science for global insight

Using the Budyko framework for calibrating a global hydrological model in ungauged catchments of the world

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1 Problem

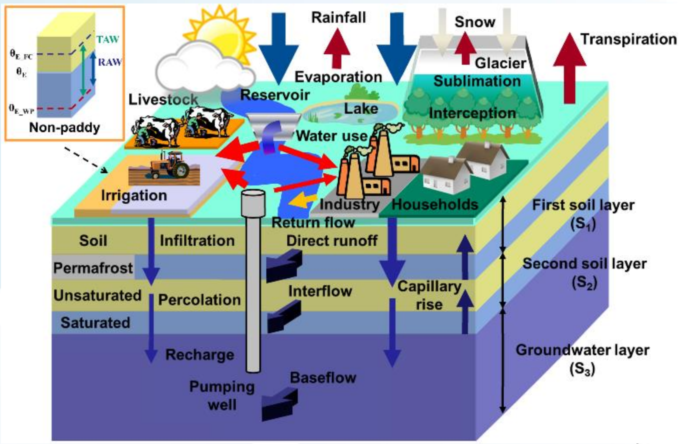
2 Idea

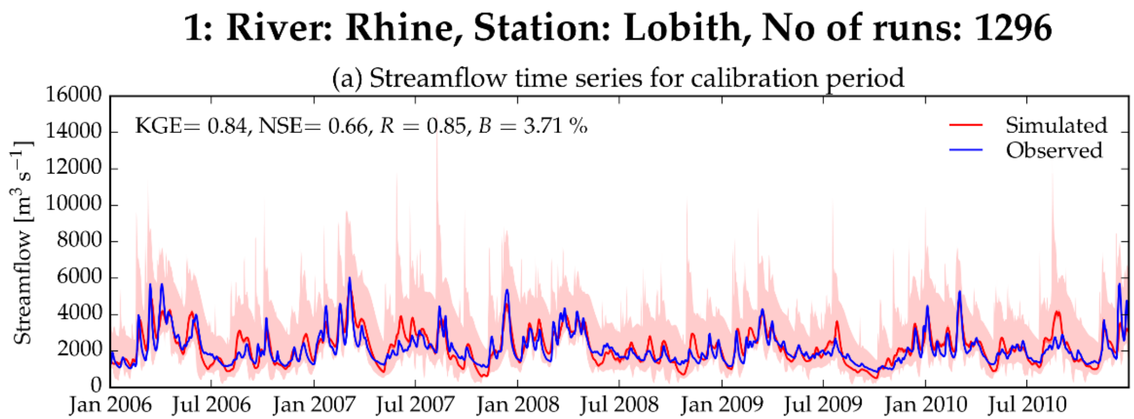
3 Method

4 Results

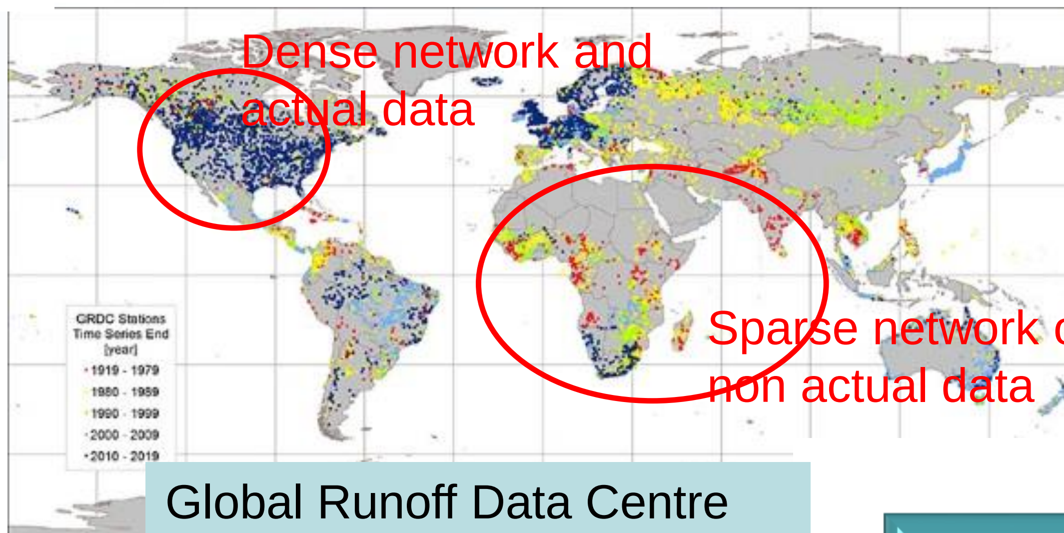
1 Problem

Calibration without discharge data





Global Hydrological Model CWATM
http://www.iiasa.ac.at/cwatm
https://cwatm.github.io/

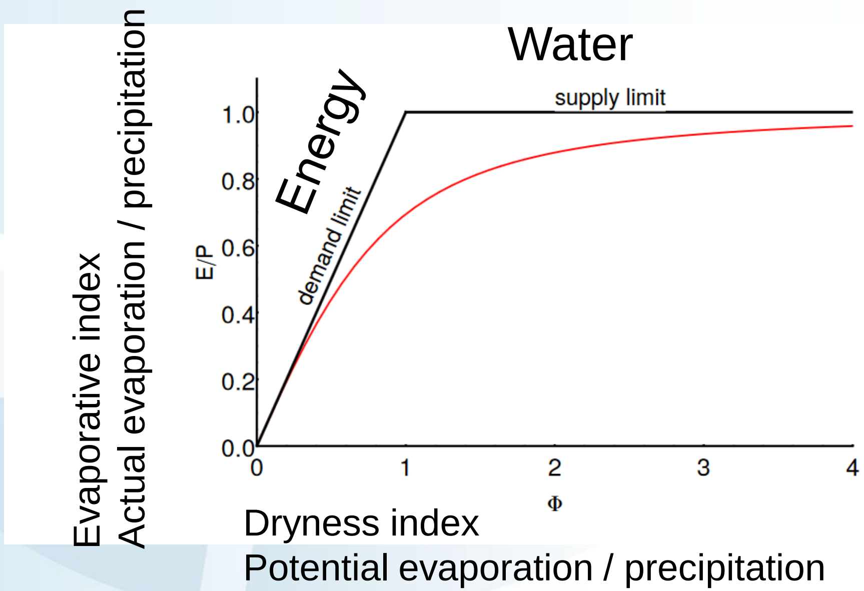


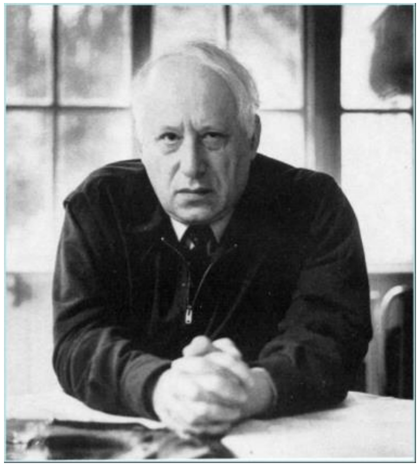
Global Runoff Data Centre

More problems

2 Idea

Using the empirical relation Budyko function for calibration





Mikhail Budyko

Budyko function
(Budyko, 1958, 1974)

Hypotheses:
Budyko calibration results will be not as good fitting simulated to the observed discharge as if it is calibrated for discharge itself, but it will be an improvement against an unfitted a priori parameter run

Advantage:
Precipitation, and evaporation is available everywhere

More ideas

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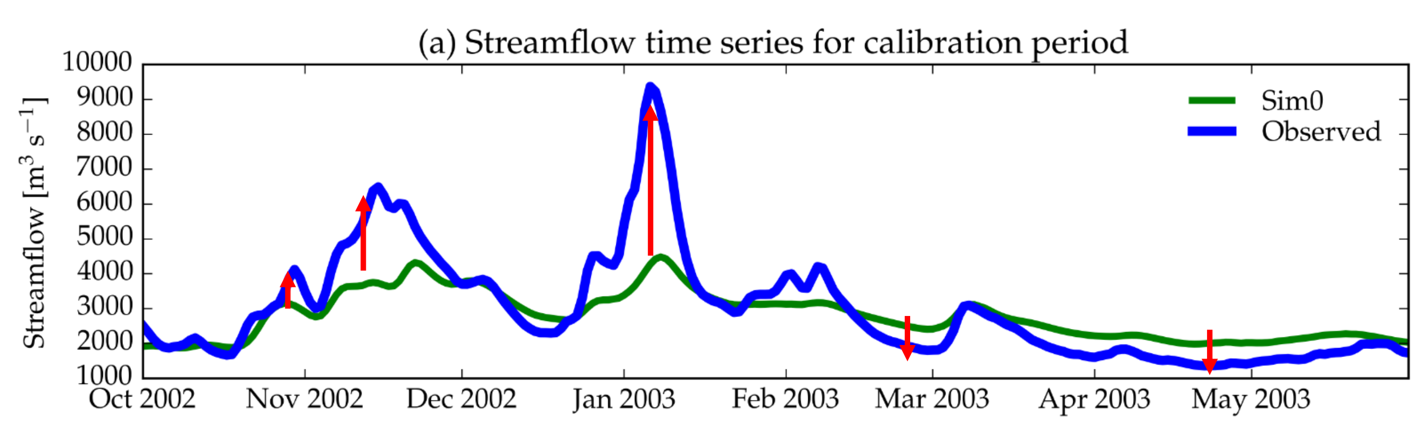
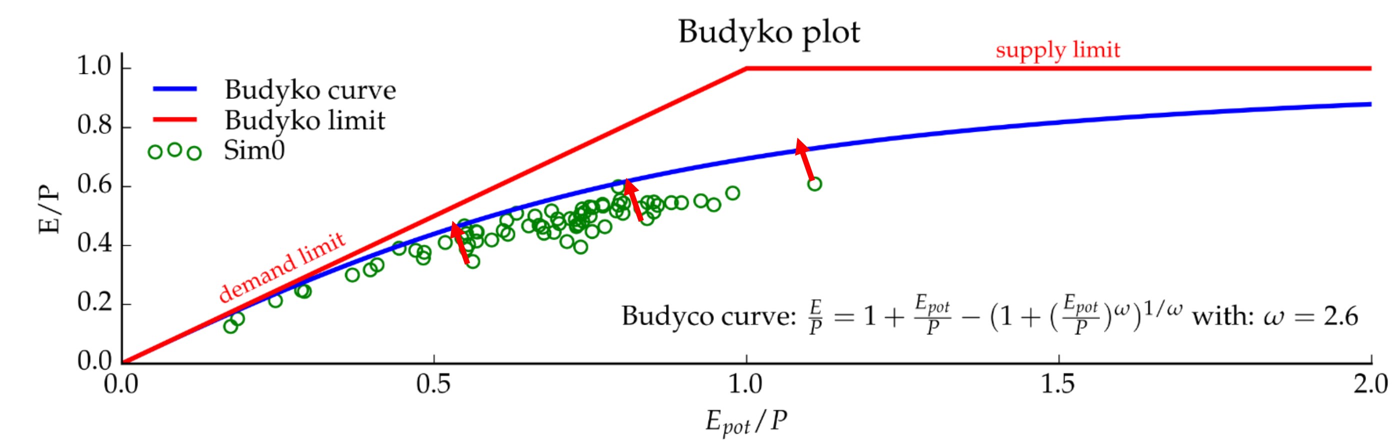
3 Method

