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The more is not the merrier – an informed selection of climate model ensembles can enhance the quantification of hydrological change

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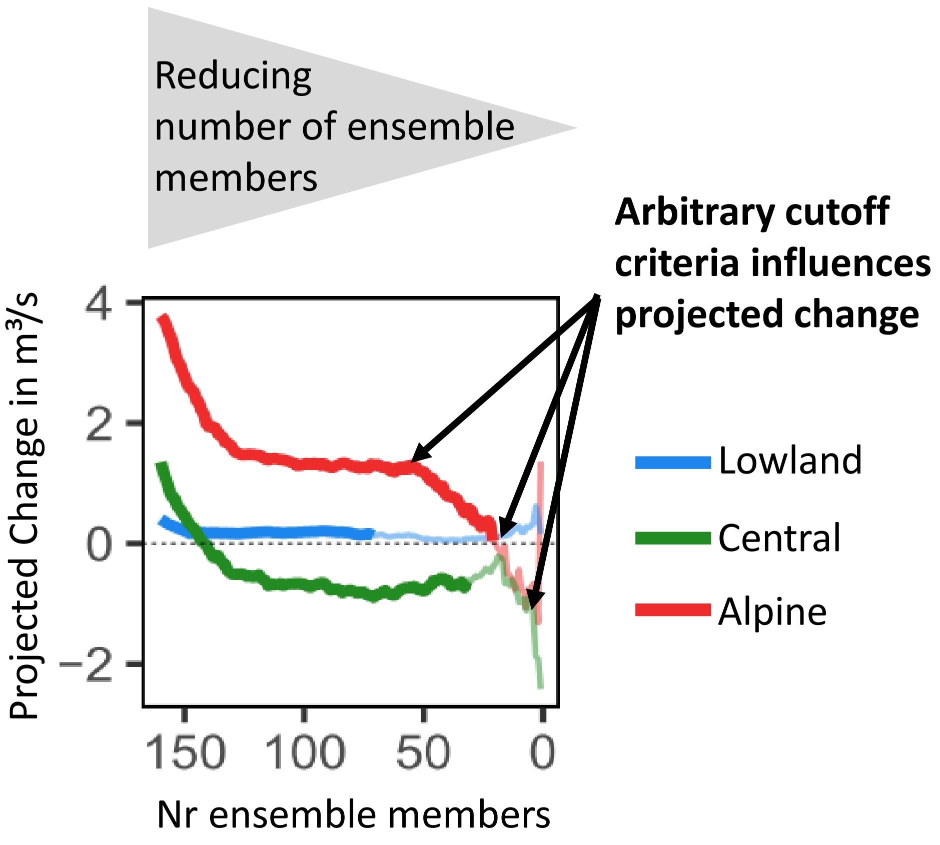
What if we can only use a limited number of ensemble members?

Projected average streamflow change in three German catchments



Kiesel et al. (2019) Ecol. Eng.

Sub-selection methods to deal with this ensemble problem

Sub-selection methods (discussed by *Eyring et al. 2019, Nat Clim Chang***)**

- democracy/full ensemble (Dem) (e.g. *IPCC 2013*)
- diversity of Global Circulation Models (DivG)
- diversity of Regional Climate Models (DivR)

(*Abramowitz et al. 2019, Earth Syst Dynam*)

- trading off information content and redundancy (MIMR) (*Pechlivanidis et al. 2018, WRR*)
- best performing climate depiction (bCl) (*Ruane and McDermid 2017, Earth Perspectives*)
- best performing variable of interest (bSf) (*Kiesel et al. 2019, Ecol Eng*)
- climate model weighing (sWGT) (*Knutti et al. 2017, Geophys Res Lett*)
- reliability ensemble average (REA) (*Tebaldi and Knutti 2007, Phil Trans R Soc A*)

