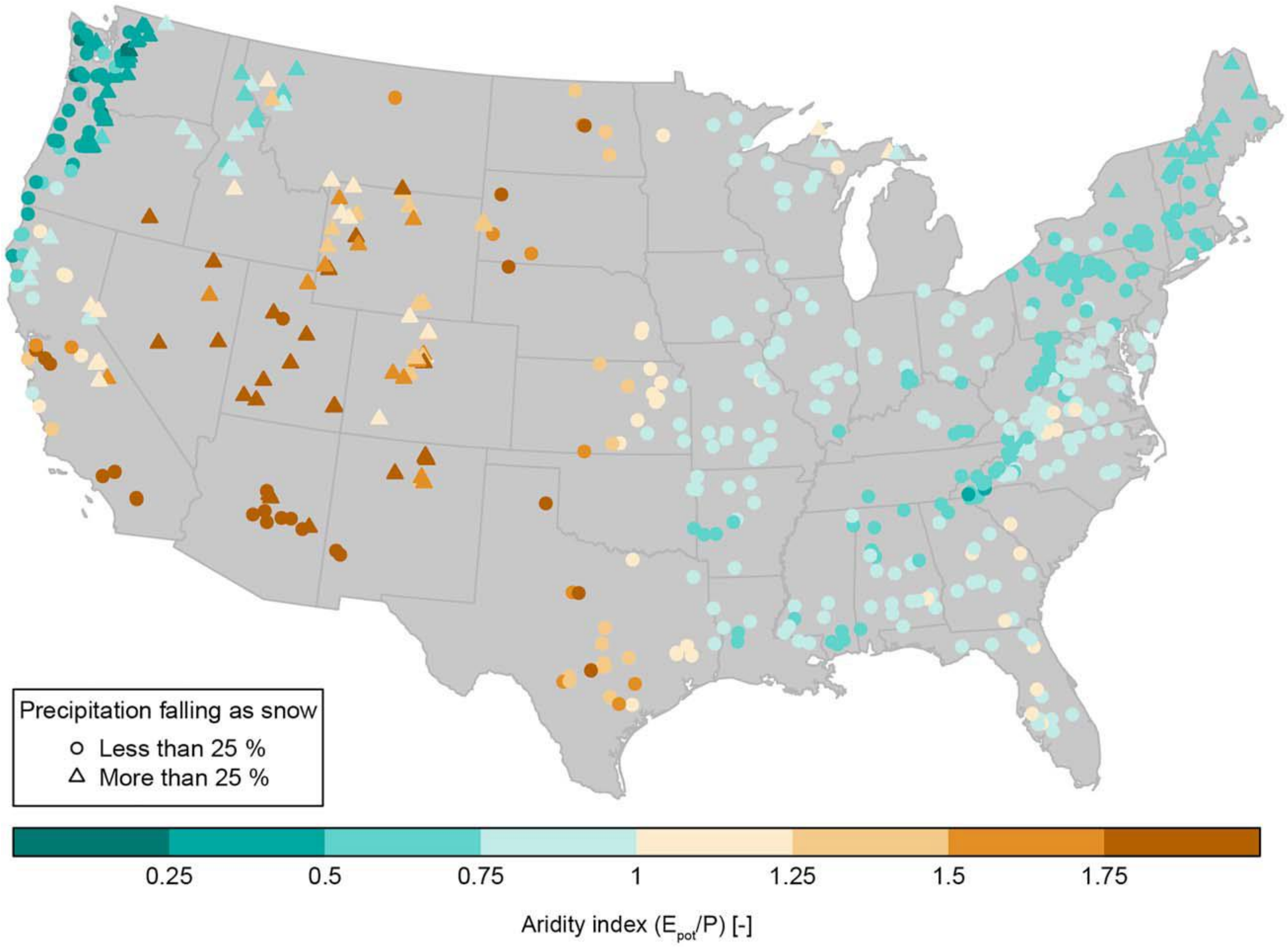


Fig.: Distribution of the study catchment and their hydroclimatic variability (from Pool et al., 2019).

We use data of more than 600 catchments from the publicly available data sets of Newman et al. (2015) and Addor et al. (2017; CAMELS).

The catchments cover a wide range of hydroclimatic and topographic conditions.

Modelling approach

Most important: we use NPE and KGE to evaluate model performance. You will see how different conclusions can be!

