



Vrije Universiteit Brussel

Assessing conceptual model uncertainty for hydrological impact analysis

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MOVED!

(6 weeks ago) from

Vrije Universiteit Brussel

KATHOLIEKE UNIVERSITEIT
LEUVEN





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Hydrology

Hydrological science is young

A lot of discussion:

- From where do we come?
- Where should we head to?
- Interdisciplinary?
- PUB
-



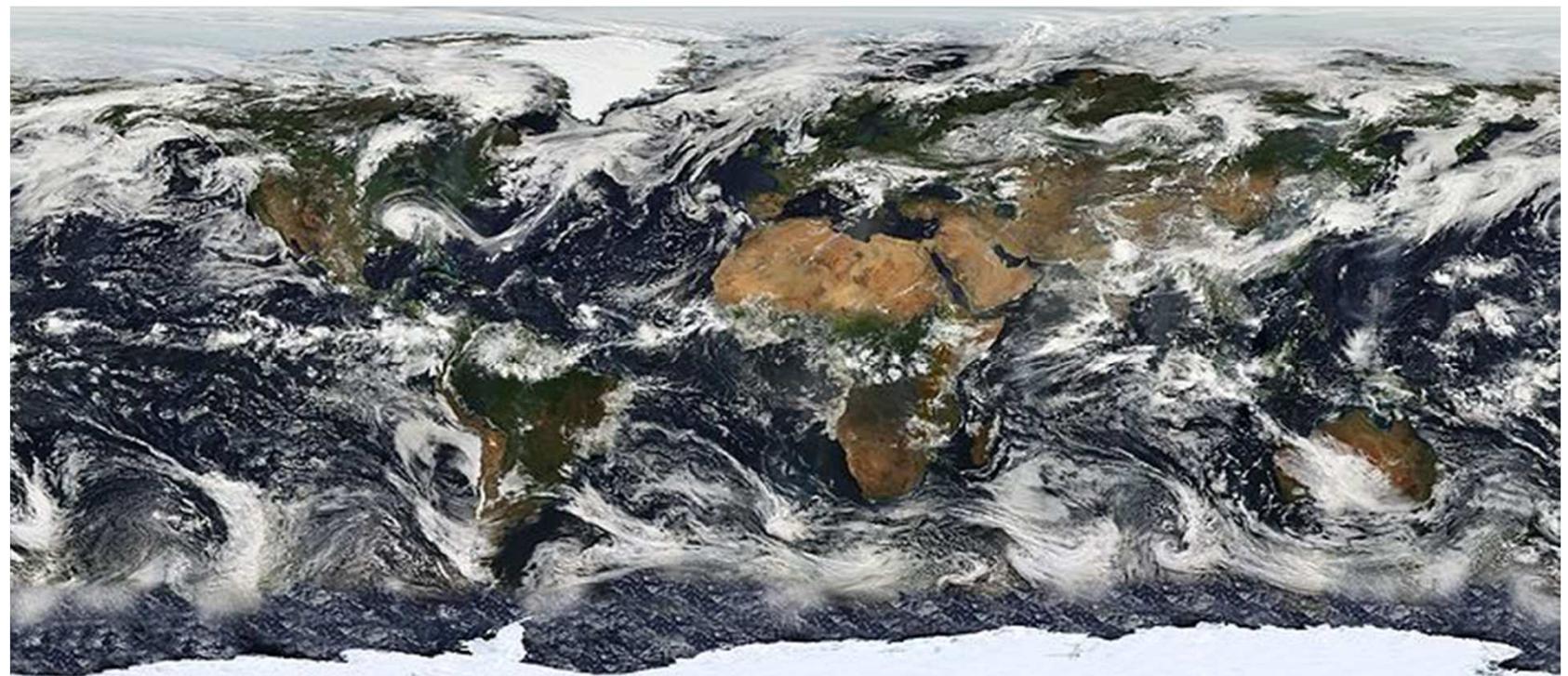
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Major challenge

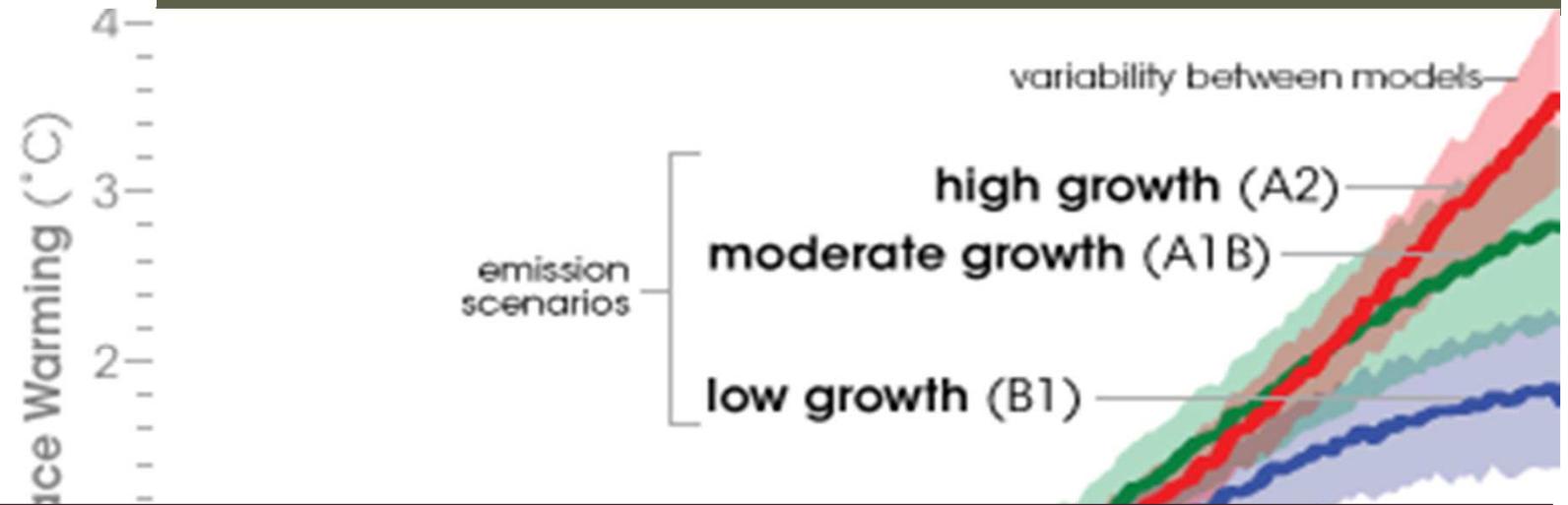
Assessing impact of climate change (CC) on hydrological cycle

(IPCC, 2007;
Peel and
Blöschle, 2011)





Uncertainty CC



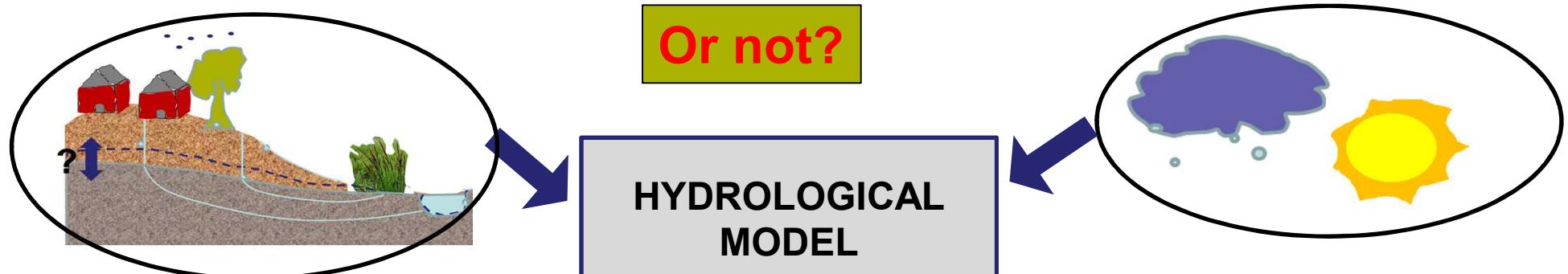
- GHG emission? GCM? Downscaling?
- Uncertainty of future temperature (ET)
- Large uncertainty of future precipitation
- Common practice: ensemble CC scenarios

Classical approach

Hydrological impact analysis of climate change:

1. Calibrating and validating hydrological model
2. Applying hydrological model under reference conditions
3. Applying hydrological model under range of CC

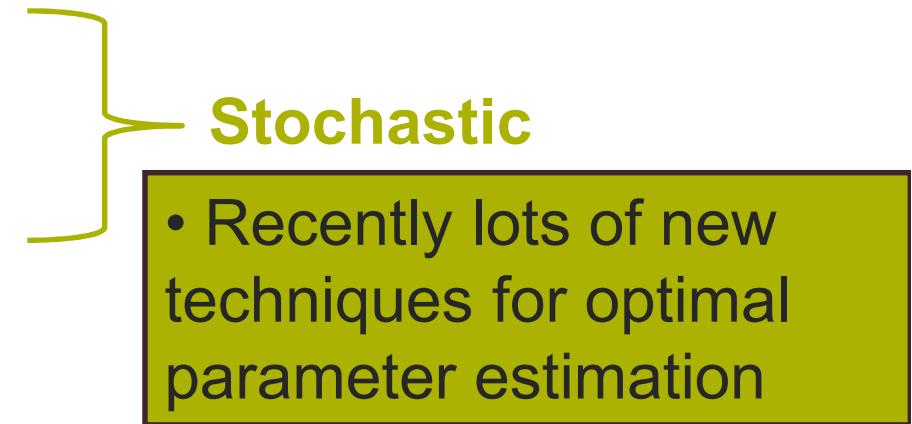
So, we can determine hydrological CC uncertainty.