Motivation

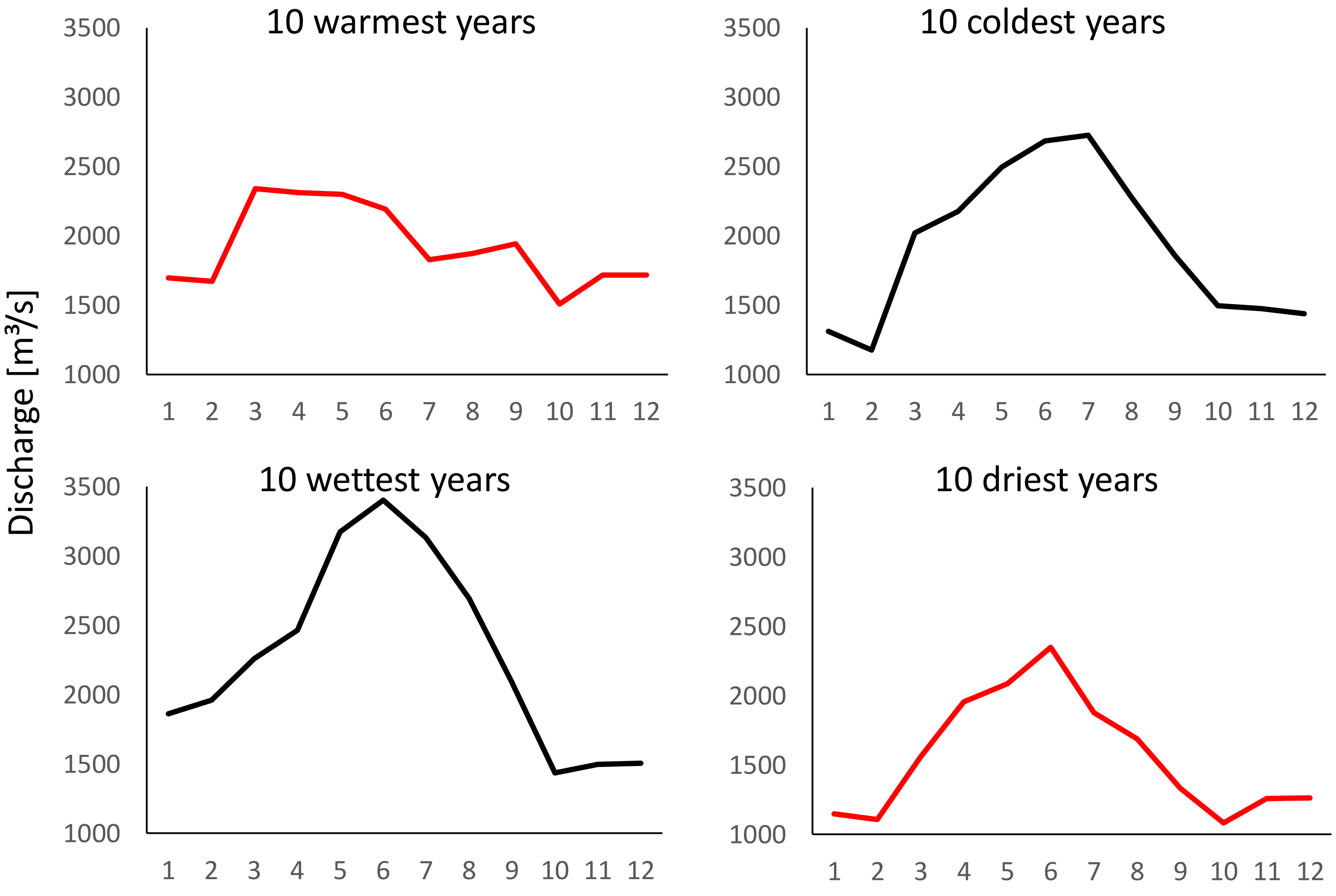
- **Is there a way to validate which of these sub-selection methods is "best"?**