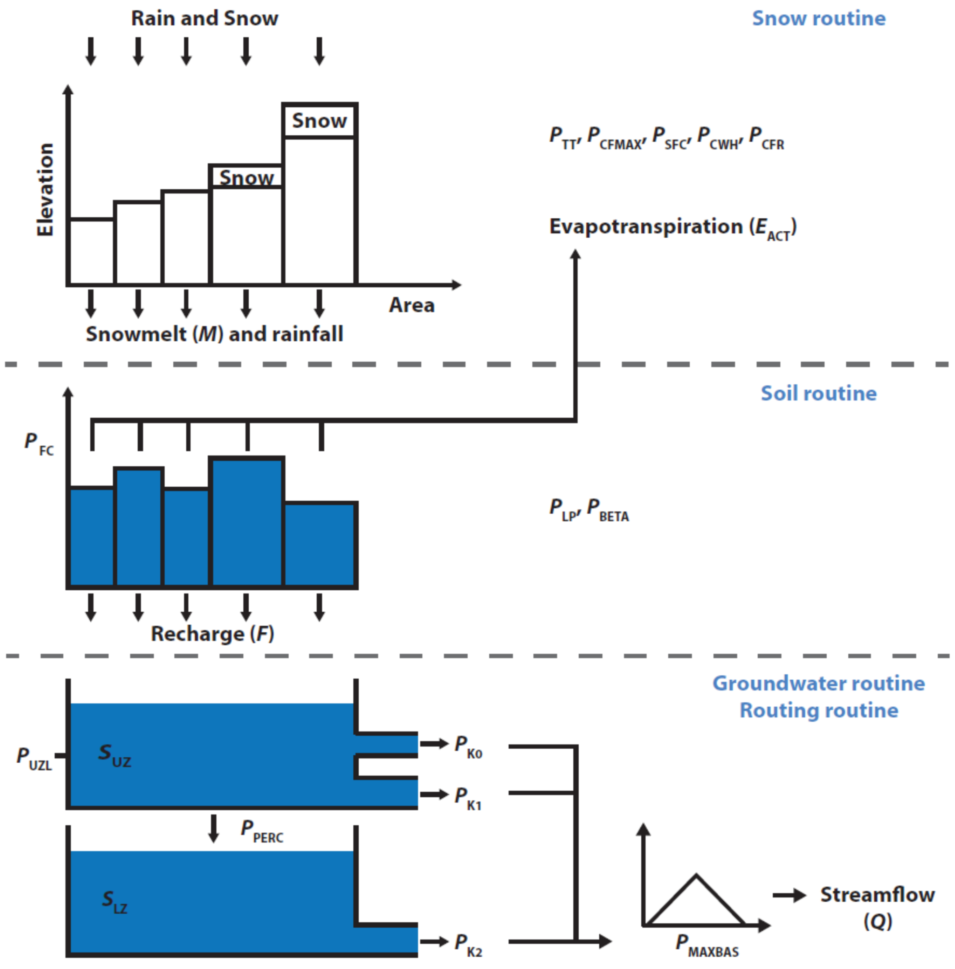


Fig.: Structure, variables, and parameters of the HBV model (adapted from Uhlenbrook et al., 1999).

HBV model:
The semi-distributed HBV-light model was used. Parameter meaning and values are listed in the appendix. (Seibert and Vis, 2012)

Calibration with NPE:
The model was calibrated for a 10 year time period using the partly non-parametric modification of the Kling-Gupta efficiency NPE proposed by Pool et al. (2018).

Evaluation with NPE and KGE:
Streamflow was predicted for each of the hypothetically ungauged basins with 19 regionalization approaches and evaluated using NPE and the Kling-Gupta efficiency KGE (Gupta et al., 2009)

