

Calibration and Uncertainty Analysis of SWAT in SWATCUP

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Strasbourg, 2024



SWATCUP Programs from 2w2e Consulting

www.2w2e.com

1. SWATCUP-2019

Algorithms: SUFI2, PSO, GLUE, ParaSol, MCMC

Objective function: Single Objective Function



Objective function

Different objective functions produce different calibration results

Ref:

Houshmand D., et al., 2017.

Sensitivity of calibrated parameters and water resource estimates on different objective functions and optimization algorithms. Water, 9, 384.

<https://www.mdpi.com/2073-4441/9/6/384>



Objective function

1=mmse

Minimize:

$$g = \frac{\sum_i (\mathcal{Q}_m - \mathcal{Q}_s)_i^2}{n_Q} * \frac{\sum_i (S_m - S_s)_i^2}{n_S} * \frac{\sum_i (N_m - N_s)_i^2}{n_N} * \dots$$

2=smse

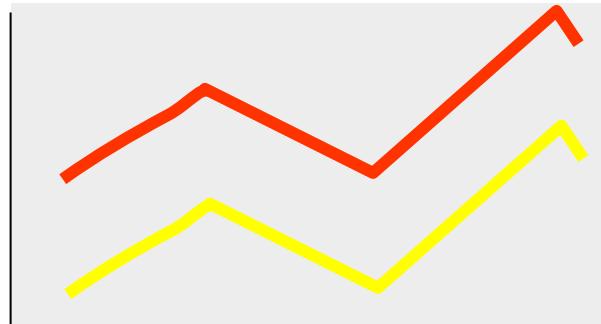
Minimize:

$$g = w_1 \sum_{i=1}^{n_1} (\mathcal{Q}_m - \mathcal{Q}_s)_i^2 + w_2 \sum_{i=1}^{n_2} (S_m - S_s)_i^2 + w_3 \sum_{i=1}^{n_3} (N_m - N_s)_i^2 + \dots$$

3=R²

Maximize:

$$R^2 = \frac{\left[\sum_i (\mathcal{Q}_{m,i} - \bar{\mathcal{Q}}_m)(\mathcal{Q}_{s,i} - \bar{\mathcal{Q}}_s) \right]^2}{\sum_i (\mathcal{Q}_{m,i} - \bar{\mathcal{Q}}_m)^2 \sum_i (\mathcal{Q}_{s,i} - \bar{\mathcal{Q}}_s)^2}$$



$$R^2 = 1$$



Objective function

4=Chi2 Minimize:

$$\chi^2 = \frac{\sum_i (Q_m - Q_s)_i^2}{\sigma_m^2}$$

5=NS Maximize:

$$NS = 1 - \frac{\sum_i (Q_m - Q_s)_i^2}{\sum_i (Q_{m,i} - \bar{Q}_m)^2}$$

6=bR² Maximize:

$$\phi = \begin{cases} |b|R^2 & \text{if } |b| \leq 1 \\ |b|^{-1}R^2 & \text{if } |b| > 1 \end{cases}$$

7=SSQR Minimize:

$$SSQR = \frac{1}{n} \sum_{i=1}^n [Q_{i,m} - Q_{i,s}]^2$$

8. PBIAS Minimize:

$$PBIAS = 100 * \frac{\sum_{i=1}^n (Q_m - Q_s)_i}{\sum_{i=1}^n Q_{m,i}}$$



Objective function

9. KGE Maximize: $KGE = 1 - \sqrt{(r - 1)^2 + (\alpha - 1)^2 + (\beta - 1)^2}$

10. RSR Minimize: $RSR = \frac{\sqrt{\sum_{i=1}^n (Q_m - Q_s)_i^2}}{\sqrt{\sum_{i=1}^n (Q_{m,i} - \bar{Q}_m)^2}}$

11. MNS Maximize: $MNS = 1 - \frac{\sum_i |Q_m - Q_s|_i^p}{\sum_i |Q_{m,i} - \bar{Q}_m|_i^p}$



SWATCUP Programs from 2w2e Consulting

www.2w2e.com

SWATCUP-2019

- **SUFI2, PSO, GLUE, ParaSol, MCMC**
- Single Objective Function

SWATCUP-Premium

- **SPE (SUFI2), PSO**
- Single-Objective Function,
- Single-Objective Function Behavioral,
- Multi-Objective Function,
- Multi-Objective Function Behavioral

SWATplusCUP

- **SPE (SUFI2), PSO**
- Single-Objective Function,
- Single-Objective Function Behavioral,
- Multi-Objective Function,
- Multi-Objective Function Behavioral



Behavioral Objective Function

e.g.,

NS > 0.6



Multiple-Objective Function

- The program uses the following function as goal function:
- Maximize:
$$\text{multi_goal} = (w_3R^2 + w_5NS + w_6BR^2 + w_9KGE + w_{11}MNS) - [w_1MMSE + w_2SMSE + w_4CHI_2 + w_7SSQR + |w_8PBIAS| + w_{10}RSR]$$
- Where wi's are the weights of the corresponding functions.
- An example of a multi-objective function is the following function:
- $\text{Multi_goal} = w_3R^2 + w_5NS - |w_8PBIAS|$

The best way to Learn about SWATCUP

- 1. The Manual** - Has detailed explanation and step-by-step instruction for building SWATCUP input files

- 2. Numerous articles that have used SWATCUP**

- 3. Videos** - <https://www.youtube.com/@2w2e-channel>

- DEM
- SOIL
- LANDUSE
- CLIMATE
- MANAGEMENT
 - Agricultural
 - Water
 - Construction
- etc.

Parameters

- Hydrology
- Water quality
- Soil erosion
- Land manag.
- Crop growth
- Clim/LU change
- Reservoir/Dam
- Nut./OM cycling
- etc.

Inputs

Model

Processes

- Calibrating Data
 - Flow
 - Sediment
 - Chemicals
 - Crop yield
- etc.



Inputs

- DEM → Available at varying resolution (1-1000 m)
- SOIL → Unreliable at any resolution (both map and database ∵ also parameters)
- LANDUSE → Relatively reliable at higher resolution
- CLIMATE →
 - Locally measure relatively reliable at higher resolution
 - Generated gridded data are unreliable
- MANAGEMENT
 - Agricultural
 - Water
 - Forest→ Often not available, local data is often relatively reliable, depending on the source
- Etc.

Processes

- Hydrology
 - Surface runoff and infiltration, Evapotranspiration, Groundwater flow, Water routing through the watershed, etc.
- Water quality
 - Nutrient cycling (e.g., nitrogen and phosphorus dynamics), Pesticide fate and transport, Bacterial contamination, etc.
- Soil erosion
 - Soil erosion due to rainfall and surface runoff, Sediment deposition and transport in streams and rivers, etc.
- Land manag.
 - Impact of agricultural practices (e.g., tillage, crop rotation, fert.), Effects of conservation practices (e.g., buffer strips, cover crops), Urbanization, Deforestation changes and their impacts, etc.
- Crop growth
 - Simulation of crop growth and yield, Interaction between farmer, soil, water, and plant systems, etc.
- Clim./LU change
 - Highly inaccurate models are available for future, etc.
- Reservoir/Dam
 - Water impoundment and release, Sediment trapping, and Nutrient retention, etc.
- Nut./OM cycling
 - Decomposition of organic matter, Transformation, and Movement of nutrients in soil and water, etc.

So, what is the story?

When we have lost of inaccurate input, lots of known and unknown processes, lots of unknown parameters....

1- The model we eventually build is highly uncertain

“All models are wrong, some are useful”

2- Calibration is not a way out and cannot do miracles, and if it does by chance, it is the miracle of an impostor!

It has cheated you somewhere, i.e., by providing the wrong parameters.

3- Your expectations should be realistic.

The fallacy in the use of the “best-fit” solution in hydrologic modeling

K.C. Abbaspour, 2022

Science of the Total Environment 802, 149713

<https://doi.org/10.1016/j.scitotenv.2021.149713>

So, what is the story?

When we have lots of inaccurate input, lots of known and unknown processes, lots of unknown parameters....

4- It is imperative to do an uncertainty analysis (i.e., parameters have to be expressed as random variables and output as 95 Percent Prediction Uncertainty, 95PPU)

So, what is the story?

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<https://doi.org/10.1016/j.scitotenv.2021.149713>

(if you get $NS=0.5$, it is not because of you!!)

Calibration protocol

Step 1: Build the model (with all the available inputs and known processes, etc.)

Step 2: Test the model

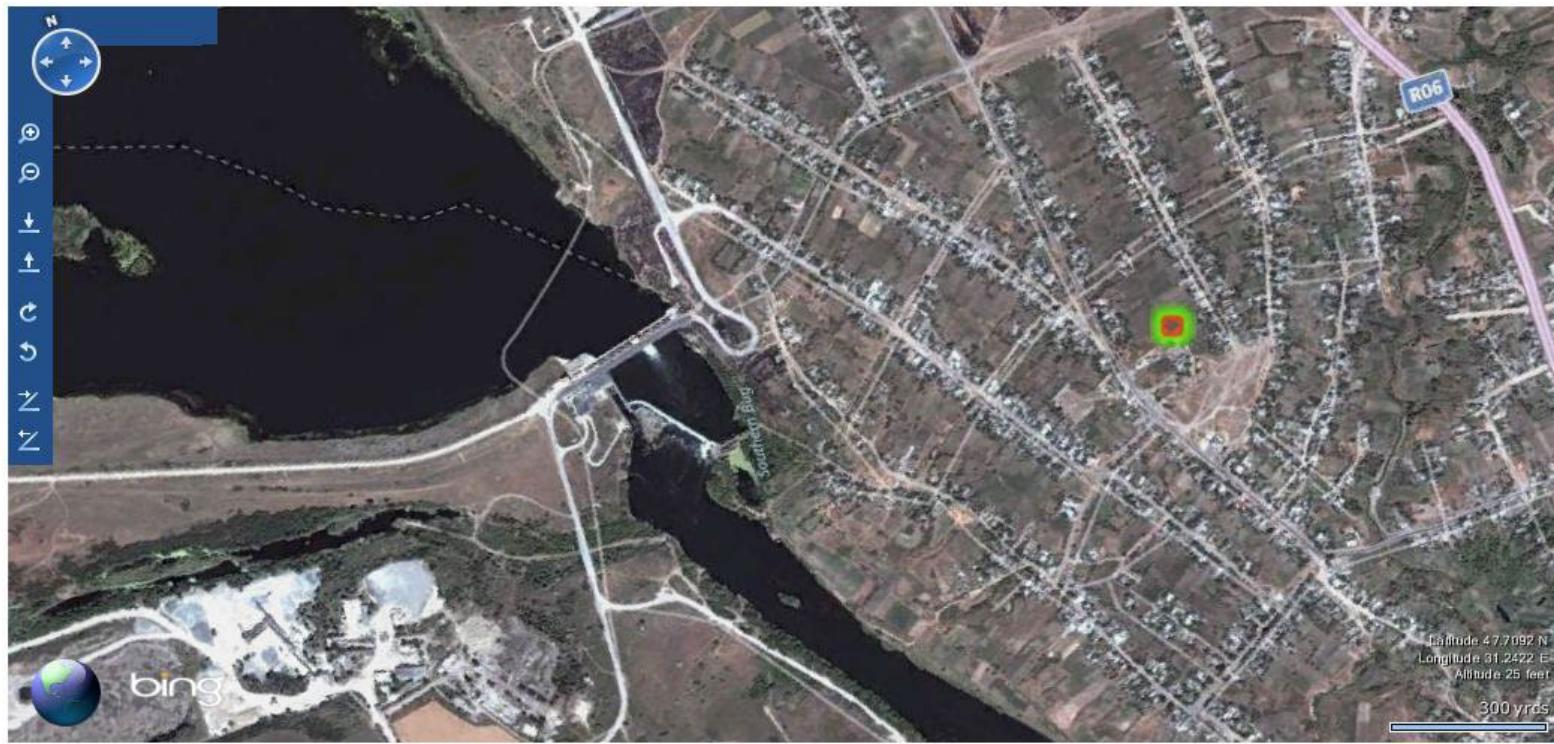
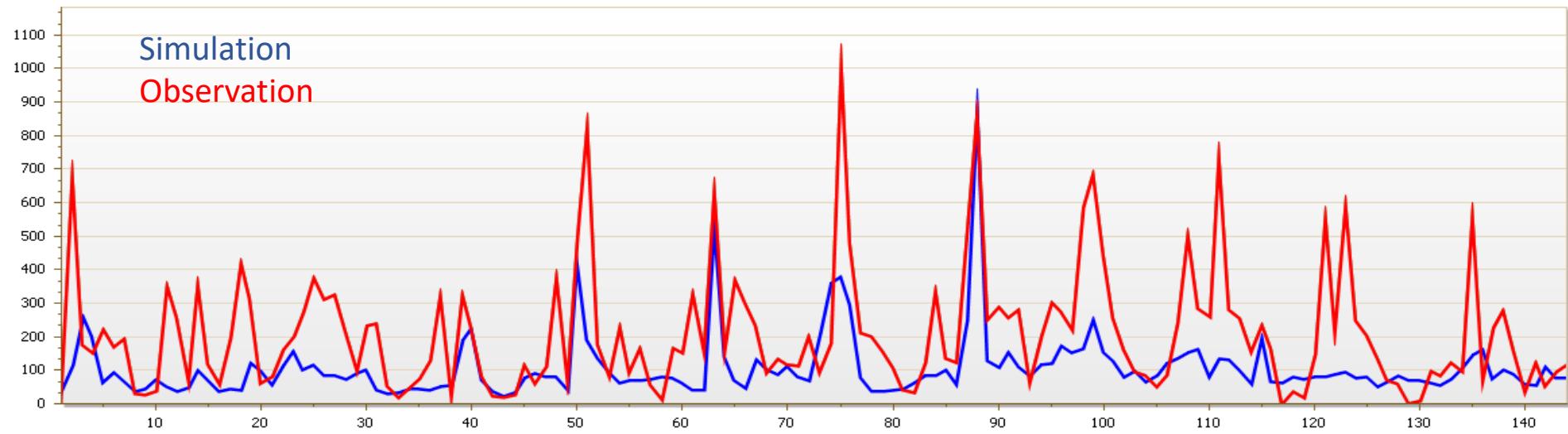
Par_inf.txt 1 : Number of Parameters

Par_inf.txt 1 : Number of simulations

v_WDPQ.bsn 0 0

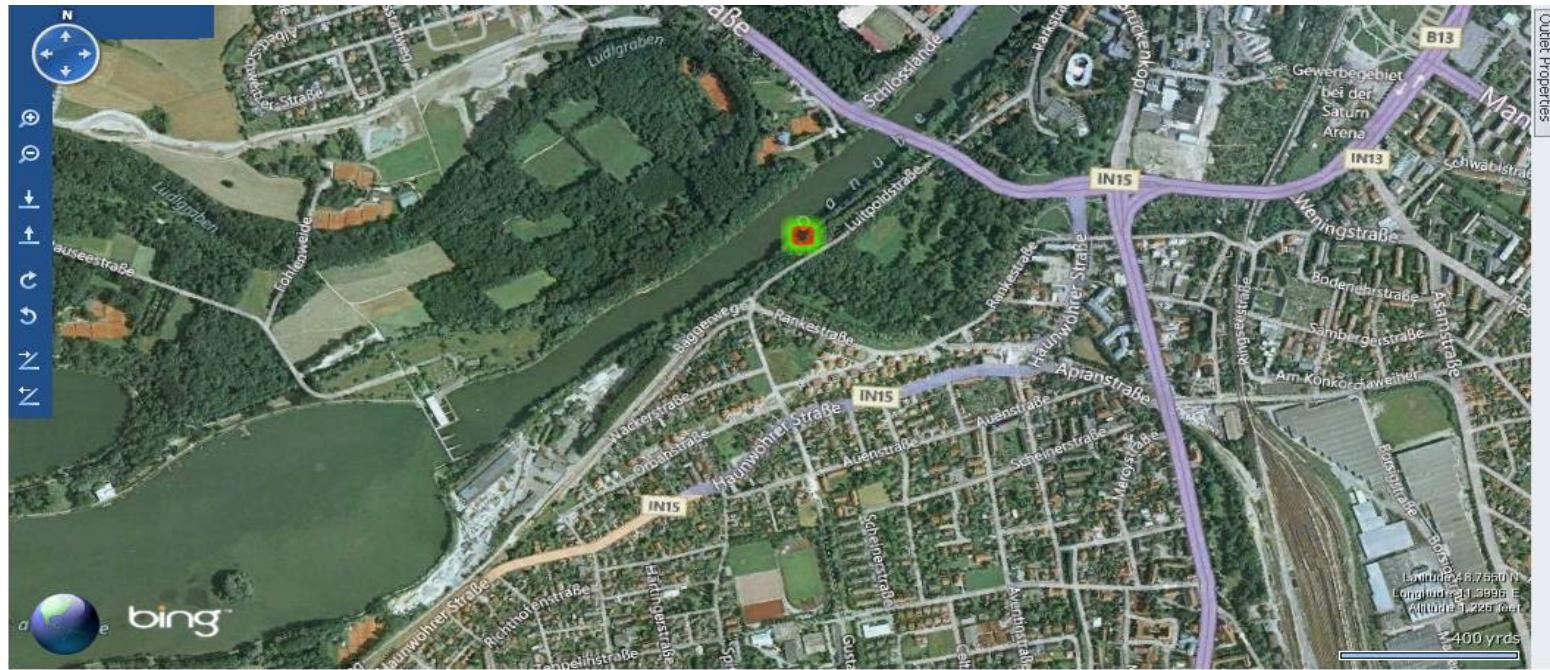
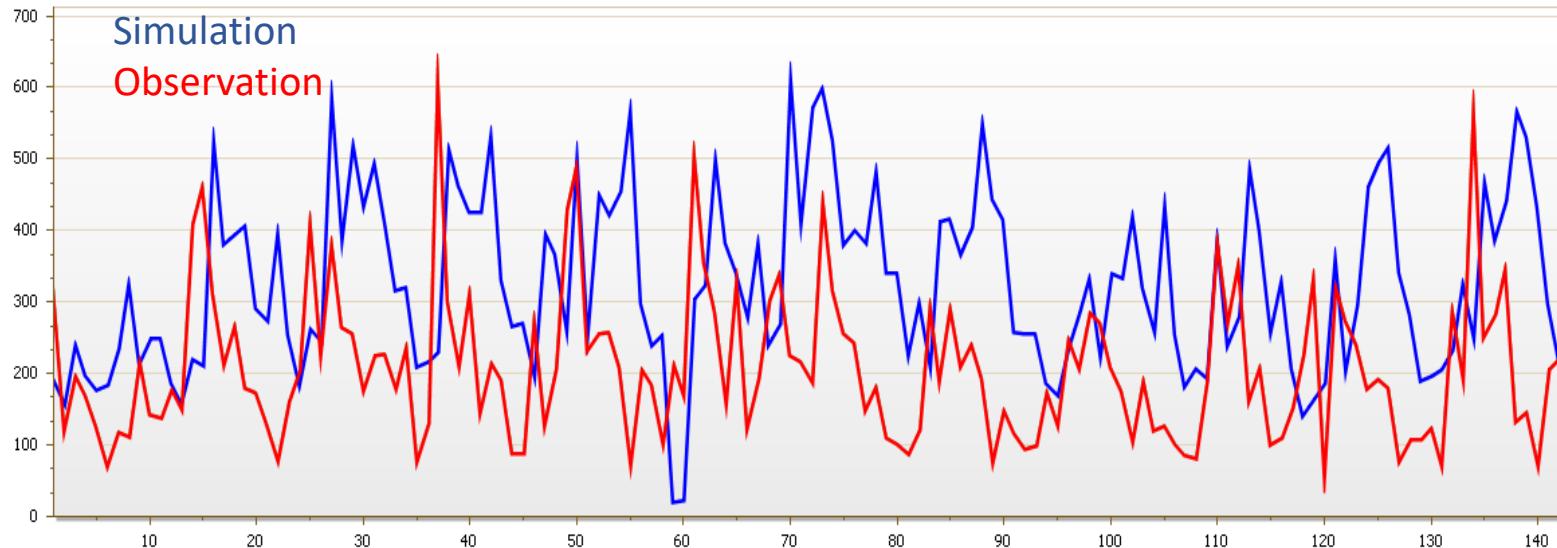
SUFI2_swEdit.def 1 : Starting simulation number

SPE_swEdit.def 1 : Ending simulation number

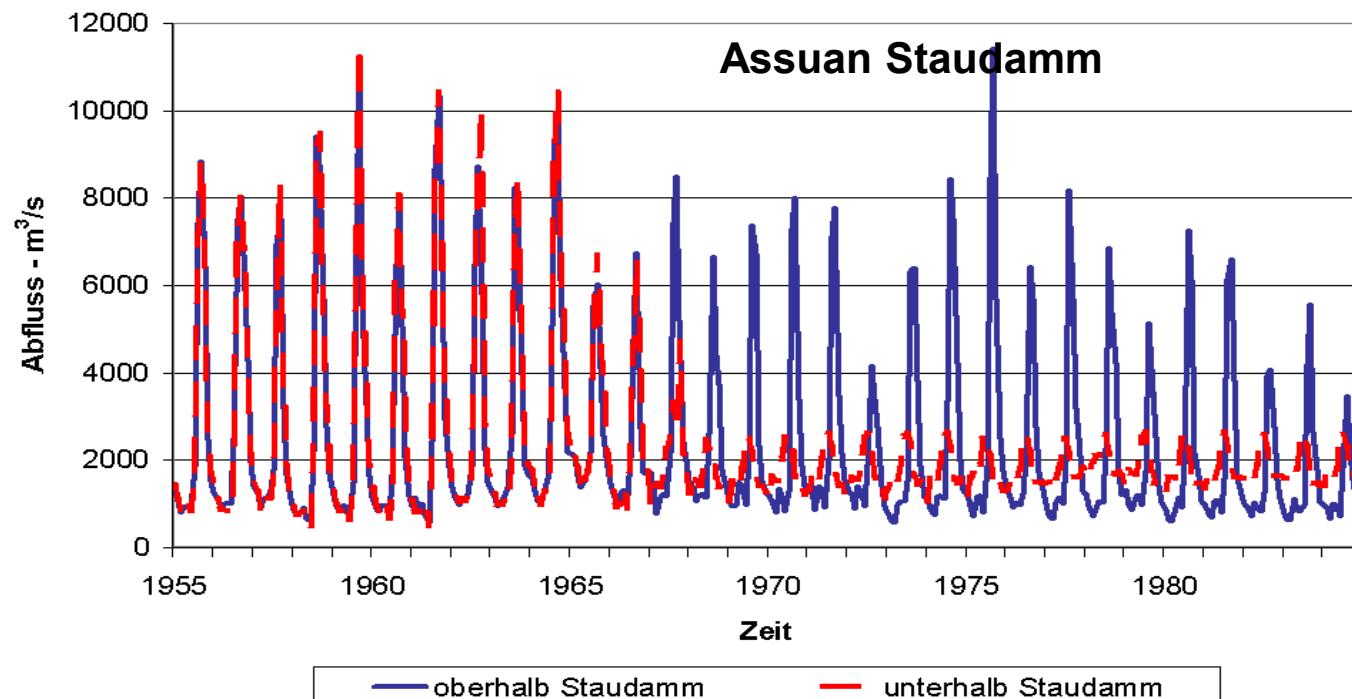


erland





Effect of Aswan dam on downstream discharge



Principle of “Correct Neglect”

If your model does not include the important processes, then the parameters may adjust to the wrong values in trying to mimic the observation.

We don't have to include all processes, and could correctly neglect some unimportant ones

If the initial model is not well, you need to check what you are missing in terms of processes, or the correctness of your input data

A Guideline for Successful Calibration and Uncertainty Analysis for Soil and Water Assessment: A Review of Papers from the 2016 International SWAT Conference

<https://doi.org/10.3390/w10010006>

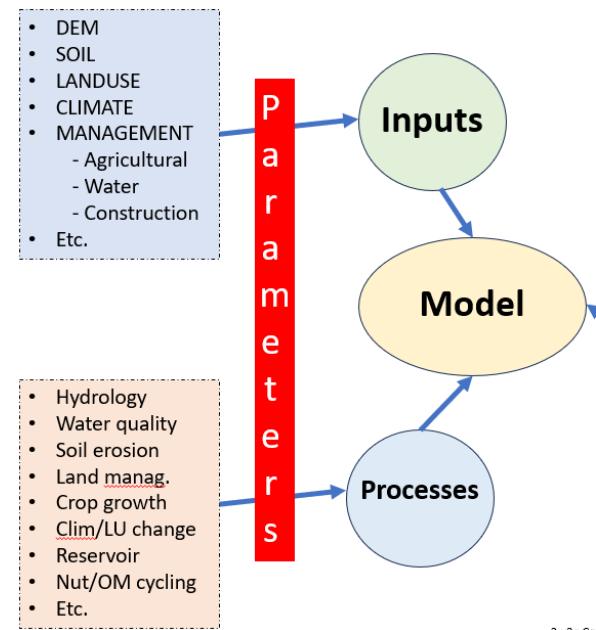
Calibration protocol

Step 3: Choose parameters to Calibrate

- i) SWAT I/O manual defines parameter and gives some indications of values for some parameters.
- ii) Literature also gives some ideas (Although in my opinion a good fraction of the literature gives wrong information about parameters).
- iii) Sensitivity analysis.