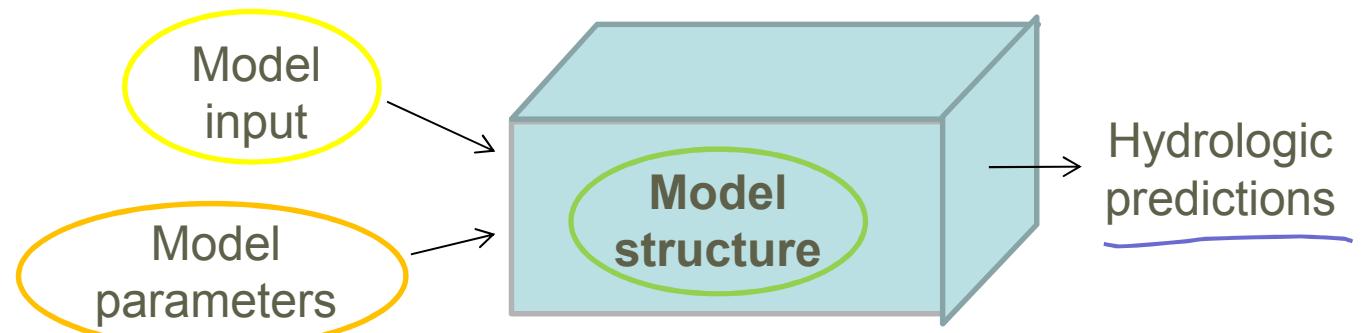
Sources of uncertainty hydrological models

- Input and output data uncertainty
- Parameter uncertainty
- Model equifinality
- Model **structural** uncertainty

• Much less attention (Refsgaard et al., 2006; Rojas et al., 2010)



HYDROLOGICAL MODEL





Objective

Our role in improving prediction of hydrological impact of climate change?

A:

Wait for more accurate climate change scenarios?

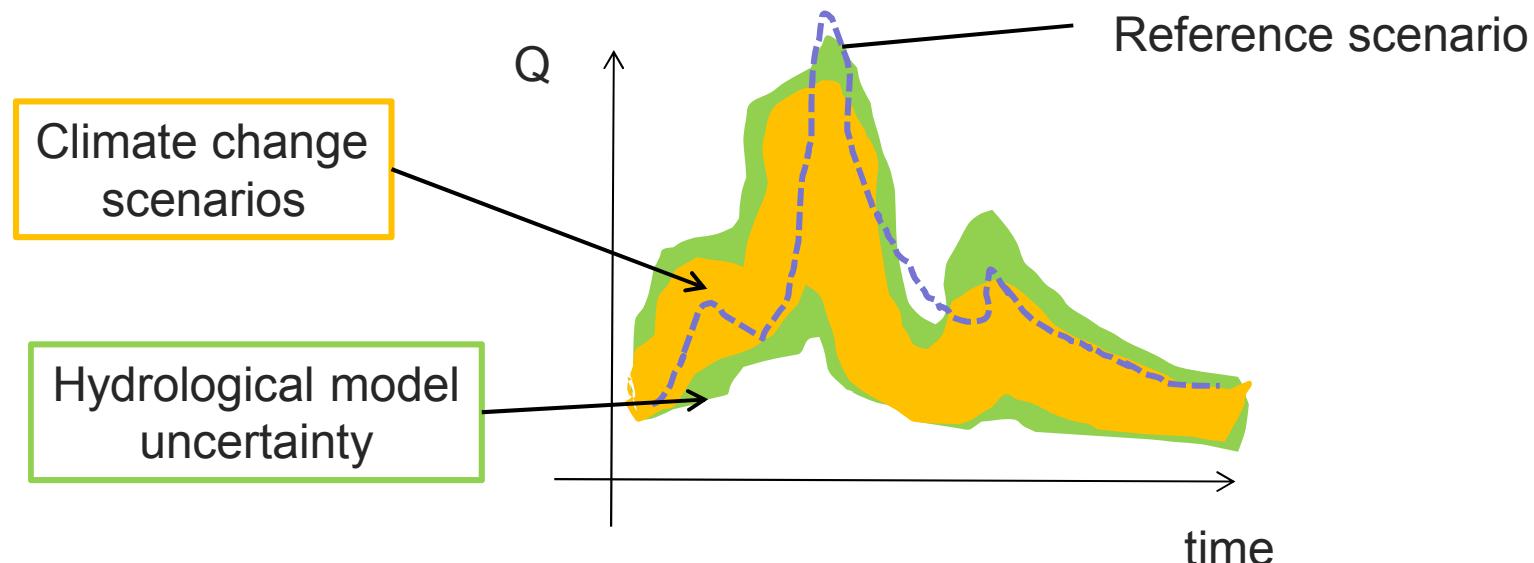


B:

Reach out to community and active role?



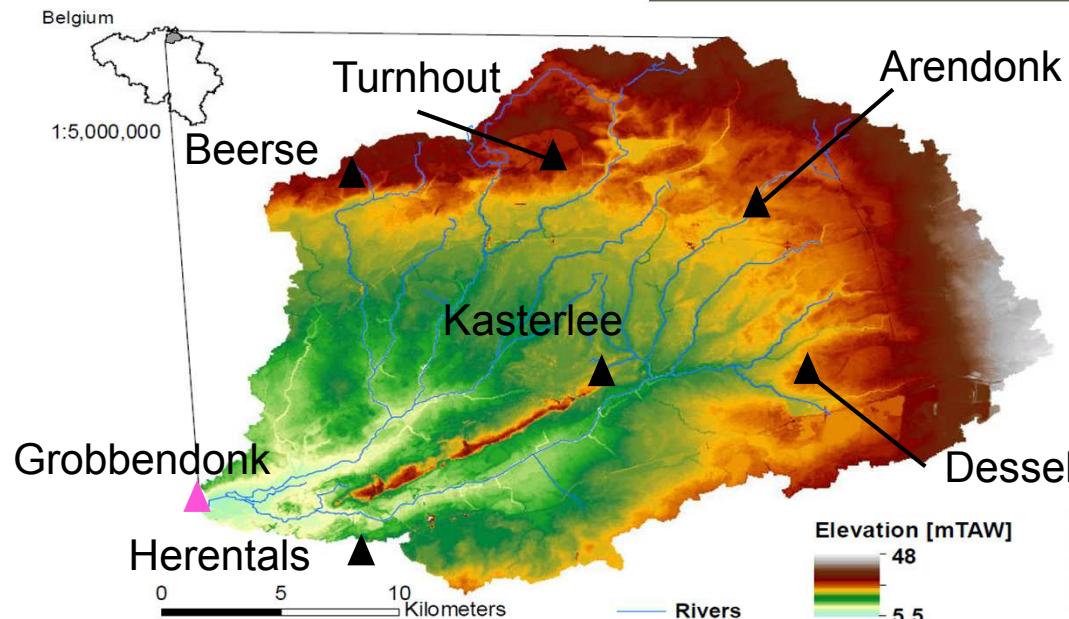
Hypothesis



- There is a large structural hydrological uncertainty, considerably contributing to the uncertainty of the impact of hydrological CC scenarios



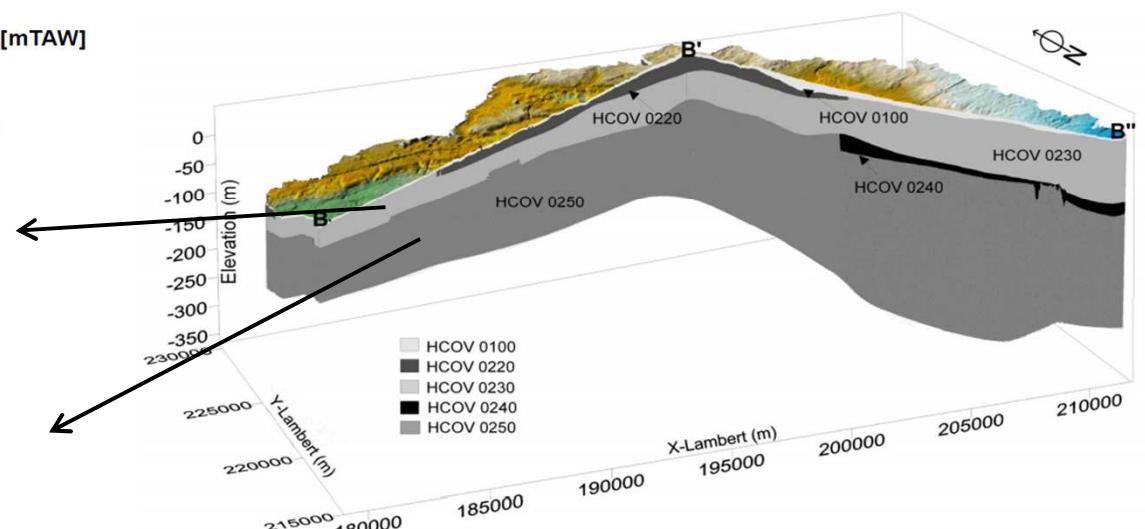
Study area



Pleistocene and Pliocene aquifer

Miocene aquifer

- Part of Scheldt Basin
- 581 km²
- Flat area, average slope 0.36%
- Sandy soil (72%)





Methodology

Reference scenario

CC scenarios:
High / mean / low



Different physically based distributed hydrological models Which? One you know...