Calibration

Instead: Finding a parameter set which represents discharge data



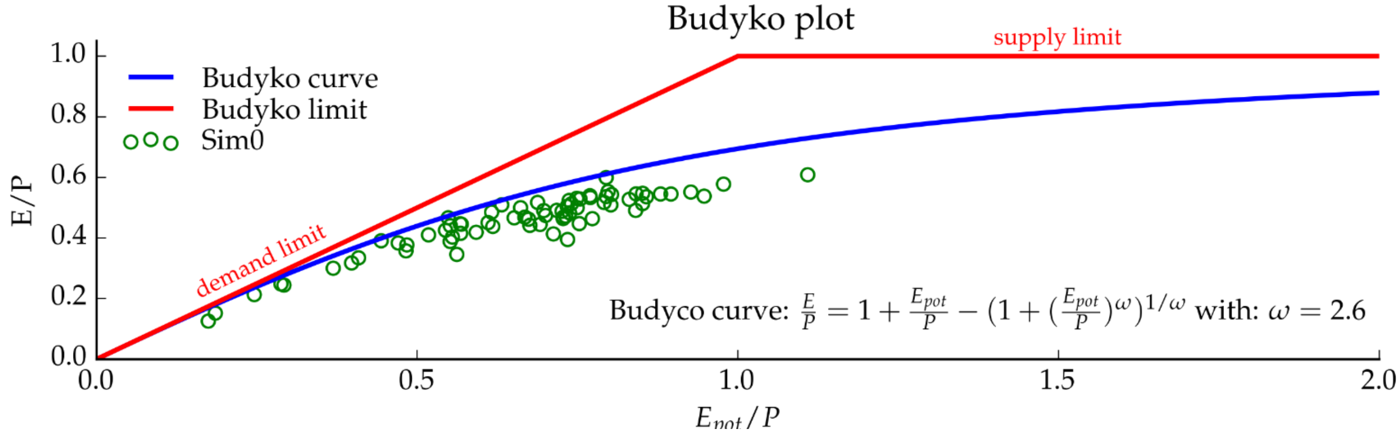
Finding a parameter set which represents the Budyko function

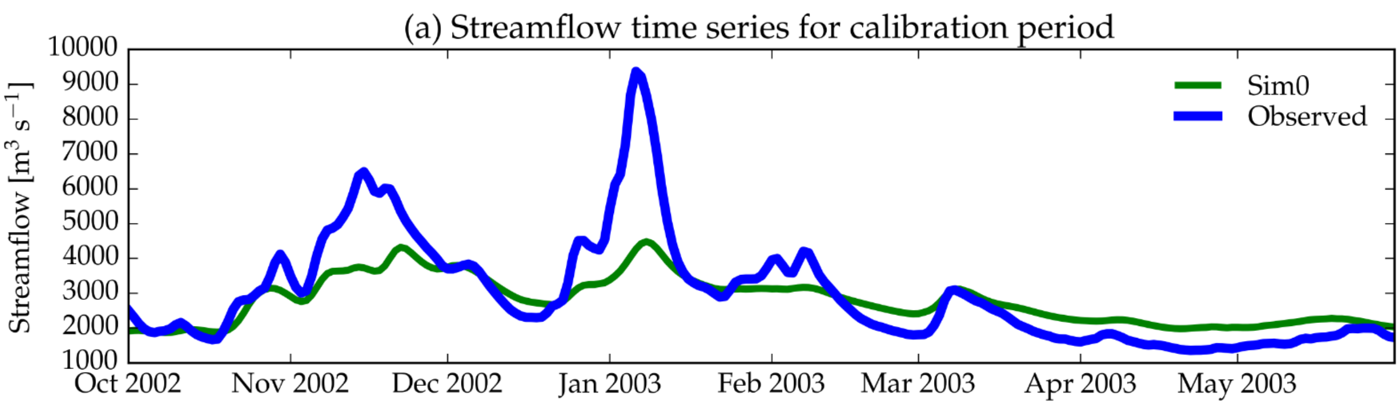


More methods

4 Results

"Budyko" Calibration For River Rhine





	Obs	Sim0
KGE		0.548
NS		0.643

Objective functions:
KGE: Kling Gupta Efficiency
NS: Nash-Sutcliffe Efficiency

More results

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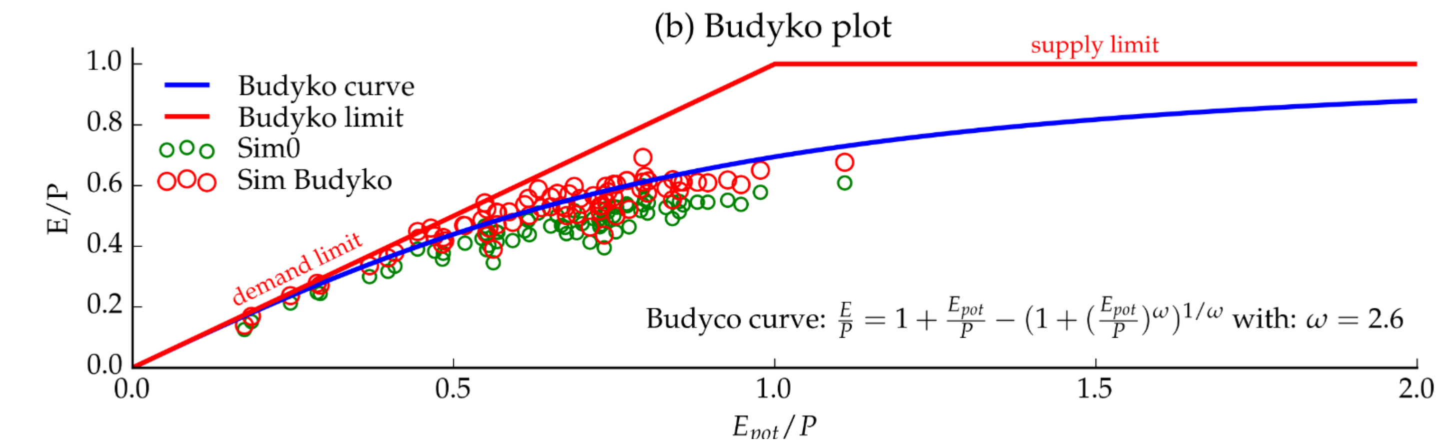
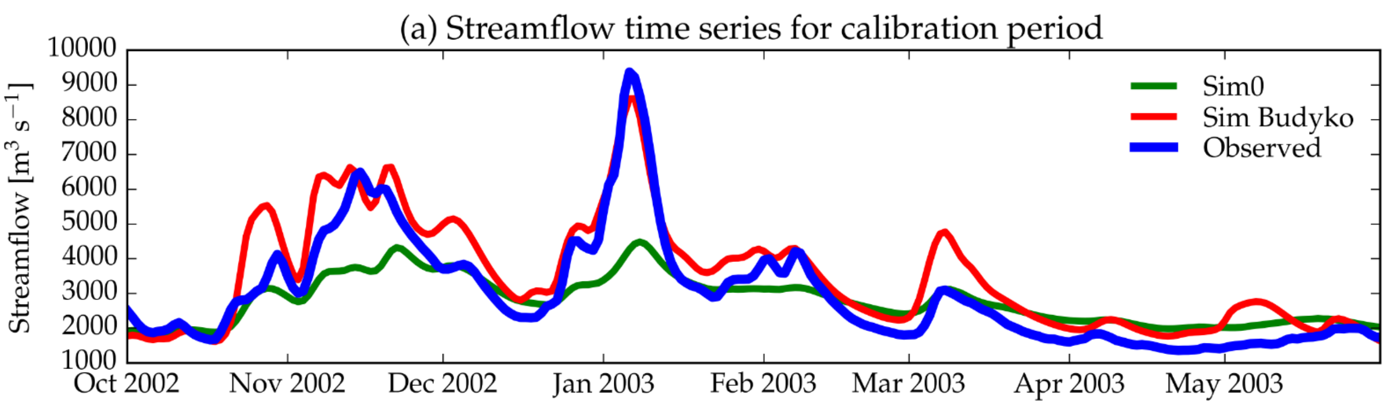
4 Results