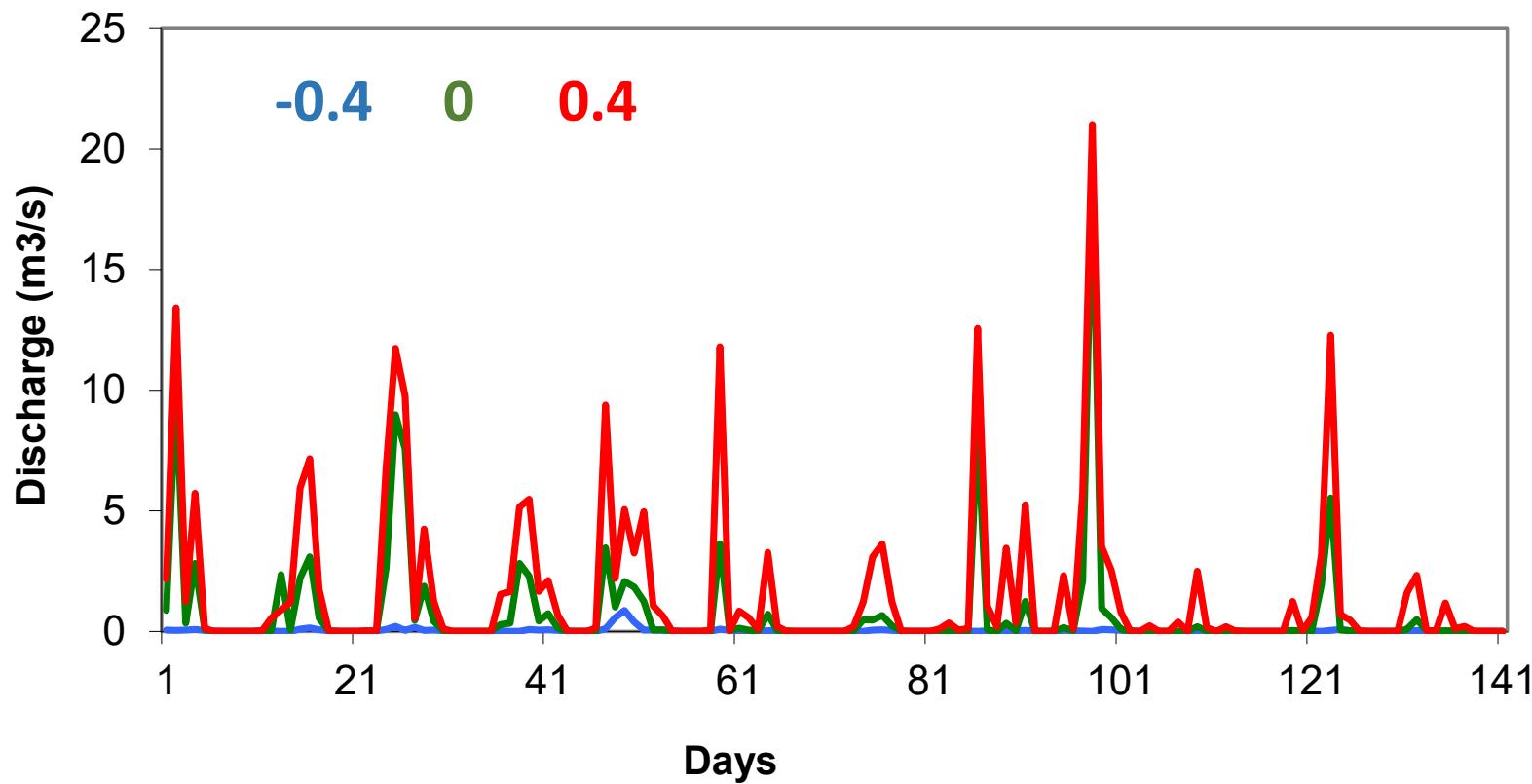
Sensitivity analysis

- Sensitivity analysis is the process of determining the significance of one or a combination of parameters w.r.t the objective function or a model output
- this is important because parameters represent processes, and we want to know what important processes are



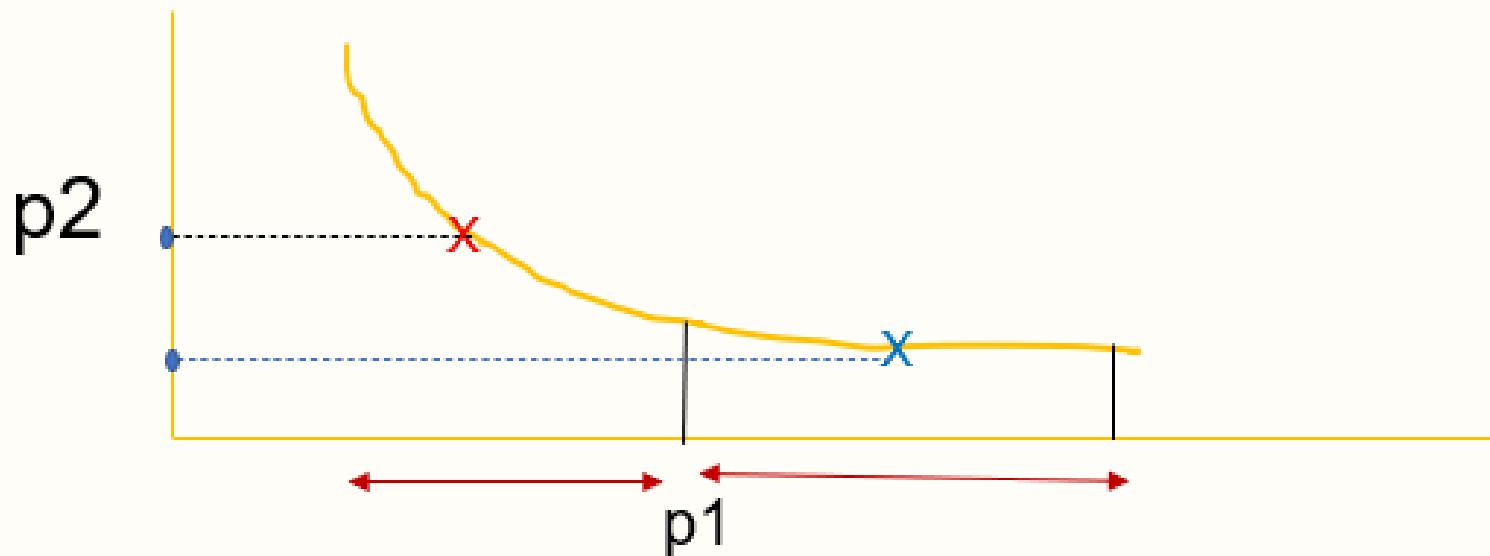
Sensitivity analysis

Sensitivity to CN2



Sensitivity analysis - one-at-a-time

- Local (one-at-a-time) sensitivity analysis



Sensitivity analysis - global

- Global sensitivity analysis

$$g = \alpha + \sum_{i=1}^m \beta_i b_i$$

Where b 's are parameters

- A t-test is then used to identify the relative significance of each parameter b_i
- This gives relative sensitivities based on linear approximations and, hence, only provides partial information about the sensitivity of the objective function to model parameters
- In this analysis, the larger, in absolute value, the value of the t-stat, and the smaller the p-value, the more sensitive the parameter



To Test the Sensitivity of one Parameter

Par_inf.txt

1	:	Number of Parameters
3	:	Number of simulations
r__CN2.mgt -0.4 0.4		

SUFI2_swEdit.def

1	:	Starting simulation number
3	:	Ending simulation number

What are the commonly known sensitive parameters?

FLOW Parameters

If in a snow mountain watershed:

Provide elevation band first

v__PLAPS.sub	0	100	Make 100 simulations
v__TLAPS.sub	-8	-4	and fix their values

v__SFTMP.bsn	-10	10	
v__SMTMP.bsn	-10	10	Make 200 simulations
v__SMFMX.bsn	0	10	also fix their values
v__SMFMN.bsn	0	10	
v__TIMP.bsn	0	1	

What are the commonly known sensitive parameters?

FLOW Parameters

r__CN2.mgt	-0.3	0.3	
v__ESCO.hru	0.7	1.0	(if dry areas 0.3 0.8)
v__GWQMN.gw	0.0	5000	
v__REVAPMN.gw	0.0	1000	
v__GW_REVAP.gw	0.01	0.1	
v__ALPHA_BF.gw	0.01	0.1	
v__RCHRG_DP.gw	0.0	1.0	
r__SOL_K().sol	-0.8	0.8	
r__SOL_BD().sol	-0.6	0.6	
r__SOL_AWC().sol	-0.5	0.5	
r__HRU_SLP.hru	-0.5	0.5	
r__OV_N.hru	-0.5	0.5	
r__SLSUBBSN.hru	-0.5	0.5	

What are the commonly known sensitive parameters?

Sediment, phosphorus

v__PRF.bsn	-0.2	0.3	Only Sediment
v__SPEXP.bsn	1.2	1.5	Only Sediment
v__SPCON.bsn	0.001	0.003	Only Sediment
v__CH_EROD.rte	0.1	0.2	Only Sediment
v__CH_COV.rte	0.15	0.3	Only Sediment
r__USLE_P.mgt	-0.3	0.3	Sediment & phosphorus
v__USLE_C.crp	-0.3	0.3	Sediment & phosphorus
r__USLE_K.sol	-0.3	0.3	Sediment & phosphorus
v__PSP.bsn	0.4	0.8	sensitive to total phosphorus only
v__ERORG.P.hru	2.0	4.0	sensitive to total phosphorus only
v__BC4.swq	0.3	0.5	sensitive to total phosphorus only
v__RS5.swq	0.06	0.1	sensitive to total phosphorus only

What are the commonly known sensitive parameters?

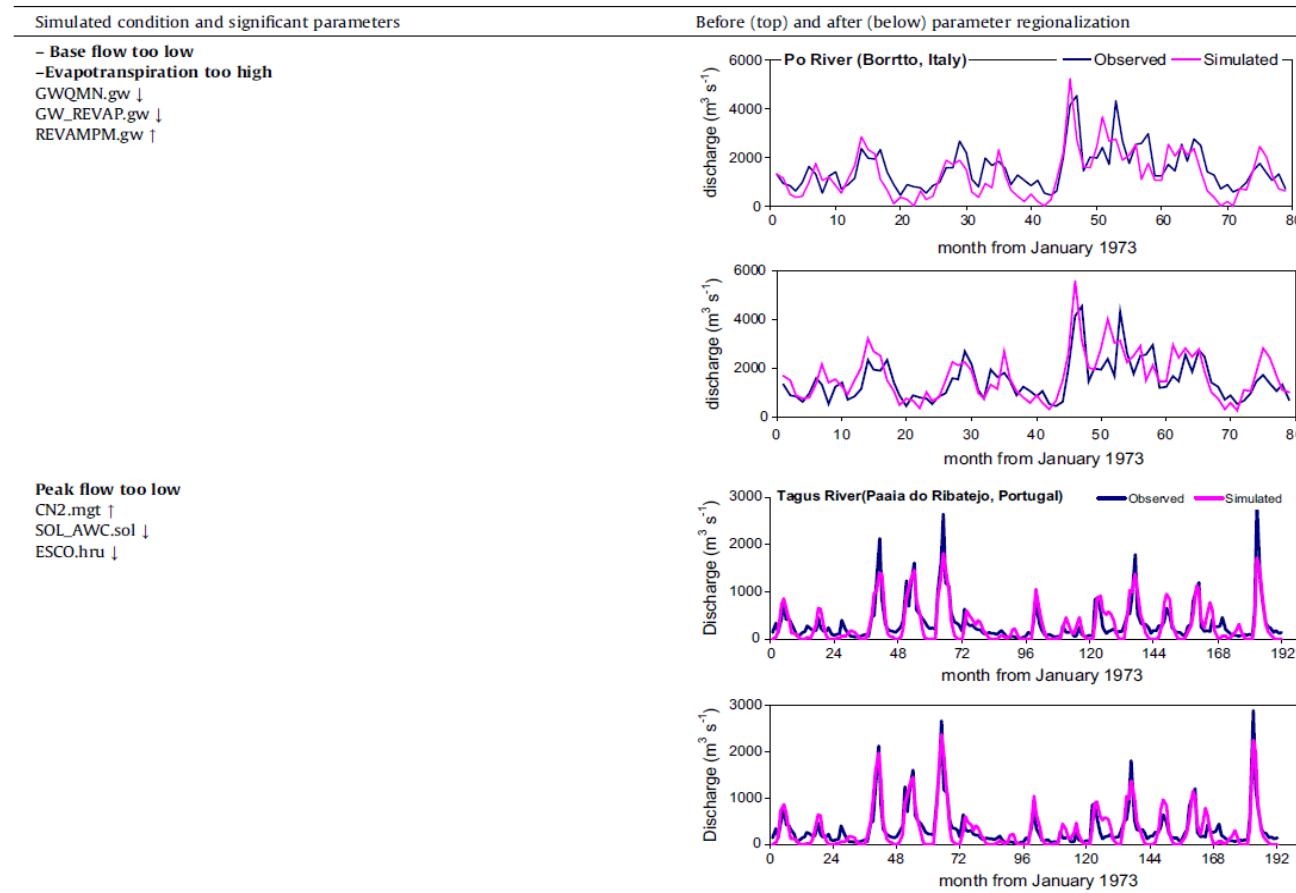
Nitrate

v__RCN.bsn	1.2	1.5	
v__UBN.bsn	5	20	
v__SHALLST_N.gw	0	100	
v__ERORGN.hru	0	5	
v__NPERCO.bsn	0	1	

How to Know What Each Parameter Does?

Table 2

Rules for parameter regionalization. ↑ indicates parameter should increase, ↓ indicates parameter should decrease. (For more detail see SWAT calibration validation literature <http://swat.tamu.edu/publications/calibrationvalidation-publications/>).



A continental-scale hydrology and water quality model for Europe:
Calibration and uncertainty of a high-resolution large-scale SWAT model
<http://dx.doi.org/10.1016/j.jhydrol.2015.03.027>

How to Choose the Initial Parameter Set?

So, you choose the initial parameters for calibration based on the initial model run.

There are sets of parameters that can:

- Increase/decrease the peaks,
- Increase/decrease the base flow,
- Shift the entire signal to the right or to the left,
- Increase or decrease nitrate load,
- Etc.

A continental-scale hydrology and water quality model for Europe:
Calibration and uncertainty of a high-resolution large-scale SWAT model
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Calibration protocol

Step 4: Prepare SWATCUP Input files

1. Par_inf.txt
2. SUFI2_swEdit.def
3. File.cio
4. Absolute_SWAT_Values
5. Observation: Observed_rch.txt, Observed_hru.txt,
Observed_sub.txt, etc.
6. Extraction: var_file_rch.txt, SUFI2_extract_rch.txt
7. Objective function: Observed.txt, var_file_name.txt
8. No_observation
9. Execution files: SUFI2_pre.bat, SUFI2_run.bat,
SUF12_extract.bat

Observation Files

Preparing Observation files – Calibration/Validation

- Split your data into calibration and validation:
 - half-half, 75%-25%, etc.
-
- Make sure both datasets have more or less similar statistics (Mean and variance)

Observation Files

Preparing Observation files – Calibration/Validation

Obderved_rch.txt, observed_hru.txt, observed_sub.txt, etc.

1 : number of observed variables

FLOW_OUT_3 : this is the name of the variable and the subbasin number to be included in the objective function
141 : number of data for this var. as it follows below. First column is a sequential number from beginning
of the simulation, second column is variable name and date (format arbitrary), third column is
variable value.

1 FLOW_OUT_1_1990 46.27
2 FLOW_OUT_2_1990 23.3
3 FLOW_OUT_3_1990 75.1
4 FLOW_OUT_4_1990 12.1

Etc.

Observation files

3 : number of observed variables

FLOW_OUT_3 : this is the name of the variable and the subbasin number to be included in the objective function
141 : number of data for this var. as it follows below. First column is a sequential number from beginning
: of the simulation, second column is variable name and date (format arbitrary), third column is
variable value.

1	FLOW_OUT_1_1990	46.27
2	FLOW_OUT_2_1990	23.3
3	FLOW_OUT_3_1990	75.1
4	FLOW_OUT_4_1990	12.1

Etc.

FLOW_OUT_4 : this is the name of the variable and the subbasin number to be included in the objective function
120 : number of data for this var. as it follows below. First column is a sequential number from beginning
: of the simulation, second column is variable name and date (format arbitrary), third column is
variable value.

1	FLOW_OUT_1_1990	46.27
2	FLOW_OUT_2_1990	23.3
3	FLOW_OUT_3_1990	75.1
4	FLOW_OUT_4_1990	12.1

Etc.

Nitrate_OUT_3 : this is the name of the variable and the subbasin number to be included in the objective function
75 : number of data for this var. as it follows below. First column is a sequential number from beginning
: of the simulation, second column is variable name and date (format arbitrary), third column is
variable value.

1	FLOW_OUT_1_1990	46.27
2	FLOW_OUT_2_1990	23.3
3	FLOW_OUT_3_1990	75.1
4	FLOW_OUT_4_1990	12.1

Etc.

Objective Function Files

Preparing Objective Function files – Calibration

Obderved.txt

```
1      : number of observed variables
5      : Objective function type, 1=mult,2=sum,3=r2,4=chi2,5=NS,6=br2,7=ssqr,8=PBIAS,9=KGE,10=RSR,11=MNS
0.5   : min value of objective function threshold for the behavioral solutions
1      : if objective function is 11=MNS (modified NS), indicate the power, p.

FLOW_OUT_3   : this is the name of the variable and the subbasin number to be included in the objective function
1      : weight of the variable in the objective function
-1     : Dynamic flow separation. Not considered if -1. If 1, then values should be added in the forth column below after
observations
-1     : constant flow separation, threshold value. (not considered if -1)
1      : if separation of signal is considered, this is weight of the smaller values in the objective function
1      : if separation of signal is considered, this is weight of the larger values in the objective function
10    : percentage of measurement error
141   : number of data points for this variable as it follows below. First column is a sequential number from beginning
      : of the simulation, second column is variable name and date (format arbitrary), third column is variable value.

1  FLOW_OUT_1_1990    46.27
2  FLOW_OUT_2_1990    23.3
3  FLOW_OUT_3_1990    75.1
4  FLOW_OUT_4_1990    12.1
Etc.
```

The engine of the program: bat files

```
SUFI2_pre.bat          :: required  
                      SUFI2_LH_sample.exe  
  
SUFI2_extract.bat     SUFI2_extract_rch.exe  
  
                      rem SUFI2_extract_hru.exe  
                      rem SUFI2_extract_sub.exe  
                      rem SUFI2_extract_res.exe  
                      rem SUFI2_extract_mgt_CropYield.exe  
                      ::  
                      rem extract_rch_No_Obs.exe  
                      rem extract_hru_No_Obs.exe  
                      rem extract_sub_No_Obs.exe
```

The engine of SWATCUP: bat files

```
SUFI2_run.bat          :: required  
                      SUFI2_execute.exe  
  
SUFI2_post.bat        :: required  
                      SUFI2_goal_fn.exe  
  
                      :: required  
                      SUFI2_new_pars.exe  
  
                      :: required  
                      SUFI2_95ppu.exe  
  
                      :: required  
                      SUFI2_95ppu_beh.exe  
  
                      ::  
rem      95ppu_NO_Obs.exe
```


Modeling steps

1- Model building

2- Calibration and uncertainty analysis

3- Validation

4- Sensitivity analysis

.....Post calibration analysis.....

5- Model application (climate/landuse change analysis, BMPs, etc.)

6- Risk analysis



1- Model Building - issues

- Often, lack of data, especially water quality
- Sometimes, too much data
There may be different data sets from different sources
- The model should account for all important and relevant processes, But often we do not know
- Have to be careful how you apply the principle of «correct neglect»

A guideline for successful calibration and uncertainty analysis for soil and water assessment
Water 2018, 10(1), 6; <https://doi.org/10.3390/w10010006>



1- Model Building - Processes

- Dams/reservoirs
- Water transfers
- Irrigation
- Snow/glacier melt
- Potholes/water harvesting
- Point sources (springs, water treatment plants, ...)
- Wetlands
- Road building
- Landuse change, etc.



1- Model Building - Data

**Input data discrimination
too much data!**



Data description and sources used in the European SWAT project.

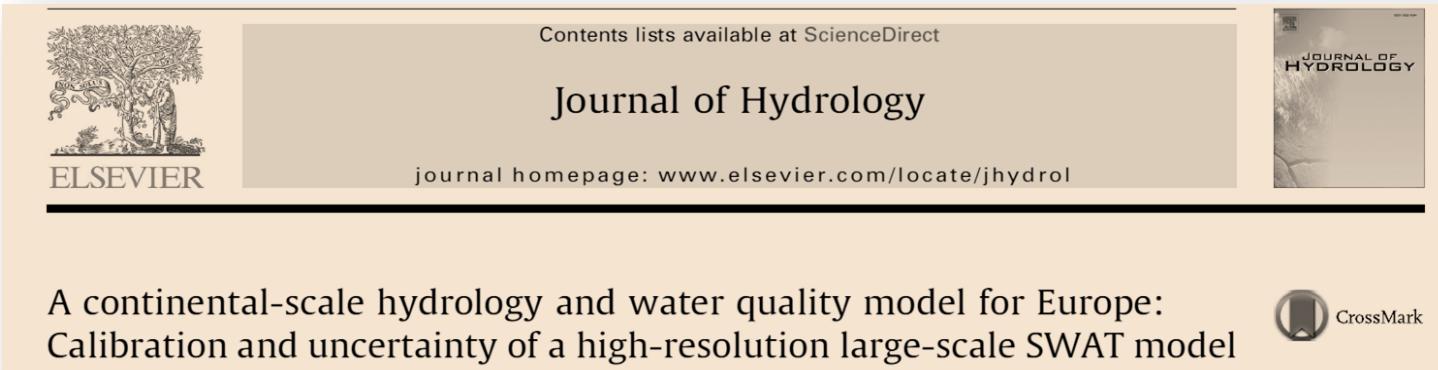
Data type	Resolution	Source
Digital Elevation (DEM)	90 m aggregated to 700 m	Shuttle Radar Topography Mission (SRTM) http://www2.jpl.nasa.gov/srtm/
Soil	5 km	FAO-UNESCO global soil map http://www.fao.org/nr/land/soils/digital-soil-map-of-the-world/en/
Landuse	-300 m -1000 m -500 m -300 m	- GlobCover European Space Agency http://due.esrin.esa.int/globcover/ - Global Landuse/Land Cover Characterization USGS http://landcover.usgs.gov/glcc/ - MODIS land cover http://modis-land.gsfc.nasa.gov/ - GlobCorine provided by European Space Agency http://www.esa.int/About_Us/ESRIN/Express_map_delivery_from_space
Climate	- Observed - 0.25° grid - 0.5° grid - 1° grid	- National Climate Data Center (NCDC), http://www.ncdc.noaa.gov/ - European Climate Assessment Dataset (ECAD), (http://www.ecad.eu/) - Climate Research Unit (CRU), http://www.cru.uea.ac.uk/ - Climate Data Guide (NCAR), https://climatedataguide.ucar.edu/
Crop yield	wheat, maize, barley	McGill University http://www.geog.mcgill.ca/landuse/pub/Data/175crops2000/NetCDF/ FAOSTA - Country-based average crop yield

Table 3

Simulated mean annual river discharges ($\text{m}^3 \text{s}^{-1}$) for a selection of European rivers based on four different climate datasets.