Compare differences

Fully distributed

- MIKE-SHE
- WaSiM-ETH
- WetSpa
- GSFLOW
- PROMET
- HydroGeoSphere

Semi-dist-HRU

- SWAT
- PRMS
- PREVAH
- HYDROTEL
- SLURP

Subbasin scale

- BHV
- LASCAM
- WetSpa

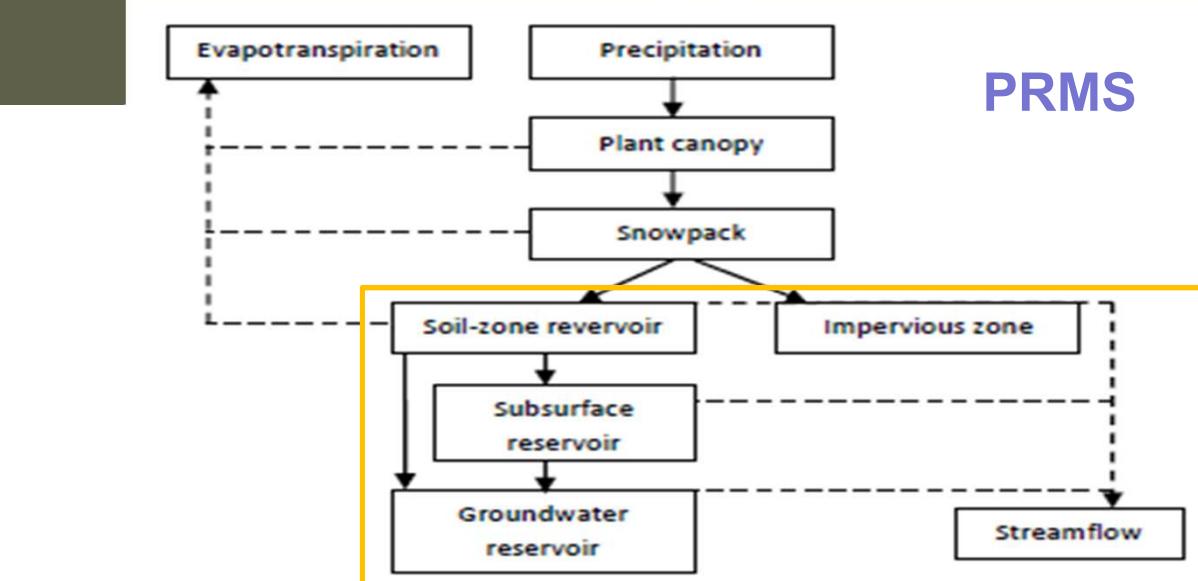
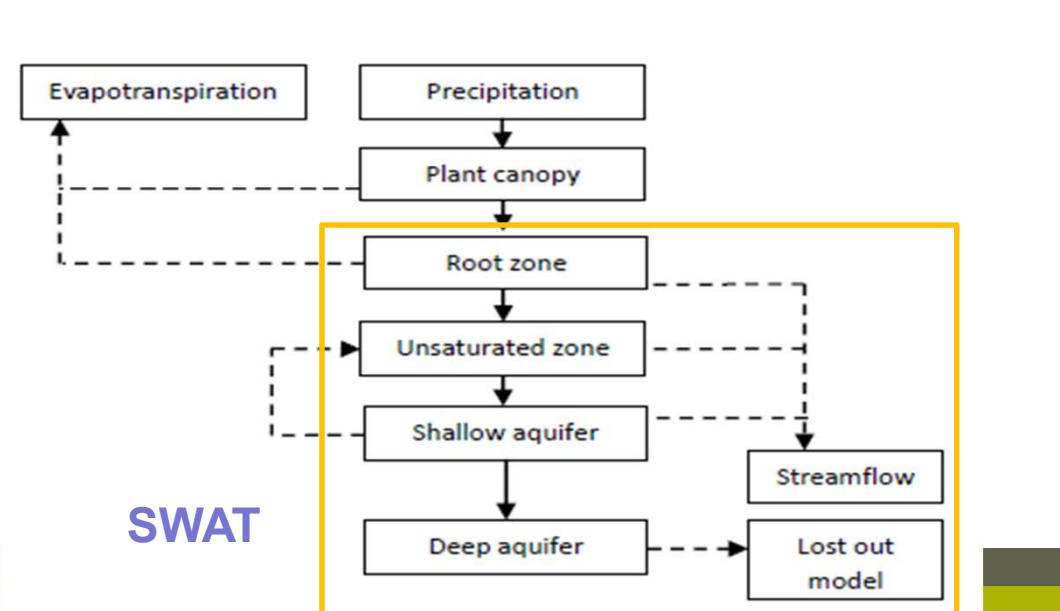
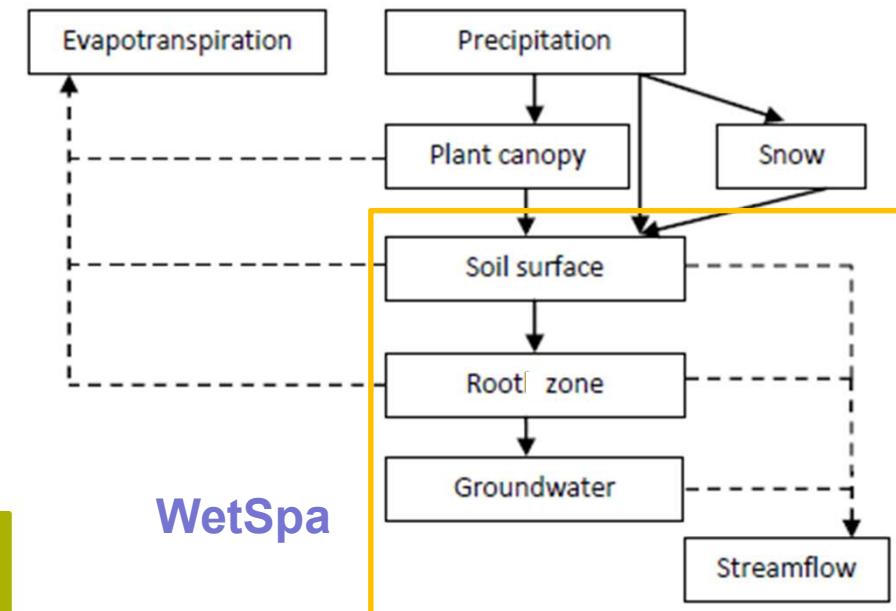
Conceptual lumped

- ...



Multi-model approach

- Dist WetSpa
- SWAT
- PRMS
- Semi-dist WetSpa





•Same boundary
•Input conditions

Description	WetSpa	SWAT	PRMS	
	semi-distributed	fully-distributed	semi-distributed (HRU)	semi-distributed (HRU)
Spatial distribution	31 sub-basins	50×50 m	6 sub-basins, 51 HRU's	56 HRU's
Time step	daily	daily	daily	daily
Spatial input data	DEM, land-use and soil texture	DEM, land-use and soil texture	DEM, land-use and soil texture	DEM, land-use and soil texture
Meteorological data	PET, mean temp and ppt	PET, min and max temp and ppt	PET, min and max temp and ppt	PET, min and max temp and ppt
Soil horizons	1	1	1	2
Snow balance	Degree based	Degree based	Energy balance	
Evaporation	PET based	PET based	PET based	
Interception	Land-cover based	LAI based	Land-cover based	
Surface runoff	Runoff coefficient method	SCS Curve number method	Non-linear variable source area method	
River routing	Diffusive wave approximation (De Smedt et al., 2000)	Muskingum routing	Kinematic wave approximation	
Interflow	Darcy's Law and kinematic wave approximation	Kinematic storage model	Non linear relation based on storage volume	
Groundwater flow	Linear reservoir	Head dependent flow	Linear reservoir	