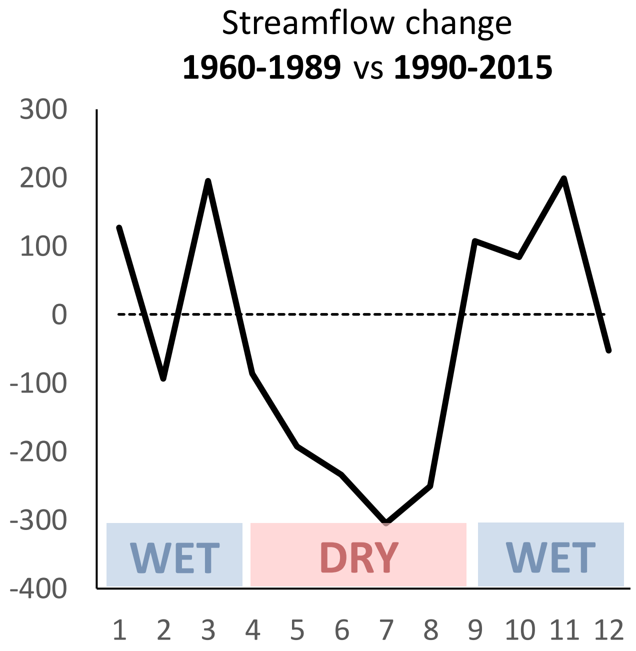
Approach

- Climate models are applied to predict the change from present to future
- We don‘t know the future…but we know the past impact of climate change (*Blöschl et al. 2017, Science*)
- **Main assumption:**
  Models that can't predict past climate change are less well suited to predict an aggravated, future change

Danube: Temporal dependence of discharge seasonality

Observed Discharge: Danube at Vienna (1901-2007)