River	Station Name	Discharge	Climate database			
			GRDC ^a	ECAD ^b	CRU ^c	NCAR ^d
Volga	Volgograd	8141	5570	6924	5951	7465
Danube	Ceatal Izmail	6415	3243	5244	4724	4204
Pechora	Oksino	4444	1849	2396	2330	2277
North. Dvina	Ust-Pinega	3331	1419	1597	1470	1705
Rhine	Lobith	2229	1725	2065	2110	1589
Rhone	Beaucairw	1709	1735	1808	1707	1364
Sava	Sremska M.	1563	411	1078	881	973
Po	Pontelagoscuro	1514	1108	1589	1424	1210
Dnieper	Dnieper P.P	1492	1987	2182	1811	2421
Vistula	Tczew	1042	462	715	620	846
.....
.....
Maros	Mako	173	9	95	86	85
Olt	Stoenesti	161	21	62	67	47
Szamos	Satu Mare	126	41	63	81	54
Trent	Colwick	85	67	65	59	61
Thames	Teddington	82	37	47	72	36
Root Mean Square Error			5500	3360	4100	3900

Pre-Calibration analysis



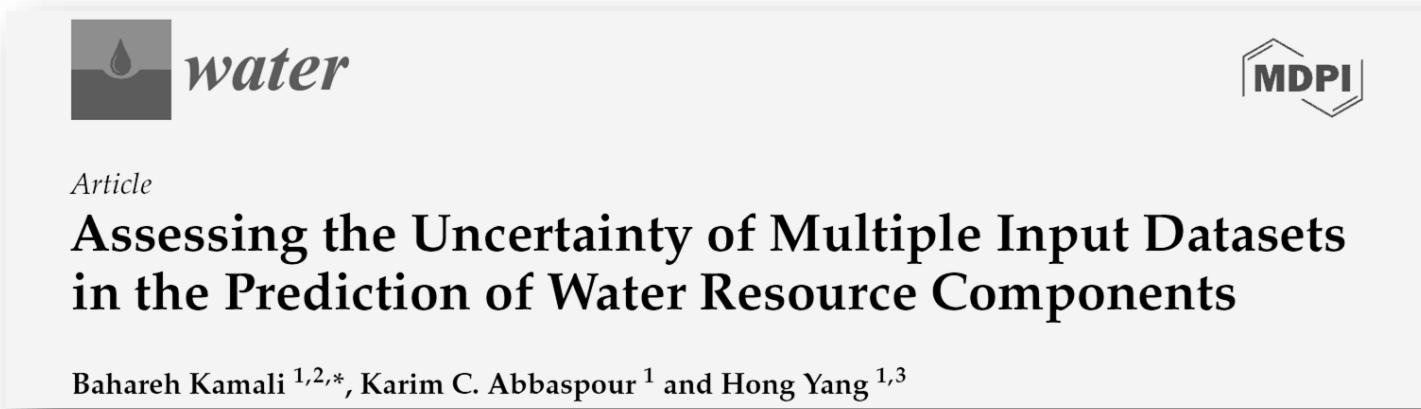
Contents lists available at ScienceDirect
Journal of Hydrology
journal homepage: www.elsevier.com/locate/jhydrol

JOURNAL OF HYDROLOGY

A continental-scale hydrology and water quality model for Europe:
Calibration and uncertainty of a high-resolution large-scale SWAT model

 CrossMark

<https://www.sciencedirect.com/science/article/pii/S0022169415001985>



water

Article

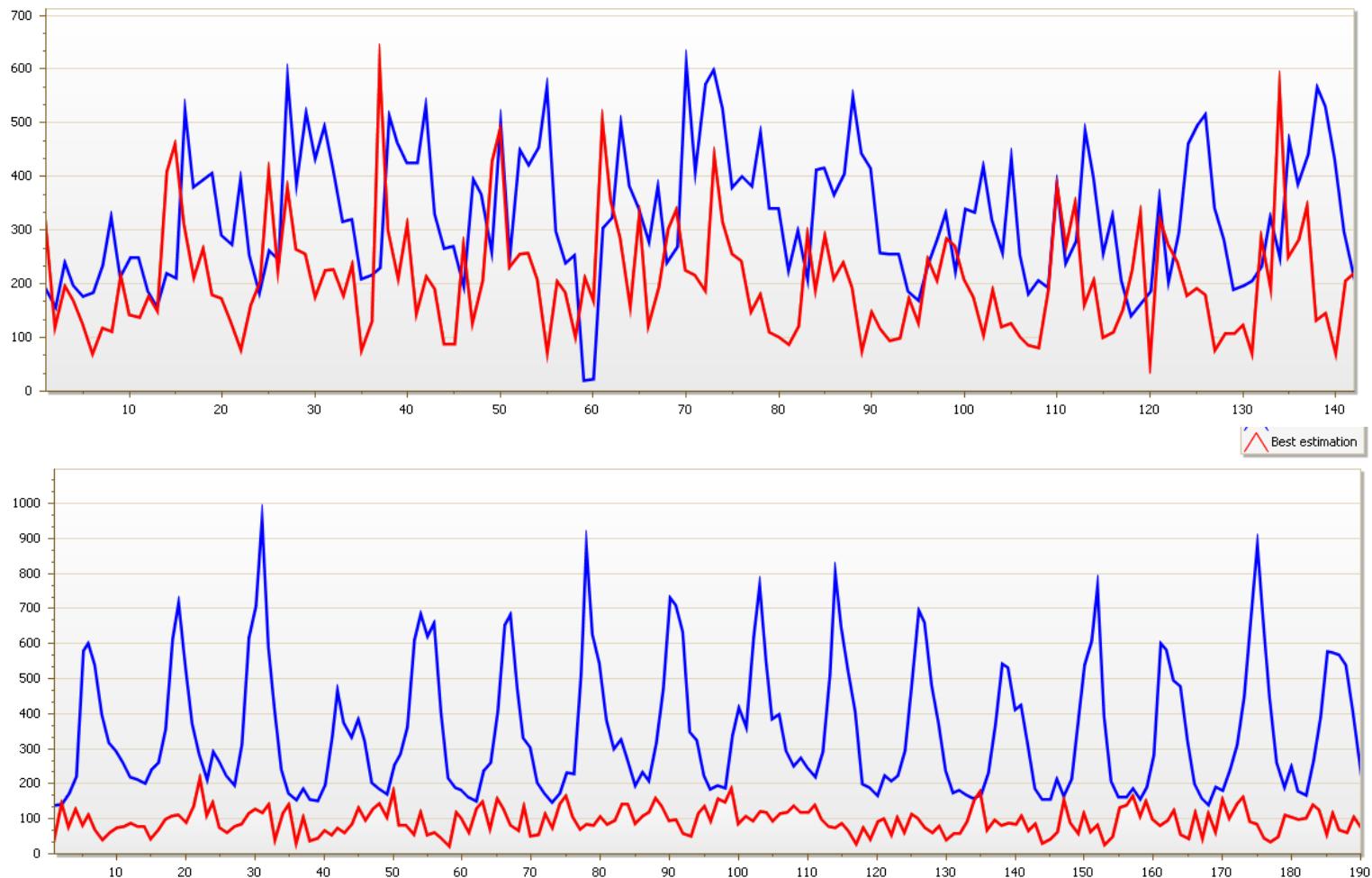
Assessing the Uncertainty of Multiple Input Datasets in the Prediction of Water Resource Components

Bahareh Kamali ^{1,2,*}, Karim C. Abbaspour ¹ and Hong Yang ^{1,3}

<https://www.mdpi.com/2073-4441/9/9/709>



Pre-Calibration analysis - Initial Simulation



The image shows a software interface for hydrological modeling, likely HEC-HMS or similar, displaying two maps side-by-side.

Top Map (3D Perspective View):

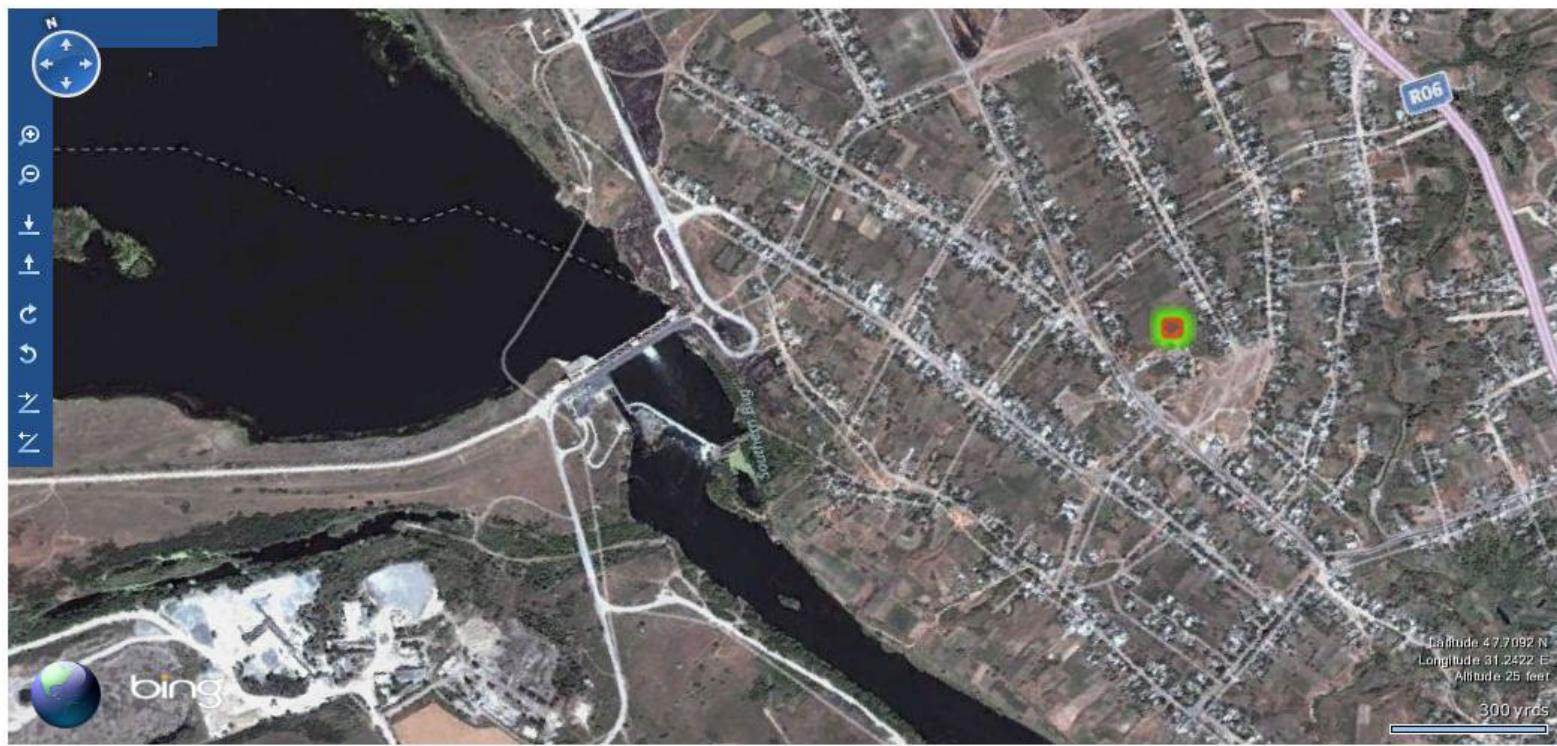
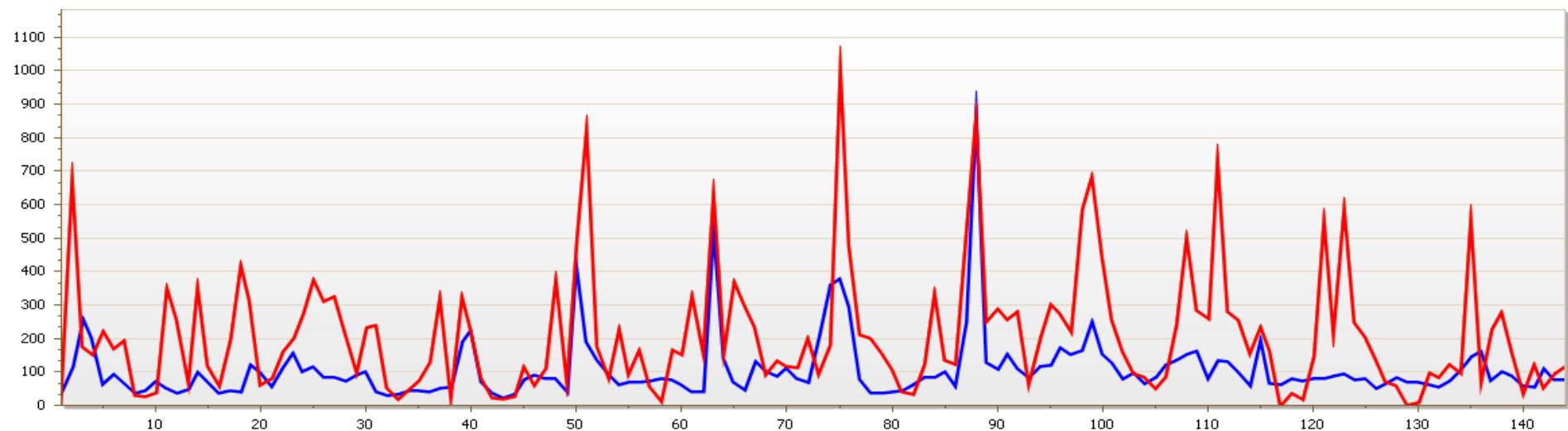
- Project Explorer:** Shows the project structure under "my_project":
 - Calibration Inputs
 - Executable Files
 - Calibration Outputs
 - Sensitivity analysis
 - Global Sensitivity
 - One-at-a-time
 - Maps
 - Outlet Map
 - Iteration History
- Map Features:** A river system with a green outlet highlighted. Labels include "Mündung der Reißeck", "Leibnizbergstraße", "S12359", "Ziel", "Donauesche", and "Universität". A "bing" logo is visible.
- Coordinates:** Latitude 48.0705 N, Longitude 12.2279 E, Altitude 1,557 feet
- Scale:** 70 yards

Bottom Map (Satellite View):

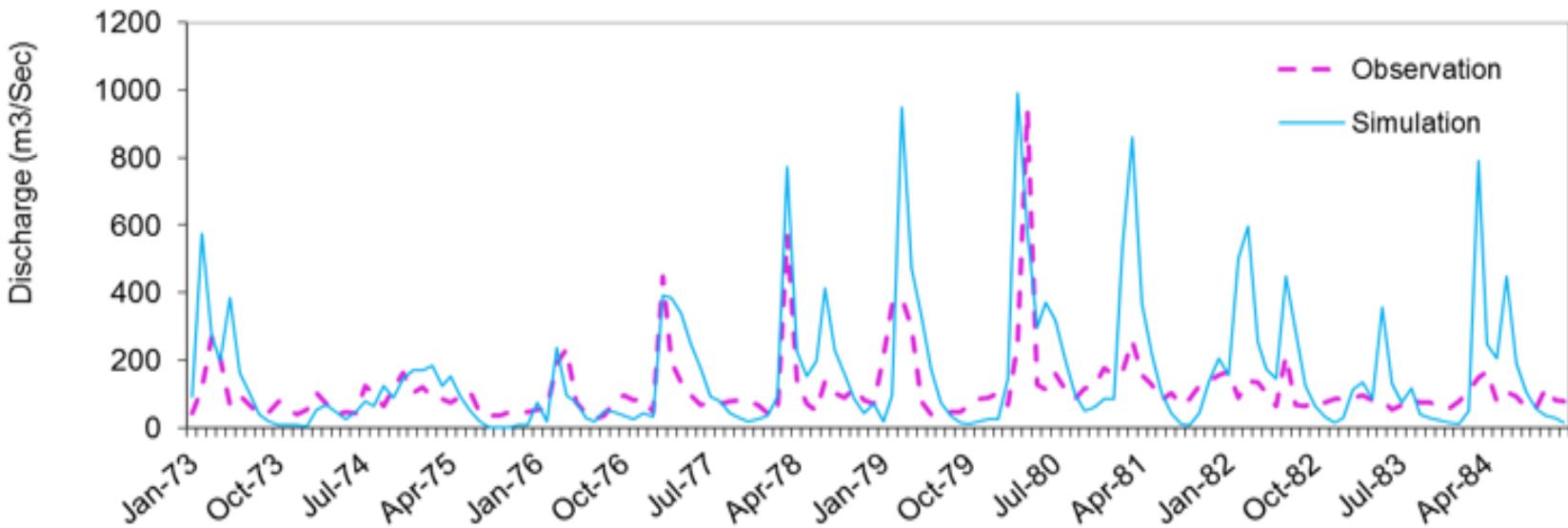
- Map Features:** A satellite view of a mountainous region with several lakes labeled:
 - Humber Provincial Park
 - Brazeau Lake
 - Cummins Lakes Provincial Park
 - Kinbasket Lake
 - Glacier Lake
 - Waterfowl Lakes
 - Chephren Lake
- Outlets:** Three outlets are marked with red circles and blue outlines, indicating potential outlet locations for runoff collection.

q_5842

95PPU
Observed
Best estimation

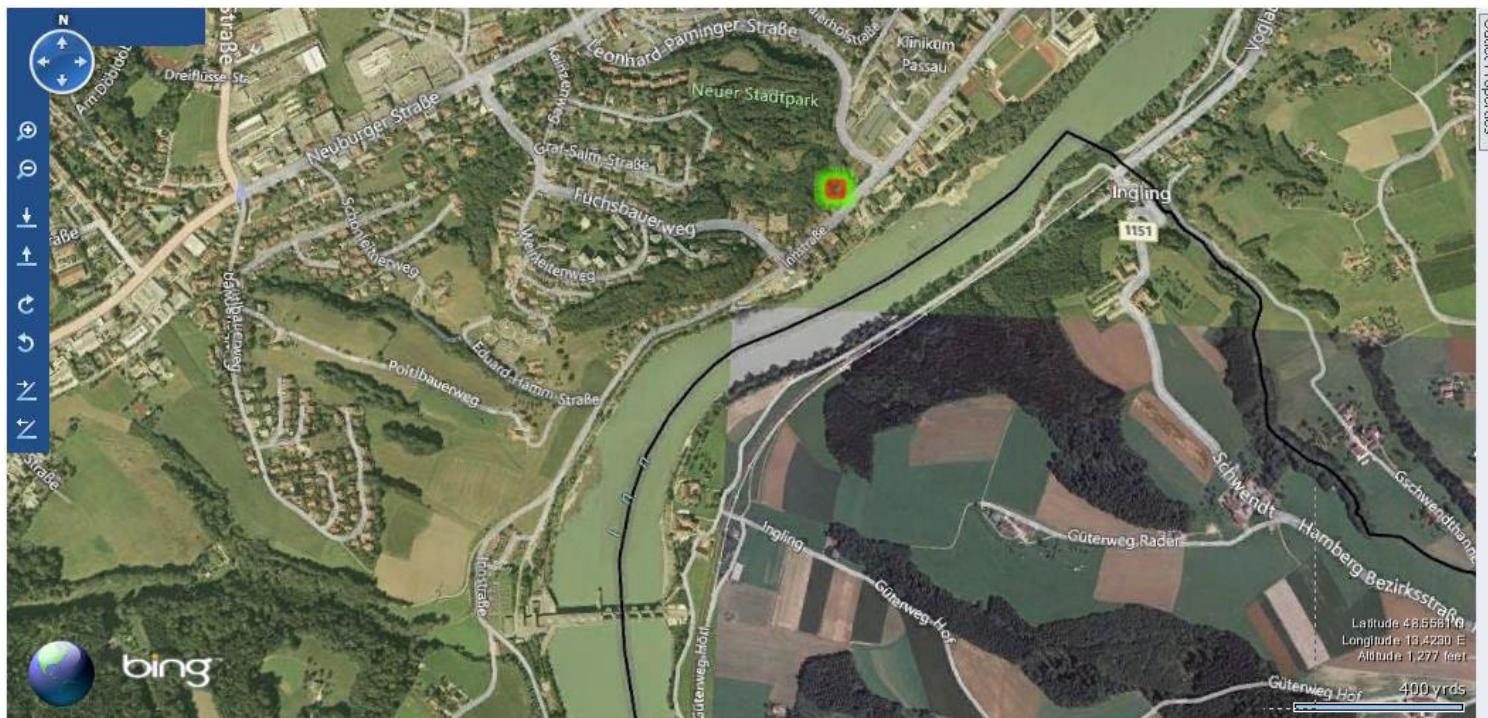
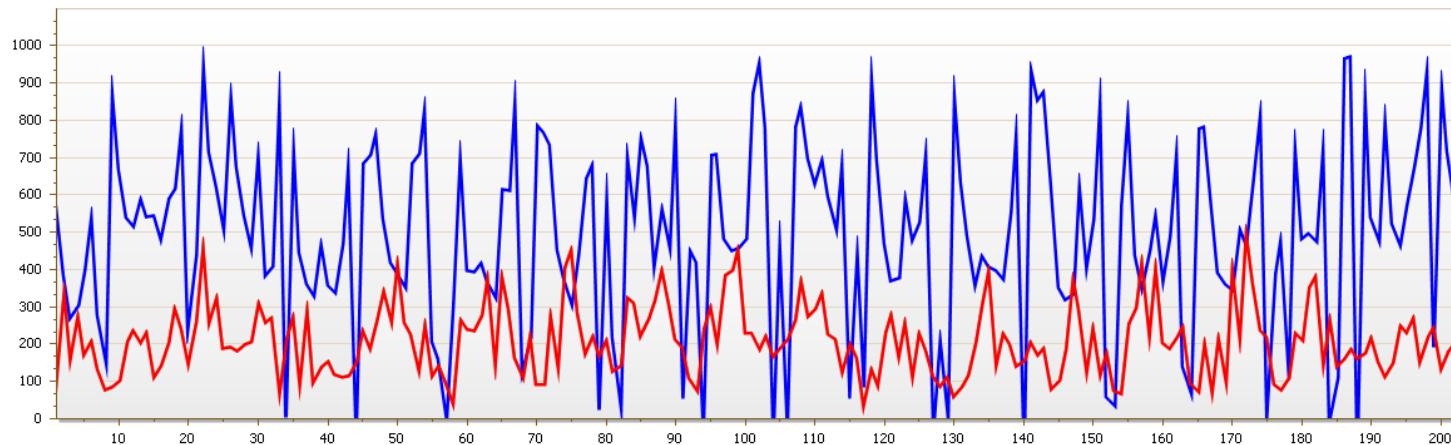