Multiple objective fct

Four different objective functions:

$$NSE = 1 - \left[\frac{\sum_{i=1}^n (Q_i^{sim} - Q_i^{obs})^2}{\sum_{i=1}^n (Q_i^{obs} - Q_{mean}^{obs})^2} \right]$$

cal: 2001-2007; val:1997-2000 (**NSE_1**)
cal: 1997-2004; val:2004-2007 (**NSE_2**)

$$LNSE = 1 - \left[\frac{\sum_{i=1}^n [\ln(Q_i^{sim} + \epsilon) - \ln(Q_i^{obs} + \epsilon)]^2}{\sum_{i=1}^n [\ln(Q_i^{obs} + \epsilon) - \ln_{mean}(Q_{mean}^{obs} + \epsilon)]^2} \right]$$

cal:2001-2007
val:1997-2000

$$HNSE = 1 - \left[\frac{\sum_{i=1}^n (Q_i^{obs} + Q_{mean}^{obs}) \times (Q_i^{sim} - Q_i^{obs})^2}{\sum_{i=1}^n (Q_i^{obs} + Q_{mean}^{obs}) \times (Q_i^{obs} - Q_{mean}^{obs})^2} \right]$$

cal:2001-2007
val:1997-2000



Hydrological models

Dist WetSpa

NSE_1, NSE_2, LNSE, HNSE

SWAT

NSE_1, NSE_2, LNSE, HNSE

PRMS

NSE_1, NSE_2, LNSE, HNSE

Semi-dist WetSpa

NSE_1, NSE_2, LNSE, HNSE

4 different model structures and 4 different objective functions → 16 hydrological models



CC scenarios 2070-2100

PRUDENCE & IPCC AR4 database

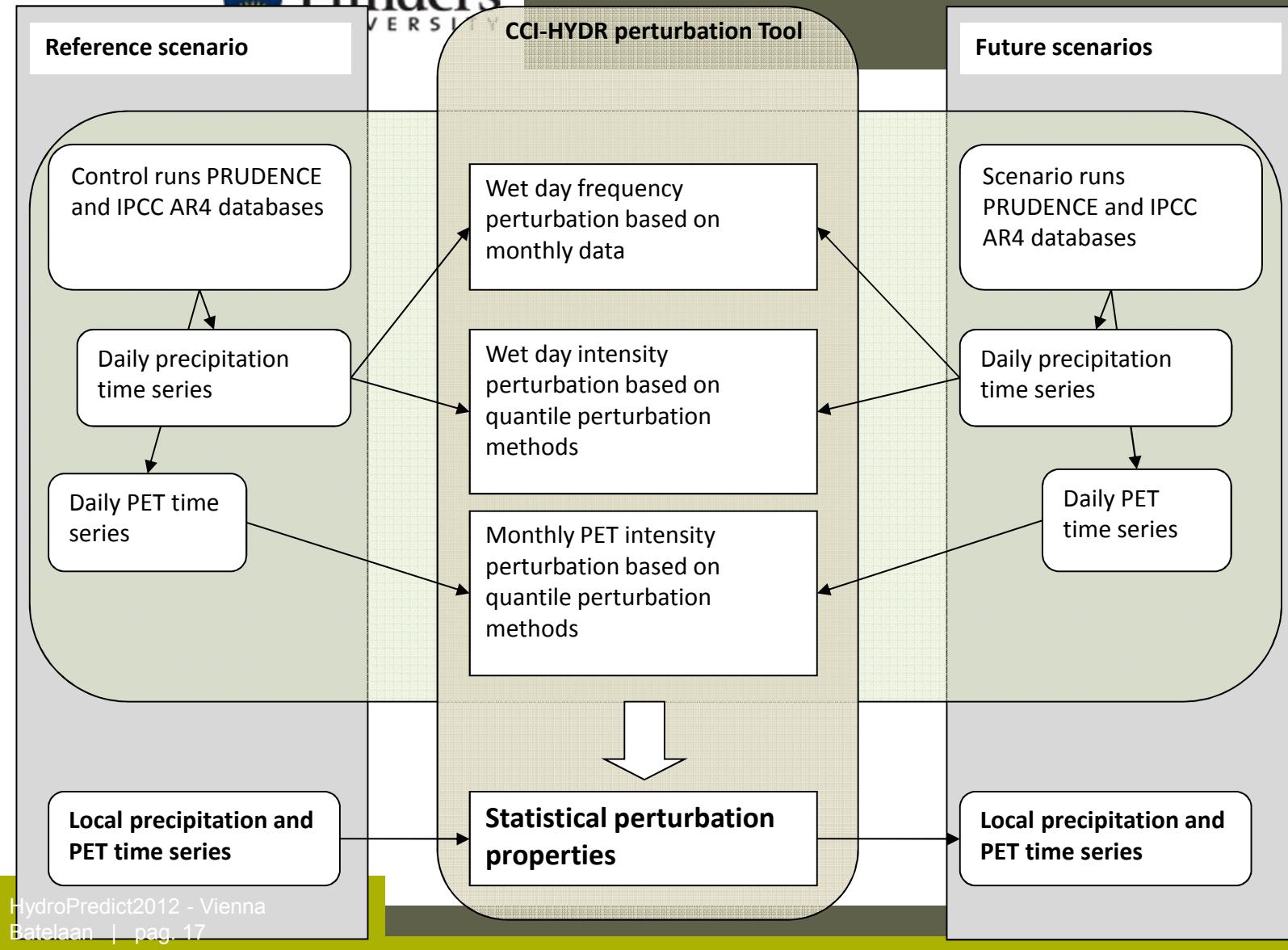
PRUDENCE scenarios (high resolution simulations, 50 km²):

- 4 GCM's, 10 RCM's, A2 and B2 simulations

IPCC AR4 scenarios (medium to coarse resolution simulations, 150-450 km²):

- 22 GCM's, A1B, A2 and B1

CC scenarios 2070-2100



- Perturbation tool (Ntegeka and Willems, 2009)
- Based on quotients calculated from differences in ref and future PPT and PET
- High, mean and low hydrological impact scenarios
- Scenarios focus on extreme events



Calibration and validation

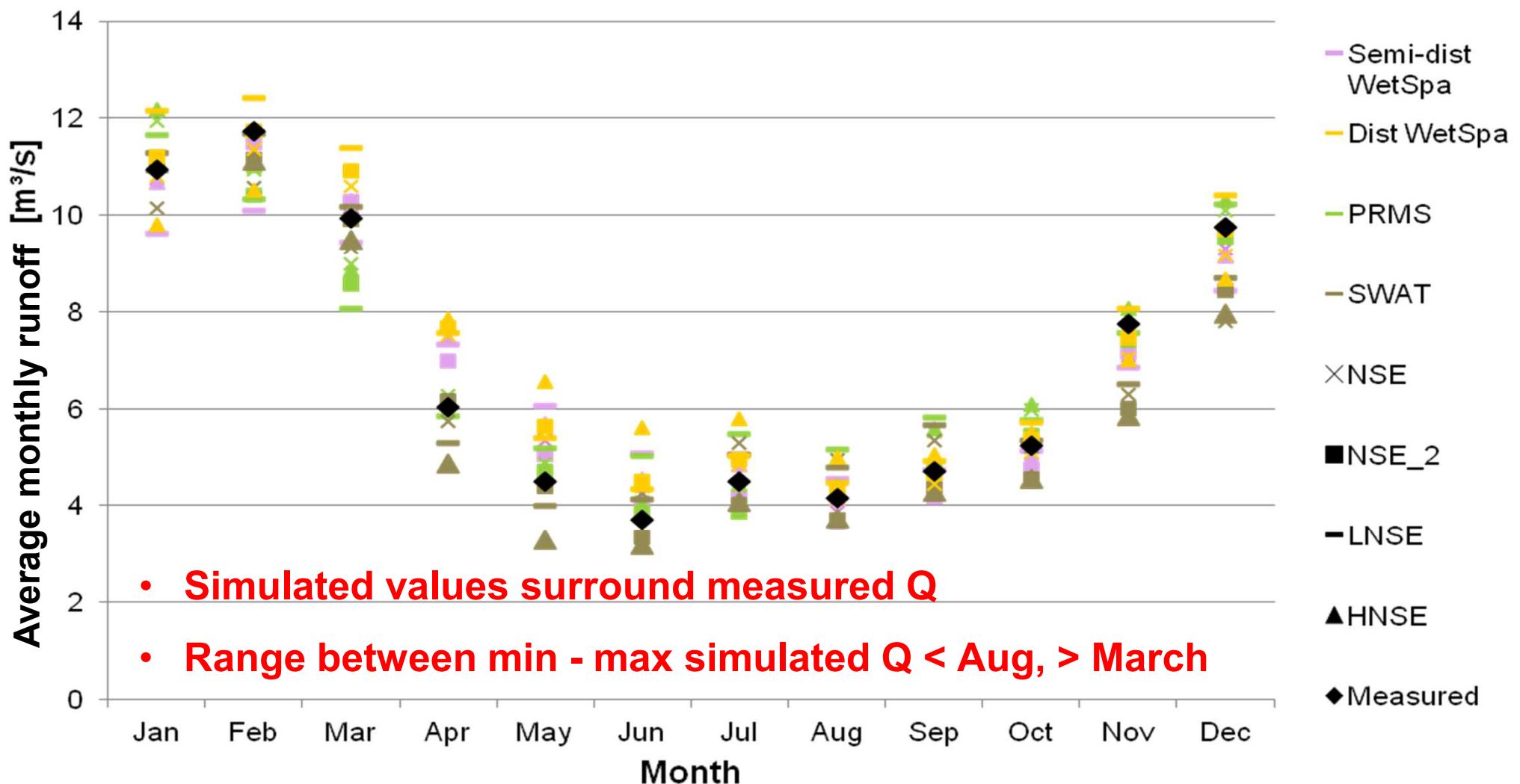
	Obj fct	Bias [%]		NSE [-]		LNSE [-]		HNSE [-]	
		cal	val	cal	val	cal	val	cal	val
PRMS	NSE_2	3.18	3.43	0.81	0.74	0.77	0.62	0.82	0.78
	NSE	-4.9	-2.1	0.80	0.85	0.66	0.76	0.80	0.86
	LNSE	3.2	5.8	0.68	0.67	0.75	0.76	0.73	0.69
	HNSE	2.4	6.3	0.78	0.81	0.68	0.78	0.81	0.82
SWAT	NSE_2	-0.9	-10.7	0.87	0.71	0.84	0.63	0.89	0.75
	NSE	-9.0	-3	0.82	0.83	0.65	0.67	0.86	0.87
	LNSE	-1.7	2.4	0.80	0.81	0.77	0.80	0.83	0.83
	HNSE	-12.7	-8.5	0.80	0.82	0.58	0.64	0.84	0.87
WetSpa Semi-dist.	NSE_2	1.74	-5.23	0.80	0.69	0.73	0.25	0.82	0.72
	NSE	-2	2.4	0.76	0.81	0.43	0.65	0.79	0.85
	LNSE	-1.8	1.9	0.69	0.76	0.67	0.71	0.69	0.77
	HNSE	0.5	4.7	0.75	0.82	0.43	0.65	0.79	0.86
WetSpa Dist.	NSE_2	4.45	-0.73	0.79	0.68	0.64	0.17	0.82	0.74
	NSE	5	9.1	0.75	0.82	0.53	0.66	0.79	0.87
	LNSE	4.4	7.6	0.70	0.78	0.64	0.70	0.72	0.82
	HNSE	9.6	13.6	0.73	0.79	0.43	0.59	0.79	0.86