"Budyko" Calibration For River Rhine





	Obs	Sim0	SimBud	SimDis
KGE		0.548	0.809	0.917
NS		0.643	0.633	0.836

Objective functions:
KGE: Kling Gupta Efficiency
NS: Nash-Sutcliffe Efficiency

More results

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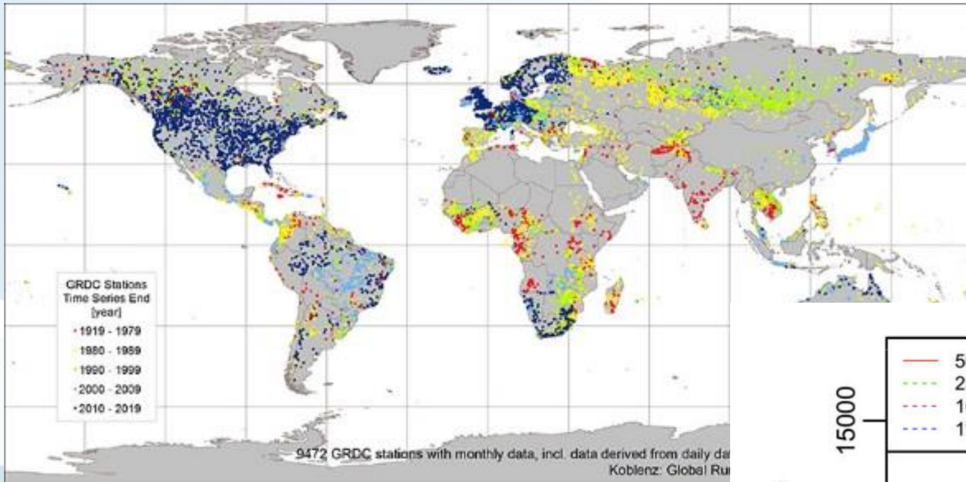
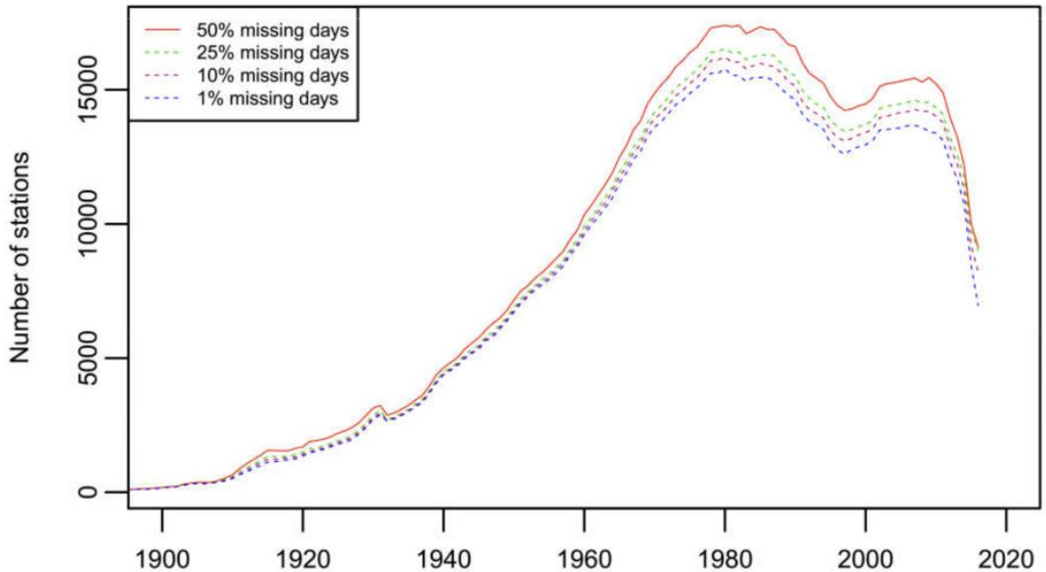
More problems

Global discharge data

The monitoring network of discharge data is sparse in large part of the globe, and there is *no* mechanism in place to collect and distribute river *discharge data globally* on a real- time base



Global Runoff Data Centre (GRDC) (2017)



Do et al. (2018): see also
EGU2018-5994 : Wed, 11 Apr, 15:30–15:45, Room 2.31

Do, H. X., Gudmundsson, L., Leonard, M., Westra, S., and Seneviratne, S. I.: The Global Streamflow Indices and Metadata Archive (GSIM) – Part 1: The production of daily streamflow archive and metadata, Earth Syst. Sci. Data Discuss., https://doi.org/10.5194/essd-2017-103, in review, 2017.

More ideas

Different ways to overcome the problem of having no discharge time series

- Regionalization of discharge data
  e.g. Barbarossa et al. 2018

- Regionalization of model parameter
  e.g. Beck et al. 2016

- Calibration with discharge from satellite derived data
  e.g. Revilla-Romero et al. (2015)

Barbarossa, V. et al. (2018): FLO1K, Global maps of mean, Maximum and Minimum Annual Streamflow at 1km Resolution From 1960 Through 2015. Sci. Data 5:180052. Doi: 10.1038/sdata.2018.52

Beck, H. E., van Dijk, A. I. J. M., de Roo, A., Miralles, D. G., McVicar, T. R., Schellekens, J., & Bruijnzeel, L. A. (2016). Global-scale regionalization of hydrologic model parameters. *Water Resources Research, 52*(5), 3599-3622

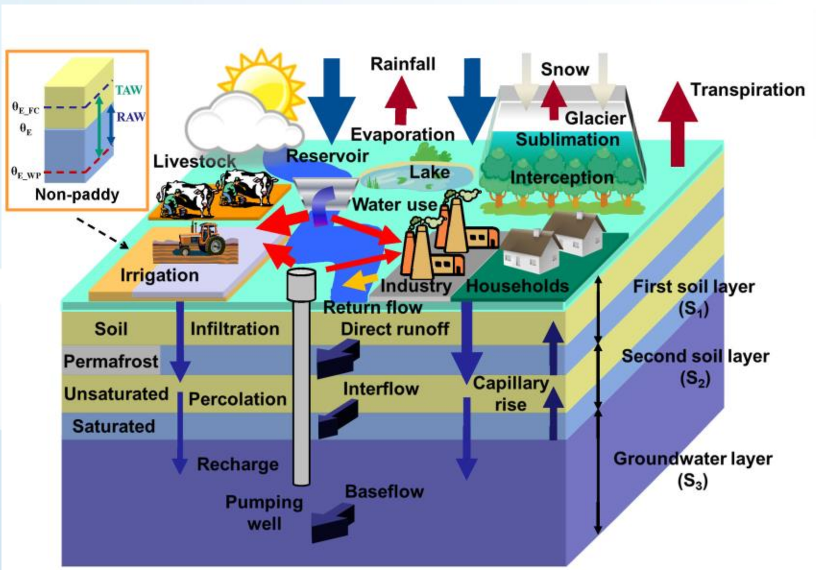
Revilla-Romero, B., Beck, H. E., Burek, P., Salamon, P., de Roo, A., & Thielen, J. (2015). Filling the gaps: Calibrating a rainfall-runoff model using satellite-derived surface water extent. *Remote Sensing of Environment, 171*, 118-131

More methods 1

Community Water Model (CWATM)

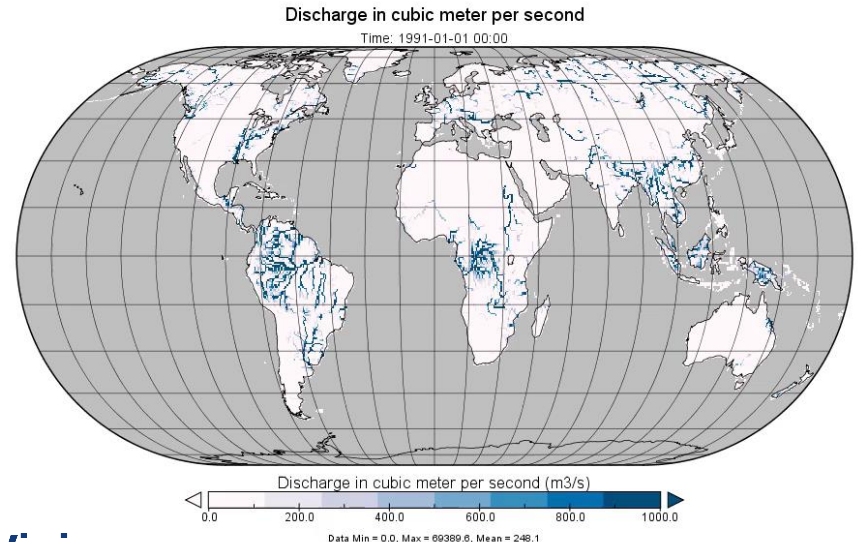
Development of a community driven global water model by WAT Program, IIASA

Model design



- CWATM represents one of the new key elements of IIASA's Water program to assess **water supply, water demand** and **environmental needs** at global and regional level
- The hydrologic model is **open source** and flexible to link in different aspects of the **water energy food nexus**

Global discharge demo



Vision

Our vision for the short to medium term work is to introduce **water quality** and to consider qualitative and quantitative measures of **transboundary river** and **groundwater governance** into an **integrated modelling framework**.

