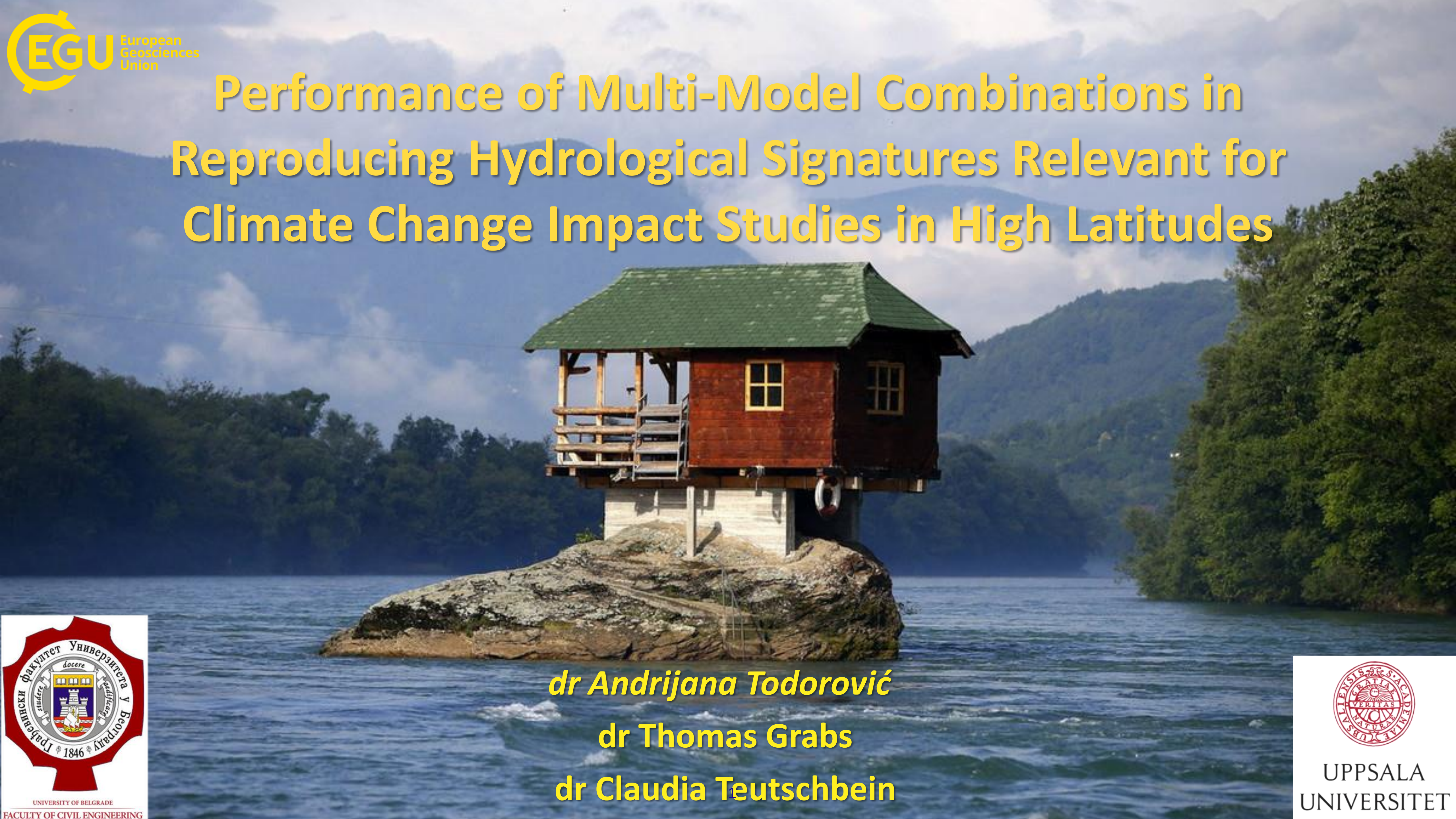


Performance of Multi-Model Combinations in Reproducing Hydrological Signatures Relevant for Climate Change Impact Studies in High Latitudes