- Good to very good cal and val results for NSE
- Very good performance for HNSE
- Efficiency of LNSE sensitive to objective function
- None of the models outperforms the other

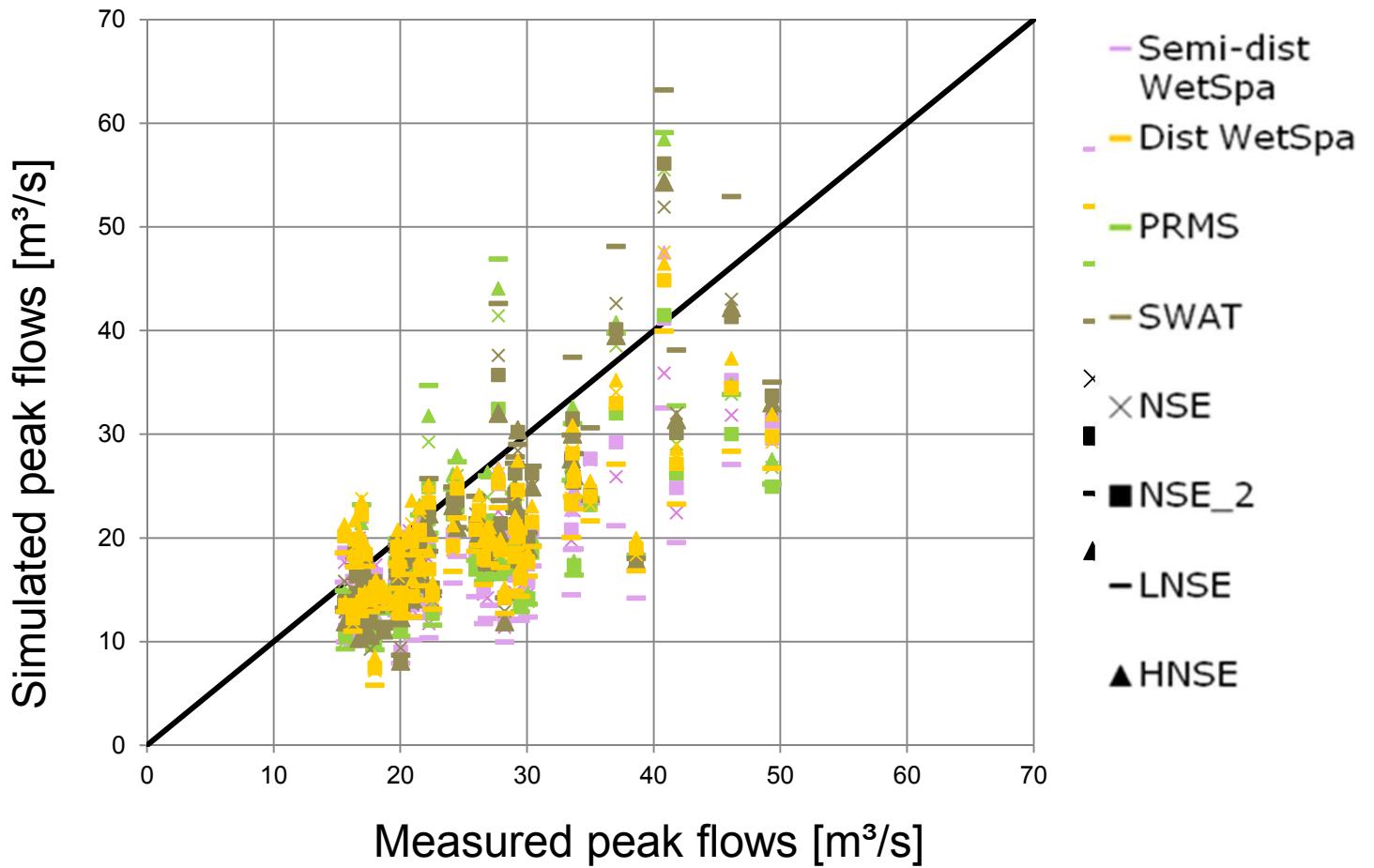
0.68 – 0.87 – 0.85 0.17 – 0.80 0.69 – 0.87



Validation avg monthly Q 1960-1990

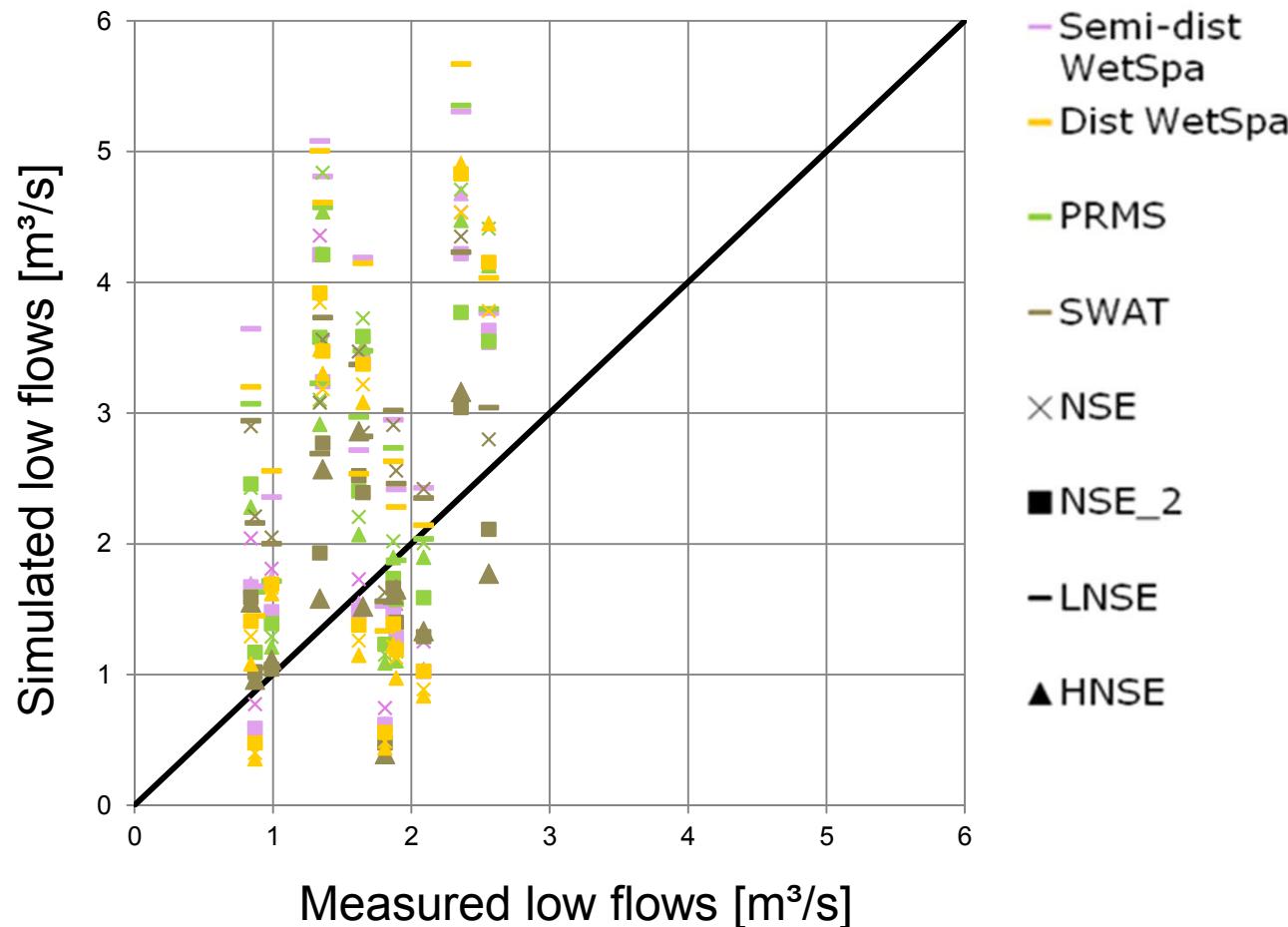


Validation extreme HIGH Q



- Average under-prediction of peak flows by 21%
- SWAT model lowest bias (-18%), semi-dist WetSpa highest bias (-28%)
- Models not calibrated on extreme flows