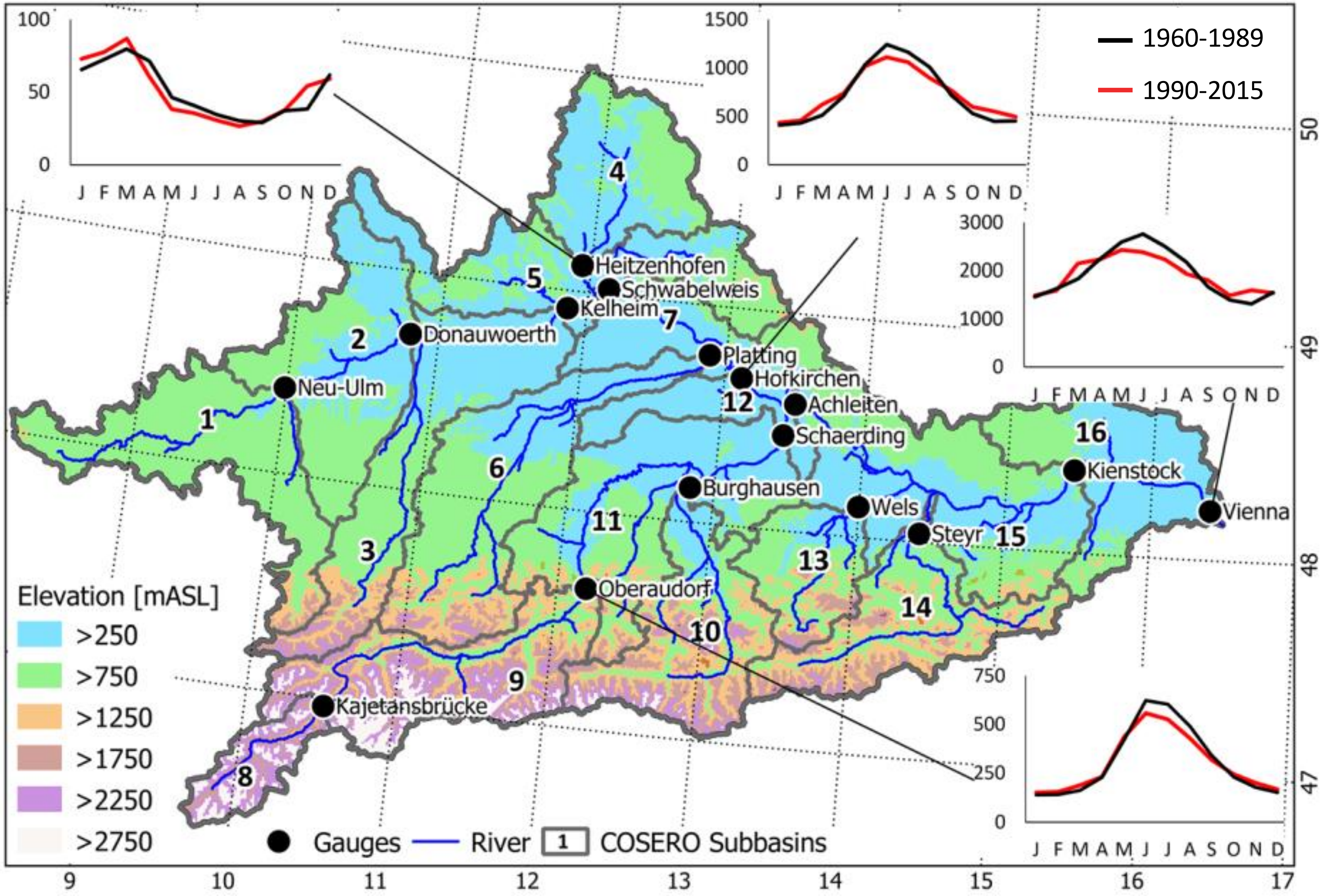




Warmer, drier climate -> less pronounced seasonality
(*Kling et al. 2012, J Hydrol*)

Evaluate which model ensemble can depict impacts of the warming climate best

Danube: Spatial dependence of discharge seasonality



Hydrological change:

- **Alpine regions**
  Reduction in summer discharge
  Slight increase in spring/autumn discharge
- **Lowland regions**
  The opposite discharge regime
- **Combined at Vienna**

Requirements on climate models:

- **1. Spatial correctness**
  In a heterogeneous catchment with alpine influence the correct spatial change pattern is crucial
- **2. Temporal correctness**
  Correct change in long-term warm/dry and cold/wet years

Climate model sub-selection assessment - Methodology

Hindcasted climate change data

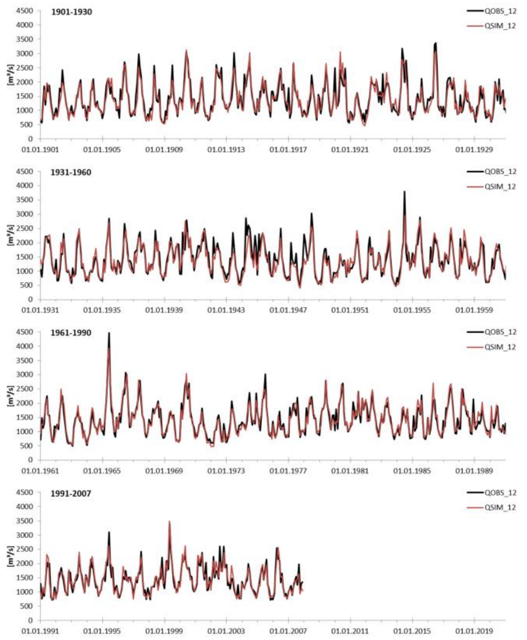
www.cordex.org

16 combinations of GCM + RCM (RCP8.5)

Linear Scaling bias correction (1960-1990)

Jacob et al. 2014, Reg Env Change
Stanzel et al. 2018, J Hydrol

COSERO Model Upper Danube

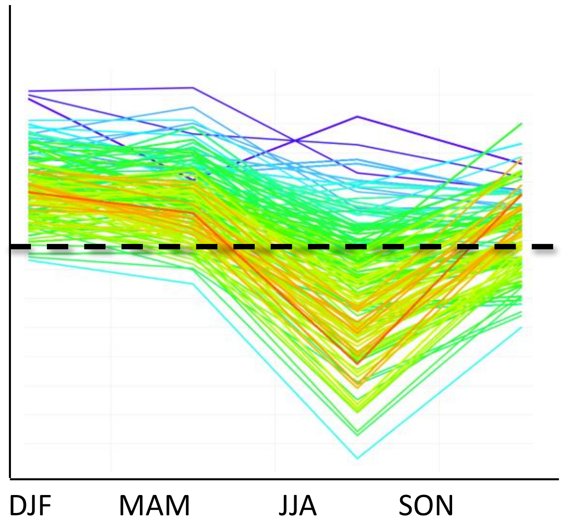


High-performance hydrological model (>100 yr)