Contact

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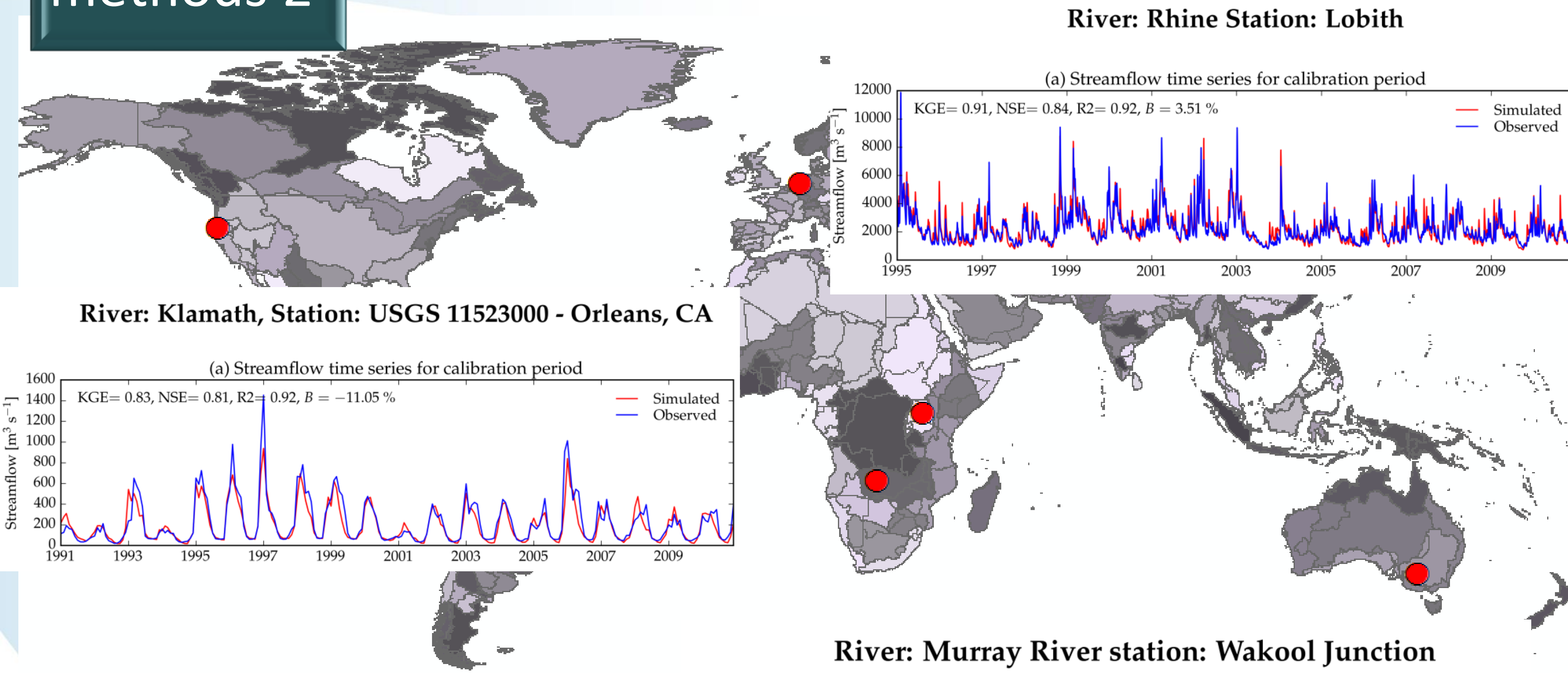
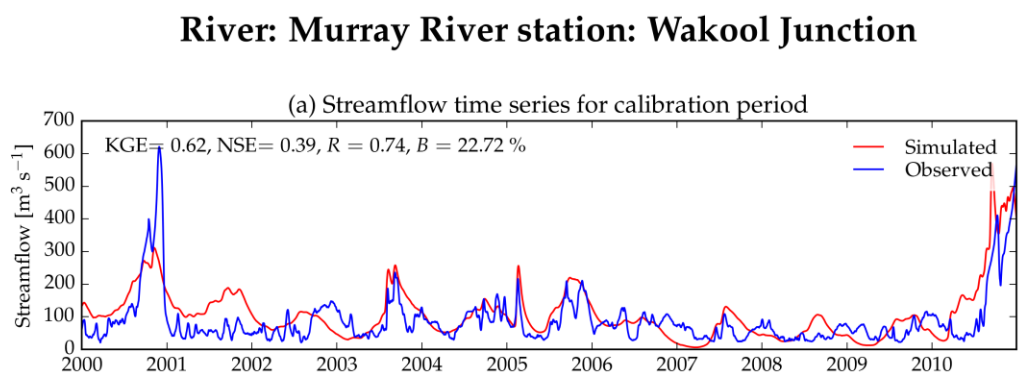
wfas.info@iiasa.ac.at

More methods 2

Calibration of river discharge





Calibration:

- Daily run of 12 to 20 years
- Compared to daily or monthly observed discharge
- Objective function: KGE’