dr Andrijana Todorović

dr Thomas Grabs

dr Claudia Teutschbein

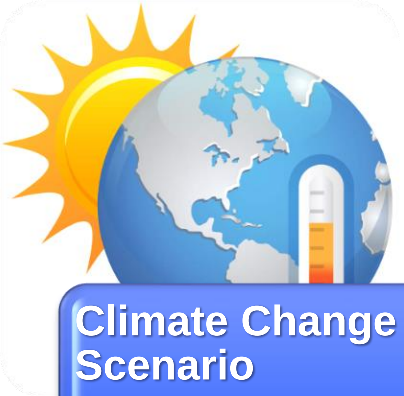
UNIVERSITY OF BELGRADE
FACULTY OF CIVIL ENGINEERING

UPPSALA UNIVERSITET

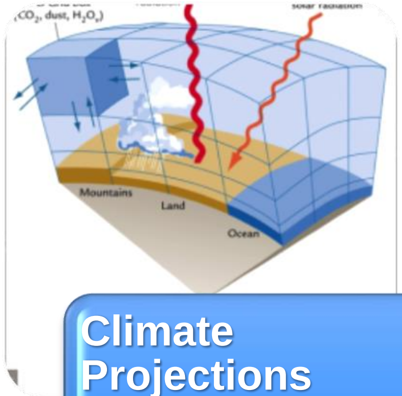
European Geosciences Union

Climate Change Impact Assessment

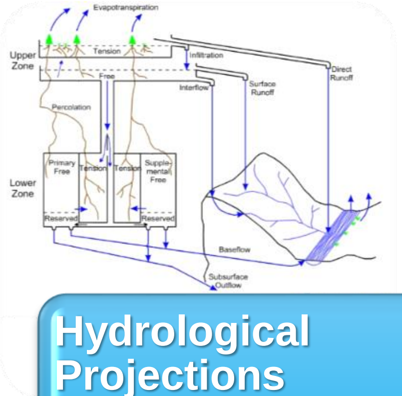
- Climate change impact assessment is key for sustainable water resources management
- Inference on climate change impacts is based on change in features of hydrological regimes, i.e., *hydrological signatures* (e.g., mean-, high- or low-flows, flow seasonality,…)
  - Climate change impact assessment relies on statistical properties of the signatures



Climate Change Scenario
- RCP



Climate Projections
- GCM
- Down-scaling
- Bias-adjustment



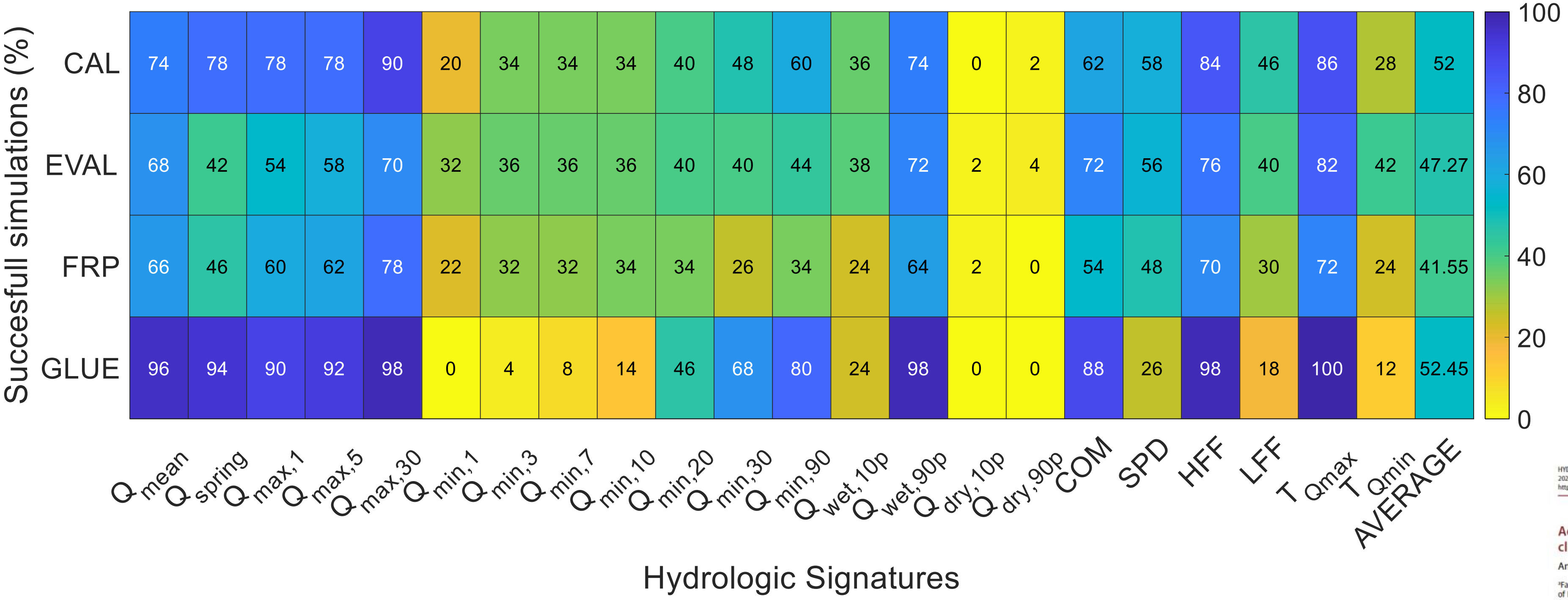
Hydrological Projections
- Hydrological models run with the climate projections

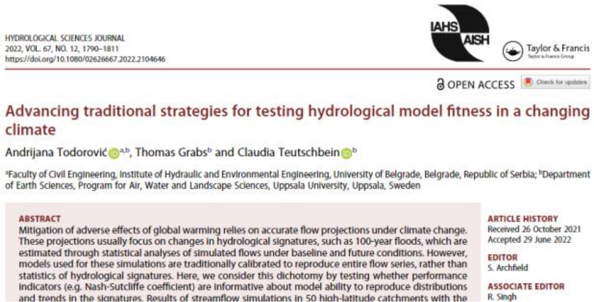
Climate change impact on hydrological regimes

Model Performance in Reproducing Hydrological Signatures

- Hydrological projections are obtained with hydrological models that are calibrated to reproduce *entire* flow series rather than statistical properties of the hydrological signatures
  - Models can have poor performance in reproducing distributions of the signatures

% of simulations with well-reproduced distributions in 50 high-latitude catchments

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Advancing traditional strategies for testing hydrological model fitness in a changing climate

