# A plethora of conceptual models is available: What are the dynamic differences?

## We investigate how climate forcing influences the streamflow simulation potential of different lumped conceptual models

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### We find 18 representative climate classes...



Selected locations are centroids from k-means clustering analysis of climate indices. Indices describe aridity (Im), aridity seasonality (Im<sub>R</sub>) and fraction P as snow (fps).

### Climate is an important control on the water balance and on water movement/partitioning - or lack thereof



Rain, temperature and potential evapotranspiration interact to control (1) aridity, (2) snowfall, (3) rainfall intensity. (1) and (2) are largely non-correlated on a global scale and are used to cluster the global climates in representative groups.



Annual average aridity, aridity seasonality & fraction P as snow control the clustering results (borders as figure at the top, colours are those of centroids).

Surface runof<sup>-</sup>

Differences with the Köppen-Geiger classes <sup>[1]</sup> occur mainly in areas with strong seasonality. What are your thoughts on these differences?



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# ...and use daily data from each as model forcing -----



### The models have different structures and represent a selection of processes (snow, soil moisture, deep store, runoff store, routing). We investigate if, given the same forcing, the models behave differently.



GR4J <sup>[2]</sup>		PENN
<b>x1</b>	[1, 2000]	ρ
x2	[-8, 14]	Smax
х3	[1, 300]	Def
<b>x4</b>	[0, 5]	g
		а

**These 3 models are chosen from a much longer** list of models for brevity and their obvious differences in structure. GR4J and PENMAN have a limited number of parameters but contain some unique elements (e.g. water exchange, deficit store), while FLEX-IS is a more traditional RR-model with a larger number of parameters.

We use Latin-Hypercube sampling to generate minimum 5000 parameter sets for each model.

**SMAX** LP PERC Kf Ks Nlagf Nlags

Climate clustering data (P, T, N, E): CRU TS v3.23 - Harris, I., et al. (2014). http://doi.org/10.1002/joc.3711



#### **FLEX\_IS**<sup>[4,5]</sup>



Model forcing data (P): MSWEP - Beck, H. E., et al. (2017). http://doi.org/10.5194/hess-21-589-2017 Model forcing data (T): BEST - Berkely Earth. (2017). http://www.berkeleyearth.org Model forcing data (E): USGS - USGS. (2017). https://earlywarning.usgs.gov/fews/product/81

# Forcing strongly controls model potential



GR4J sampling (25000 parameter sets x 18 climates = 450000 samples) summarized as signature values. Black circles are observations from 410 MOPEX catchments.

Top: climate forcing determines model potential - which regions of the output space a model can reach. Arid climates limit simulation potential more than wet ones (red regions tend to be smaller than green ones). Bottom: **PENMAN's deficit store enhances this effect.** FLEX-IS shows that more parameters don't necessarily increase model simulation potential.



Limitations: number of parameter samples and models is too low. Both will be addressed in future work, allowing hypotheses about what makes models different.

[1] Peel, M. C., et al. (2007). http://doi.org/10.5194/hess-11-1633-2007 [2] Perrin, C., et al. (2003). http://doi.org/10.1016/S0022-1694(03)00225-7 [3] Wagener, T., et al. (2004). ISBN: 978-186094-466-6





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EGU2017-8057





Fraction flow reversals

[4] Fenicia, F., et al. (2008). http://doi.org/10.1029/2006WR005563 [5] Nijzink, R., et al. (2016). http://doi.org/10.5194/hess-2016-427