Tested regionalization approaches

	Regionalization approach	Description: origin of the donated parameter values	Incl. volume	Incl. spat. distance
(1)	Upper benchmark	The receiver catchment itself.	-	-
(2)	Lower benchmark (random)	1000 randomly selected parameter values.	-	-
(3)	Lower benchmark (US)	All 600+ catchments.	-	-
(4)	Geographic area classification	All catchments within the same watershed region (HUC2) from USGS (2020).	-	✓
(5)	Climate classification	All catchments within the same climate group (aridity; precipitation seasonality; snowfall fraction) from Berghuijs et al. (2014).	-	-
(6)	Water balance classification	All catchments within the same water balance group (groundwater loosing or gaining).	✓	-
(7)	Signature classification	All catchments within the same signature group (runoff ratio; mean annual, winter, and summer Q; q95; half-flow date) from Jehn et al. (2020).	✓	
(8)	Best donors	The three best donor catchments available.	-	-
(9)	Random donors	Three randomly selected catchments from all 600+ catchments.	-	-
(10)	Closest donors	The three geographically closest catchments.	-	✓
(11)	RMSE	The three catchments with the smallest RMSE for 12 observations in the ungauged basin	✓	
(12)	RMSE & distance	The three catchments that are among the ten best ones in terms of RMSE and are geographically closest.	✓	✓
(13)	Attributes	The three catchments that are most similar in terms of attributes (area; aridity; precipitation seasonality; snowfall fraction; wetland fraction; clay fraction; forest fraction).	-	-
(14)	Signatures	The three catchments that are most similar in terms of hydrological signatures (runoff ratio; mean annual Q; mean half-flow date; q95; q05; recession slope).	✓	-
(15)	Distance & attributes	The three catchments that are geographically closest and most similar in terms of attributes.		✓
(16)	Distance & signatures	The three catchments that are geographically closest and most similar in terms of hydrological signatures.	✓	✓
(17)	Attributes & signatures	The three catchments that most similar in terms of attributes and hydrological signatures.	✓	-
(18)	Distance & attributes & signatures	The three catchments that are geographically closest and most similar in terms of attributes and hydrological signatures.	✓	✓
(19)	Qobs transfer (closest)	Mean streamflow time series from the three geographically closest catchments.	-	✓

19 regionalization approaches!

We tested methods that are among the most commonly used ones.

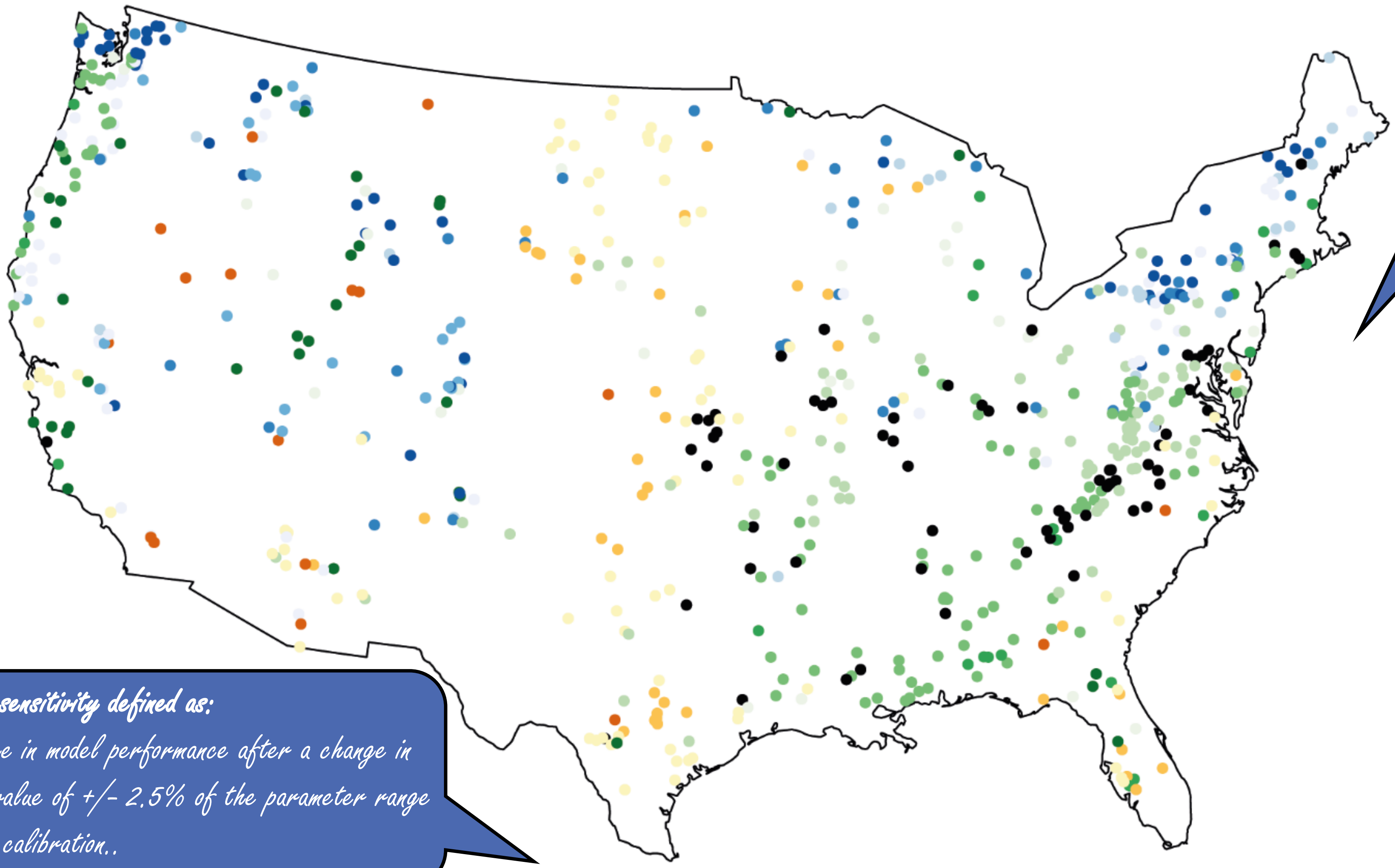
And compare them against benchmarks.