KGE’: modified Kling-Gupta efficiency

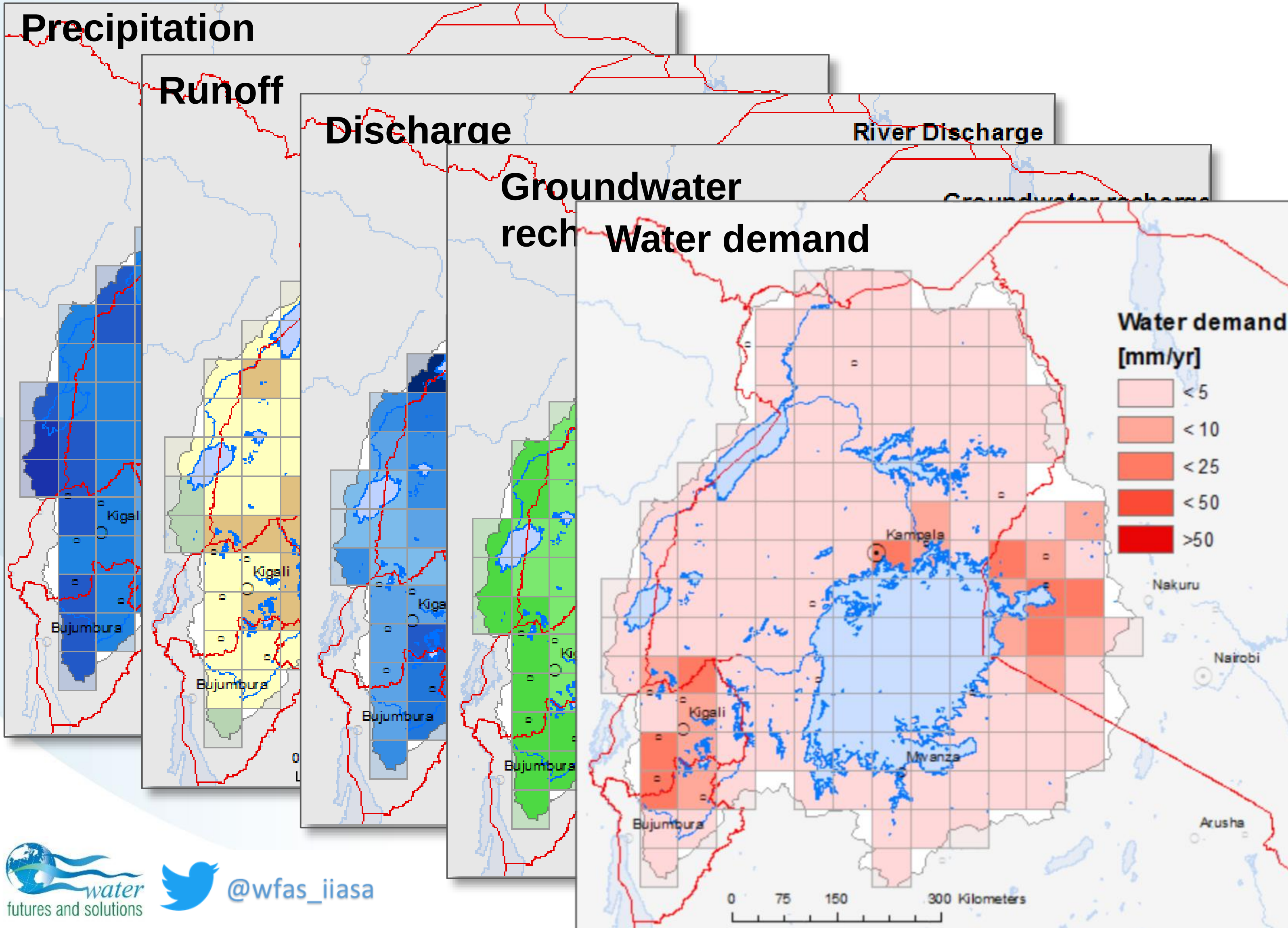
NSE: Nash-Sutcliffe Efficiency

R2: Correlation coefficient

B: Bias

More methods 3

CWATM Lake Victoria

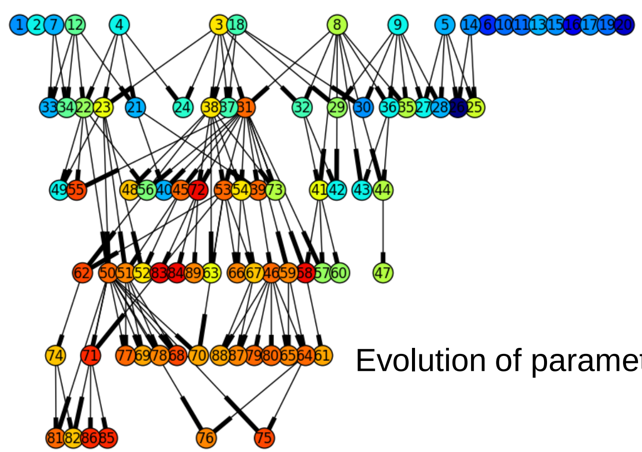


@wfas_iiasa

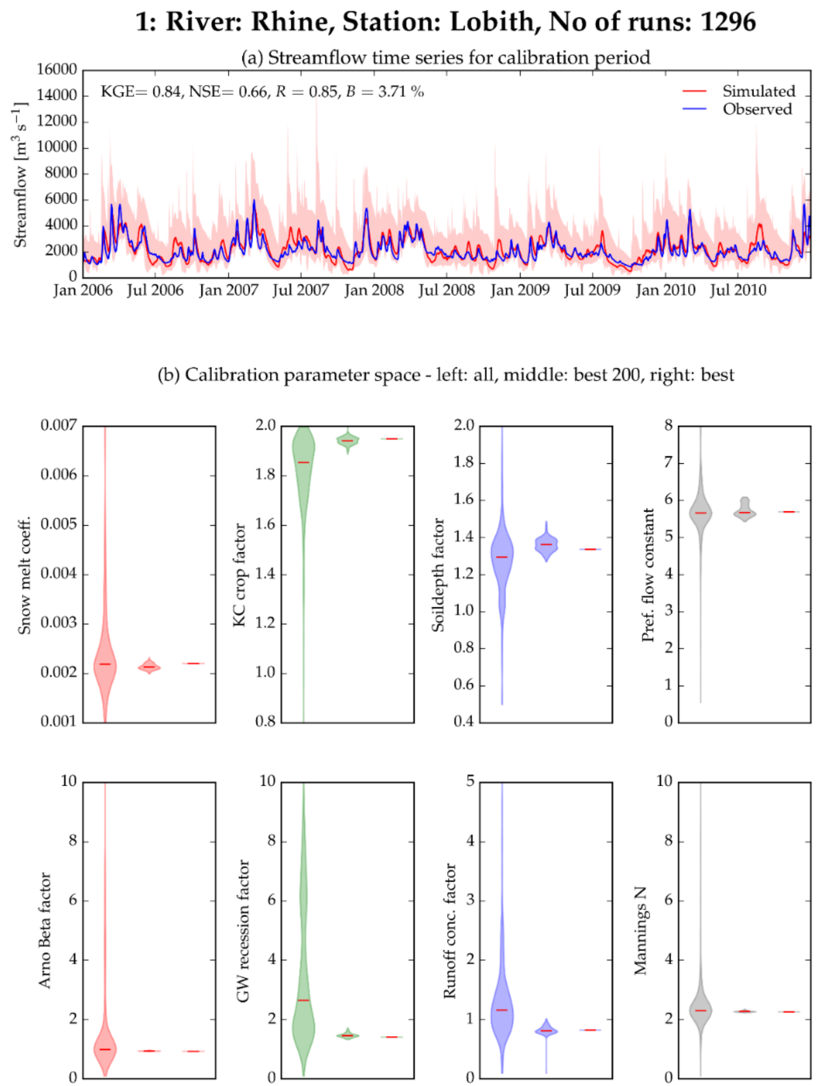
More methods 4

Calibration

Calibration is using an evolutionary computation framework in Python called DEAP (Fortin et al., 2012). DEAP implemented the evolutionary algorithm NSGA-II (Deb et al., 2002) which is used here as single objective optimization.



Evolution of parameter space



Parameter space for 8 parameter

Félix-Antoine Fortin, François-Michel De Rainville, Marc-André Gardner, Marc Parizeau and Christian Gagné, “DEAP: Evolutionary Algorithms Made Easy”, Journal of Machine Learning Research, vol. 13, pp. 2171-2175

Deb, K., A. Pratap, S. Agarwal and T. Meyarivan (2002). “A fast and elitist multiobjective genetic algorithm: NSGA-II.” IEEE Transactions on Evolutionary Computation 6(2): 182-197.

More methods 5

Calibration

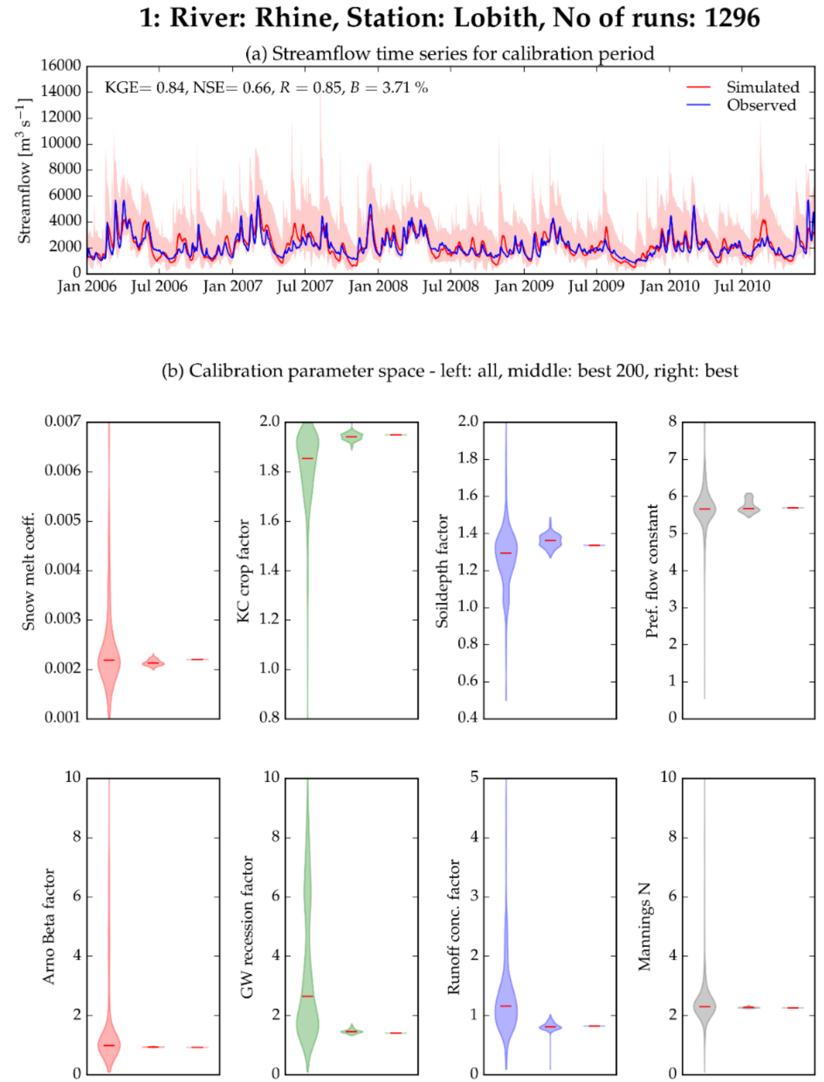
Discharge:
Daily (or monthly) pairs of observed and simulated discharge at gauging stations

Objective function:
Modified version of the Kling-Gupta Efficiency (Kling et al., 2012),

$$KGE' = 1 - \sqrt{(r-1)^2 + (\beta-1)^2 + (\gamma-1)^2}$$

$$\text{where: } \beta = \frac{\mu_s}{\mu_o} \text{ and } \gamma = \frac{CV_s}{CV_o} = \frac{\sigma_s/\mu_s}{\sigma_o/\mu_o}$$

Where:
r as the correlation coefficient between simulated and observed discharge (dimensionless), β as the bias ratio (dimensionless) and γ as the variability ratio. CV is the coefficient of variation, μ is the mean streamflow [$m^3\ s^{-1}$] and σ is the standard deviation of the streamflow [$m^3\ s^{-1}$]. KGE', r, β and γ have their optimum at unity.

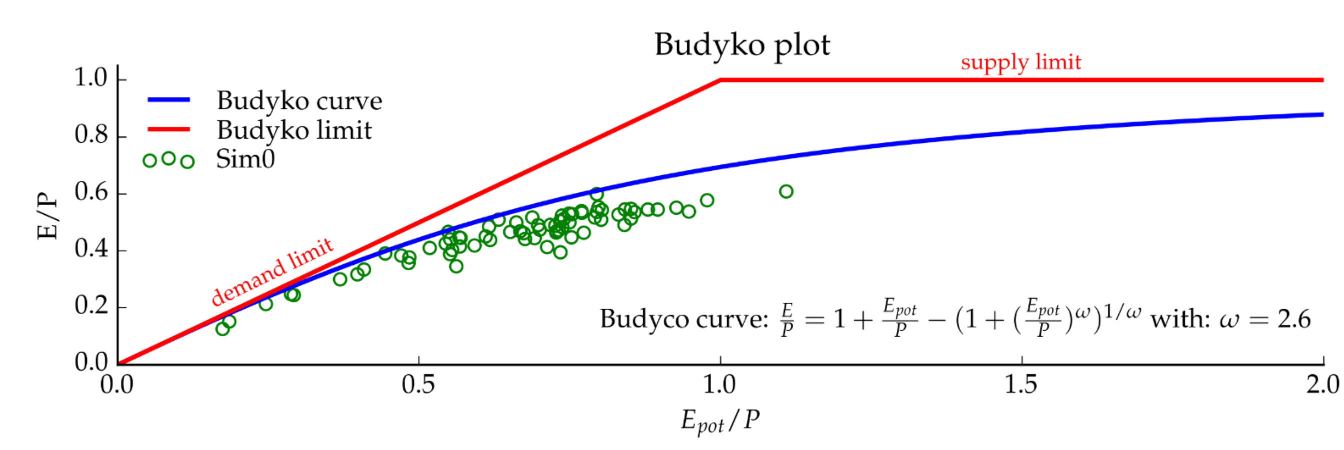


Parameter space for 8 parameter

Gupta, H. V., H. Kling, K. K. Yilmaz and G. F. Martinez (2009). "Decomposition of the mean squared error and NSE performance criteria: Implications for improving hydrological modelling." Journal of Hydrology 377(1-2): 80-91
Kling, H., M. Fuchs and M. Paulin (2012). "Runoff conditions in the upper Danube basin under an ensemble of climate change scenarios." Journal o Hydrology 424-425: 264-277

More methods 6

"Budyko" Calibration



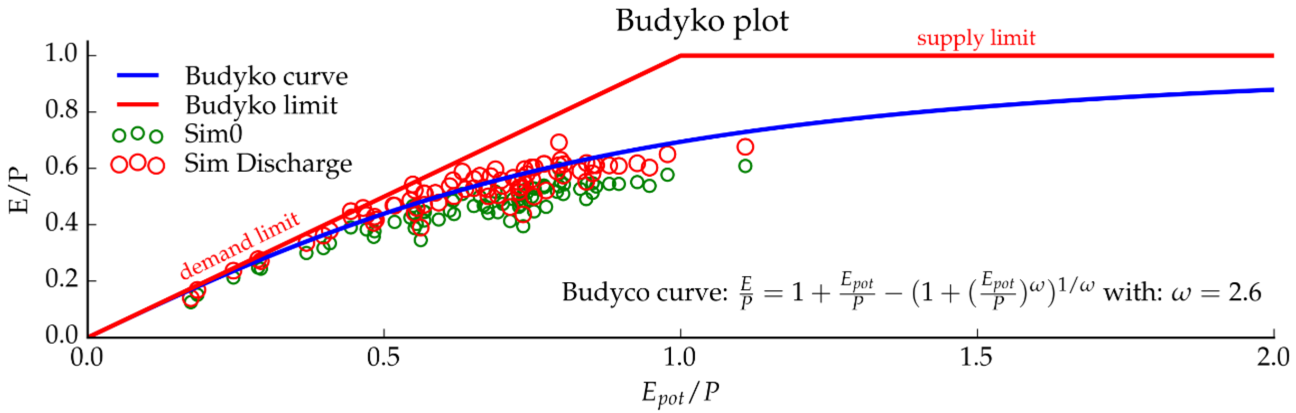
For discharge calibration 12 parameters are calibrated. For each important hydrological process – snow, evaporation, soil, groundwater, routing, lakes up to 3 parameters are used.