5-step evaluation (*Krysanova et al. 2018*)

Kling et al. 2012, J Hydrol

Hindcasted seasonality (1960-1989 vs 1990-2015)



For 16 GCM-RCM

All possible medians

Kiesel et al. 2020, Clim Change

Evaluation

$\left.\begin{array}{l}\text{bCI}\\\text{bSf}\\\text{Dem}\\\text{DivG}\\\text{DivR}\\\text{MIMR}\\\text{REA}\\\text{sWgt}\end{array}\right\}$ Median selection

RMSE against observed change

Kiesel et al. 2020, Clim Change

Climate change and hydrological modelling

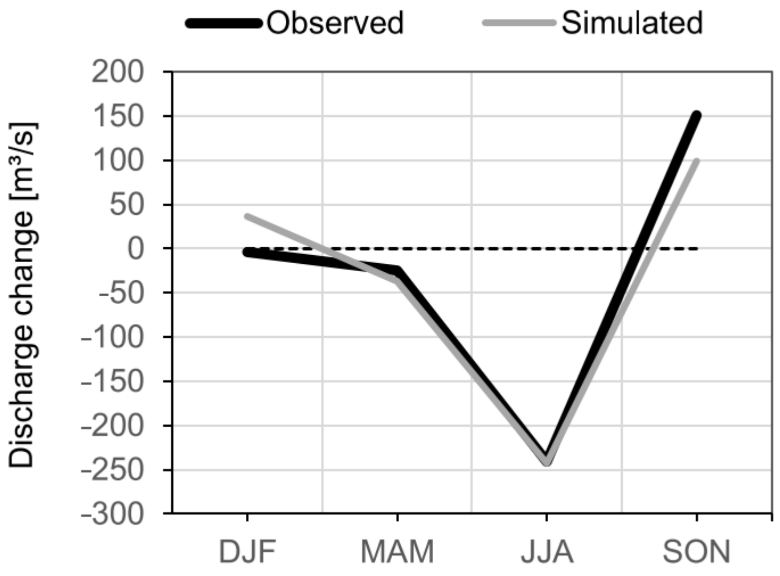
Correct streamflow prediction requires a spatio-temporal integration of climate data (strong performance filter)

Reduction from two to one parameter, but adding an additional layer of uncertainty (the hydrological model)