Effect of Aleksandrovsk Bulgaria

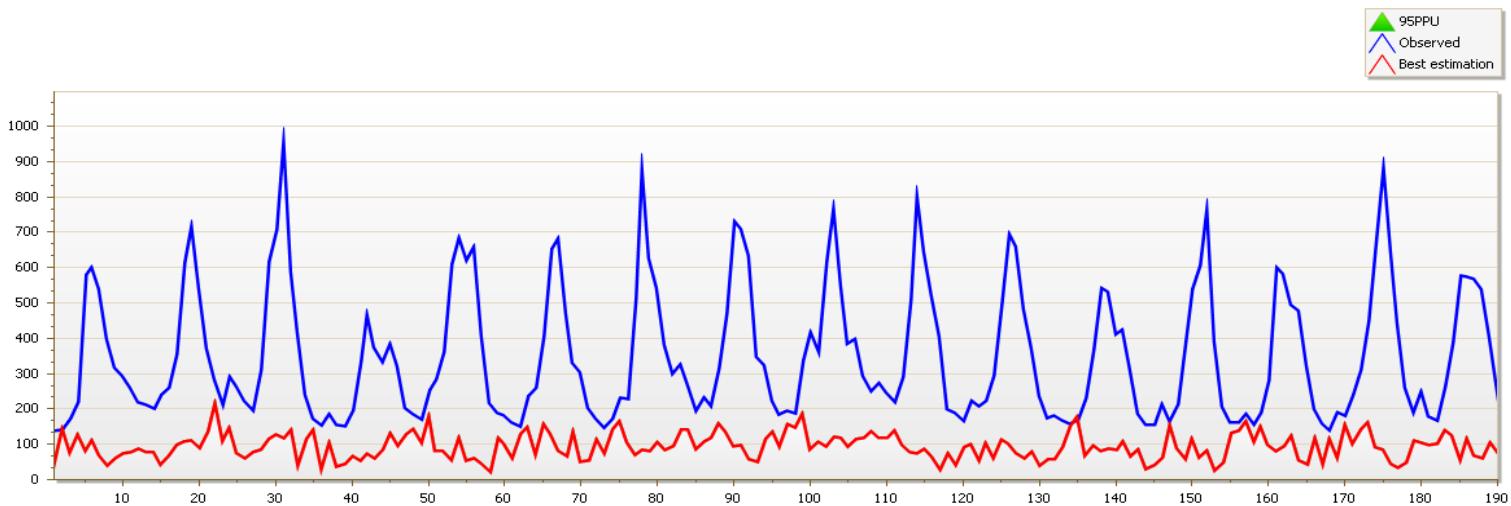


q_7460

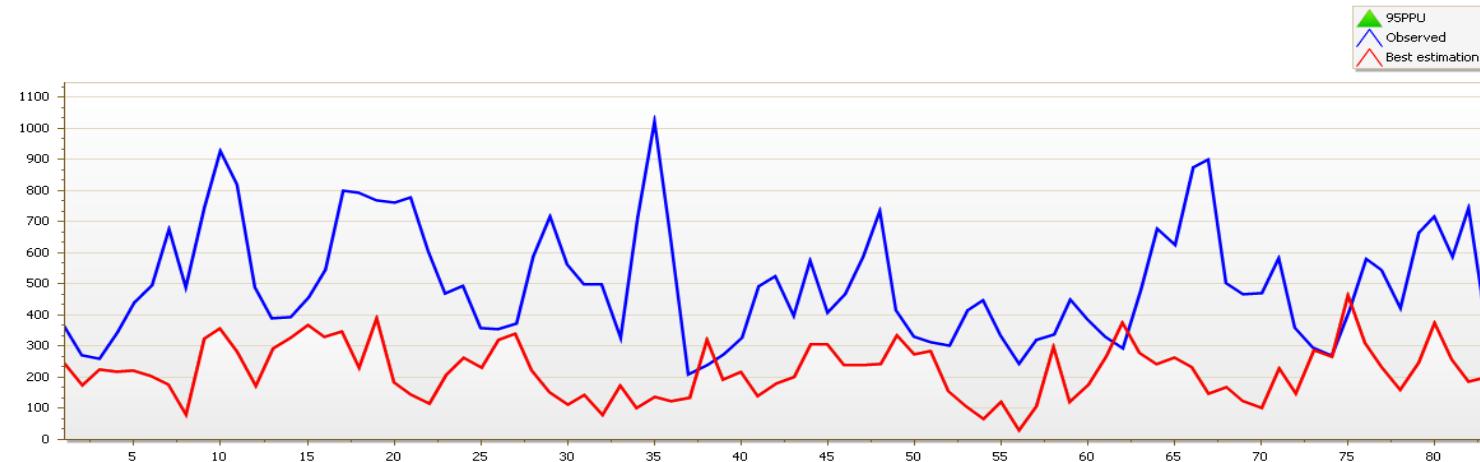
95PPU
Observed
Best estimation



q_8136

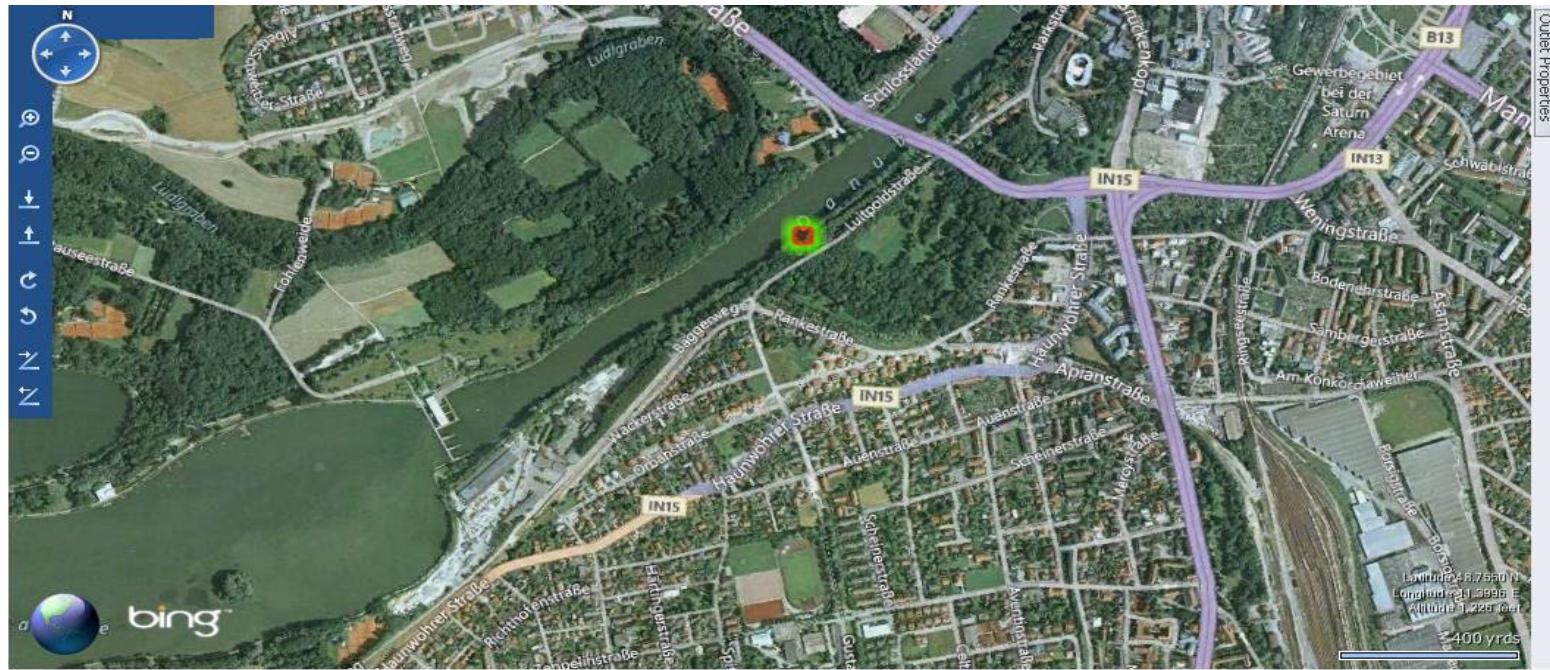
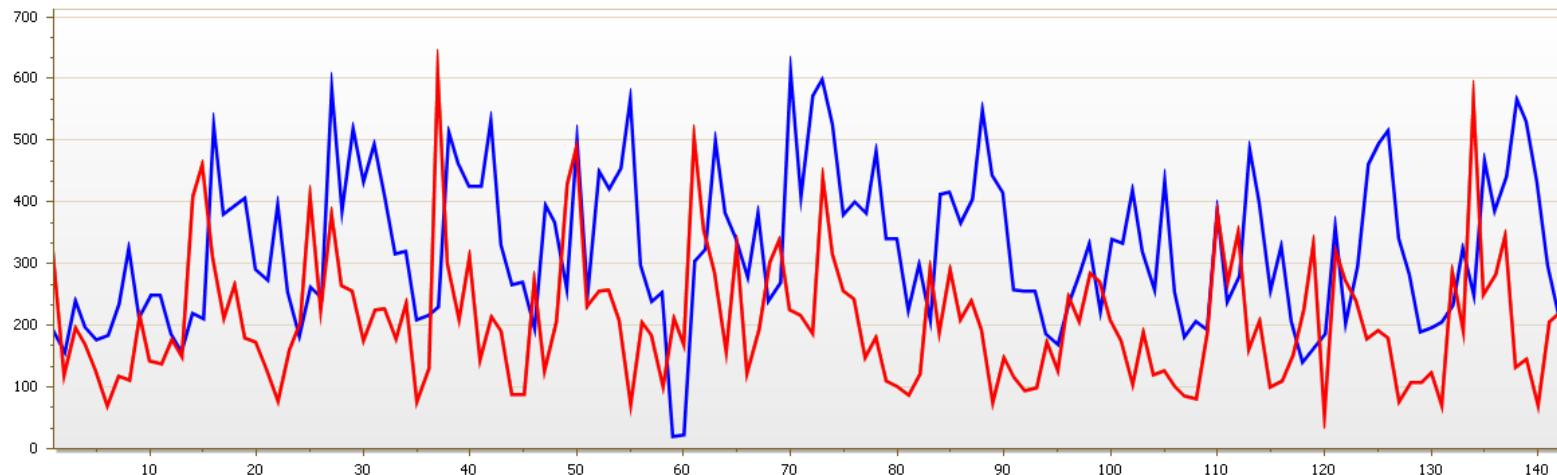


q_9977



q_7144

95PPU
Observed
Best estimation



2. Calibration

Also known as parameter fitting, inverse modeling, parameter estimation, history matching

- Calibration is adjusting model inputs with the purpose of achieving the best simulation match with observation
- Therefore, calibration boils down to the optimization of an objective function

Min:
$$g(B) = \sum_{i=1}^{n_1} (Q_o - Q_s)_i^2$$



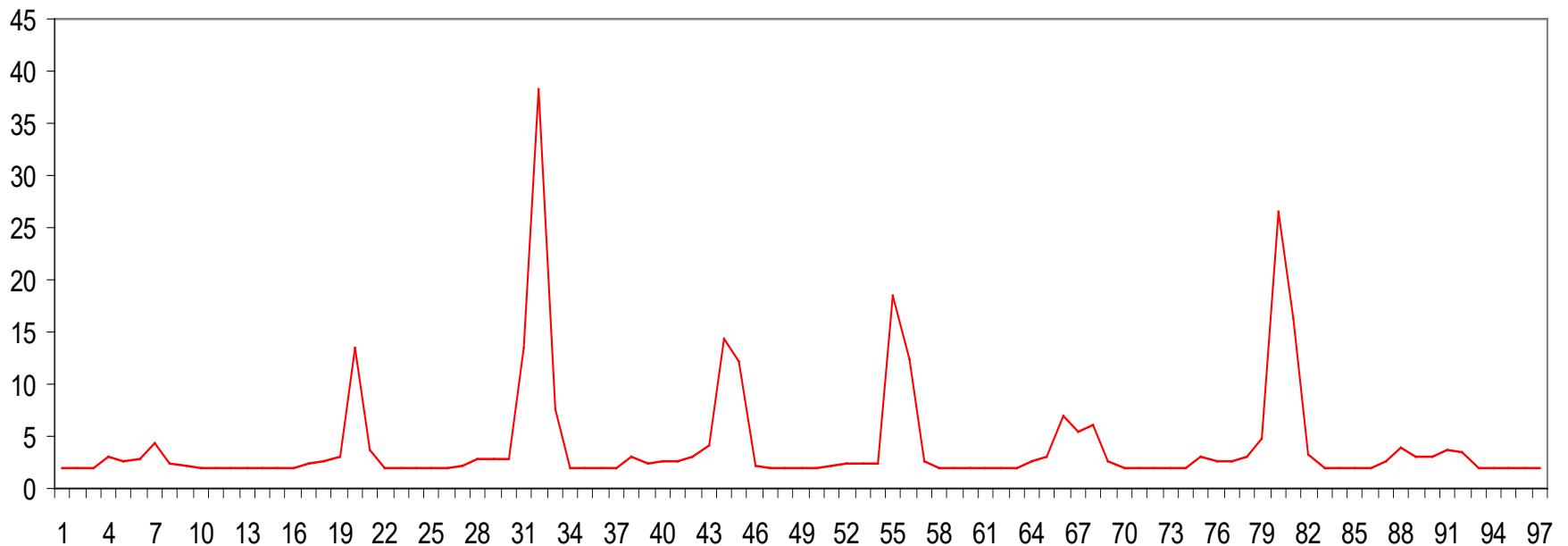
2. Uncertainty analysis

Uncertainty analysis is the process of:

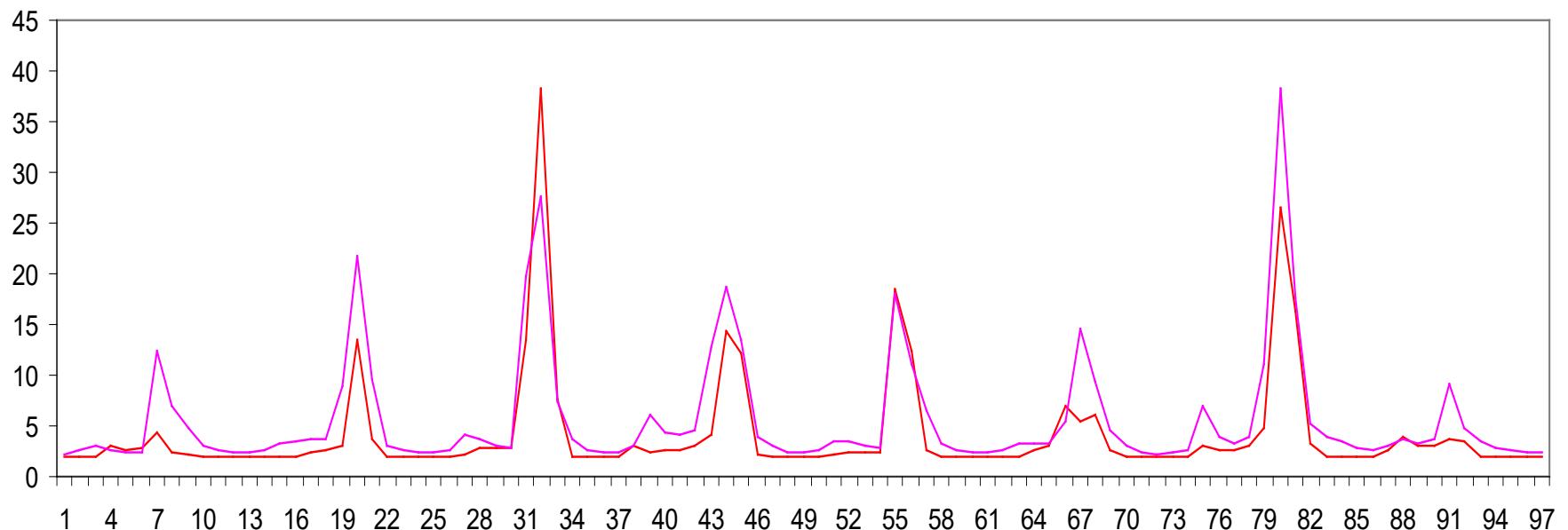
- Quantifying and propagating the errors/uncertainties in the model inputs – data, parameters
- Contrary to the belief that calibration is different from uncertainty analysis, calibration, and uncertainty are intimately linked



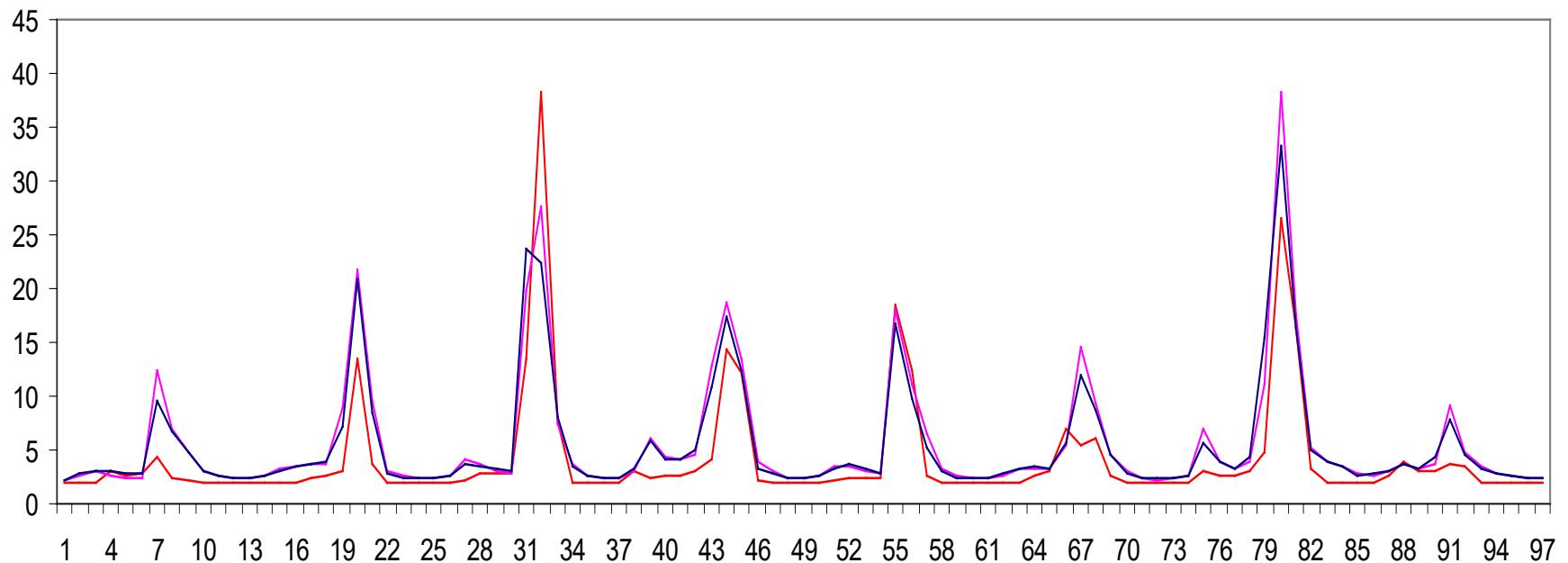
Calibration is subjective



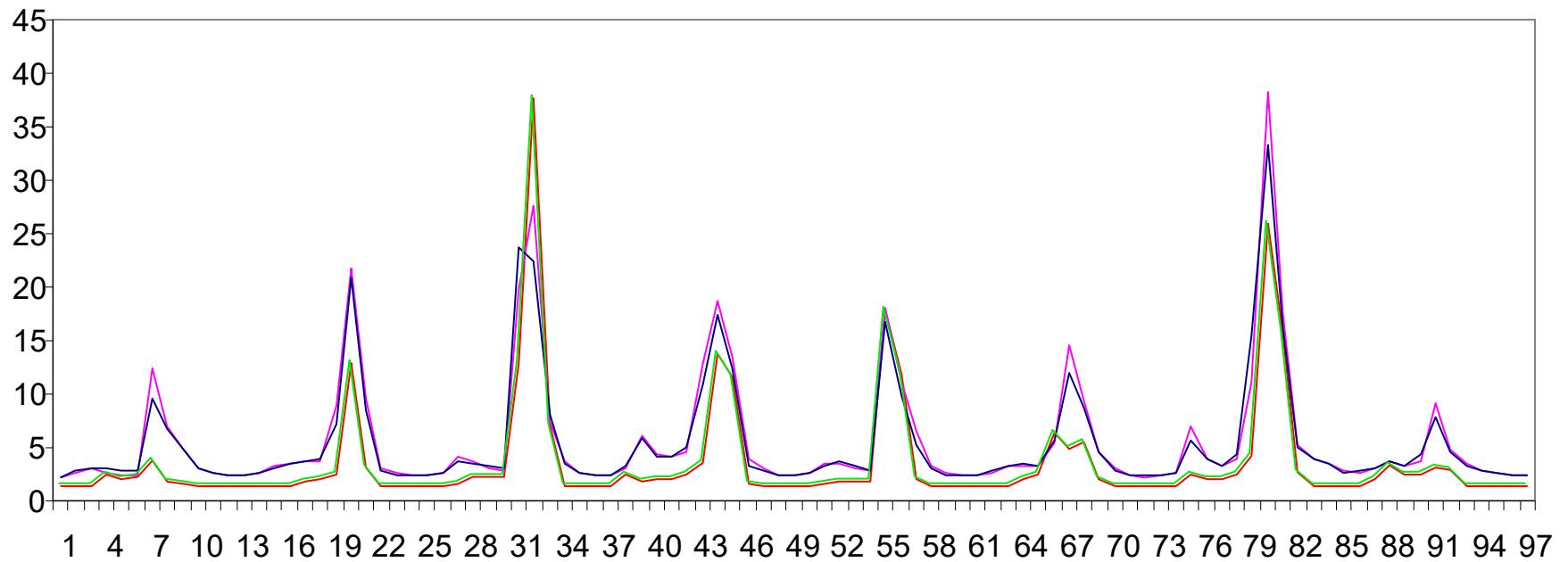
Calibration is subjective



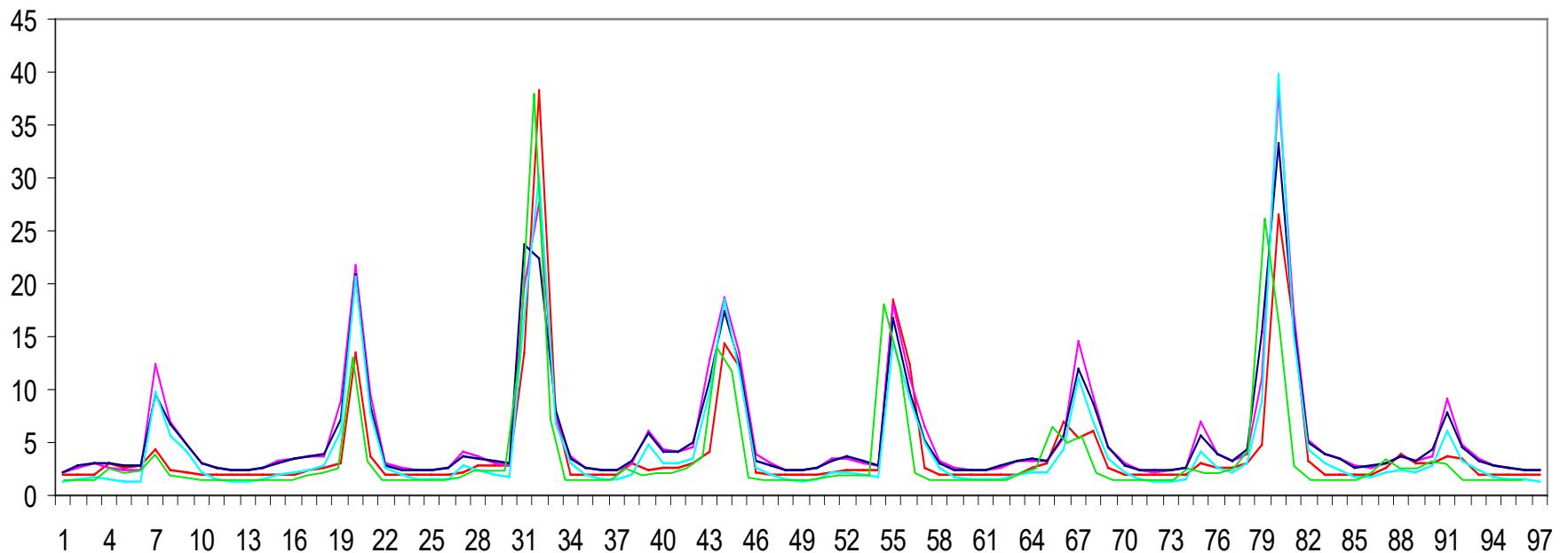
Calibration is subjective



Calibration is subjective



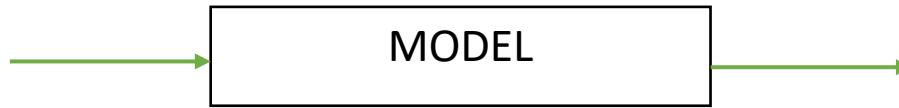
Calibration is subjective



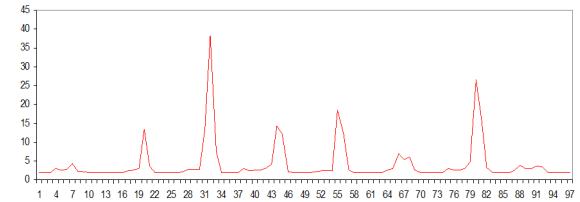
Stochastic vs Deterministic

- Deterministic Modelling

single-valued
input parameters

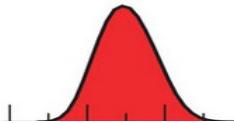


single-valued
output variables

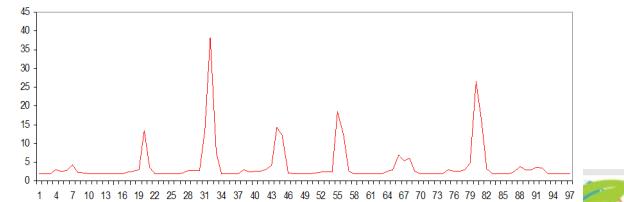


- Calibration (Stochastic Modelling)

distribution
of input parameters



distribution of
output variables



3. Validation

- Validation is the process of testing the calibrated parameters with an independent set of data without further changes to the parameters or model structure



3. Validation

- For validation you have to use the same range of parameters as the calibration

To select validation data:

- The data used for validation should have almost the same statistics as the data used for calibration (mean, standard deviation)



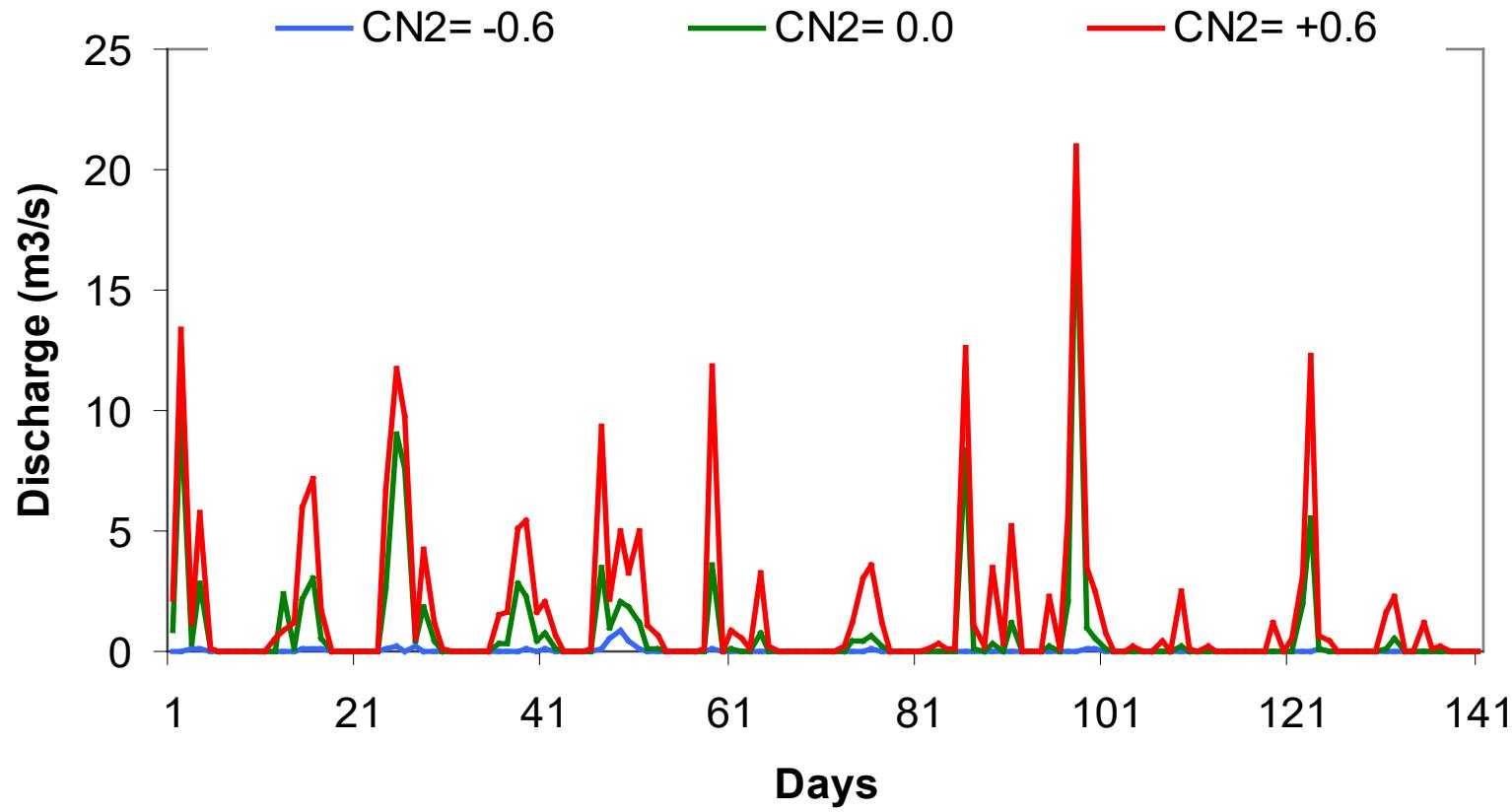
4. Sensitivity analysis

- Sensitivity analysis is the process of determining the significance of one or a combination of parameters w.r.t the objective function or a model output
- this is important because parameters represent processes, and we want to know what important processes are



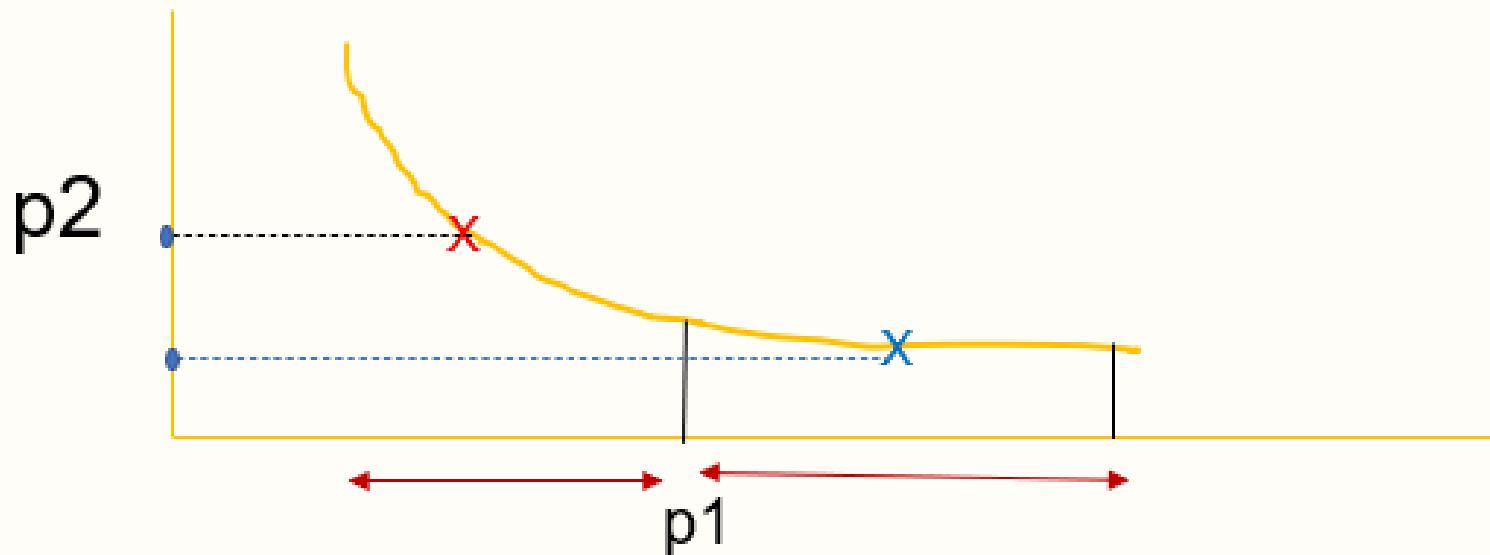
4. Sensitivity analysis

Sensitivity to CN2



4. Sensitivity analysis - one-at-a-time

- Local (one-at-a-time) sensitivity analysis



4. Sensitivity analysis - global

- Global sensitivity analysis

$$g = \alpha + \sum_{i=1}^m \beta_i b_i$$

Where b 's are parameters

- A t-test is then used to identify the relative significance of each parameter b_i
- This gives relative sensitivities based on linear approximations and, hence, only provides partial information about the sensitivity of the objective function to model parameters
- In this analysis, the larger, in absolute value, the value of the t-stat, and the smaller the p-value, the more sensitive the parameter



Modeling steps

- 1- Model building
- 2- Calibration and uncertainty analysis
- 3- Validation
- 4- Sensitivity analysis

.....Post calibration analysis.....