Because the Budyko curve looks at runoff generation (and evaporation) at grid cell level the runoff concentration and the routing processes are not sensitive to the objective function of the Budyko calibration. Therefore only 5 parameters are calibrated.

Budyko, M.: The Heat Balance of the Earth, Leningrad, 1956 (in Russian), Translation by N. A. Stepanova, US Weather Bureau, Washington, p. 255, 1958.
Budyko, M.: Climate and life, Academic Press, New York, USA, p. 508, 1974.
Greve, P., L. Gudmundsson, B. Orlowsky and S. I. Seneviratne (2016). "A two-parameter Budyko function to represent conditions under which evapotranspiration exceeds precipitation." Hydrology and Earth System Sciences 20(6): 2195-2205.

More methods 7

“Budyko” Calibration



For each grid cell the sum of daily precipitation (P), potential evaporation (ETP) and actual evapotranspiration (ETA) is calculated. From these three sums the coordinate in the “Budyko space” are calculated:

$$x = \frac{ETP}{P}; y = \frac{ETA}{P}$$

Depending on the period of calibration the sum is calculated for 10 to 15 years. The “Budyko space” spanned by x,y for each grid cell should be close to the Budyko curve:

$y = 1 + x - (1 + x^{\omega})^{1/\omega}$ with fixed ω = 2.6.

Here the distance of Kolmogorov-Smirnov (maximum distance of a point to the function) is used as objective function and the calibration algorithm is minimizing this distance.

More methods 8

Improvements

- Using another test than KS for Budyko e.g. min distance of all points to a function, or other statistical test e.g. Anderson-Darling
- A fixed $\omega = 2.6$ is used for all station. Could be variable depending on the climate zone.
- At the moment only the water balance of a grid cell without incoming discharge and evaporation from rivers and lakes are estimated.
  Precipitation = Runoff + Evaporation
  The storage term is not used:
  Precipitation = Runoff + Evaporation + ΔS

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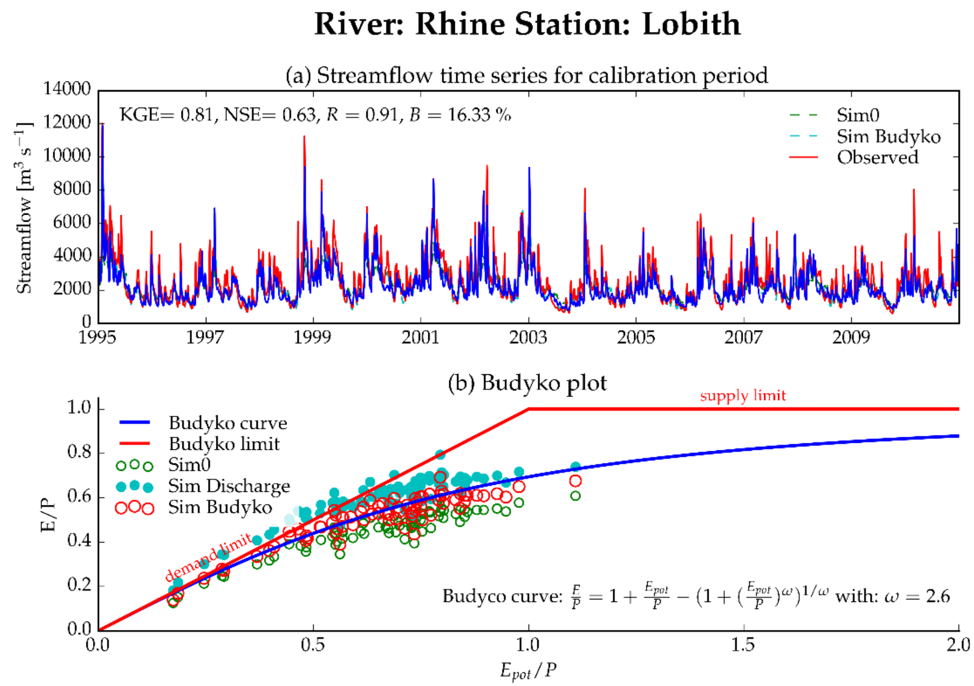
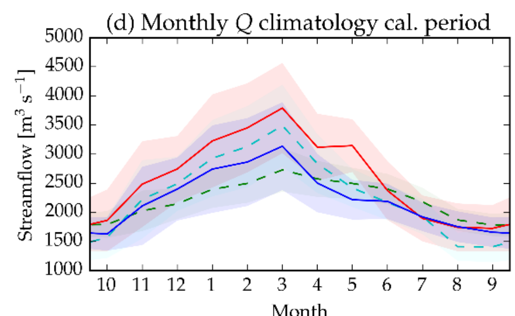
More results 1

Rhine - Lobith, Germany

Rhine (Lobith, Germany)
The “Budyko” run gives a good improve compared to the a priori parameter run (Sim0).



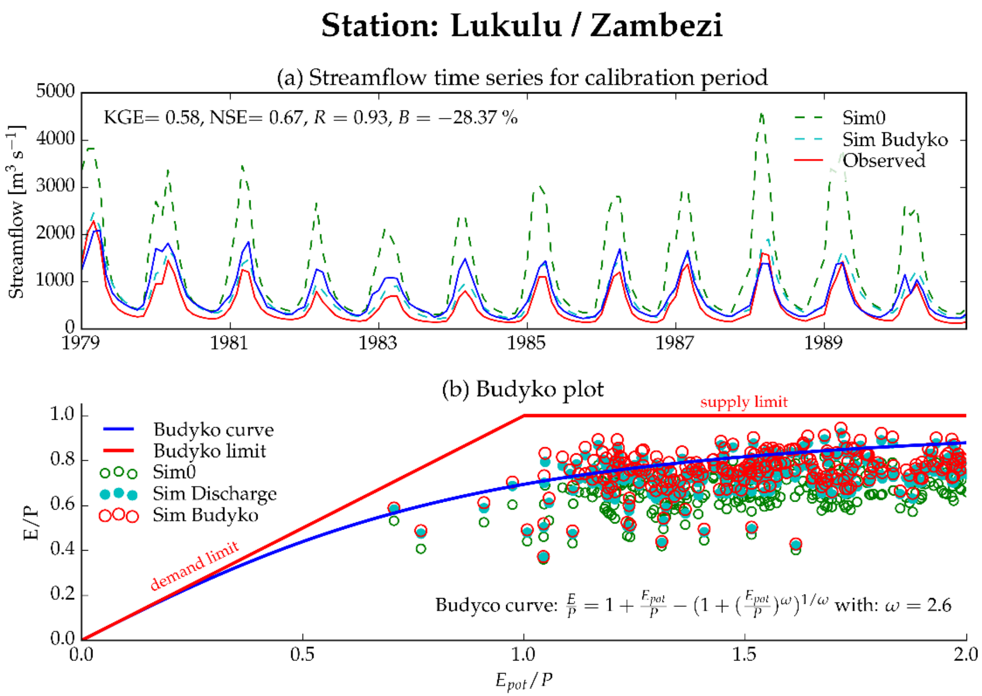
	Obs	Sim0	SimBud	SimDis
KGE		0.548	0.809	0.917
NS		0.643	0.633	0.836
NSlog		0.729	0.633	0.775
R		0.850	0.913	0.924
Bias		-0.78%	16.33%	3.20%
RMSE		672	682	456
MAE		422	508	351
Mean	2258	2240	2627	2330
Min	788	1092	592	621
5 %	1136	1375	1003	944
50 %	1956	2135	2342	2075
95 %	4387	3470	5290	4675
99 %	6451	4046	6891	6355
Max	11885	5282	12028	10089



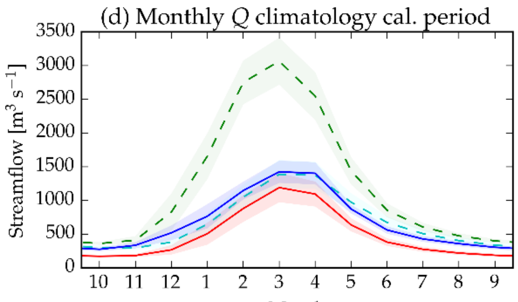
More results 2

Zambezi - Lukulu, Zambia

The a priori parameter run is overestimating observed discharge by far (84%) while the Budyko run is even underestimating observed discharge.
Overall Budyko cal. is a major improvement



	Obs	Sim0	SimBud	SimDis
KGE		0.113	0.576	0.913
NS		-2.900	0.667	0.829
NSlog		0.162	0.367	0.844
R		0.899	0.926	0.916
Bias		84.24%	-28.37%	-0.47%
RMSE		905	264	190
MAE		597	221	135
Mean	706	1301	506	703
Min	196	306	122	219
5 %	236	335	143	246
50 %	515	789	314	548
95 %	1652	3393	1380	1573
99 %	1980	3899	1962	2137
Max	2084	4659	2289	2458