Andrijana Todorović[a,b], Thomas Grabs[b] and Claudia Teutschbein[b]

[a]Faculty of Civil Engineering, Institute of Hydraulic and Environmental Engineering, University of Belgrade, Belgrade, Republic of Serbia; [b]Department of Earth Sciences, Program for Air, Water and Landscape Sciences, Uppsala University, Uppsala, Sweden

ABSTRACT
Mitigation of adverse effects of global warming relies on accurate flow projections under climate change. These projections usually focus on changes in hydrological signatures, such as 100-year floods, which are estimated through statistical analyses of simulated flows under baseline and future conditions. However, models used for these simulations are traditionally calibrated to reproduce entire flow series, rather than statistics of hydrological signatures. Here, we consider this dichotomy by testing whether performance indicators (e.g. Nash-Sutcliffe coefficient) are informative about model ability to reproduce distributions and trends in the signatures. Results of streamflow simulations in 50 high-latitude catchments with the

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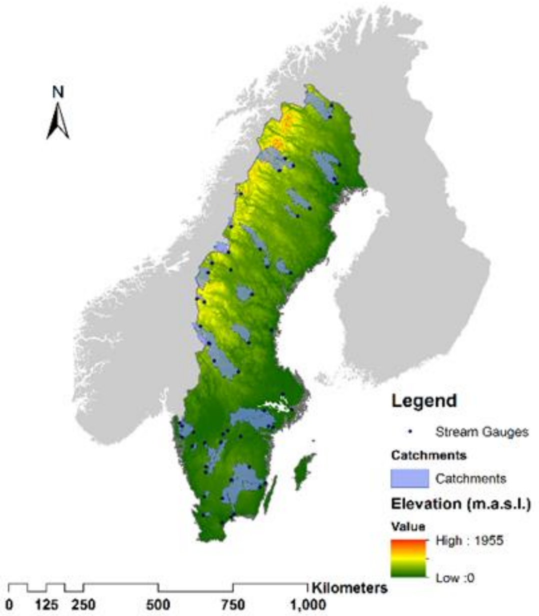
Multi-Model Combination Methods

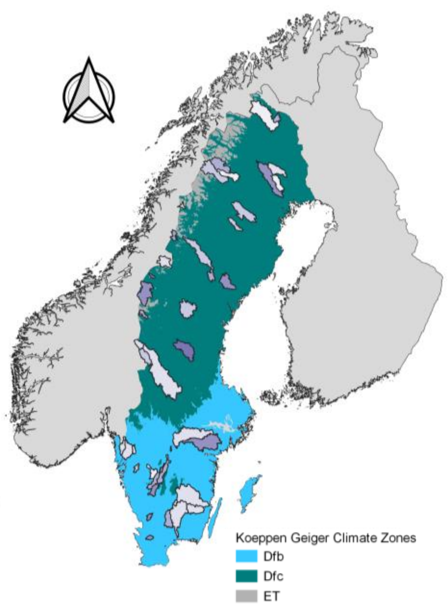
- Multi-model combination methods (MMCMs) can improve model performance
  - Multi-model combination methods: application of a weighting scheme to combine outputs of an ensemble of models ("team-of-rivals") to outperform individual models
- Research questions:
  1. Can MMCMs improve model performance in reproducing distributions of the signatures?
  2. Can "targeting" specific signatures improve performance in reproducing their distributions?

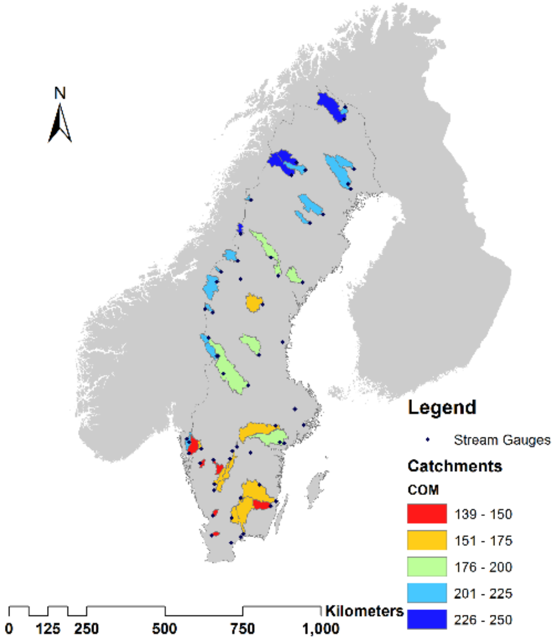
Source: https://www.istockphoto.com/photos/ants-carrying-log-teamwork

Catchments and Data

- Analyses are conducted in 50 catchments across Sweden
  - Three climate zones according to the Köppen- Geiger classification: polar tundra (ET), subarctic boreal climate (Dfc) and warm summer hemiboreal climate (Dfb)
  - Rainfall-, transitional-, and snow-dominated hydrological regimes
- Daily data over 60-year long record period: precipitation, temperature and flows
  - ➢ Potential evapotranspiration is calculated with daily temperatures by using the Hamon method





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DATA ARTICLE | Open Access

CAMELS-SE: Long-term hydroclimatic observations (1961–2020) across 50 catchments in Sweden as a resource for modelling, education, and collaboration

Claudia Teutschbein

First published: 15 February 2024 | https://doi.org/10.1002/gdj3.239

Dataset details

Identifier: https://doi.org/10.57804/t3rm-v029.