- 5- Model application (climate/landuse change analysis, BMPs, etc.)
- 6- Risk analysis



5. Climate / Landuse change (www.2w2e.com)



2W2E GmbH
Water Weather Energy Ecosystem

Products About Contact

Sign out

Climate Change Data for SWAT model (CMIP5) [ReadMore](#)

Select Area

From Latitude

To Latitude

From Longitude

To Longitude

Select Models

GFDL-ESM2M

HadGEM2-ES

IPSL-CM5A-LR

MIROC

NoerESM1-M

Select Scenarios

RCP2.6 (2006-2099)

RCP4.5 (2006-2099)

RCP6.0 (2006-2099)

RCP8.5 (2006-2099)

historical (1950-2005)

Select Data Type

Precipitation

Temperature



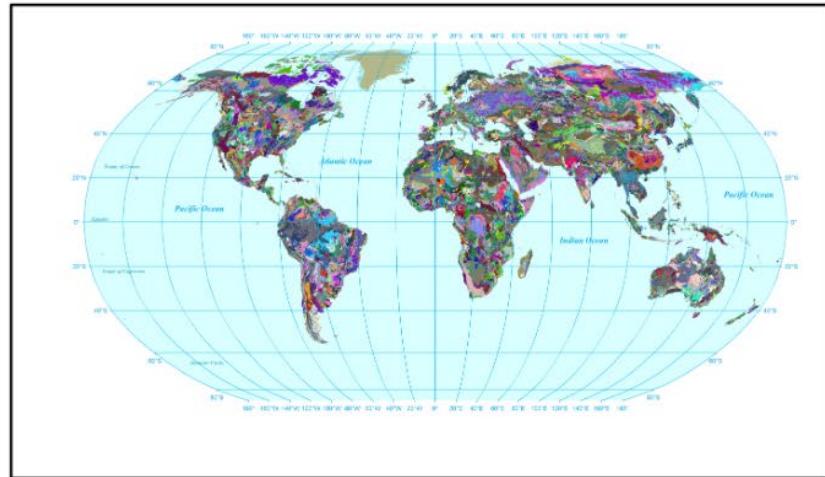
Global_Soil_FAO-UNESCO

The world's FAO/UNESCO soil map was prepared using the topographic map series of the American Geographical Society of New York at a nominal scale of 1:5,000,000, consisting of a 30 cm topsoil layer and a 70 cm subsoil layer.

Associated files include: "Lookup_Soil_FAO-UNESCO.txt", and "SWAT2012.mdb". These files are directly usable in ArcSWAT models. The database contains parameters from 4,932 soil units globally.

The provided soil map has the "WGS-84 Spatial reference" without projection. The users will have to project this map before using it in ArcSWAT or QSWAT.

Download related article from "Nature Scientific Data":

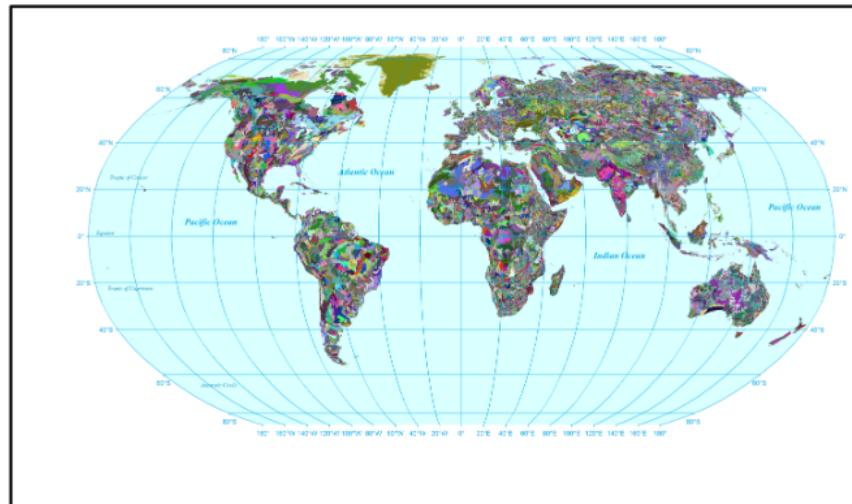


Global_Soil_HWSD(v121)

The Food and Agriculture Organization of the United Nations (FAO) and the International Institute for Applied Systems Analysis (IIASA) combined the available regional and national soil information with the information already contained within the 1:5,000,000 scale FAO-UNESCO map into a new comprehensive Harmonized World Soil Database (HWSD_v121) at a resolution of about 1 km (30 arc seconds) consisting of a 30 cm topsoil layer, and a 70 cm subsoil layer.

Associated files include: "Lookup_Soil_HWSD(v121).txt", and "SWAT2012.mdb". These files are directly usable in ArcSWAT models. The database contains parameters from 16,328 soil units globally.

The provided soil map has the "WGS-84 Spatial reference" without projection. The users will have to project this map before using it in ArcSWAT or QSWAT.



GlobeCover

The Globcover global Land Cover map is a European Space Agency initiative to develop global composites and land cover maps using input observations from the 300m MERIS sensor onboard the ENVISAT satellite mission.

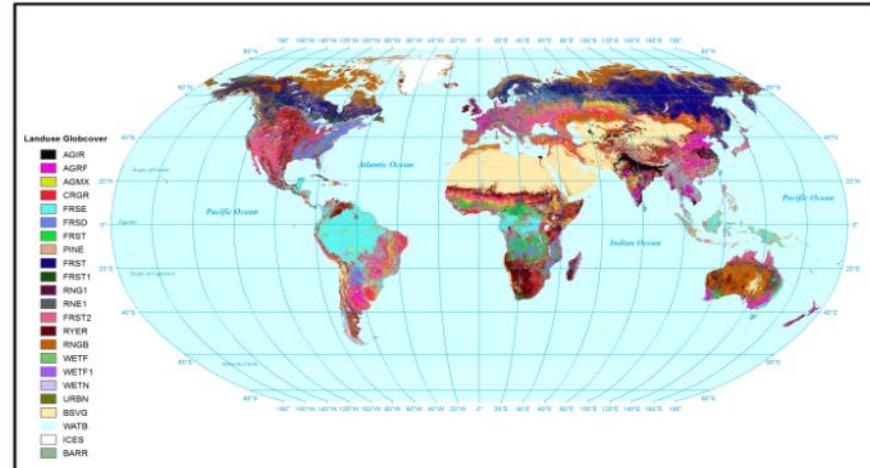
The Globcover covered December 2004 - June 2006 and was derived by an automatic and regionally tuned classification of a MERIS full resolution surface reflectance time series ([Link](#)).

The LandCover map contains 23 numerical classes corresponding to specific land cover types.

Associated files include: "Lookup_Landuse_Globcover.txt", and "SWAT2012.mdb".

Download related article from "Nature Scientific Data":

<https://www.nature.com/articles/s41597-019-0282-4>



Global Landuse USGS

Global Land Cover Characterization (GLCC) (Global_Landuse_USGS) is a land cover classification dataset based primarily on the unsupervised classification of 1-km AVHRR (Advanced Very High-Resolution Radiometer) 10-day NDVI (Normalized Difference Vegetation Index) composites.

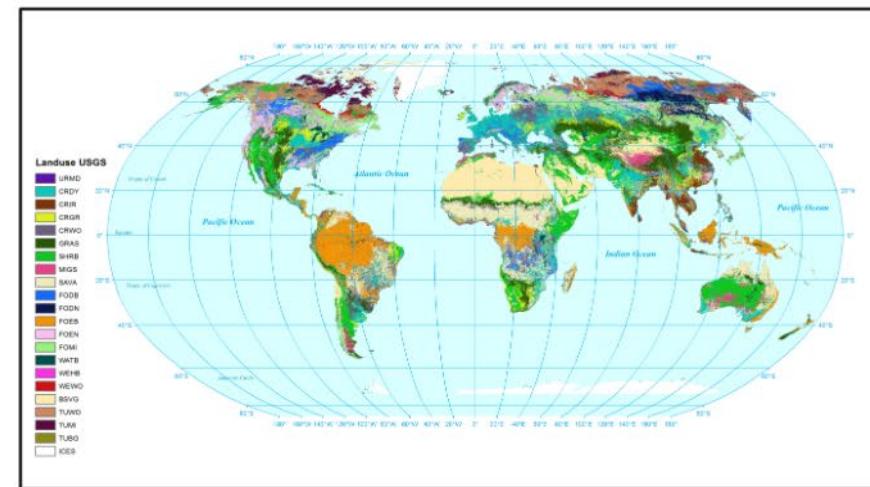
The AVHRR source imagery dates from April 1992 through March 1993 ([Link](#)).

The GLCC contains 22 numerical classes corresponding to specific land cover types.

Associated files include: "Lookup_Landuse_USGS.txt", and "SWAT2012.mdb".

Download related article from "Nature Scientific Data":

<https://www.nature.com/articles/s41597-019-0282-4>



5. Climate/landuse change analysis

A toolkit for climate change analysis and pattern recognition for extreme weather conditions – Case study: California-Baja California Peninsula

Saeid Ashraf Vaghefi, Nazanin Abbaspour, Bahareh Kamali, Karim C. Abbaspour
Environmental Modelling & Software, 217;96:181-198
<https://doi.org/10.1016/j.envsoft.2017.06.033>

Water Resources of the Black Sea Catchment under Future Climate and Landuse Change Projections

Elham Rouholahnejad, Karim C. Abbaspour, Anthony Lehmann
Water 2017, 9(8), 598; <https://doi.org/10.3390/w9080598>

Spatiotemporal Modelling of Water Balance Components in Response to Climate and Landuse Changes in a Heterogeneous Mountainous Catchment

Tayebzadeh Moghadam, N., Abbaspour, K.C., Malekmohammadi, B. et al. Water Resour Manage 35, 793–810 (2021). <https://doi.org/10.1007/s11269-020-02735-w>



5. Climate/landuse change analysis

Assessing the impact of climate change on water resources in Iran

Karim C. Abbaspour, Monireh Faramarzi, Samaneh Seyed Ghasemi, Hong Yang

Water Resources Research, 2009;45(10).

<https://doi.org/10.1029/2008WR007615>

Analyses of the impact of climate change on water resources components, drought and wheat yield in semiarid regions: Karkheh River Basin in Iran

S. Ashraf Vaghefi, S. J. Mousavi, K. C. Abbaspour, R. Srinivasan, H. Yang

Water 2017, 9(8), 598; <https://doi.org/10.1002/hyp.9747>

Optimal water allocation of the Zayandeh-Roud Reservoir in Iran based on inflow projection under climate change scenarios

Fatemeh Saedi; Azadeh Ahmadi; Karim C. Abbaspour. Journal of Water and Climate Change (2021) 12 (5): 2068–2081. <https://doi.org/10.2166/wcc.2021.219>



6. Risk analysis - Decision-making under uncertainty

$$Risk = Pr(F) \cdot Cost(F)$$

$Pr(F)$ = Probability of a threshold being exceeded in a system

$Cost(F)$ = cost of clean up, or increase or a decrease in uncertainty

A Guideline for Successful Calibration and Uncertainty Analysis for Soil and Water Assessment: A Review of Papers from the 2016 International SWAT Conference

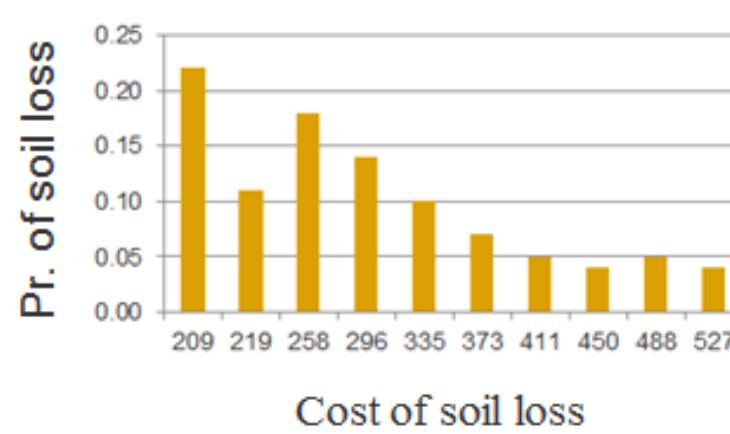
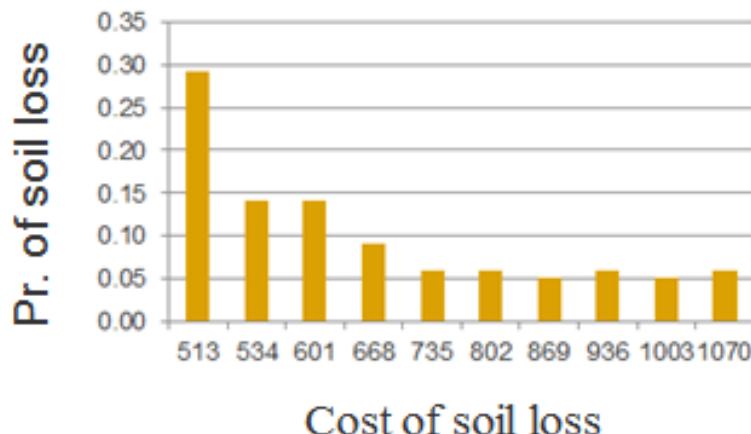
Karim C. Abbaspour, Saeid Ashraf Vaghefi, Raghvan Srinivasan. Water 2018, 10(1), 6;
<https://doi.org/10.3390/w10010006>



6. Risk analysis

Table 2. Statistics of cumulative distribution for soil loss resulting from model uncertainty.

Before Terracing				After Terracing				
Soil Loss (tn ha ⁻¹)	Cost of Soil Loss (\$ ha ⁻¹)	Prob. of Soil Loss	Risk of Soil Loss (\$ ha ⁻¹)	Soil Loss (tn ha ⁻¹)	Cost of Soil Loss (\$ ha ⁻¹)	Prob. of Soil Loss	Risk of Soil Loss (\$ ha ⁻¹)	Gain (\$ ha ⁻¹)
513	5130	0.29	1501	209	2090	0.41	460	1041
534	5340	0.14	747	219	2190	0.59	241	506
601	6010	0.14	841	258	2580	0.72	464	376
668	6680	0.09	601	296	2960	0.78	414	187
735	7350	0.06	441	335	3350	0.86	335	106
802	8020	0.05	481	373	3730	0.91	261	220
869	8690	0.05	434	411	4110	0.94	206	229
936	9360	0.06	562	450	4500	0.95	180	382
1003	10,030	0.05	502	488	4880	0.98	244	258
1070	10,700	0.06	642	527	5270	1.00	211	431
Expectation				6751			3016	3735



6. Risk analysis - Decision-making under uncertainty

7. Compare two distributions (Zscore)

https://www.youtube.com/watch?v=X6A90J1M_cQ

8. Decision making under uncertainty

<https://www.youtube.com/watch?v=eMCzhWUra8M>

9(1). Risk analysis under uncertainty (Terrasing and soil loss)

<https://www.youtube.com/watch?v=iKWI2f4Y7I8>

9(2). Risk analysis under uncertainty (Terrasing and soil loss)

<https://www.youtube.com/watch?v=-E7wZfXuknM>

Design Filter Strip under uncertainty

<https://www.youtube.com/watch?v=WJN4LhXBAfU&t=374s>

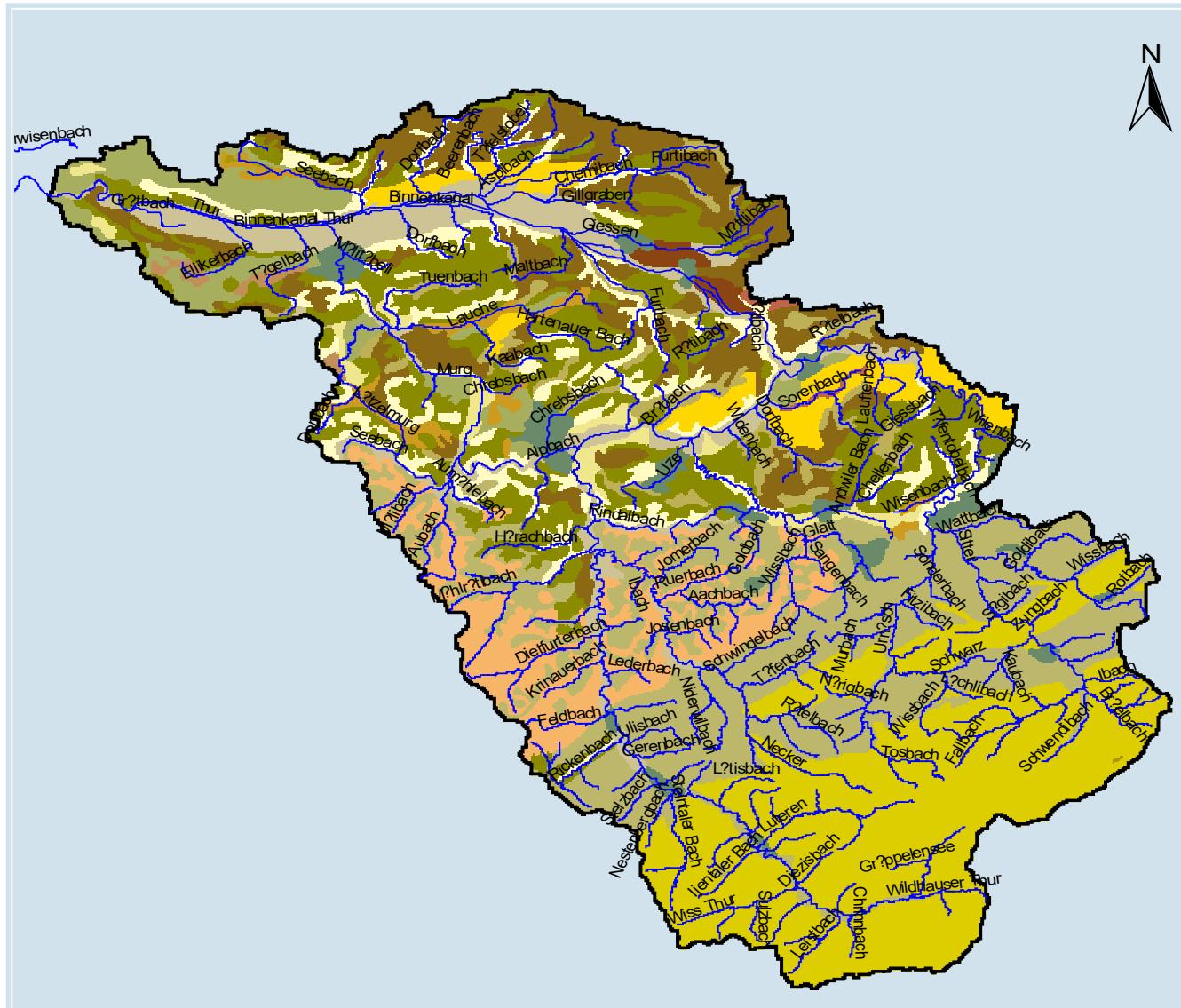
Issues w.r.t. calibration of distributed watershed models

- Parameterization (regionalization of parameters)
(most important, difficult, and neglected aspect of calibration)
 - Objective function definition
(most surprising aspect of calibration)
 - Optimization algorithm
(most confusing aspect of calibration)
 - Non-uniqueness (Uncertainty)
(most difficult part to quantify and communicate)
 - Parameter conditionality
(most disappointing aspect of calibration)
 - Time constraint
(makes some projects impossible to build and run)
-
- Position of observed outlets
(causes the biggest headache in calibration)



Parameterization

- Which parameters to use?
- How to regionalize the parameters



Parameterization

X__<parname>.<ext>__<hydrogrp>__<solttext>__<landuse>__<subbsn>__<slope>

Where x=

v__ means the existing parameter value is replaced by a given value,

a__ means the given value is added to the existing parameter value, and

r__ means the existing parameter value is multiplied by (1+the given value);



Parameterization

Soil parameters

Parameter identifiers	Description
r_SOL_K(1).sol	K of Layer 1 of all HRUs
r_SOL_K(1-3).sol	K of Layer 1,2,3 of all HRUs
r_SOL_K().sol	K of All layers and all HRUs
r_SOL_K(1).sol_FSL	K of layer 1 of HRUs with soil texture FSL
r_SOL_K(1).sol_FSL_PAST	K of layer 1 of HRUs with soil texture FSL and landuse PAST
r_SOL_K(1).sol_FSL_PAST_1-3	K of layer 1 of subbasin 1,2, and 3 with HRUs containing landuse PAST
v_SOL_K(1).sol_FSL_PAST_0-10	K of layer 1 for HRUs with slope 0-10



Parameterization

Management parameters

Parameter identifiers	Description
v__HEAT_UNITS{rotation no,operation no}	Management parameters that are subject to operation/rotation must have both specified
v__CNOP{[],1}.mgt	change an operation's parameters in all rotations [] means every rotation that has the specified operation.
v__CNOP{2,1,plant_id=33}.mgt v__CNOP{[],1,plant_id=33}.mgt	Operation filters could be applied as shown The changes are applied to crop 33 only
v__CNOP{[],1,plant_id=33}.000010001.mgt	To modify just one file, it could be given as shown



Parameterization

Crop parameters

Parameter identifiers	Description
V__T_OPT{30}.CROP.DAT	Parameter T_OPT for crop number 30 in the crop.dat file
v__PLTNFR(1){3}.CROP.DAT	Nitrogen uptake parameter #1 for crop number 3 in crop.dat file