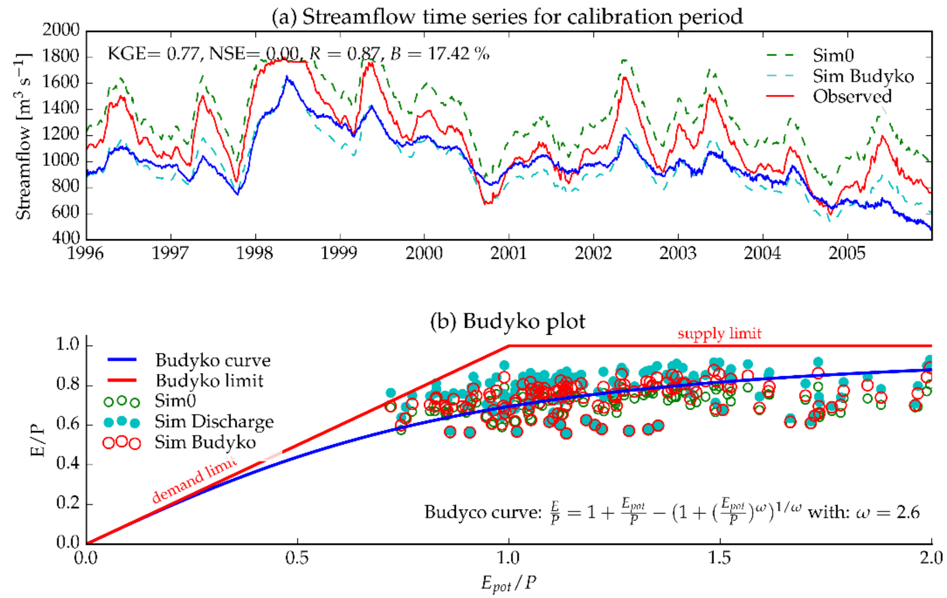
More results 3

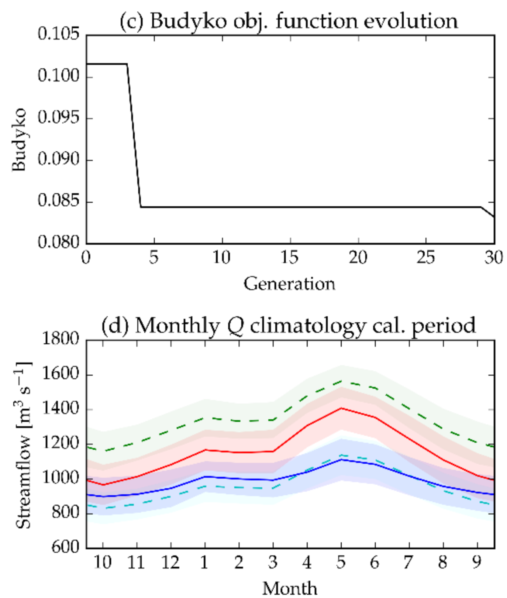
Upper Nile – Lake Vitoria (Jinja, Uganda)

The a priori parameter run is overestimating (36%) observed discharge. Discharge calibrated discharge fit very well (KGE = 0.92, NSE = 0.85)

Budyko cal. is half way from uncalibrated to discharge calibrated.
Overall it is an improvement

River: Nile station: Jinja





	Obs	Sim0	SimBud	SimDis
KGE		0.571	0.772	0.922
NS		-1.877	0.002	0.846
NSlog		-1.181	0.180	0.798
R		0.852	0.870	0.930
Bias		35.68%	17.42%	-2.78%
RMSE		377	222	87
MAE		354	184	72
Mean	992	1346	1165	965
Min	474	820	594	529
5 %	642	956	743	649
50 %	971	1312	1124	914
95 %	1394	1774	1743	1380
99 %	1588	1785	1774	1595
Max	1661	1801	1809	1646

More results 4

Sacramento River -Wilkins Slough, California, USA

The a priori parameter run is overestimating observed discharge.
Budyko cal. is a reasonable improvement towards discharge calibration

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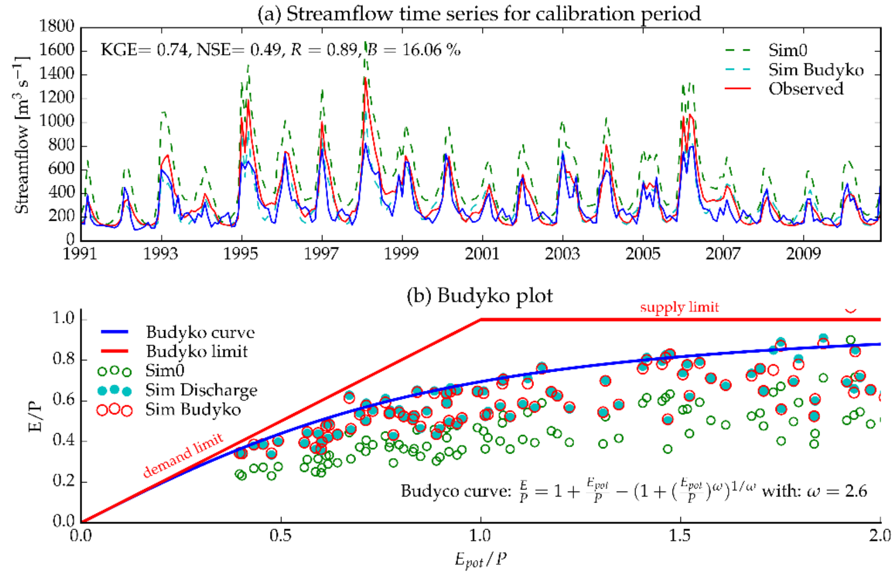
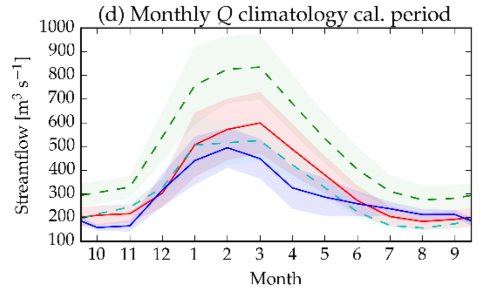
Station: USGS 11390500



	Obs	Sim0	SimBud	SimDis
KGE		0.286	0.742	0.851
NS		-1.463	0.492	0.691
NSlog		-0.360	0.582	0.558
R		0.914	0.890	0.869
Bias		70.83%	16.06%	6.87%
RMSE		262	119	93
MAE		216	85	75
Mean	297	507	344	317
Min	96	143	130	128
5 %	126	165	135	135
50 %	234	430	275	263
95 %	660	1040	755	657
99 %	785	1357	1094	931
Max	824	1713	1377	1122

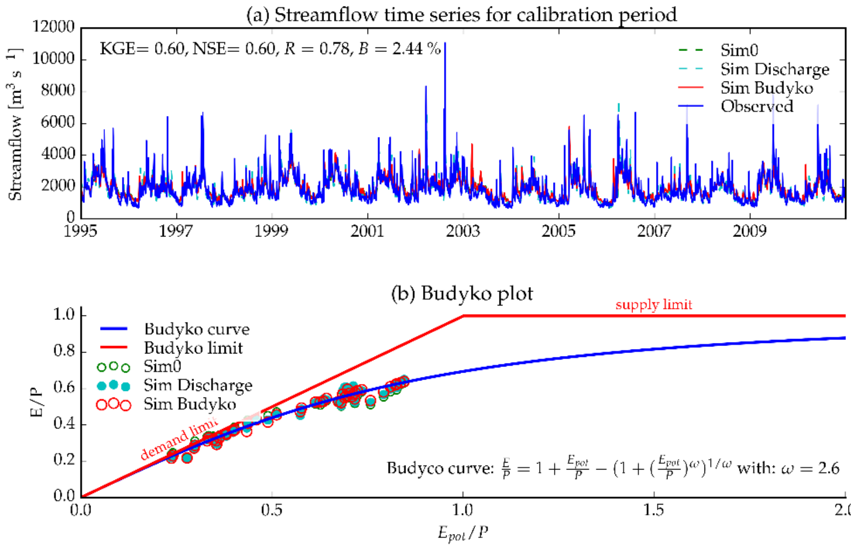


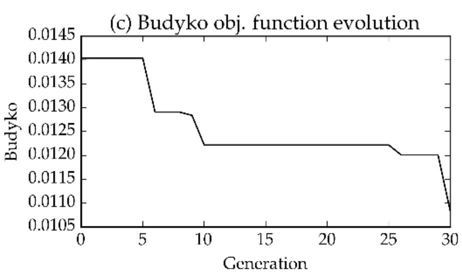
More results 5

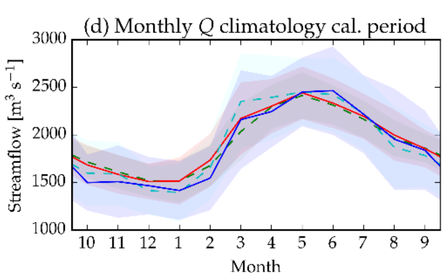
Danube - Kienstock, Austria
catchment area: 96,000km^2