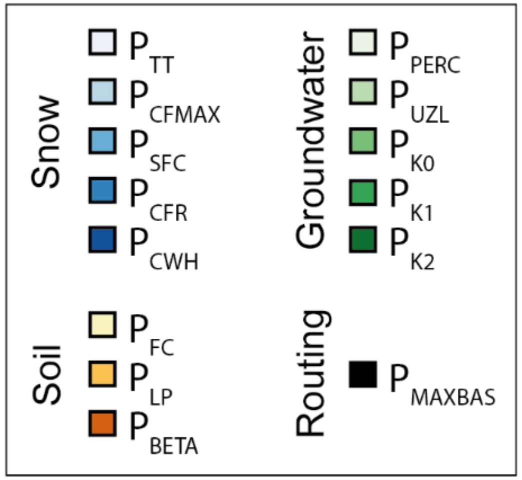
We always transferred entire parameter sets.

Results 1: Most sensitive parameter per catchment

Parameter sensitivity is spatially well-organized.

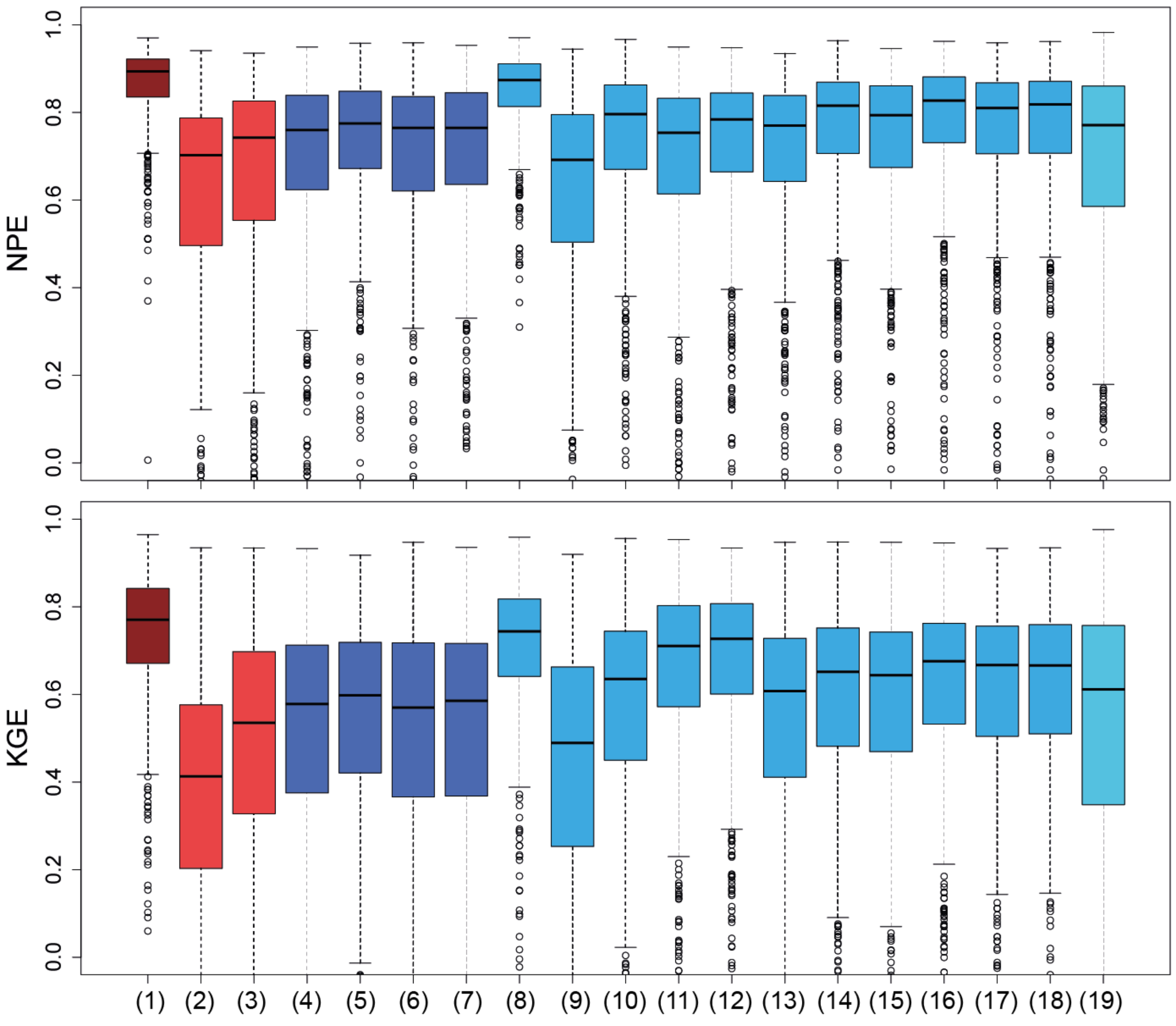
Does that help us to find the best donors?