Parameterization

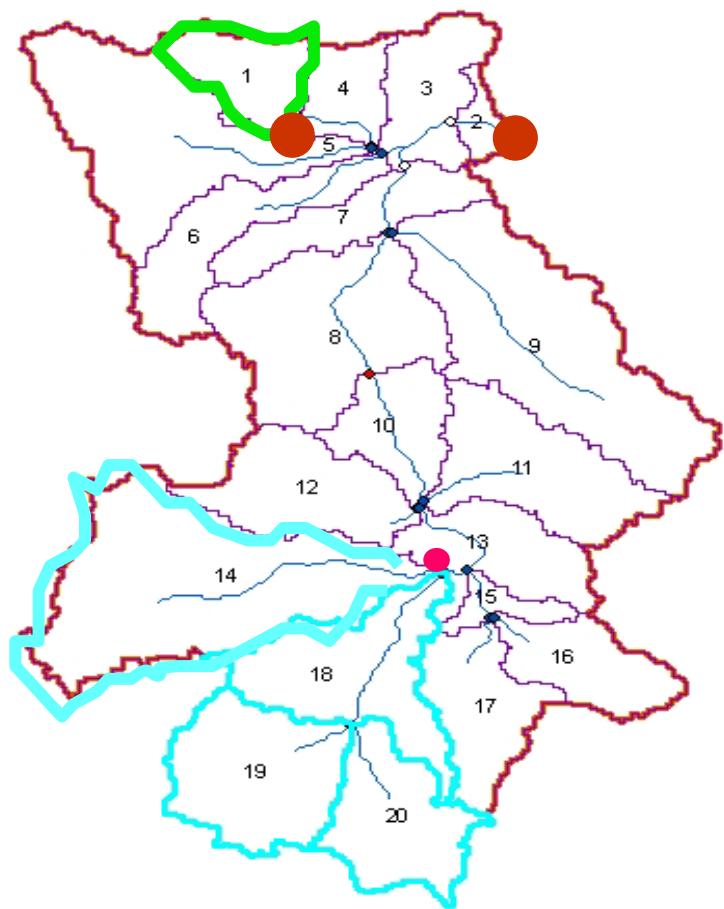
Rainfall parameters

Parameter identifiers	Description
v_precipitation(1){1977300}.pcp1.pcp	(1) means column number 1 in the pcp file {1977300} specifies year and day
v_precipitation(1-3){1977300}.pcp1.pcp	(1-3) means column 1, 2, and3 {1977300} specifies year and day
v_precipitation(){1977300,1977301}.pcp	() means all columns (all stations) {1977300,1977301} means 1977 days 300 and 301
v_precipitation(){1977001-1977361,1978001-1978365,1979003}.pcp	() means all columns from day 1 to day 361 of 1977, and from day 1 to day 365 of 1978, and day 3 of 1979



Parameterization

r_HRU_SLP.hru	14,18,19,20	0	0.3
r_OV_N.hru	14,18,19,20	0	-0.5
r_SLSUBBSN	14,18,19,20	-0.5	-0.2
r_CN2.mgt	14,18,19,20	-0.3	-0.1
r_SOL_BD().sol	14,18,19,20	-0.2	0.01
r_SOL_AWC().sol	14,18,19,20	0.1	0.3
r_CN2.mgt	1	0.0	0.2
r_SOL_BD().sol	1	0.0	0.3
r_SOL_AWC().sol	1	-0.5	-0.3
r_CN2.mgt	2-17	-0.25	0.0
r_SOL_BD().sol	2-17	-0.02	0.01
r_SOL_AWC().sol	2-17	-0.5	-0.3



Issues w.r.t. calibration of distributed watershed models

- Parameterization (regionalization of parameters)
(most important, difficult, and neglected aspect of calibration)
 - Objective function definition
(most surprising aspect of calibration)
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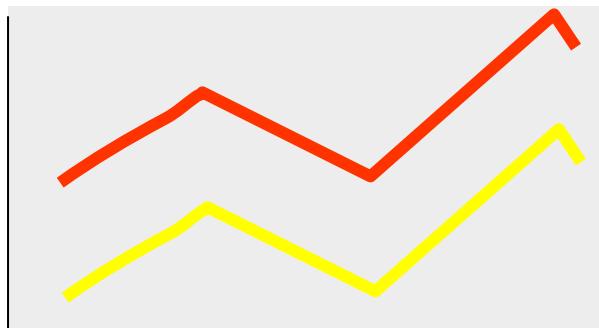
Objective function

Different objective functions produce different calibration results

1=mmse Minimize:
$$g = \frac{\sum_i (\mathcal{Q}_m - \mathcal{Q}_s)_i^2}{n_Q} * \frac{\sum_i (S_m - S_s)_i^2}{n_S} * \frac{\sum_i (N_m - N_s)_i^2}{n_N} * \dots$$

2=smse Minimize:
$$g = w_1 \sum_{i=1}^{n_1} (\mathcal{Q}_m - \mathcal{Q}_s)_i^2 + w_2 \sum_{i=1}^{n_2} (S_m - S_s)_i^2 + w_3 \sum_{i=1}^{n_3} (N_m - N_s)_i^2 + \dots$$

3=R² Maximize:
$$R^2 = \frac{\left[\sum_i (\mathcal{Q}_{m,i} - \bar{\mathcal{Q}}_m)(\mathcal{Q}_{s,i} - \bar{\mathcal{Q}}_s) \right]^2}{\sum_i (\mathcal{Q}_{m,i} - \bar{\mathcal{Q}}_m)^2 \sum_i (\mathcal{Q}_{s,i} - \bar{\mathcal{Q}}_s)^2}$$



Objective function

4=Chi2 Minimize:

$$\chi^2 = \frac{\sum_i (Q_m - Q_s)_i^2}{\sigma_m^2}$$

5=NS Maximize:

$$NS = 1 - \frac{\sum_i (Q_m - Q_s)_i^2}{\sum_i (Q_{m,i} - \bar{Q}_m)^2}$$

6=bR² Maximize:

$$\phi = \begin{cases} |b|R^2 & \text{if } |b| \leq 1 \\ |b|^{-1}R^2 & \text{if } |b| > 1 \end{cases}$$

7=SSQR Minimize:

$$SSQR = \frac{1}{n} \sum_{i=1}^n [Q_{i,m} - Q_{i,s}]^2$$

8. PBIAS Minimize:

$$PBIAS = 100 * \frac{\sum_{i=1}^n (Q_m - Q_s)_i}{\sum_{i=1}^n Q_{m,i}}$$



Objective function

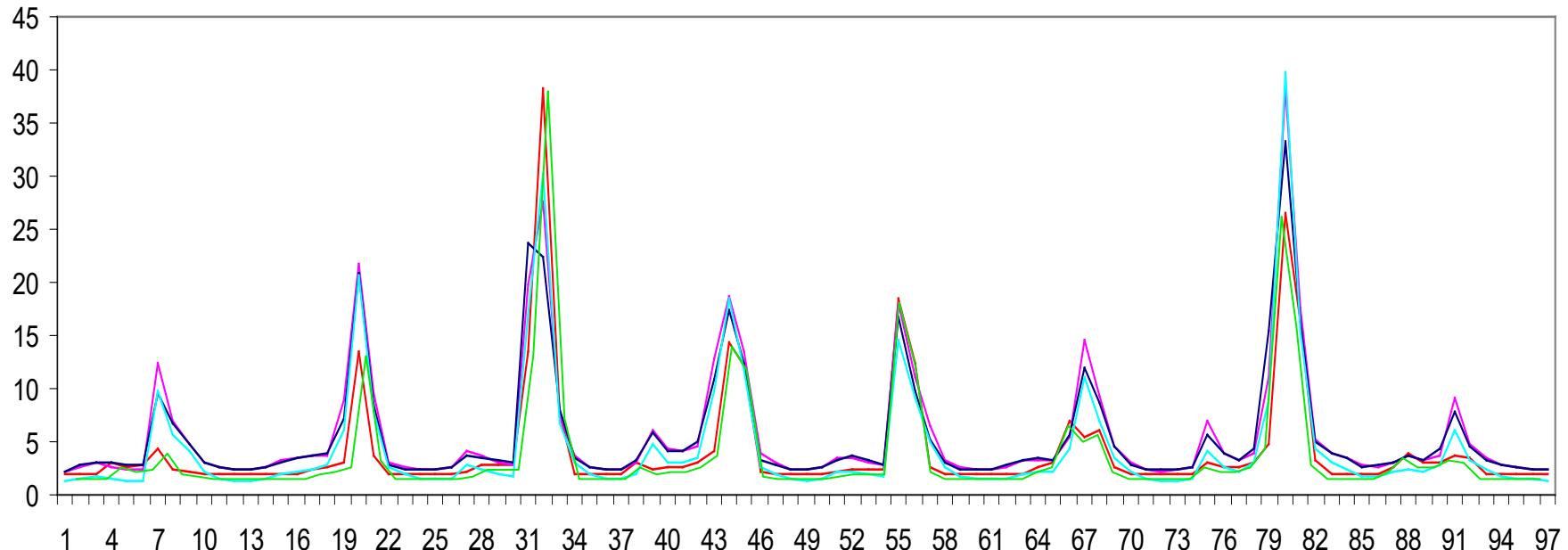
9. KGE Maximize: $KGE = 1 - \sqrt{(r - 1)^2 + (\alpha - 1)^2 + (\beta - 1)^2}$

10. RSR Minimize: $RSR = \frac{\sqrt{\sum_{i=1}^n (Q_m - Q_s)_i^2}}{\sqrt{\sum_{i=1}^n (Q_{m,i} - \bar{Q}_m)^2}}$

11. MNS Maximize: $MNS = 1 - \frac{\sum_i |Q_m - Q_s|_i^p}{\sum_i |Q_{m,i} - \bar{Q}_m|_i^p}$



Calibration is subjective - objective function



	RMSE	R2	NS	bR2
S1	29.90	0.79	0.67	0.54
S2	29.70	0.90	0.67	0.42
S3	23.50	0.84	0.83	0.58
S4	21.10	0.75	0.80	0.62
S5	23.30	0.84	0.80	0.75



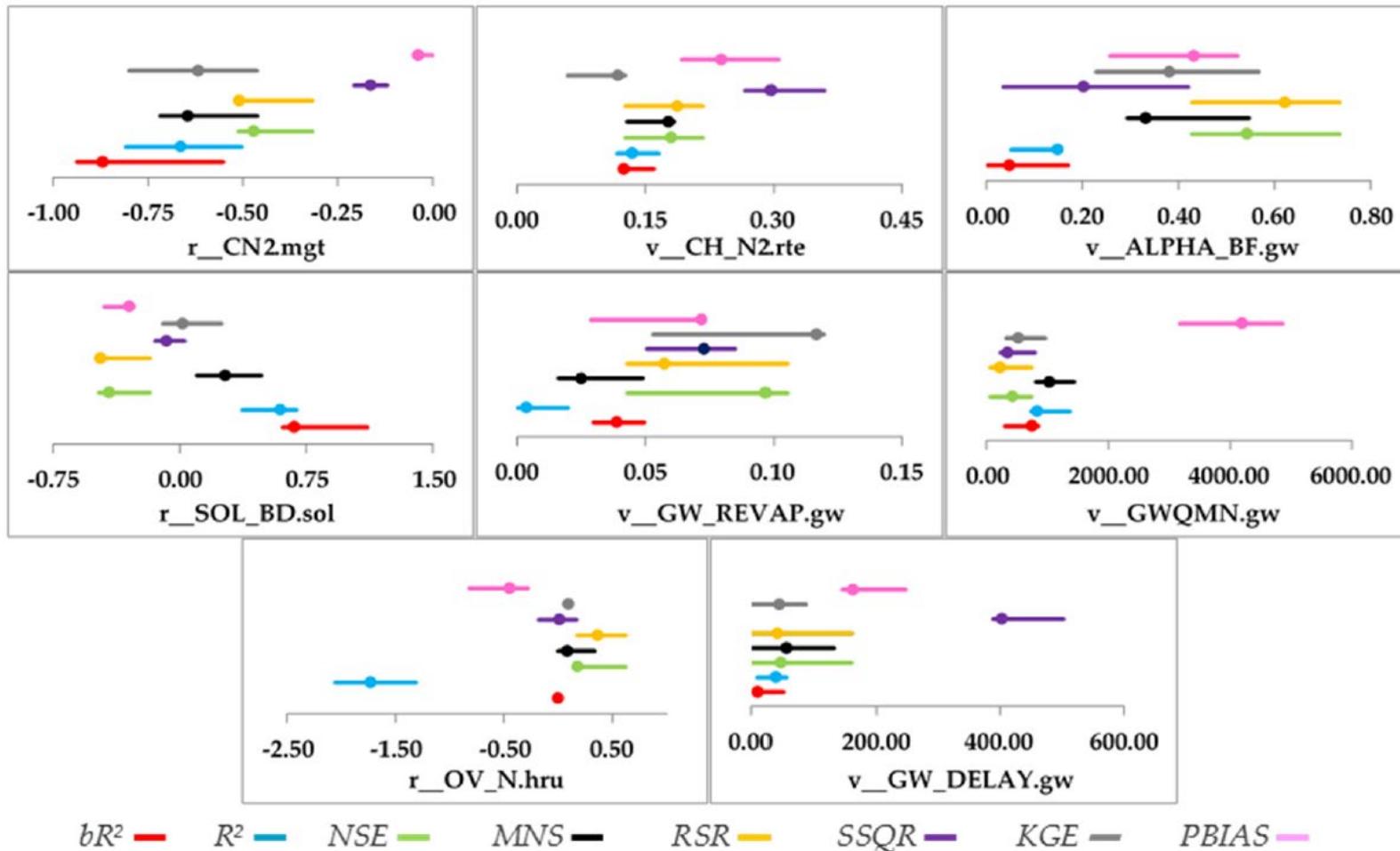
Objective function - parameters

	CN2	ALPHA_BF	REVAPMN	GW_REVAP	RCHRG_DP	SOL_AWC	SOL_K	SOL_BD
s1	-0.206	0.25	83.46	0.059	0.095	-0.195	0.572	-0.135
s2	0.110	0.59	66.06	0.056	0.191	-0.256	0.456	-0.191
s3	0.338	0.35	86.14	0.071	0.194	-0.047	0.300	0.086
s4	0.297	0.50	32.87	0.073	0.290	-0.165	0.297	-0.075
s5	0.115	0.40	55.87	0.032	0.101	-0.055	0.355	-0.032

	RMSE	R2	NS	bR2
S1	29.90	0.79	0.67	0.54
S2	29.70	0.90	0.67	0.42
S3	23.50	0.84	0.83	0.58
S4	21.10	0.75	0.80	0.62
S5	23.30	0.84	0.80	0.75



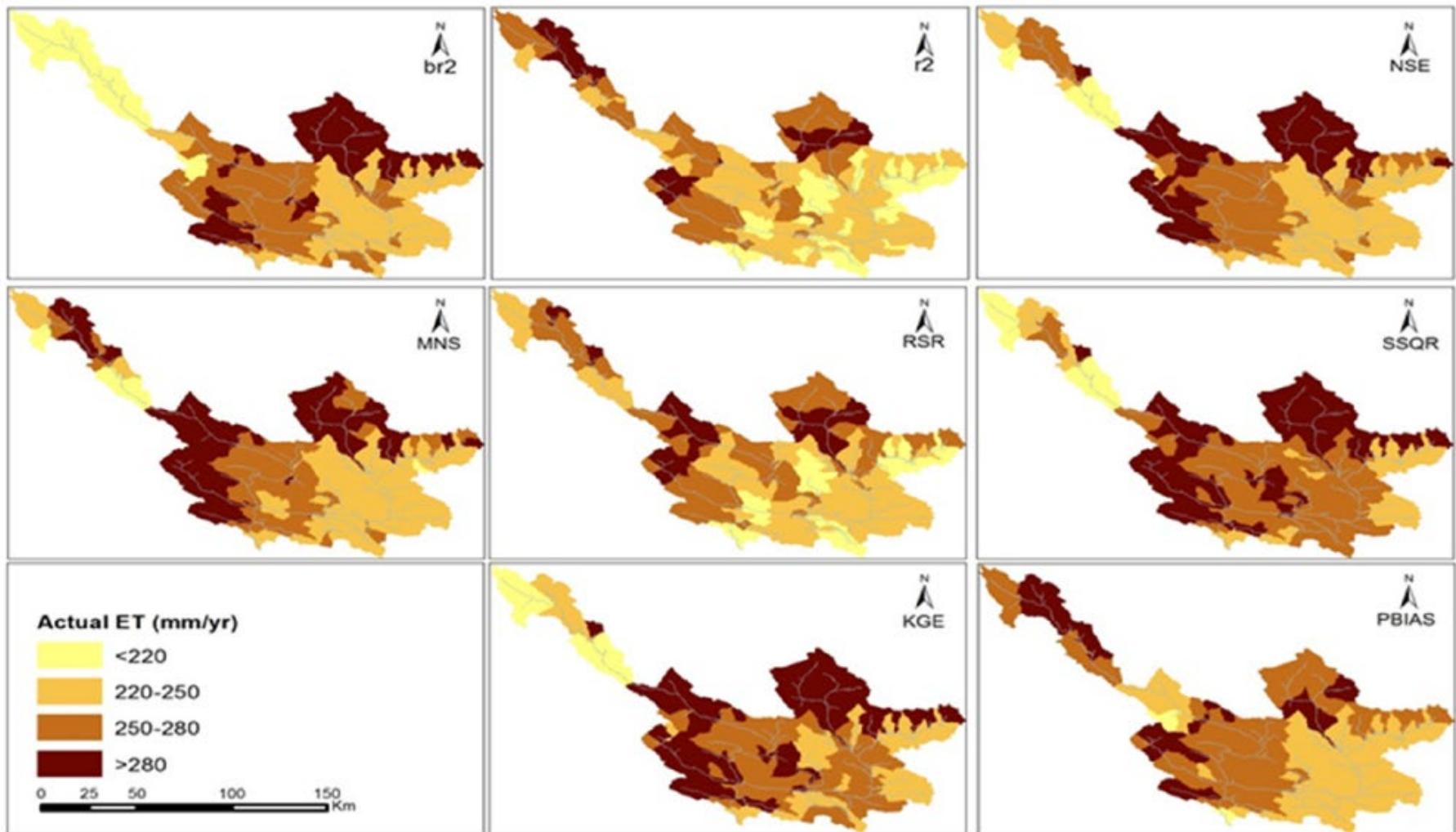
Impact of objective functions on calibrated parameters



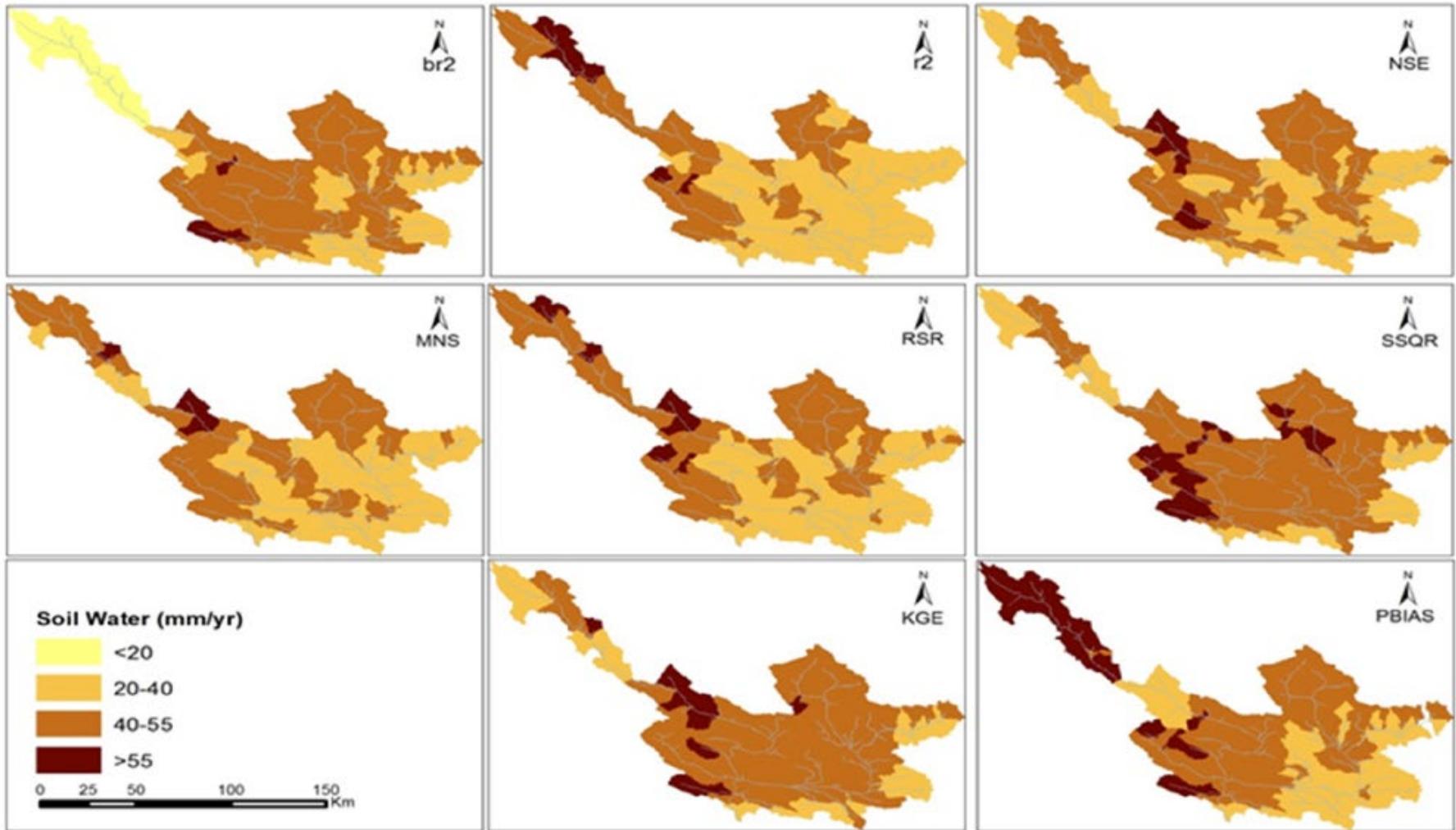
Sensitivity of Calibrated Parameters and Water Resource Estimates on Different Objective Functions and Optimization Algorithms

Houshmand et al., Water 2017, 9(6), 384; <https://doi.org/10.3390/w9060384>

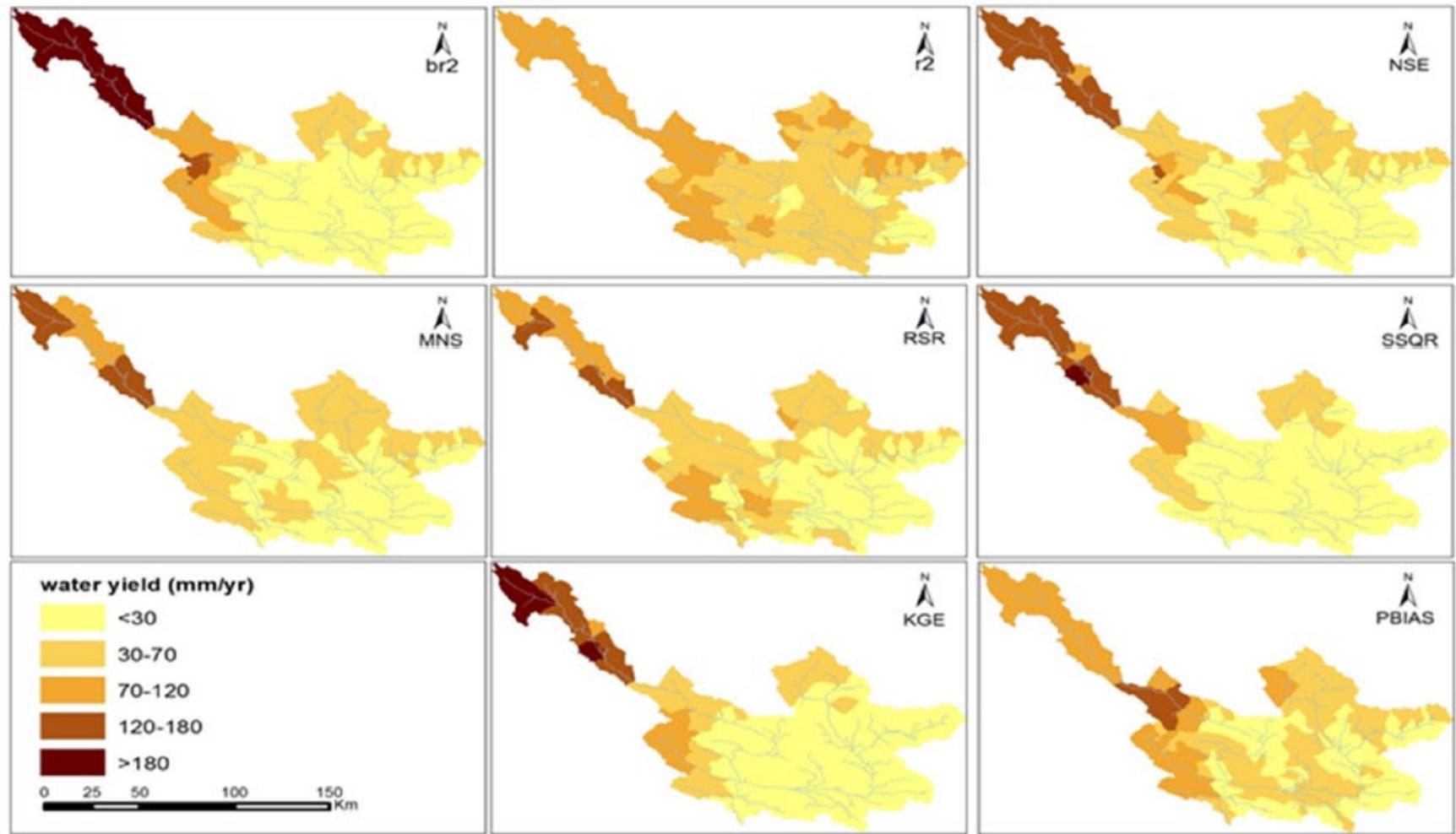
Impact of the objective function on AET



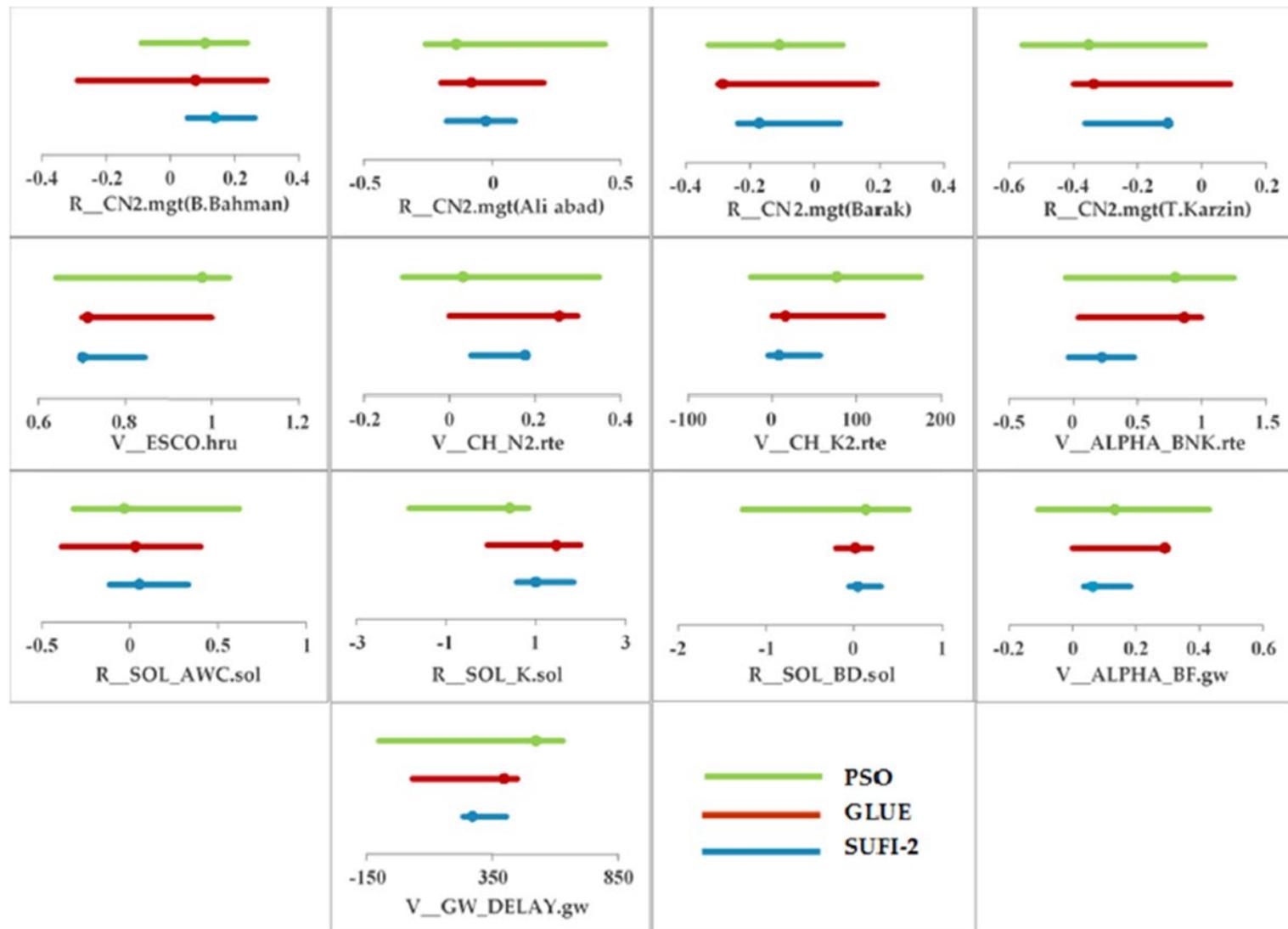
Impact of the objective function on soil water