Creator: Claudia Teutschbein.

Hydrological Models

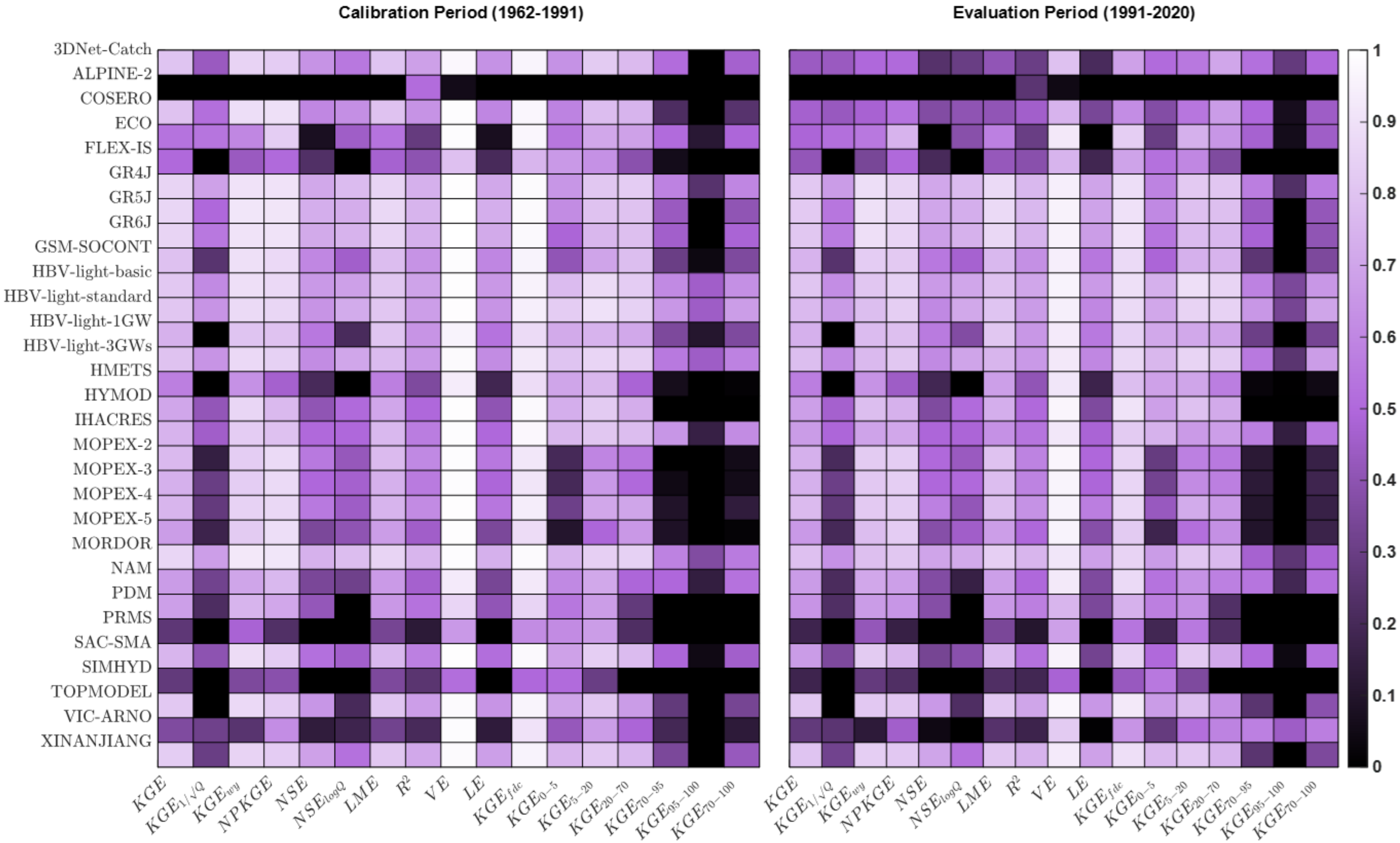
- 29 bucket-style, spatially lumped models
  - Models of varying complexity
  - All models include a snow routine

- Hydrological simulations are performed with daily time step
  - Calibration period: water years 1962-1991
  - Evaluation period: water years 1991-2020