Parameter sensitivity defined as:
Mean change in model performance after a change in parameter value of +/- 2.5% of the parameter range used during calibration..

Results 2: Regionalization performance



(1) Upper benchmark

(2) Lower benchmark (random)
(3) Lower benchmark (US)

(4) Geographic area classification
(5) Climate classification
(6) Water balance classification
(7) Signature classification

(8) Best donors
(9) Random donors
(10) Closest donors
(11) RMSE
(12) RMSE & distance
(13) Attributes
(14) Signatures
(15) Distance & attributes
(16) Distance & signatures
(17) Attributes & signatures
(18) Distance & attributes & signatures

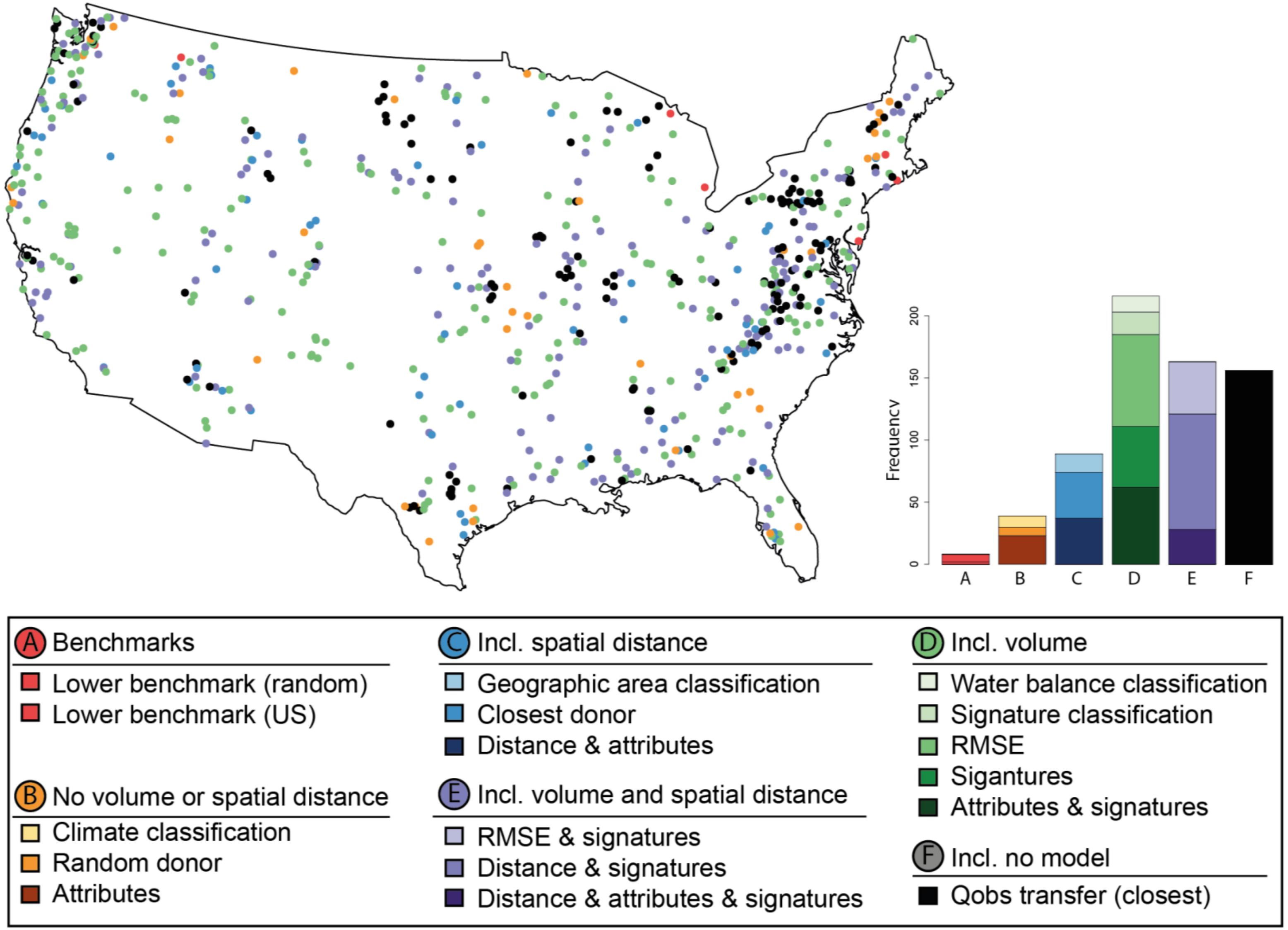
(19) Qobs transfer (closest)

The evaluation criteria influences how we rate a regionalization approach.

Look for example at the effect of having good volume information (method 11 ,12), it is much more important for KGE than for NPE.

Can you find more examples?

Results 3: The best regionalization approaches



Lets focus on NPE:

The availability of volume information is important to choose donors.

If no volume info is available, then spatial proximity might be helpful to guide the selection of donors.

A simple averaging of time series from neighboring basin can be surprisingly good.

… we still need to do some more work to explore the spatial pattern.