Zimnicea, Romania
catchment area: 648,400km^2

River: Danube Station: Kienstock, AT

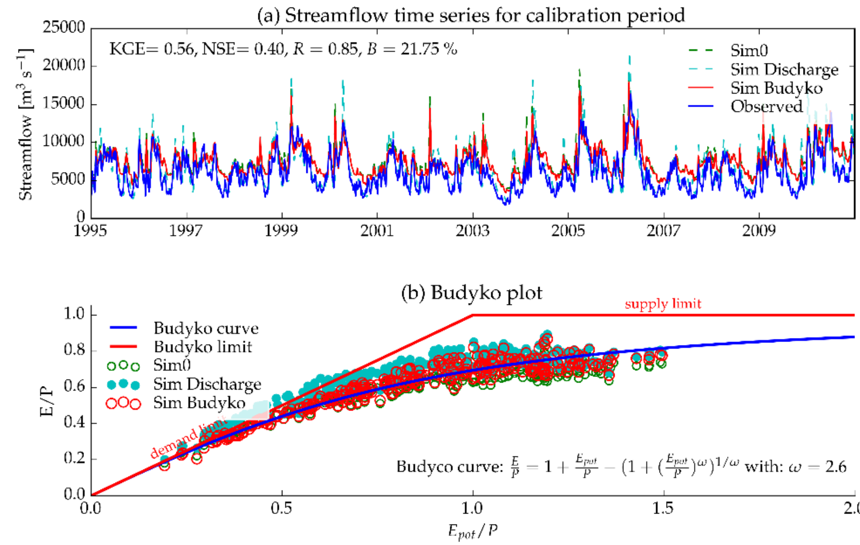


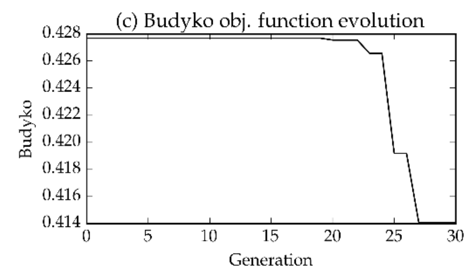


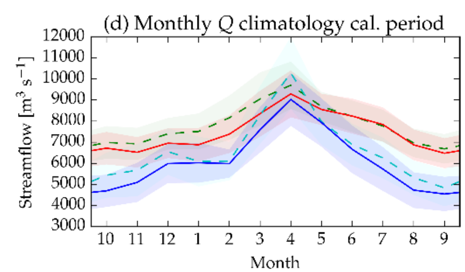


	Obs	Sim0	SimBud	SimDis
KGE		0.495	0.605	0.806
NS		0.502	0.602	0.648
NSlog		0.580	0.660	0.703
R		0.722	0.784	0.817
Bias		1.39%	2.44%	1.66%
RMSE		625	558	525
MAE		411	372	350
Mean	1899	1926	1946	1931
Min	667	948	908	659
5 %	906	1226	1173	901
50 %	1709	1863	1846	1768
95 %	3479	2868	3049	3457
99 %	5042	3414	3841	4346
Max	11072	4597	5813	7542

River: Danube Station: Zimnicea, RO







	Obs	Sim0	SimBud	SimDis
KGE		0.524	0.565	0.837
NS		0.204	0.404	0.639
NSlog		0.129	0.291	0.688
R		0.837	0.852	0.867
Bias		27.12%	21.75%	7.72%
RMSE		2119	1834	1427
MAE		1819	1563	1070
Mean	6166	7838	7507	6642
Min	1740	3667	3403	2252
5 %	3060	5419	5052	3361
50 %	5830	7586	7251	6051
95 %	10622	11103	10762	11570
99 %	12800	14222	13280	15608
Max	16400	19613	17907	21994

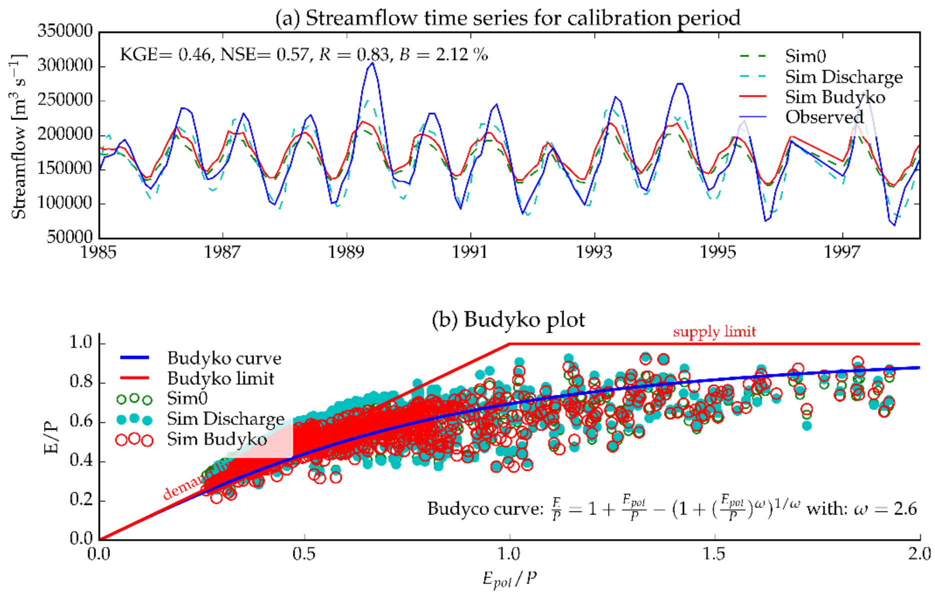
More results 6

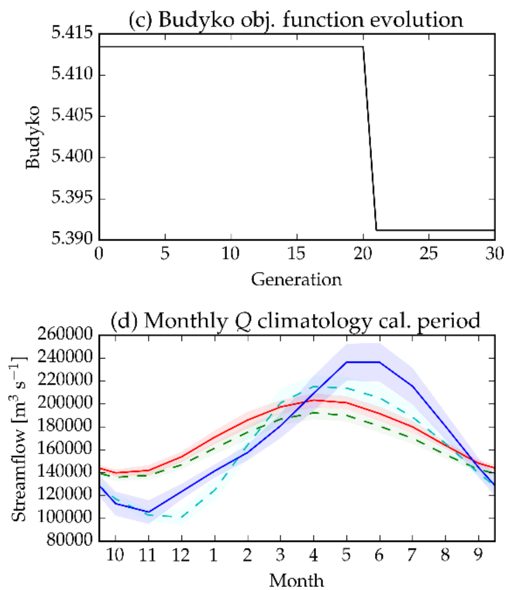
Amazonas - Obidos, Brasil

The catchment area of this basin is 4.7 Mio. km². The average observed discharge is 170.000 m³/s.
Discharge at this station depends mostly on the timing, that means mostly on the routing and lake parameters.

Therefore Budyko cal. does not significantly improve the a priori parameter run.

River: Amazonas: Obidos





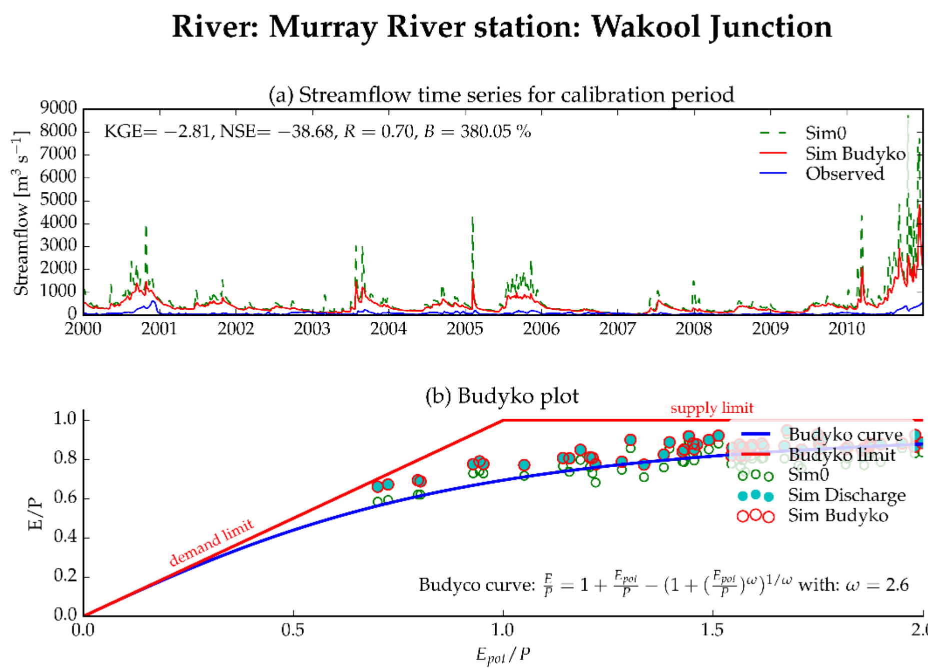
	Obs	Sim0	SimBud	SimDis
KGE		0.428	0.456	0.888
NS		0.529	0.570	0.800
NSlog		0.563	0.554	0.805
R		0.832	0.830	0.910
Bias		-2.97%	2.12%	-4.82%
RMSE		34150	32618	22244
MAE		27192	27638	18146
Mean	170294	165235	173905	162081
Min	69271	125182	127722	81348
5 %	99296	132169	136676	95302
50 %	163081	166069	175884	160757
95 %	257238	200774	213216	231666
99 %	288781	205734	218252	244276
Max	306317	208600	220559	250812

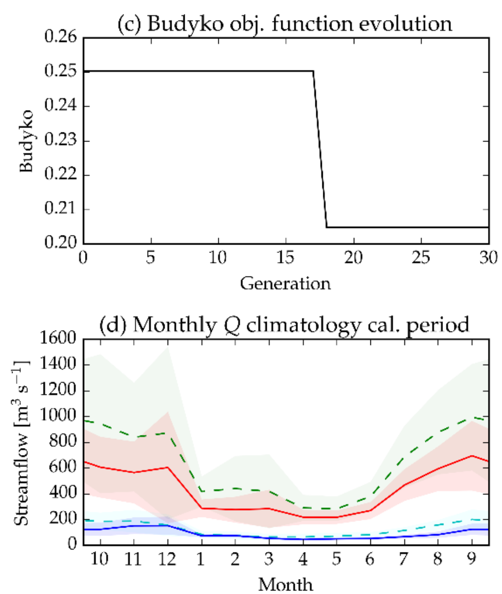
More results 7

Murray-Darling - Wakool Junction, Australia

Murray river is running through a semi-arid region. Most of the discharge is lost during this transfer.
As the Budyko cal. is only looking at the grid-cell balance, it cannot be expected to be effective.

The a priori parameter run is overestimating observed discharge by 600%.
Transmission lost is calibrated by the routing process.
Discharge calibration gives reasonable good results and Budyko improves the results a little bit, but still not sufficient.





	Obs	Sim0	SimBud	SimDis
KGE		-5.040	-2.814	0.558
NS		-117.894	-38.677	0.004
NSlog		-8.529	-5.793	-0.358
R		0.604	0.698	0.765
Bias		601.85%	380.05%	37.40%
RMSE		878	507	80
MAE		534	338	56
Mean	89	623	426	122
Min	21	47	37	10
5 %	29	117	100	22
50 %	69	403	305	93
95 %	251	1903	1155	322
99 %	456	3866	2240	655
Max	621	8759	4814	779

IIASA