Impact of the objective function on water yield



Impact of calibration algorithm on calibrated parameters



Impact of calibration algorithm on calibrated parameters

Criterion	GLUE	ParaSol	SUFI-2	Bayesian inference with cont. autoregr. error model	
				MCMC	IS
Goal function	Nash-Sutcliffe	Nash-Sutcliffe	Nash-Sutcliffe	post. prob. density	post. prob. density
a_CN2.mgt	-16.8 (-29.6, -9.8) ¹	-21.0 (-21.9, -20.1)	-26.9 (-30.0, -7.2)	-14.2 (-16.8, -11.6)	-19.60
v_ESCO.hru	0.76 (0.02, 0.97)	0.67 (0.65, 0.69)	0.82 (0.43, 1.0)	0.74 (0.63, 0.75)	0.62
v_EPCO.hru	0.22 (0.04, 0.90)	0.16 (0.13, 0.20)	1 (0.34, 1.0)	0.94 (0.39, 0.98)	0.27
r_SOL_K.sol	-0.16 (-0.36, 0.78)	-0.37 (-0.41, -0.34)	-0.1 (-0.58, 0.34)	-0.29 (-0.31, 0.78)	0.01
a_SOL_AWC.sol	0.11 (0.01, 0.15)	0.07 (0.08, 0.08)	0.07 (0.05, 0.15)	0.12 (0.1, 0.13)	0.05
v_ALPHA_BF.gw	0.12 (0.06, 0.97)	0.12 (0.08, 0.13)	0.51 (0.23, 0.74)	0.14 (0.11, 0.15)	0.91
v_GW_DELAY.gw	159.58 (9.7, 289.3)	107.7 (91.2, 115.2)	190.07 (100.2, 300)	25.5 (17.8, 33.3)	33.15
r_SLSUBBSN.hru	-0.45 (-0.56, 0.46)	-0.59 (-0.60, -0.58)	-0.52 (-0.60, 0.03)	-0.55 (-0.56, 0.15)	0.58
a_CH_K2.rte	78.19 (6.0, 144.8)	35.70 (27.72, 37.67)	83.95 (69.4, 150.0)	78.3 (68.0, 86.2)	147.23
a_OV_N.hru	0.05 (0.00, 0.20)	0.11 (0.07, 0.10)	0.06 (0.00, 0.11)	0.12 (0.00, 0.19)	0.08
² σ _{dry}	-	-	-	0.93 (0.81, 1.10)	0.87
² σ _{wet}	-	-	-	2.81 (2.4, 3.9)	2.30
² τ _{dry}	-	-	-	38.13 (29.5, 53.8)	28.47
² τ _{wet}	-	-	-	3.42 (2.4, 8.0)	0.92
NS for cal (val)	0.80 (0.78)	0.82 (0.81)	0.80 (0.75)	0.77 (0.77)	0.64 (0.71)
R ² for cal (val)	0.80 (0.84)	0.82 (0.85)	0.81 (0.81)	0.78 (0.81)	0.70 (0.72)
³ p-factor cal(val)	79% (69%)	18% (20%)	84% (82%)	85% (84%)	-
⁴ d-factor cal(val)	0.65 (0.51)	0.08 (0.07)	1.03 (0.82)	1.47 (1.19)	-
Uncertainty described by parameter uncertainty	All sources of uncertainty	Parameter uncertainty only	All sources of uncertainty	Parameter uncertainty only	Parameter uncertainty only
Difficulty of implement.	very easy	easy	easy	more complicated	more complicated
N _u	Comparing uncertainty analysis techniques for a SWAT application to the Chaohe Basin in China Yang et al., 2008: 1-23. https://doi.org/10.1016/j.jhydrol.2008.05.012				

Issues w.r.t. calibration of distributed watershed models

- Parameterization
(most important, difficult, and neglected aspect of calibration)
 - Objective function definition
(most surprising aspect of calibration)
 - Optimization algorithm
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(most difficult part to quantify and communicate)
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(most disappointing aspect of calibration)
 - Time constraint
(makes some projects impossible to build and run)
-
- Position of observed outlets
(causes the biggest headache in calibration)



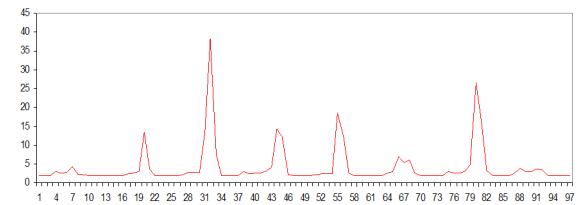
Non-uniqueness - inherent to calibration

Deterministic Modelling:

single-valued
input parameters

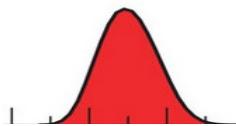


single-valued
output variables

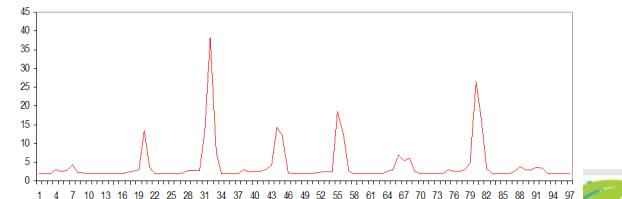


Calibration (Stochastic Modelling):

distribution
of input parameters

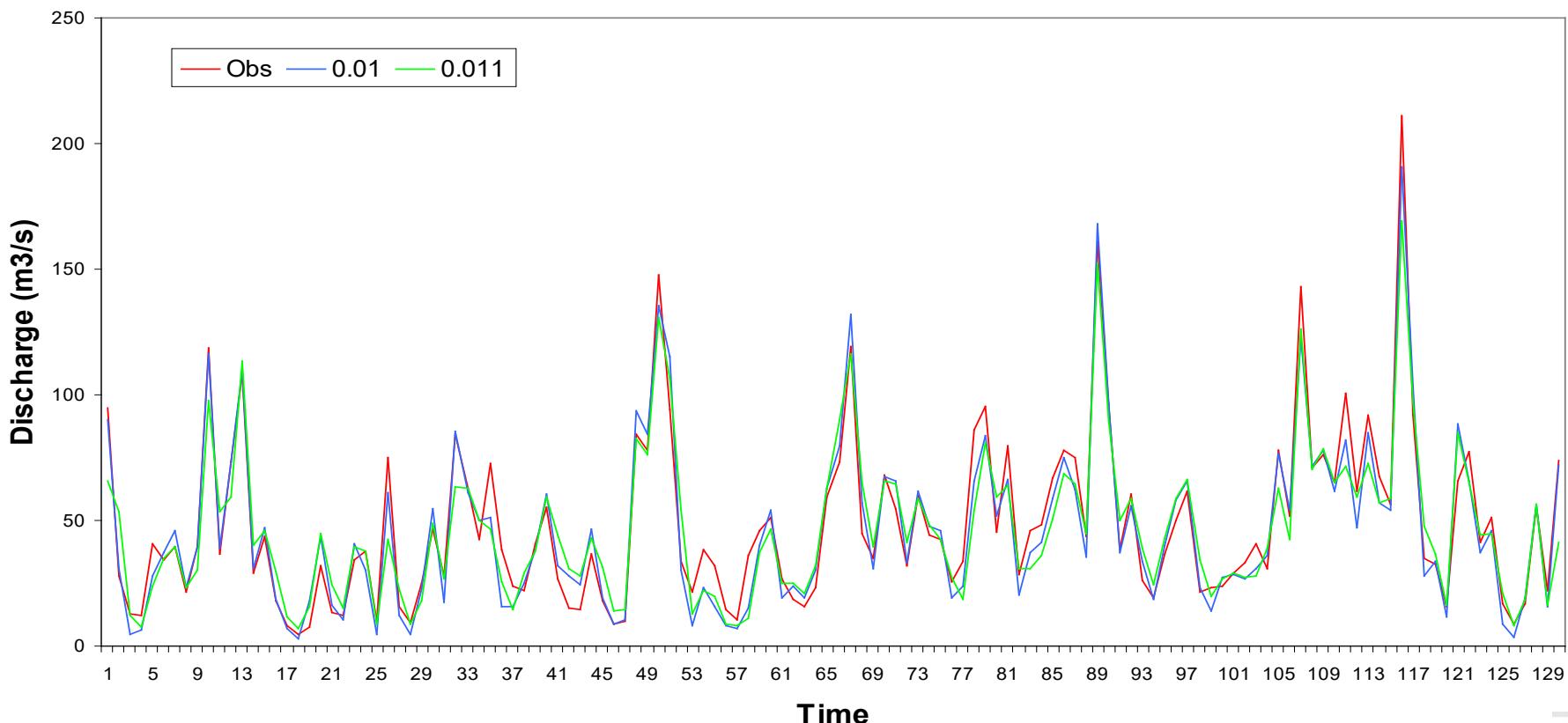


distribution of
output variables

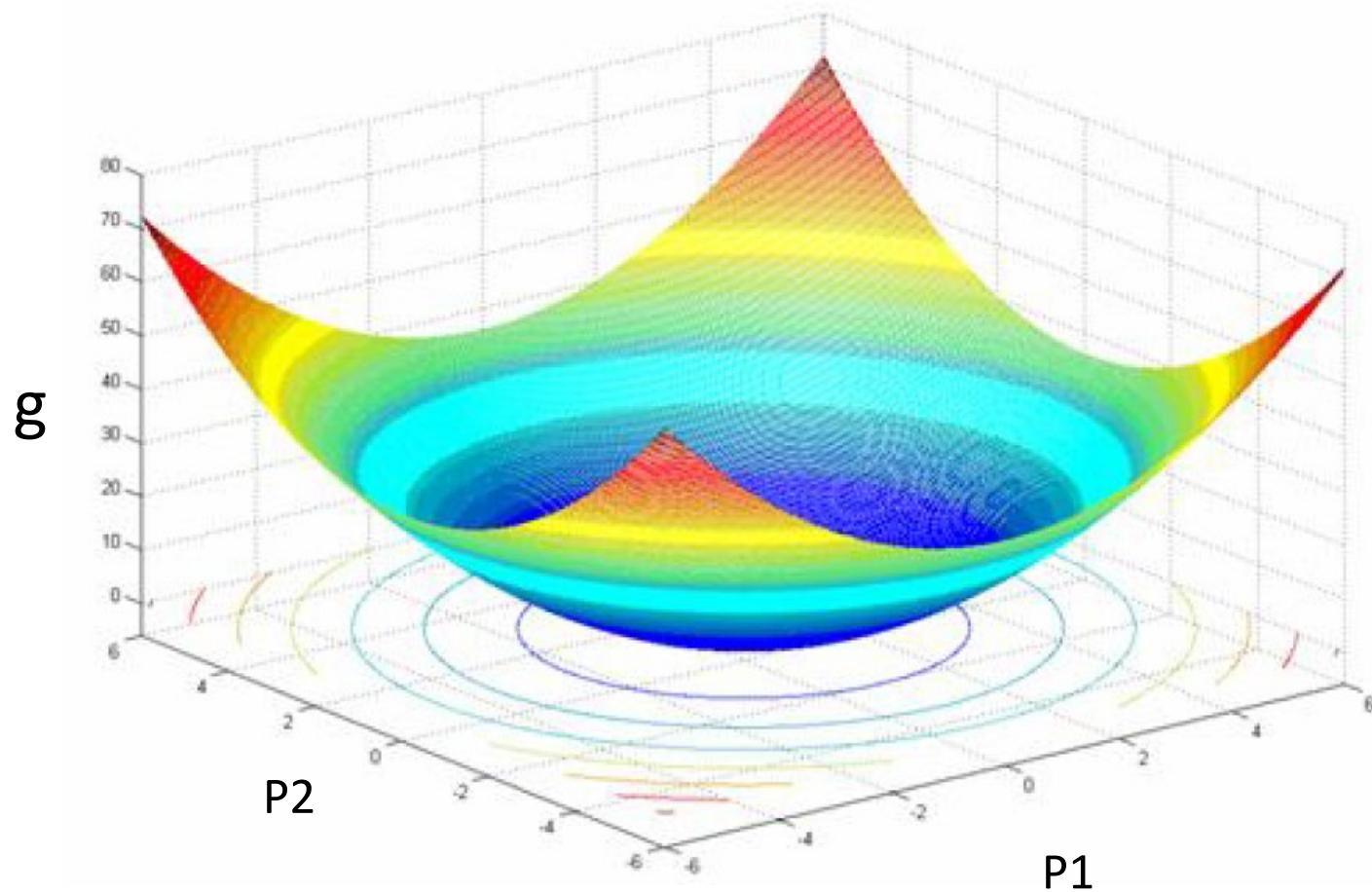


Non-uniqueness - inherent to calibration

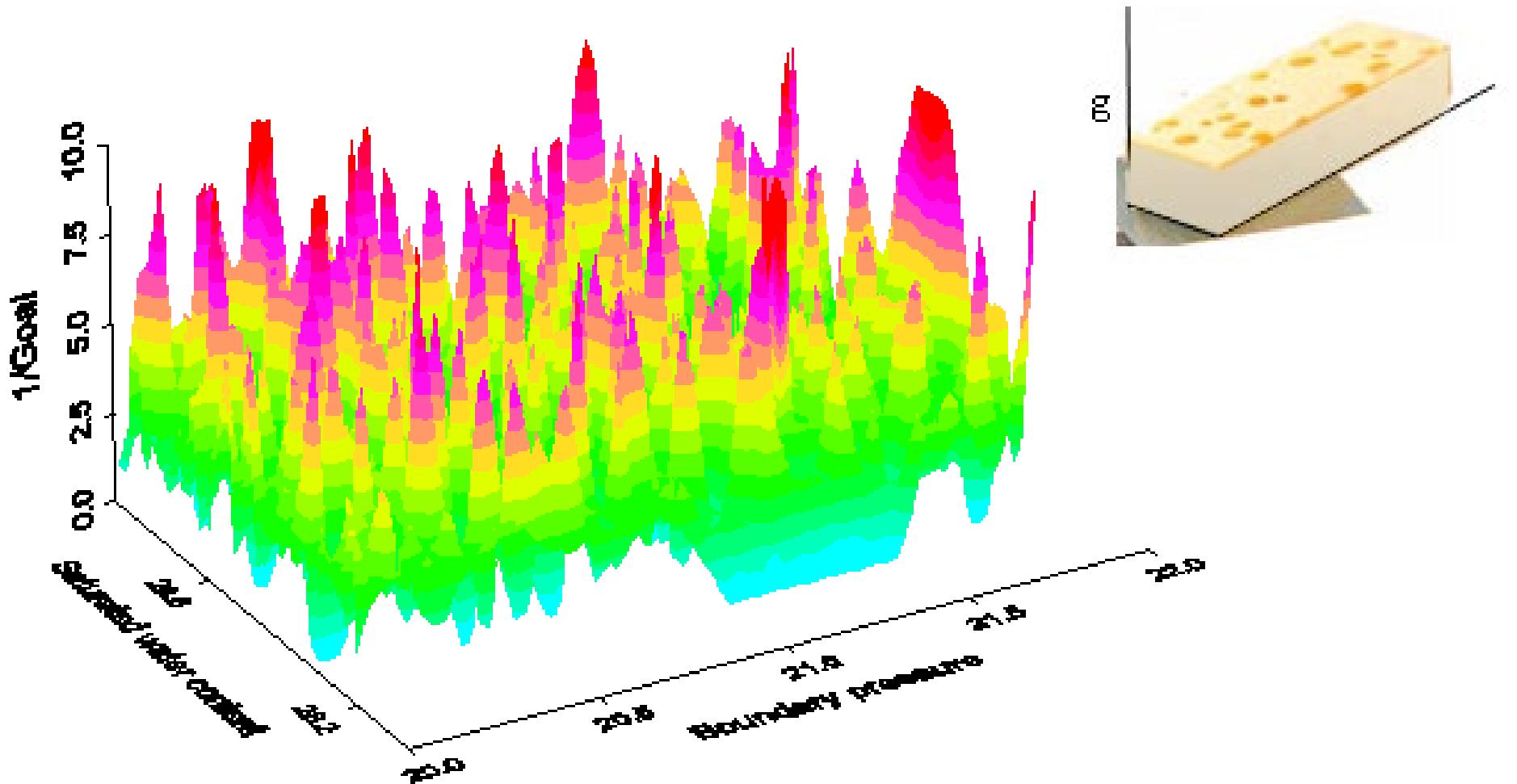
GW_DELAY	CH_N2	CN2	REVAPMN	Sol_AWC	g
3.46	0.0098	50	0.8	0.11	0.010
0.34	0.131	20	2.4	0.23	0.011



Objective function response surface



The Swiss Cheese Effect (multimodality of the objective function response surface)



Non-uniqueness - inherent to calibration

In SWATCUP File:

SUFI2.OUT\goal.txt

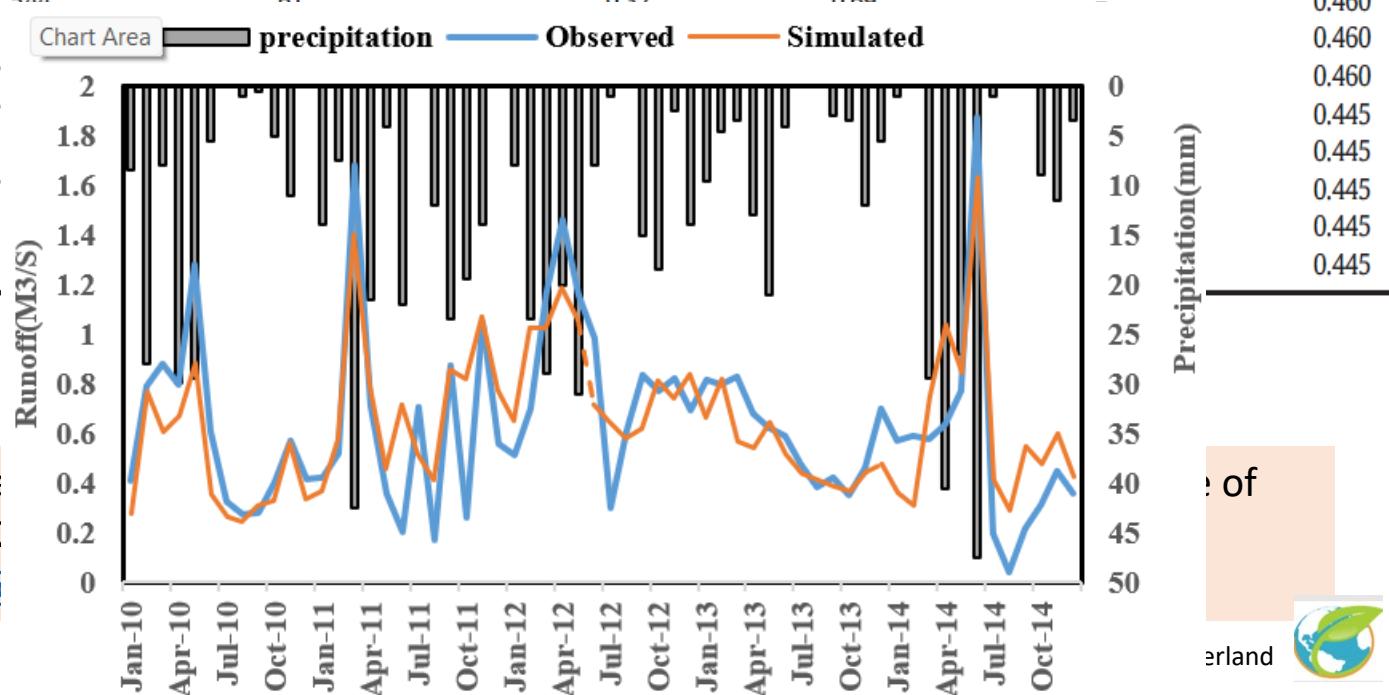
C:\....\SPE.OUT\Single_Obj\ Single_Obj_goal.txt

Table 1

Model parameters and their associated objective function values (NSE) showing similar objective functions obtained with significantly different parameters.

r_CN2	v_ESCO	v_GWQMN	v_GW_DELAY	r_SOL_K	r_SOL_BD	Others	NSE
0.03	0.72	558	77	0.14	0.82	-	0.470
-0.08	0.85	779	53	-0.12	0.76	-	0.466
-0.07	0.87	544	61	0.22	0.60	-	0.460
0.13	0.80						0.460
0.11	0.70						0.460
-0.02	0.87						0.445
-0.08	0.78						0.445
0.22	0.72						0.445
0.11	0.73						0.445
0.28	0.71						0.445

r_ represents a relative change, v_ represents



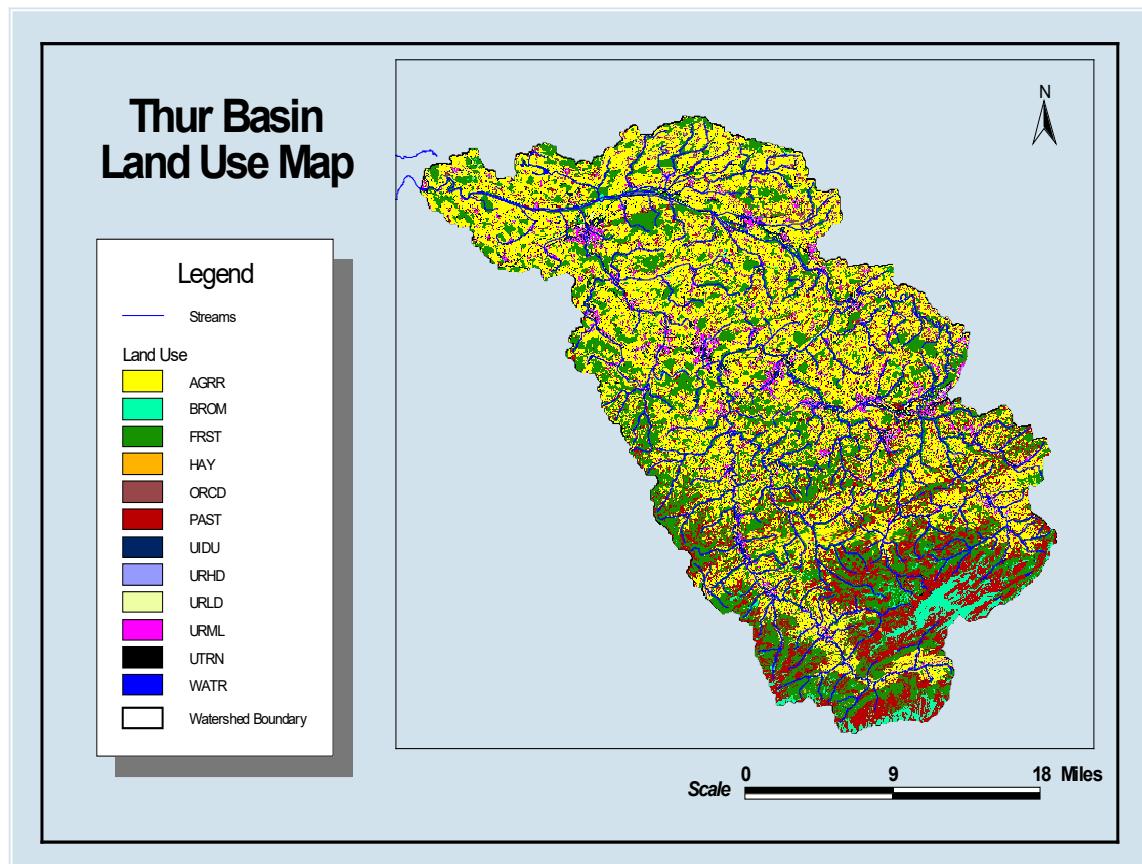
Abbaspour, KC. The fallacy of non-uniqueness in hydrological model calibration. Journal of Hydrology. 2015; 510: 12–21.
<https://doi.org/10.1016/j.jhydrol.2013.11.030>