Conclusions

Lesson learnt 1:

Good donors do exist, but are hard to find.

Lesson learnt 2:

Better use a random donor than random parameter values.

Lesson learnt 3:

The choice of the evaluation criteria can influence the performance of a regionalization approach.

Lesson learnt 4:

A few streamflow gauges might improve your predictions.

Lesson learnt 5:

Spatially close donors might improve your predictions.

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Appendix: HBV model parameters

Parameter	Meaning	Unit	Min. value	Max. value
Snow routine				
P_{TT}	Threshold temperature	°C	-2	2.5
P_{SFC}	Snowfall correction factor	-	0.5	1.2
P_{CFMAX}	Degree-day factor	$mm°C^{-1}d^{-1}$	0.5	10
P_{CFR}	Refreezing coefficient	-	0	0.1
P_{CWH}	Water holding capacity	-	0	0.2
Soil routine				
P_{FC}	Max. soil moisture storage	mm	100	550
P_{BETA}	Shape coefficient	-	1	5
P_{LP}	Threshold for reduction of evaporation	-	0.3	1
Groundwater routine				
P_{UZL}	Max. storage in shallow groundwater box	mm	0	70
P_{PERC}	Percolation from shallow to deep groundwater box	mmd^{-1}	0	4
P_{K0}	Recession coefficient of fast response	d^{-1}	0.1	0.5
P_{K1}	Recession coefficient of intermediate response	d^{-1}	0.01	0.2
P_{K2}	Recession coefficient of baseflow	d^{-1}	0.00005	0.1
Routing routine				
P_{MAXBAS}	Length of weighting function	d	1	5