Validation extreme LOW Q

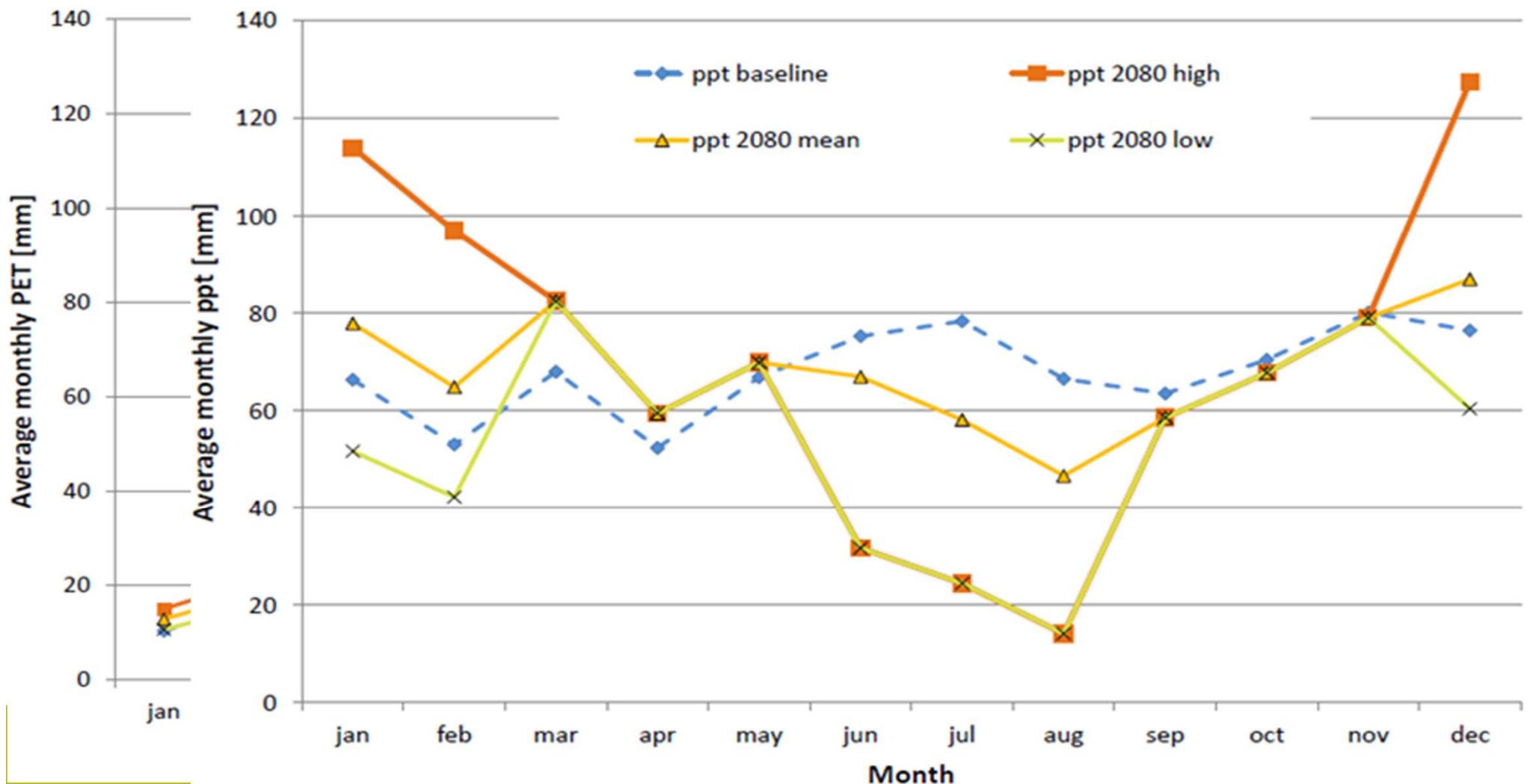


- Average overprediction of the peaks by 80%
- SWAT and distributed WetSpa perform best: overprediction +52%
- Models not calibrated on extreme flows