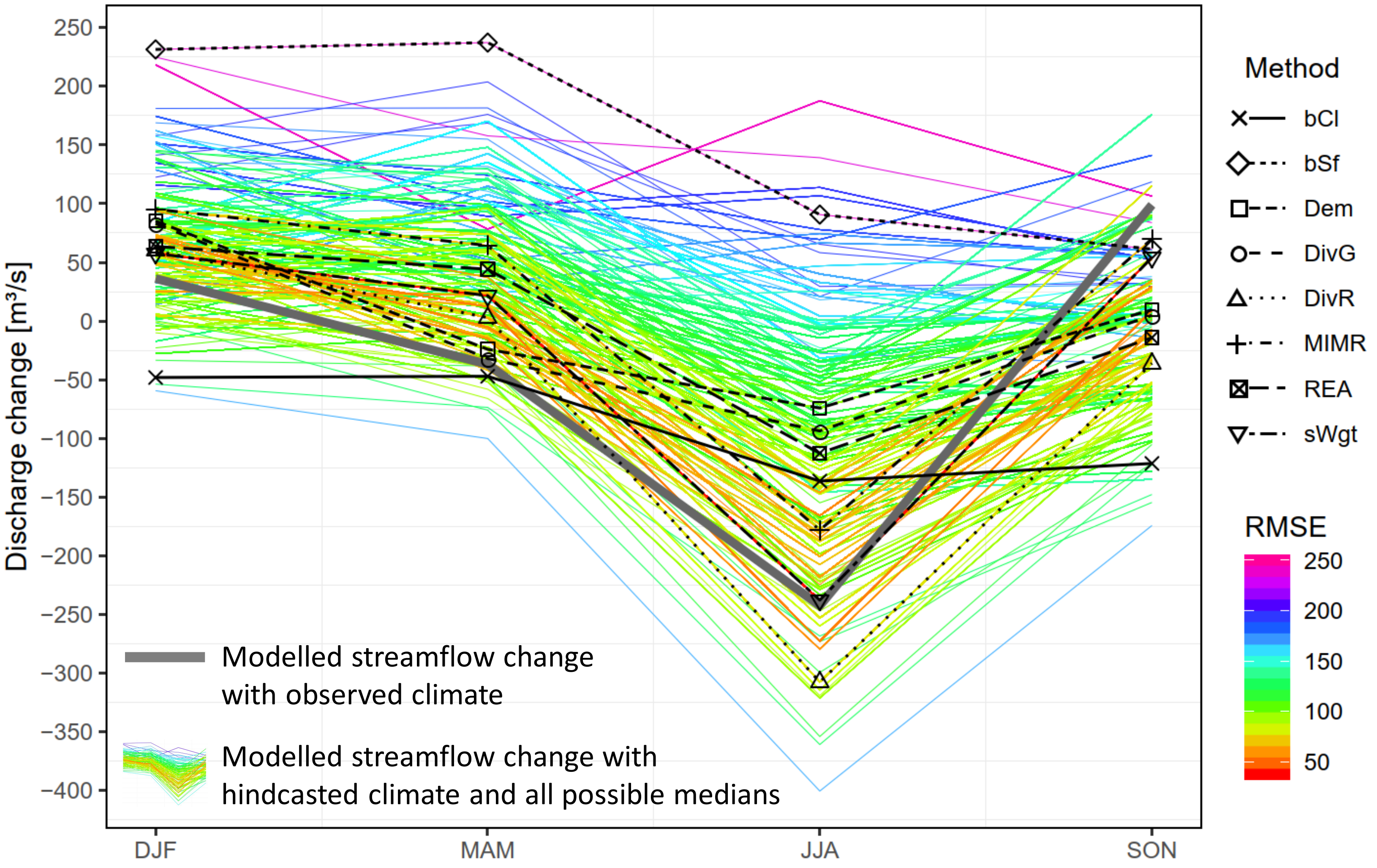
Reduce uncertainty in hydrological model: 5-step evaluation *(Krysanova et al. 2018)*

1) High quality data sources (climate and streamflow)
2) Model performs well for different climate conditions
3) Model performs well for all 16 subbasins
4) Reproduces the observed streamflow shift
5) No trend in observation and simulation

Gauge	Sub	Years	KGE’
Neu-Ulm	1	54	0.89
Donauwörth	2	84	0.88
Kelheim	3	107	0.87
Heitzenhofen	4	87	0.81
Schwabelweis	5	84	0.86
Platten	6	82	0.84
Hofkirchen	7	107	0.84
Kajetansbrücke	8	57	0.95
Oberaudorf	9	107	0.97
Burghausen	10	107	0.93
Schärding	11	57	0.96
Achleiten	12	107	0.92
Wels	13	57	0.91
Steyr	14	57	0.91
Kienstock	15	77	0.92
Vienna	16	107	0.91
Vienna	16	10 warmest	0.90
Vienna	16	10 coldest	0.88
Vienna	16	10 wettest	0.86
Vienna	16	10 driest	0.85