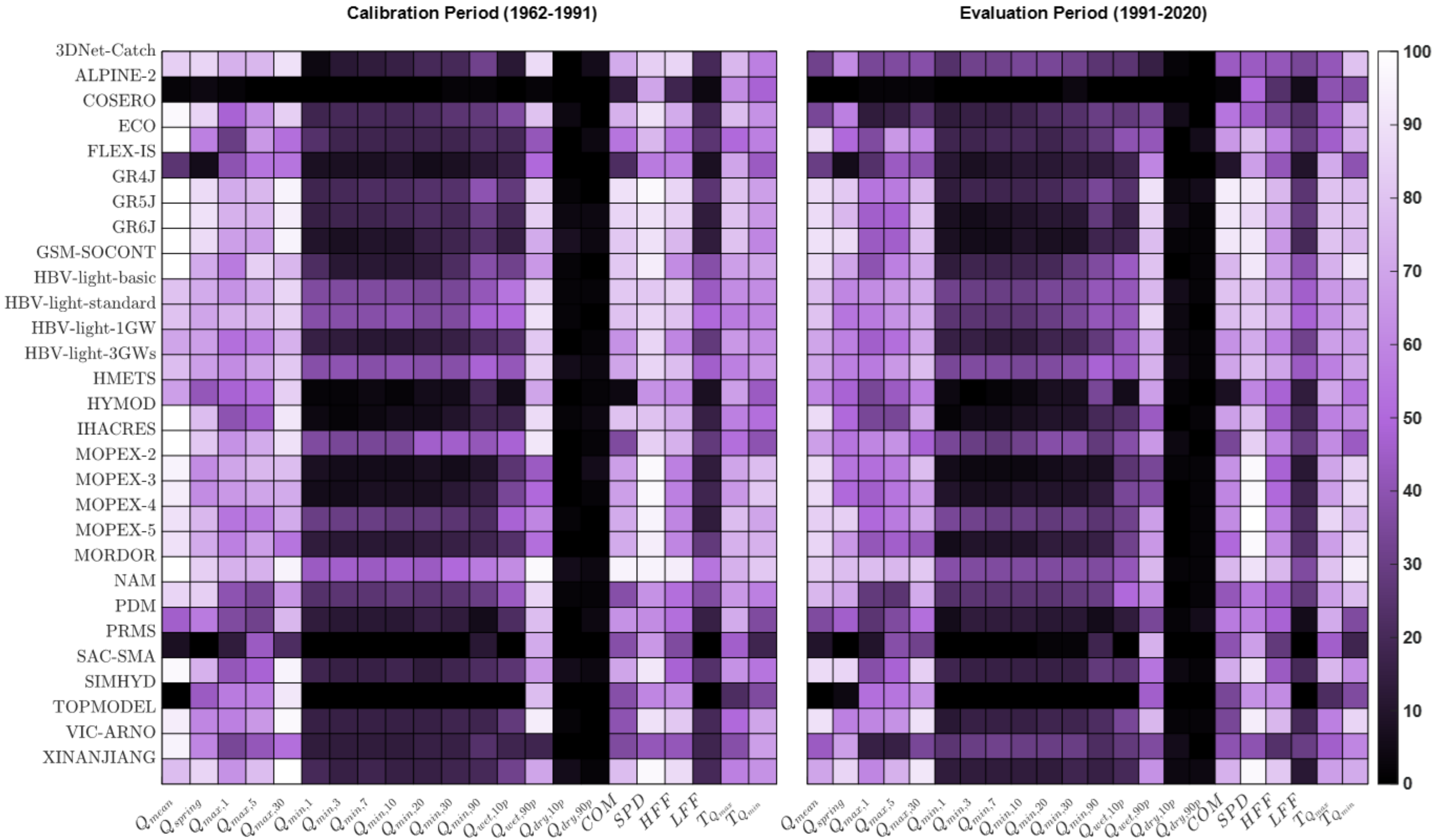
- Model calibration: maximization of the non-parametric version of *KGE* (*NPKGE*) in each catchment

№	Model	Number of Free Parameters	Number of Storages
1	3DNet-Catch	21	7
2	ALPINE-2	6	2
3	COSERO	18	7
4	ECHO	16	7
5	FLEX-IS	10	5
6	GR4J	6	2
7	GR5J	7	2
8	GR6J	8	3
9	GSM-SOCONT	8	3
10	HBV-light – basic version	15	3
11	HBV-light – standard version	16	3
12	HBV-light – one GW box	15	2
13	HBV-light – three GW boxes	15	4
14	HMETS	21	3
15	HYMOD	8	5
16	IHACRES	11	3
17	MOPEX 2	7	5
18	MOPEX 3	8	5
19	MOPEX 4	10	5
20	MOPEX 5	12	5
21	MORDOR	13	5
22	NAM	12	6
23	PDM	10	4
24	PRMS	18	7
25	SAC-SMA	15	6
26	SIMHYD	11	4
27	TOPMODEL	10	2
28	VIC/ARNO	12	4
29	XINANJIANG	13	4