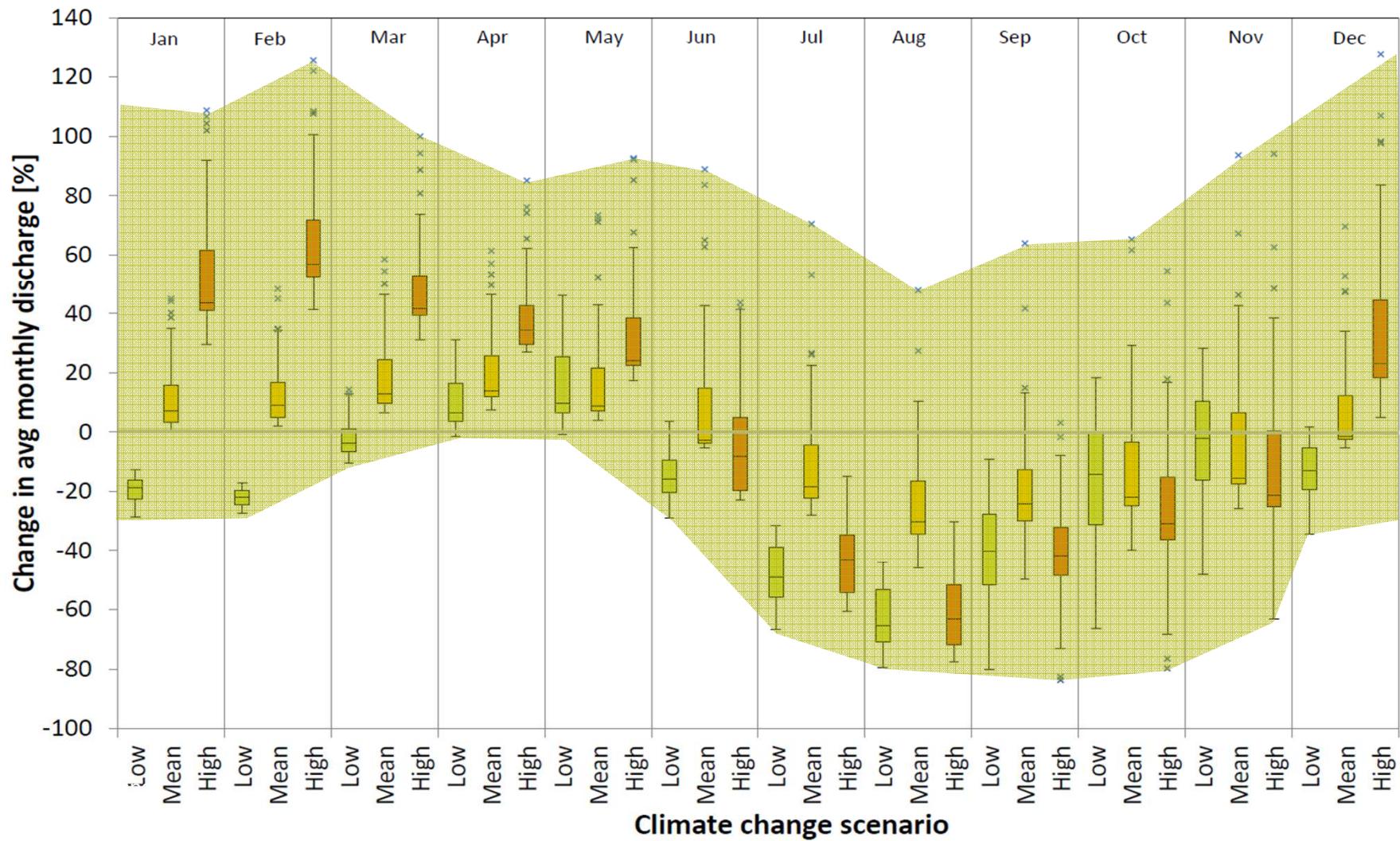
Climate change scenarios

Potential evapotranspiration Precipitation

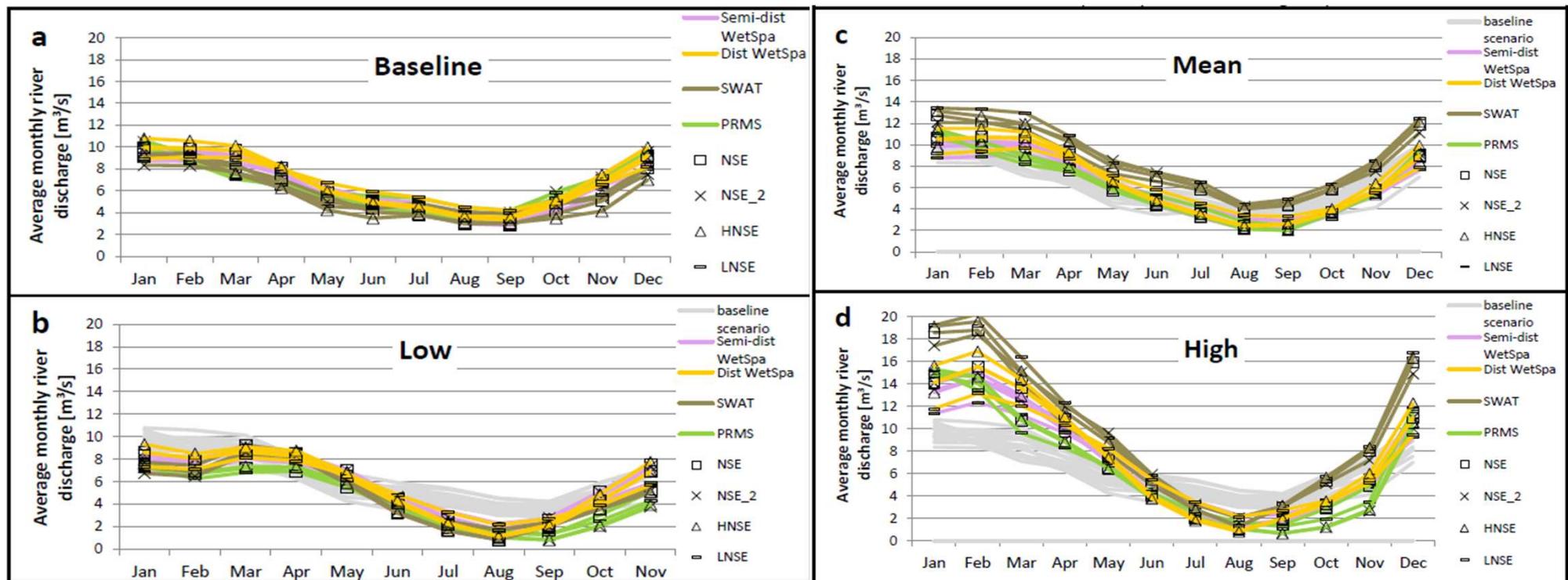




Monthly average discharge CC scenario's

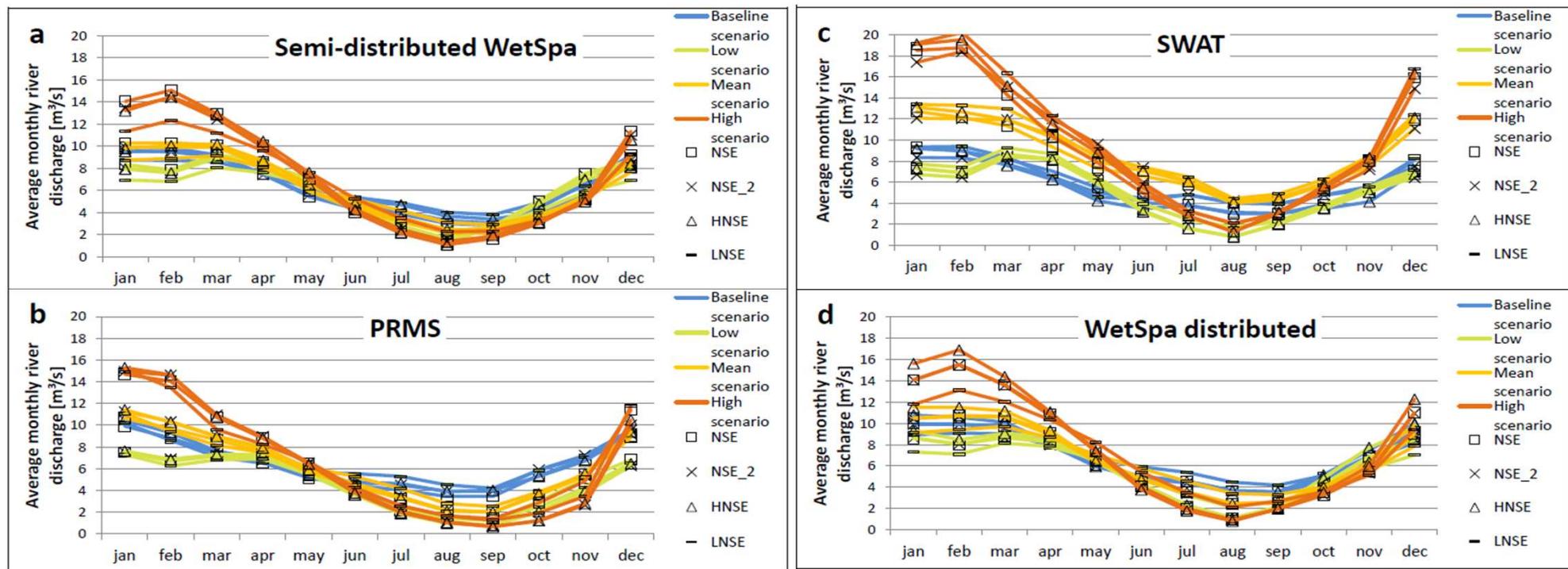


Uncertainty hydrological models

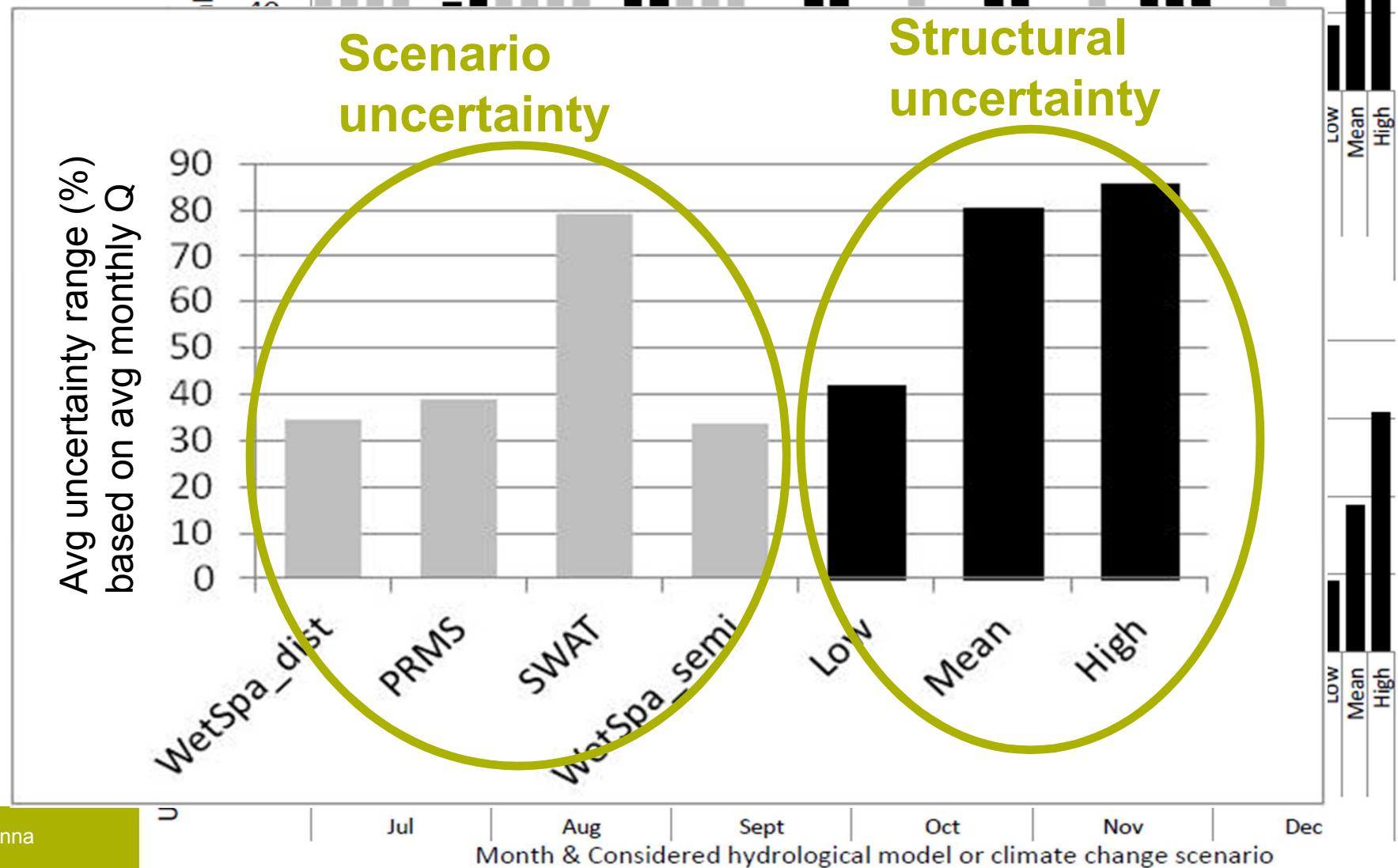


Range between minima en maxima monthly Q per CC scenario indicates the **uncertainty introduced by hydrological models**