Sub-selection methods: Agreement with observed change



Institute	GCM	RCM	Method	RMSE	Rank
KNMI	EC-EARTH	RACMO22E	**sWgt**	38	1
-	-	-	**MIMR**	68	2
CLMcom	HadGEM2-ES	CCLM	**DivG**	78	3
DMI	EC-EARTH	HIRHAM5	**DivR**	91	4
CLMcom	CERFACS	CCLM		94	5
MPI	M-MPI-ESMr1	REMO2009		95	6
-	-	-	**REA**	96	7
-	-	-	**Dem**	99	8
KNMI	HadGEM2-ES	RACMO22E		107	9
SMHI	EC-EARTH	RCA4		117	10
CLMcom	EC-EARTH	CCLM	**bCl**	130	11
SMHI	M-MPI-ESM	RCA4		141	12
IPSL	IPSL-CM5A-MR	WRF331F		142	13
CLMcom	M-MPI-ESM	CCLM		157	14
SMHI	CERFACS	RCA4		157	15
SMHI	HadGEM2-ES	RCA4		168	16
CNRM	CERFACS	ALADIN53		169	17
MPI	M-MPI-ESMr2	REMO2009	**bSf**	238	18
SMHI	IPSL-CM5A-MR	RCA4		241	19

Best RMSE **Worst RMSE**

- All streamflow changes from hindcasted climate models and their medians show a wide spread (coloured lines)
- Sub-selection methods are mostly able to select models that agree with the observed change-pattern (dashed lines)
- Clear difference between the selection methods

Conclusions

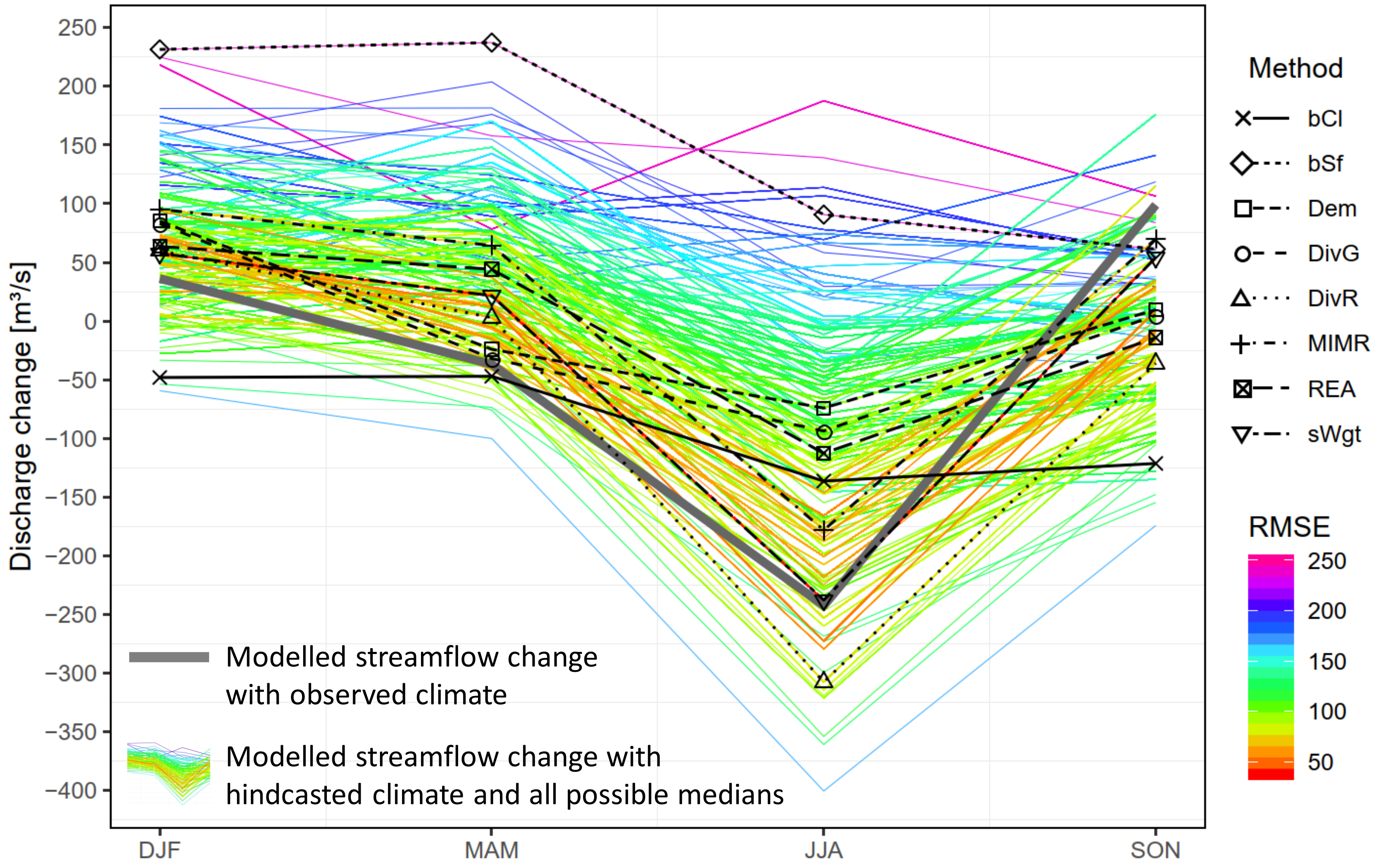
- Splitting historic observations into a reference and evaluation period can be beneficial to assess historic climate change impact
- Wide range of performance differences between sub-selection methods indicates that the selection matters
- Methods maintaining and maximizing diversity and information content clearly outperformed methods that reproduce historical climate or streamflow best
- To yield more robust conclusions, we suggest to test the proposed methods using multiple hydrological models in multiple basins located under a strong hydro-climatic gradient