Performance of the Calibrated Models



Performance of the Calibrated Models



Multi-Model Combination Methods

– 10 multi-model combination methods: $X = \sum_{m=1}^{M} \omega_m X_m^T$

№	Method	Description and Equations
1	Equal weights ("democracy"), EW	$\omega = \frac{1}{M}$
2	Akaike information criterion, AIC	$\omega_{AIC,m} = \frac{\exp(0.5\,\Delta_{AIC,m})}{\sum_{i=1}^{M}\exp(0.5\,\Delta_{AIC,i})}$ $\Delta_{AIC,m} = AIC_m - \min_i AIC_i$ $AIC_m = -2\ln L + 2p_m$ $-2\ln L = N\log S_m^2 + N$
3	Corrected Akaike information criterion, AICc	AICc differs from AIC according to the penalty term, which is modified to account for size of the dataset. $\omega_{AICc,m} = \frac{\exp(0.5\,\Delta_{AICc,m})}{\sum_{i=1}^{M}\exp(0.5\,\Delta_{AICc,i})}$ $\Delta_{AICc,m} = AIC_{c,m} - \min_i AIC_{c,i}$ $AIC_{c,m} = AIC_m + \frac{2p_m(p_m+1)}{N-p_m-1}$
4	Bayesian information criterion, BIC	$\omega_{BIC,m} = \frac{\exp(0.5\,\Delta_{BIC,m})}{\sum_{i=1}^{M}\exp(0.5\,\Delta_{BIC,i})}$ $\Delta_{BIC,m} = BIC_m - \min_i BIC_i$ $BIC_m = -2\ln L + p_m \ln N$ $-2\ln L = N\log S_m^2 + N$
5	Hannan-Quinn information criterion, HQIC	$\omega_{HQIC,m} = \frac{\exp(0.5\,\Delta_{HQIC,m})}{\sum_{i=1}^{M}\exp(0.5\,\Delta_{HQIC,i})}$ $\Delta_{HQIC,m} = HQIC_m - \min_i HQIC_i$ $HQIC_m = -2\ln L + p_m \ln(\ln N)$ $-2\ln L = N\log S_m^2 + N$
6	Kashyap information criterion, KIC	$\omega_{KIC,m} = \frac{\exp(0.5\,\Delta_{KIC,m})}{\sum_{i=1}^{M}\exp(0.5\,\Delta_{KIC,i})}$ $\Delta_{KIC,m} = KIC_m - \min_i KIC_i$ $KIC_m = -2\ln L + 2p_m \ln\left(\frac{N}{2\pi}\right) + \ln FI$ $-2\ln L = N\log S_m^2 + N$
7	Bates-Granger method, BG	$\omega_m = \frac{1/S_m^2}{\sum_{i=1}^{M} 1/S_i^2}$ S_m is the sample variance of residual series ε_m of the m[th] model in the calibration period: $\varepsilon_m = X_m - Y$
8	Granger-Ramanathan method, GR	This method yields a column-vector of the set of weights Ω: $\Omega = (X^T X)^{-1} X^T Y$
9	Mallows method, MM	Model weight vector Ω_m is obtained by minimising the Mallows criterion, which penalises model complexity, i.e., number of parameters of the m[th] model, p_m: $C(\Omega) = \sum_{i=1}^{N}(Y_{i,1} - \Omega X_{i,m})^2 + 2\sum_{m=1}^{M}\Omega_m p_m S_m^2$ S_m is an estimate of the variance of the residual series. Optimisation is performed with the AMALGAM algorithm (Vrugt et al., 2009).
10	Mallows method with simplex weights, $MM_{simplex}$	Non-simplex model weights obtained by applying the Mallows method are rescaled to have non-negative values that sum up to one. In case of negative weights obtained by applying the Mallows method, their value is set to 0 (following recommendations by Lee and Song, 2021).

Effects of Application of Multi-Model Combination Methods

1. Can MMCMs improve model performance in reproducing distributions of the signatures?
   - MMCM weights are obtained from daily series over the calibration period
   - MMCM performance is compared to the performance of the *reference model*
     - Reference model: (on average) best performing individual model
   - Performance is assessed by applying the Wilcoxon rank sum test over the annual series of the signatures
   - Numerous hydrological signatures are considered

Source: https://favtutor.com/blogs/wilcoxon-rank-sum-test-r

Hydrological Signature
Mean annual flow, Q_{mean}
Mean spring flow, Q_{spring}
1-, 5- and 30-day maximum annual flows
1-,3-, 7-, 10-, 20-, 30- and 90 day minimum flows
10^{th} and 90^{th} flow percentiles in wet seasons, $Q_{wet,10p}$ and $Q_{wet,90p}$
10^{th} and 90^{th} flow percentiles in dry seasons, $Q_{dry,10p}$ and $Q_{dry,90p}$
Timing of the centre of mass of annual flow, COM
Spring onset (spring “pulse day”), SPD
High flow frequency, HFF
Low-flow frequency, LFF
Timing of the maximum annual flow, T_{Qmax}
Timing of the minimum annual flow, T_{Qmin}