Uncertainty CC

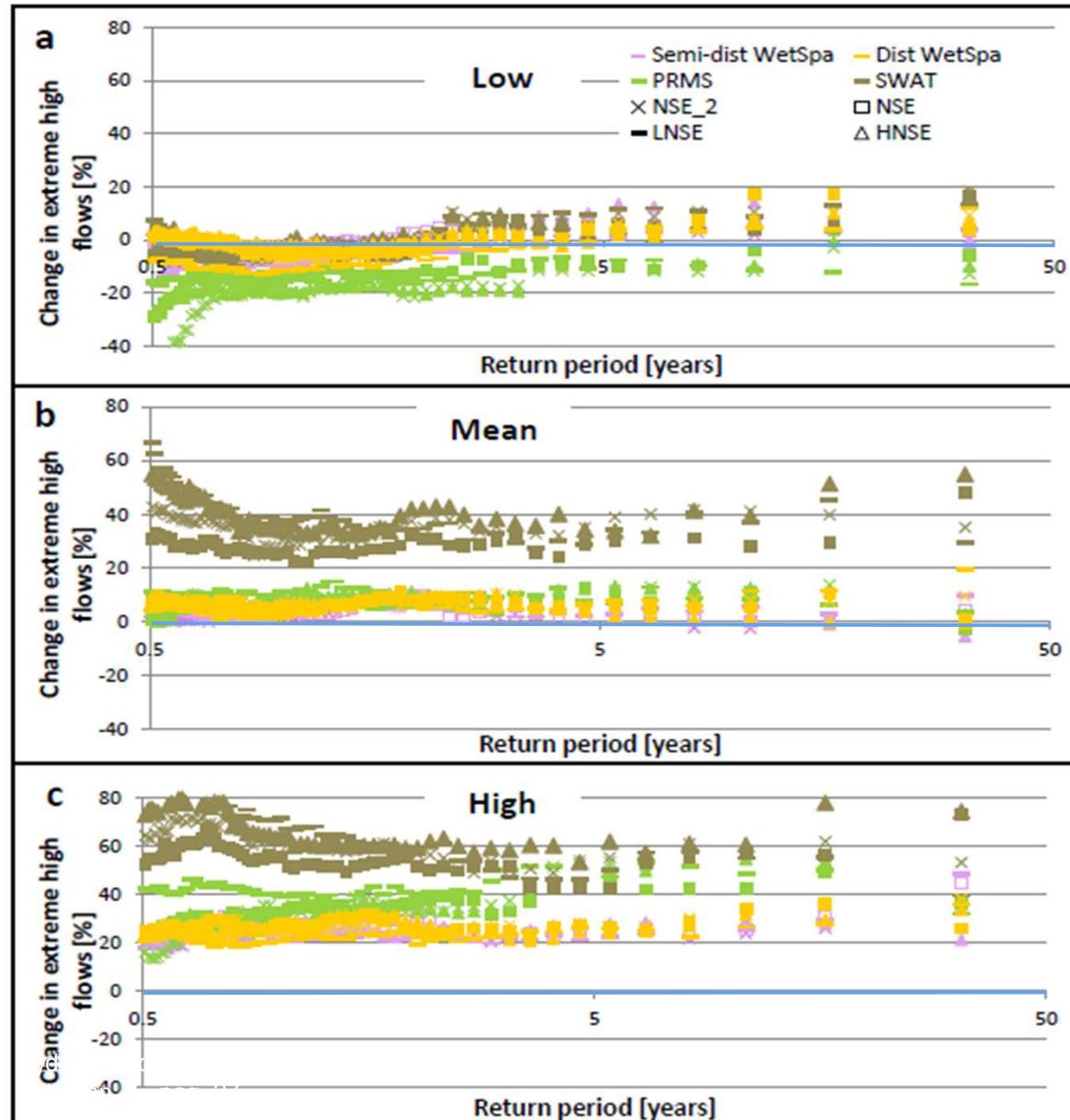


Range between minima en maxima monthly Q per hydrological model indicates the **uncertainty introduced by CC**





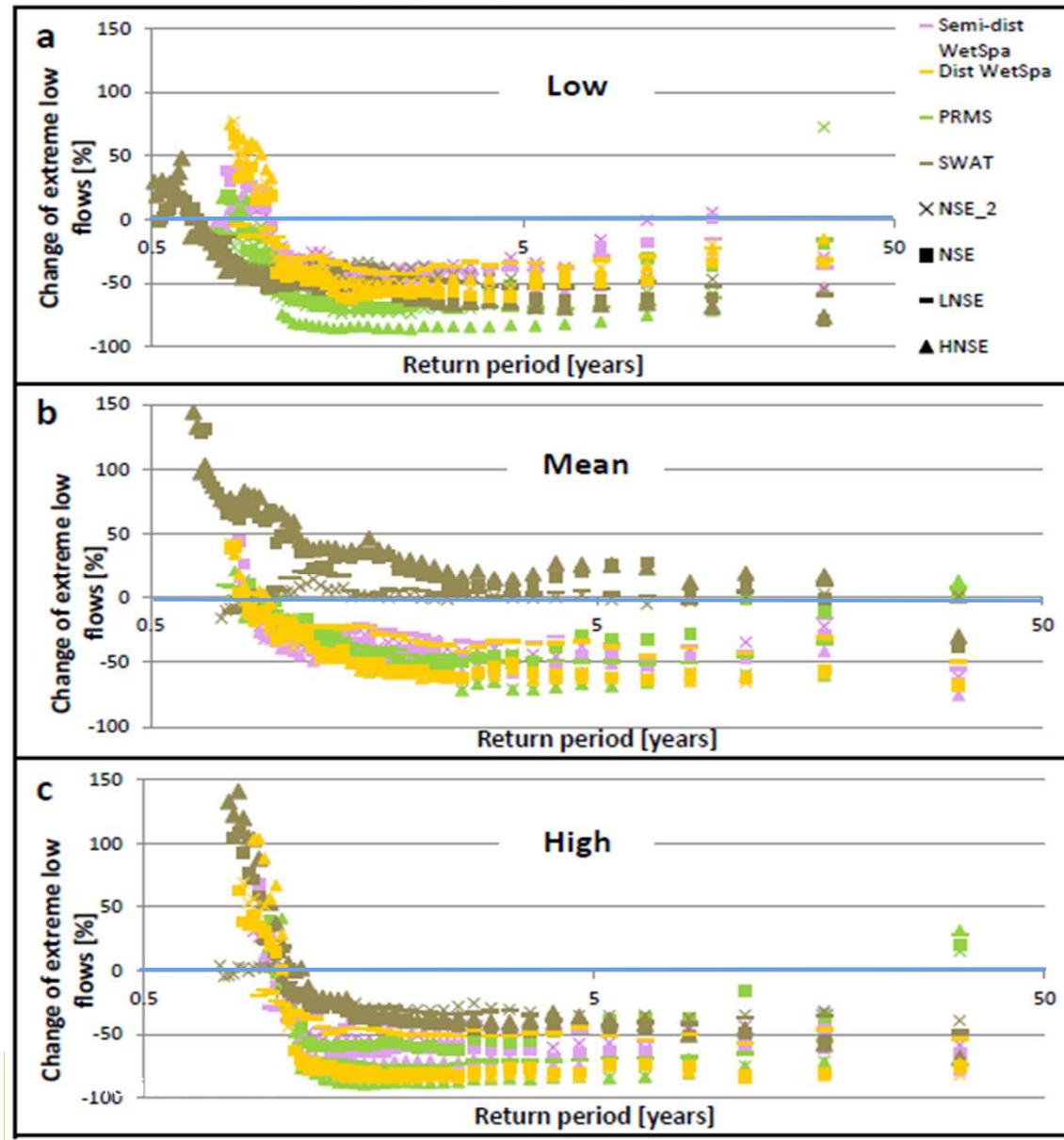
Extreme high flows



- Increase of highest flows in all scenarios
- High increases for High scenarios, low changes for Low and Mean scenario
- In Mean scenario SWAT model deviates from other models



Extreme low flows



- Reduction of lowest flows for all scenarios
- Highest decrease for High impact scenario ($\text{PET}_{\text{+}}$, $\text{PPT}_{\text{+}}$); slightly lower decrease for Low ($\text{PET}_{\text{-}}$, $\text{PPT}_{\text{-}}$) and Mean scenario ($\text{PPT}_{\text{+}}$)





Conclusions

Q CHANGE

So, on what output results
Increase in avg Spring Q none
do scenario's and models
Decrease avg summer Q SWAT-mean

Decrease extreme low Q

Taking into account uncertainty'

Increase in high Q, R>1.6yr

CC-model DISAGREE

none

SWAT-mean

SWAT-mean

PRMS-low

AGREE or DISAGREE?



Conclusions

- Large impact of hydrological model structure on predicted change in discharge
- Large climatic change → large model structure uncertainty
- Need for flexible model structures
- No model validation possible, alternative: model guided learning

**Remember there are still
unknown unknowns...**