Thank you for your interest!

Kiesel J, Stanzel P, Kling H, Fohrer N, Jähnig S, Pechlivanidis I. 2020. Streamflow-based evaluation of climate model sub-selection methods. Climatic Change, https://doi.org/10.1007/s10584-020-02854-8. In: Krysanova V, Hattermann FF, Kundzewicz ZW. 2020. How evaluation of hydrological models influences results of climate impact assessment—an editorial.

Supplementary Material

Climate models: Agreement with observed sign of change



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Correct reproduction of direction of change in all seasons

- All streamflow changes from hindcasted climate models and their medians show a wide spread (coloured lines)
- Sub-selection methods are mostly able to select models that agree with the observed change-pattern (dashed lines)
- Clear difference between the selection methods

Reliability Ensemble Average (REA) sub-selection

$$W_{Ti} = 1 - \frac{RMSE_{Ti} - min[RMSE_{Ti}]_{i=1}^{i=n}}{max[RMSE_{Ti}]_{i=1}^{i=n} - min[RMSE_{Ti}]_{i=1}^{i=n}} \quad [1]$$

$$W_{Pi} = 1 - \frac{RMSE_{Pi} - min[RMSE_{Pi}]_{i=1}^{i=n}}{max[RMSE_{Pi}]_{i=1}^{i=n} - min[RMSE_{Pi}]_{i=1}^{i=n}} \quad [2]$$

$$W_{Ci} = 1 - \frac{\left|\Delta Q_i - \widetilde{\Delta Q}\right| - min\left[\left|\Delta Q_i - \widetilde{\Delta Q}\right|\right]_{i=1}^{i=n}}{max\left[\left|\Delta Q_i - \widetilde{\Delta Q}\right|\right]_{i=1}^{i=n} - min\left[\left|\Delta Q_i - \widetilde{\Delta Q}\right|\right]_{i=1}^{i=n}} \quad [3]$$

$$W_i = W_{Ti} + W_{Pi} + W_{Ci} \quad [4]$$

where W is the weight for temperature T, precipitation P and model consensus C for each ensemble member i, n is the number of ensemble members, $RMSE$ the root mean squared error of the seasonality between observed and hindcasted temperature or precipitation, ΔQ the difference between average annual streamflow of the reference- and evaluation period.

Maximum Information Minimum Redundancy (MIMR) sub-selection

Two models contain 90% of the information content