Effects of Application of Multi-Model Combination Methods

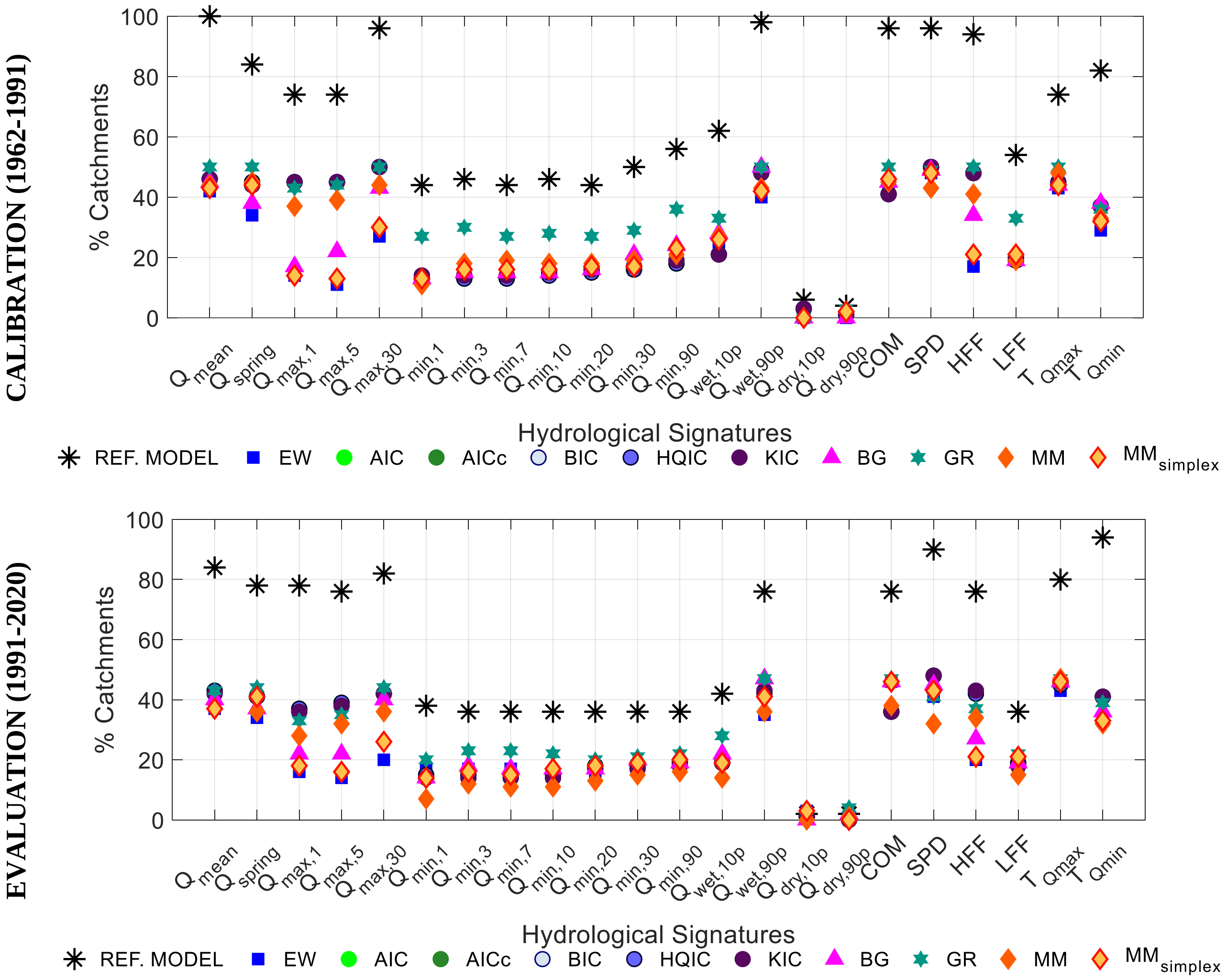
2. Can “targeting” specific signatures improve performance in reproducing their distributions?
    - Focus is on the series of extreme flows (annual maxima and minima of different duration)
    - The MMCMs’ weights are obtained from the annual series of extreme flows in the calibration period

Source: https://balkaninsight.com/2014/05/19/serbia-faces-severe-floods-in-danube-basin/

Source: https://www.moneycontrol.com/news/photos/world/historic-droughts-reveal-long-submerged-relics-9078991.html

Performance in Reproducing Distributions of Signatures

Performance: percentage of catchments with well reproduced distribution of a signature



Todorović et al, 2024.

https://doi.org/10.1016/j.jhydrol.2024.130829

Performance in Reproducing Distributions of Signatures

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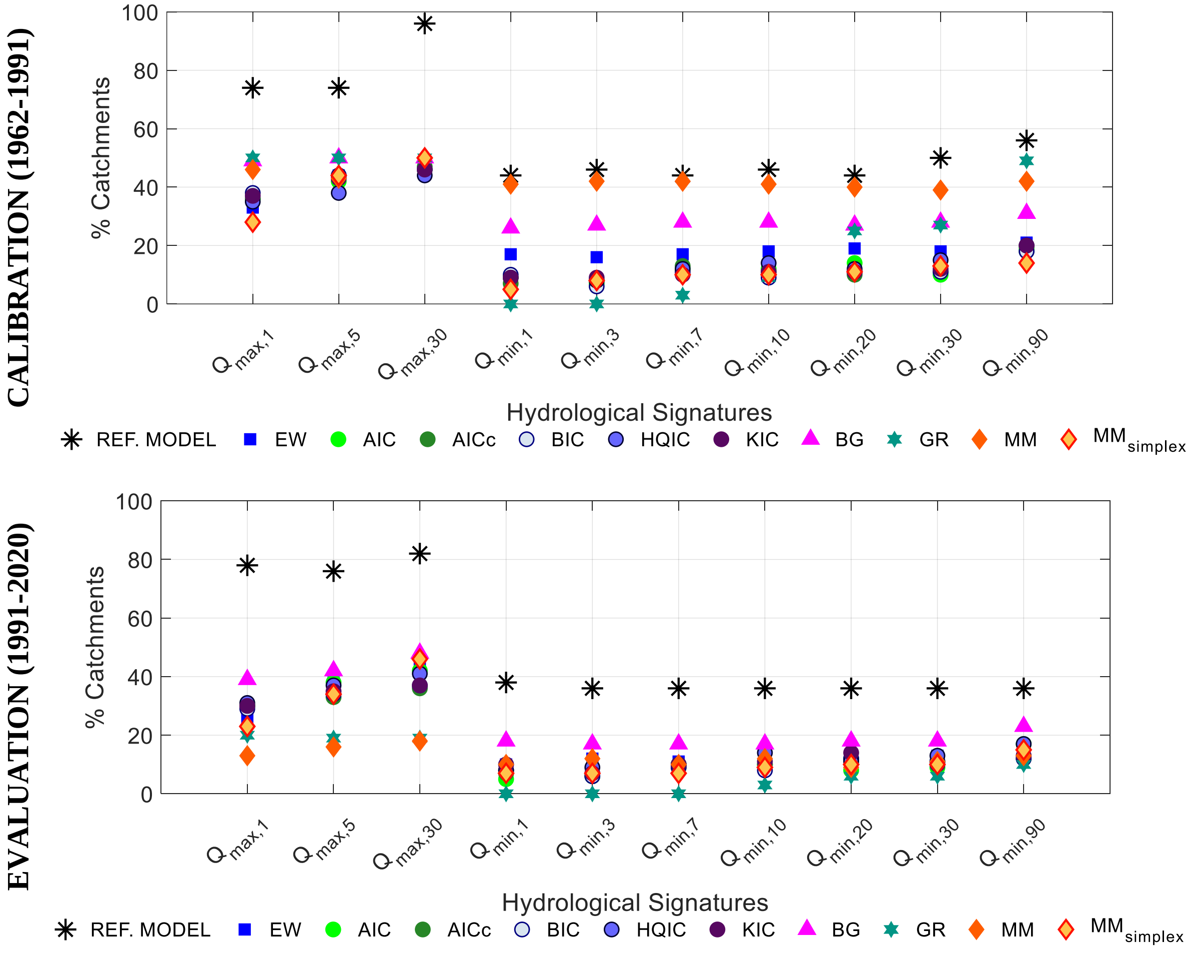


Todorović et al, 2024.

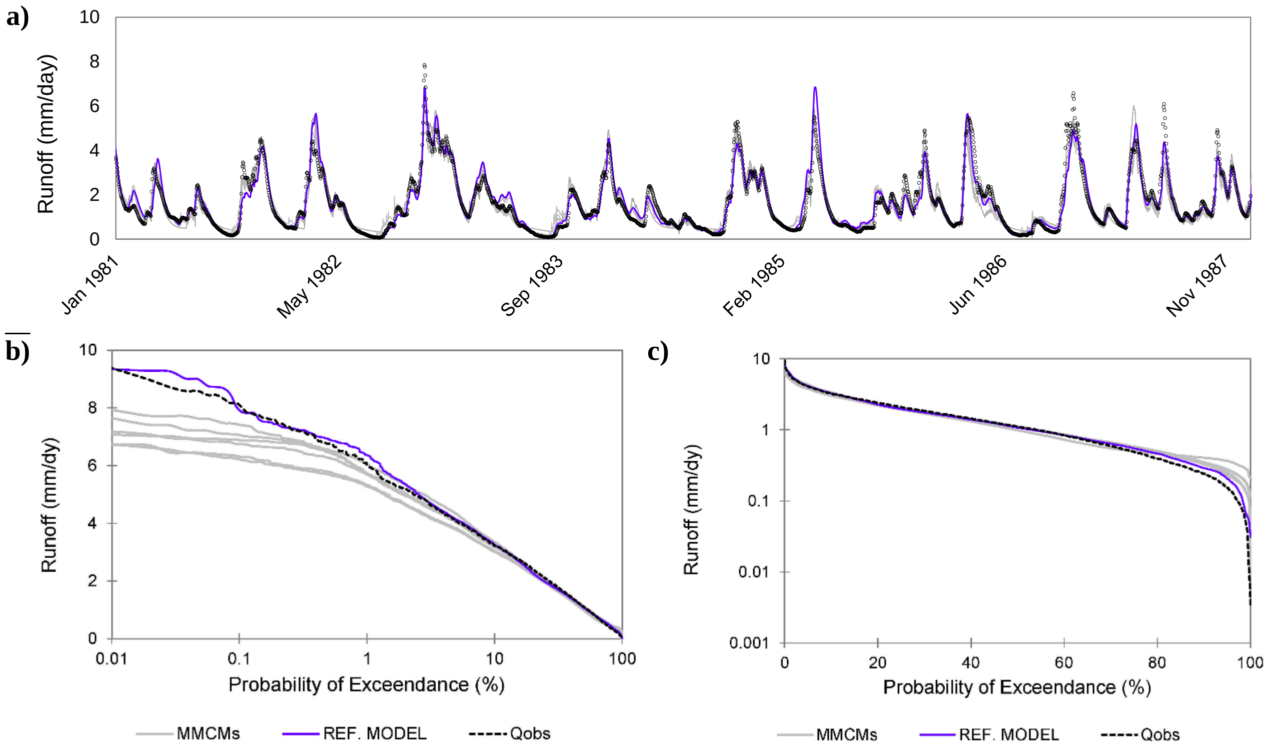
https://doi.org/10.1016/j.jhydrol.2024.130829

Concluding Remarks

- Application of multi-model combination methods (MMCMs) may improve performance in terms of some numerical indicators, but not in reproducing distributions of the signatures
  - MMCMs can cause "squeezing" of the distributions
  - Reproducing distributions of extreme flows remains challenging

- Further research is needed to improve model performance in reproducing statistical properties of the signatures

Source: https://images.app.goo.gl/BKPVwtYKngtpd5Tq9



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Thank you for your attention!

atodorovic@grf.bg.ac.rs