Thur Watershed Application - Constraint-optimization to reduce uncertainty

$$g = \frac{1}{\sigma_{Q_m}^2} \sum_{i=1}^{130} (Q_m - Q_s)_i^2 + \frac{1}{\sigma_{S_m}^2} \sum_{i=1}^{130} (S_m - S_s)_i^2 + \frac{1}{\sigma_{N_m}^2} \sum_{i=1}^{130} (N_m - N_s)_i^2 + \frac{1}{\sigma_{P_m}^2} \sum_{i=1}^{130} (P_m - P_s)_i^2$$

$0.1 \leq S_{\text{Forest}} \leq 0.3$
$1.5 \leq S_{\text{Agricultural}} \leq 6$
$2.2 \leq N_{\text{Forest}} \leq 16$
$19 \leq N_{\text{Agricultural}} \leq 47$
$15 \leq N_{\text{Pasture}} \leq 25$
$0.02 \leq P_{\text{Forest}} \leq 0.1$
$0.5 \leq P_{\text{Agricultural}} \leq 2.4$
$0.3 \leq P_{\text{Pasture}} \leq 1.2$



Issues w.r.t. calibration of distributed watershed models

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 - Time constraint
(makes some projects impossible to build and run)
-
- Position of observed outlets
(causes the biggest headache in calibration)



Model Conditionality

(B)

- watershed parameterization
- type of the objective function/algorithm
- weights in the objective function
- conceptual model (model structure)
- experimental procedure (to collect the calibrating data)
- input (driving or forcing) data
- number and type of variables (in the objective function)
- location of outlets
-



Model Conditionality

- A calibrated model is always **conditioned** on the situation that it was calibrated for
- Care must be taken to apply it outside this boundary
- Should obtain **unconditional** parameter sets



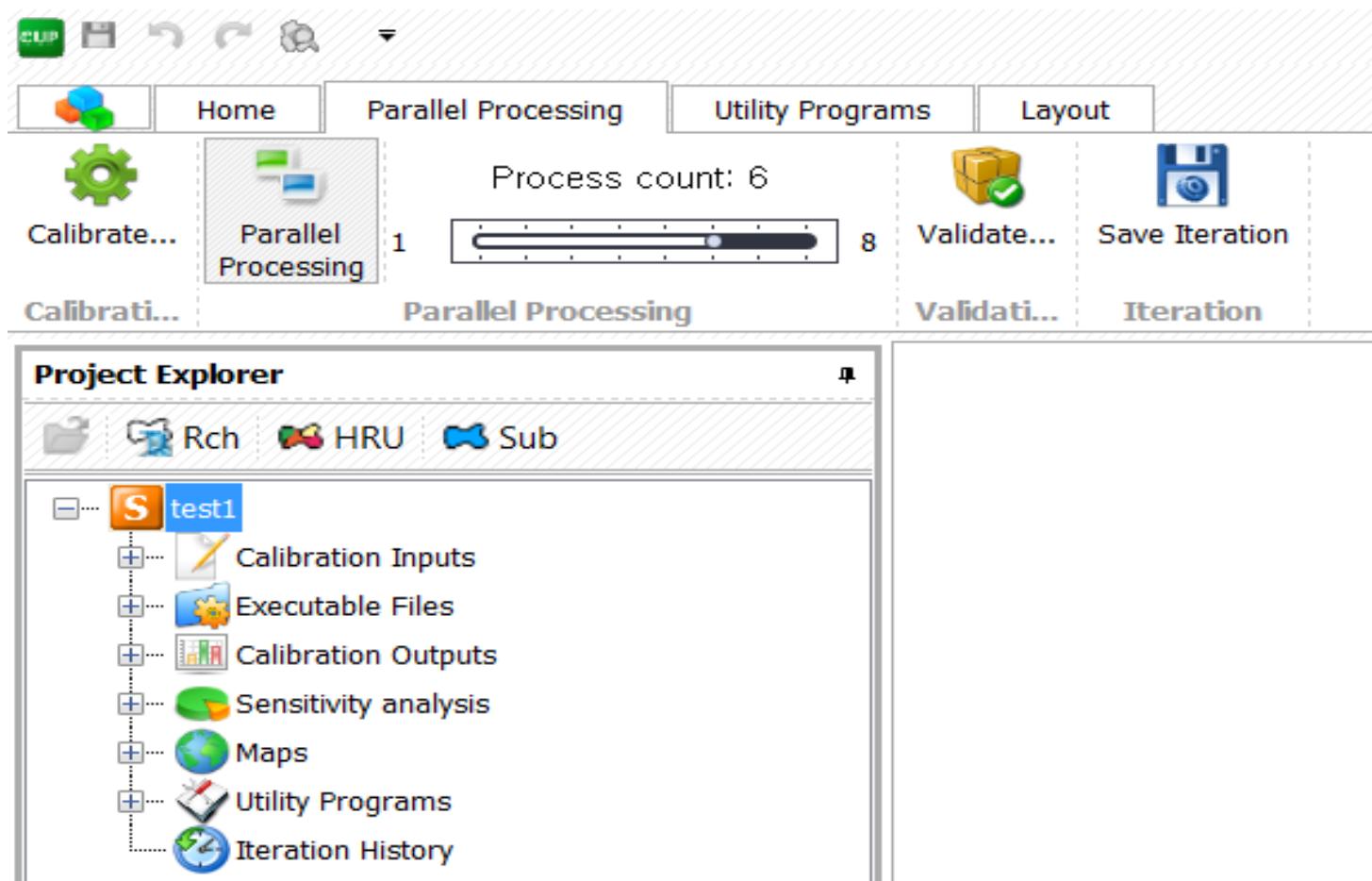
Issues w.r.t. calibration of distributed watershed models

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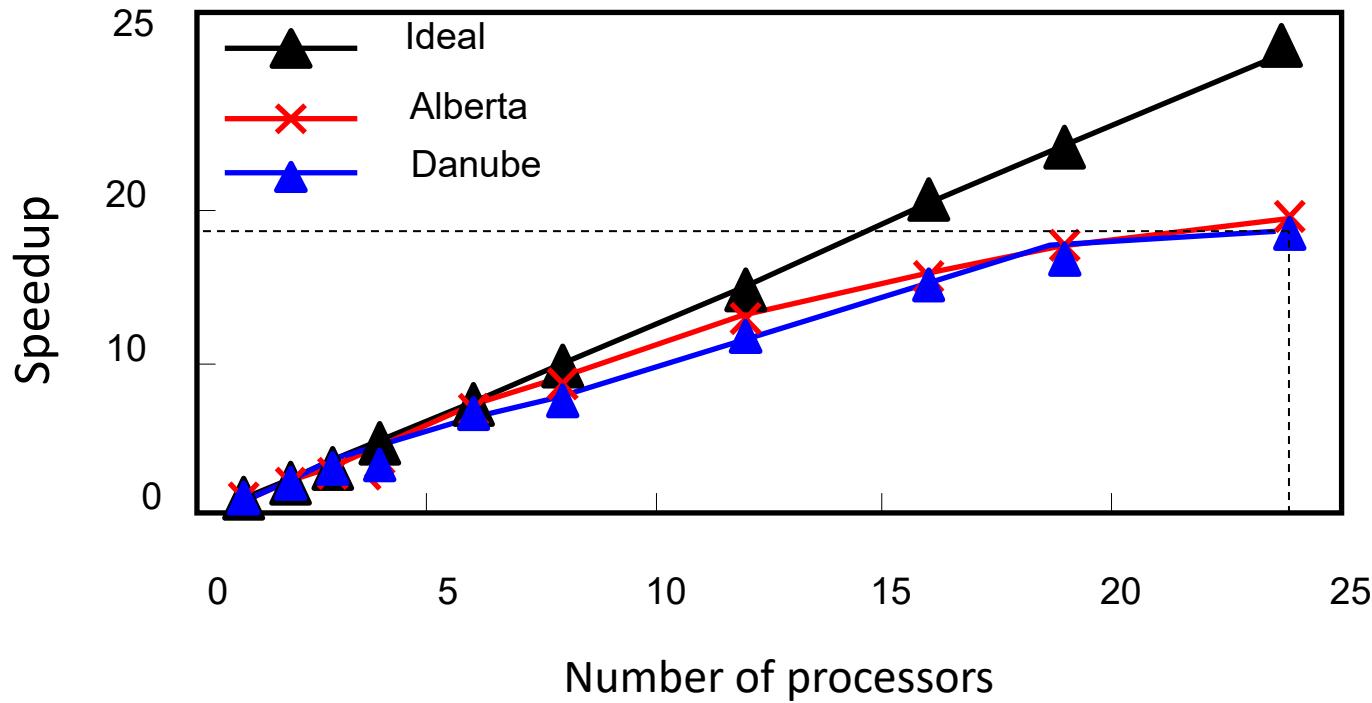
-
- Position of observed outlets
(causes the biggest headache in calibration)



Parallel Processing



Parallel Processing



A parallelization framework for calibration of hydrological models

Rouholahnejad et al., Env. Modelling & Software, 2012; 31:28-36.

<https://doi.org/10.1016/j.envsoft.2011.12.001>



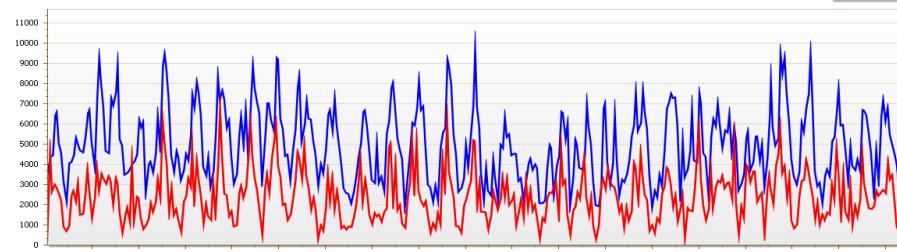
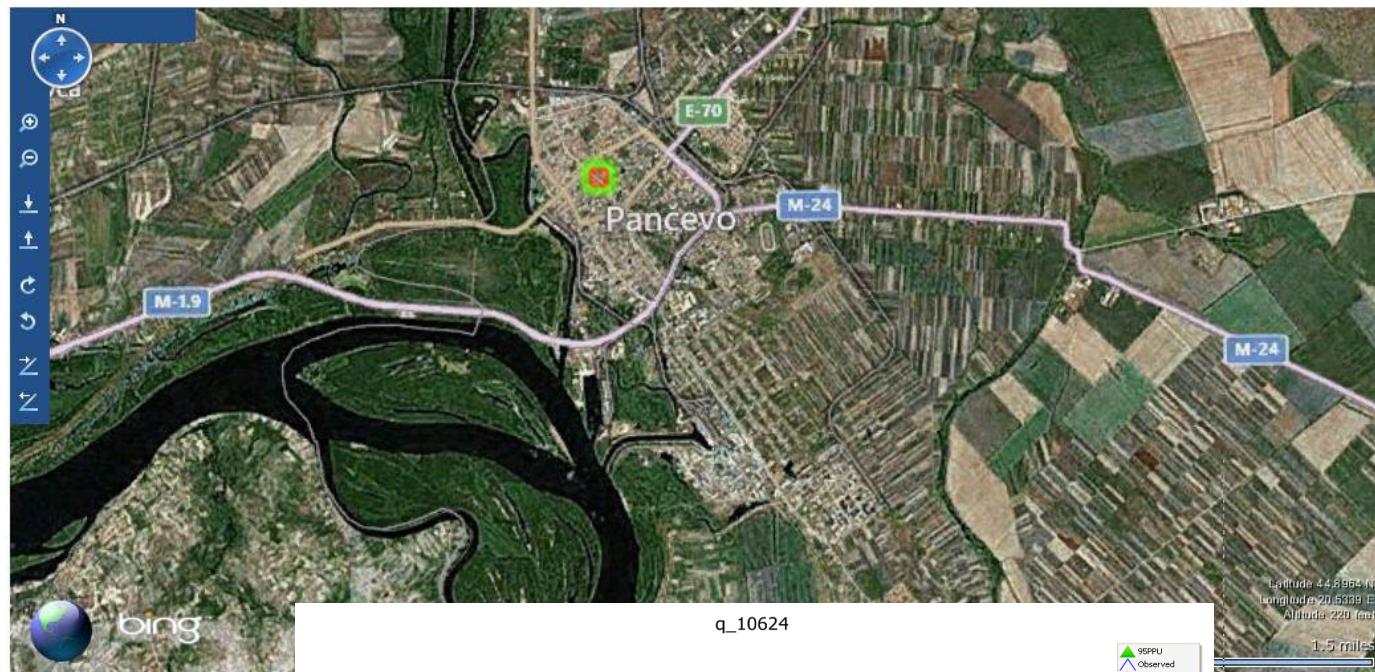
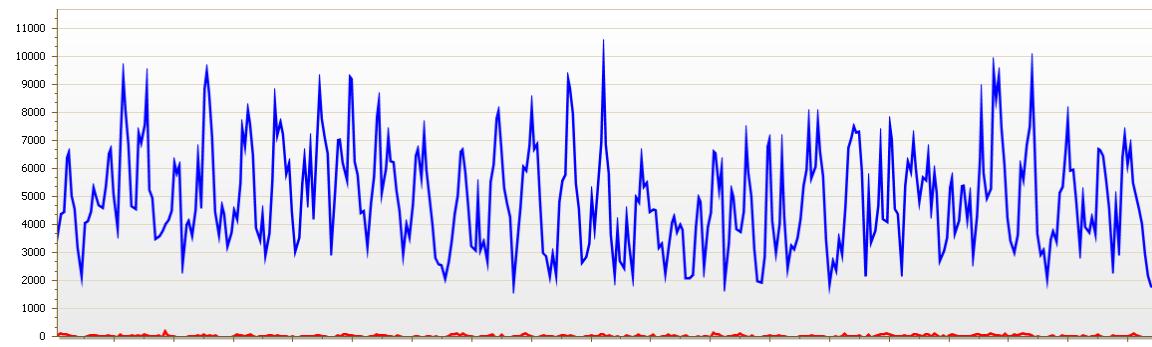
Position of outlets

- Parameterization
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(most surprising aspect of calibration)
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-
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q_10565

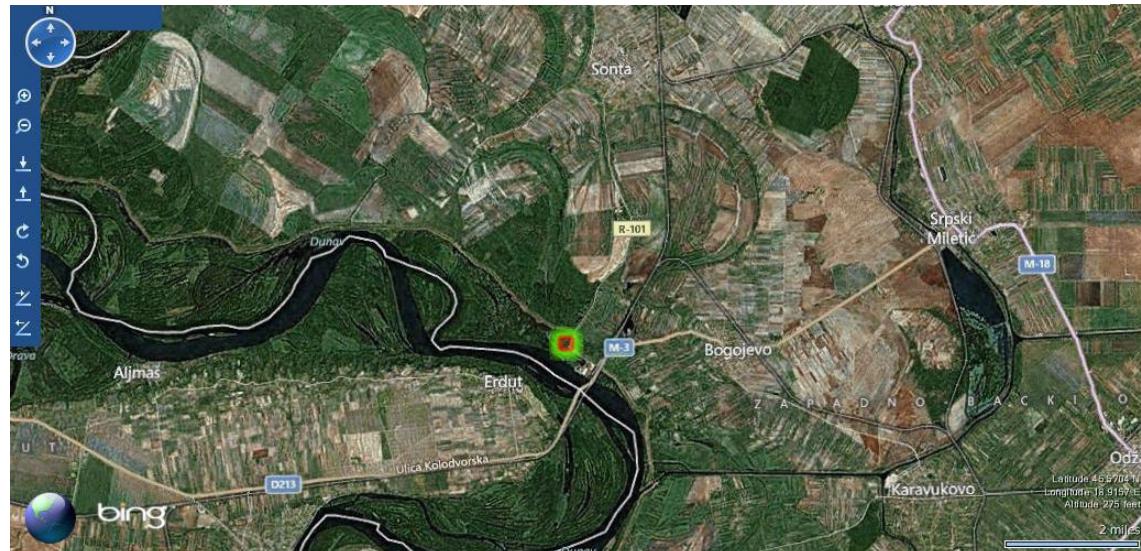
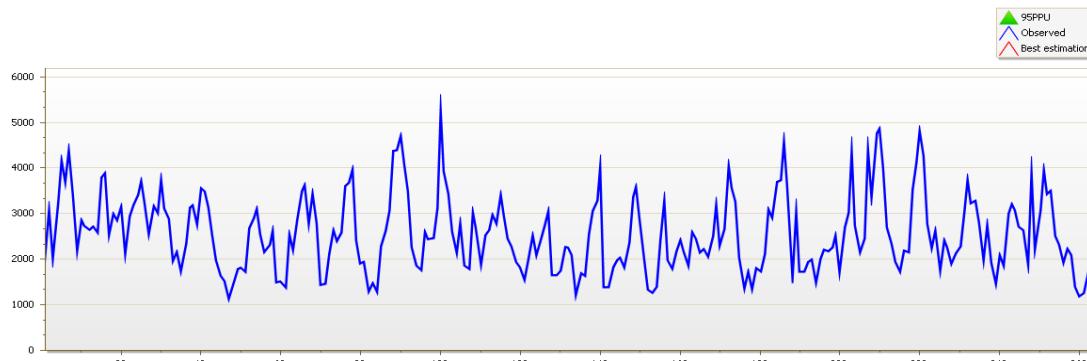
95PPU
Observed
Best estimation



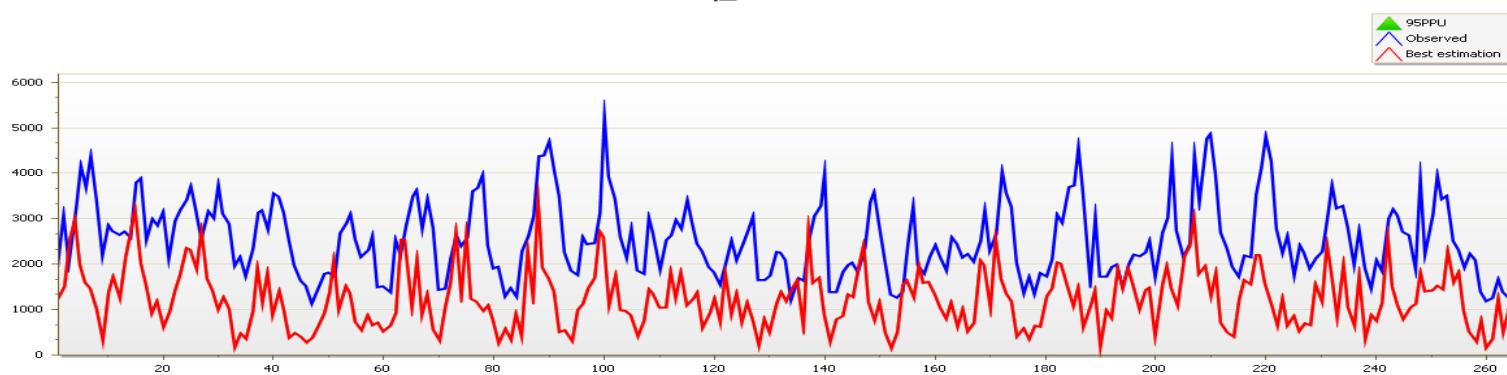
nbH, Duebendorf, Switzerland



q_10137



q_10140



ZwZ Consulting, Gmbh, Duebenaart, Switzerland

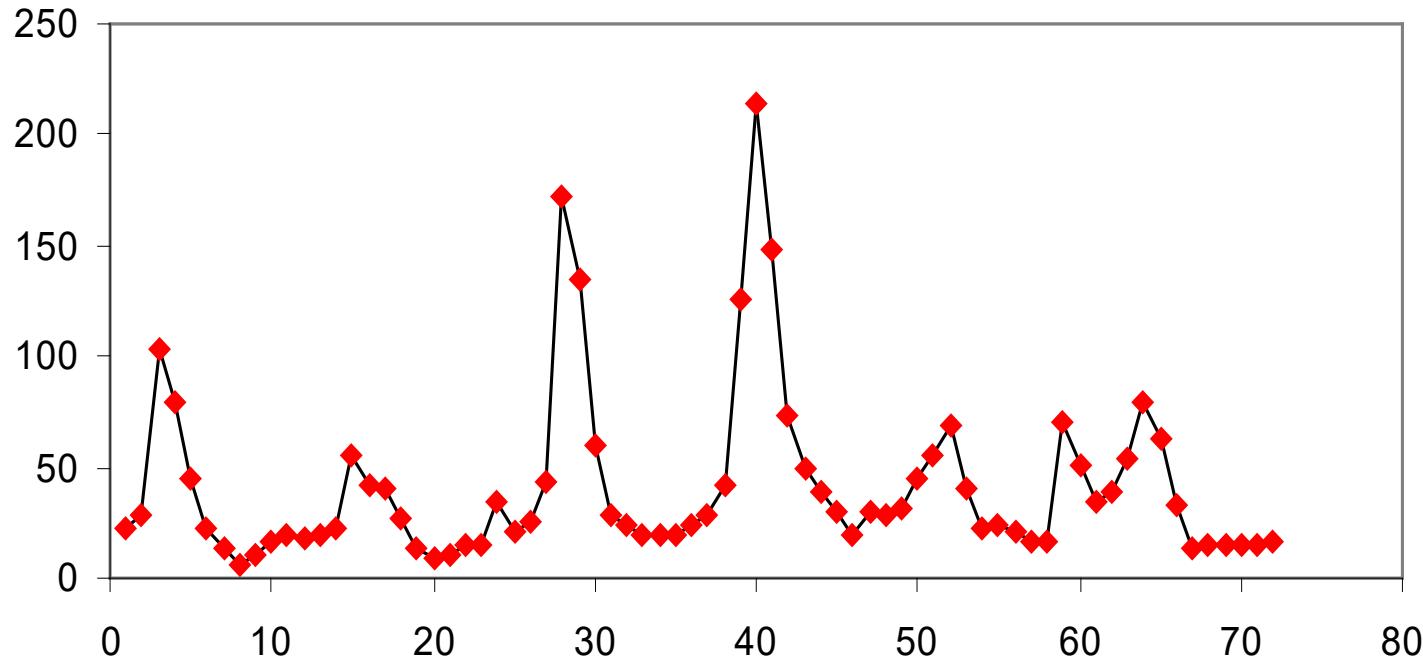


Model Uncertainty

Model Uncertainty

“All models are wrong - but some models are useful”
G. Box

Ideal situation



Sources of Model Uncertainty

Error, uncertainty, simplification of processes, lack of information:

- Input data (rainfall, landuse, discharge, etc.)
- Model parameters
- Conceptual model



Sources of Model Uncertainty

Error, uncertainty, simplification of processes, lack of information:

Also:

- Processes occurring in the watershed but not accounted for in the model (wetland processes, glacier melting, etc.)
- Processes accounted for in the model, but their occurrences are not known in the watershed (water transfers, unusual erosion, etc.)







2w2e Consulting, GmbH, Duebendorf, Switzerland













5 2 2006



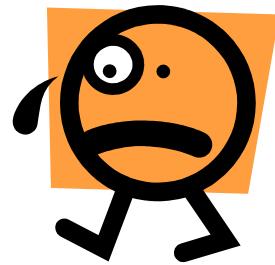




Sources of Model Uncertainty

Finally...

Modeler!



SWAT-CUP

www.2w2e.com



2W2E GmbH
Water Weather Energy Ecosystem

Areas of Expertise

Tools and Data

Projects

Our Team

Contact

Sign in



Areas of Expertise

We are experts in integrated water resources, sustainable energy resources and technologies, climate change adaptation, and ecosystem services technologies.



SWAT-CUP Premium

SWAT-CUP Premium is an improved version of SWAT-CUP, which allows behavioral and multi-objective calibration.

[Download](#)



SWAT-CUP 2019

SWAT-CUP is a Calibration Uncertainty Program for SWAT. It can also be used to perform validation and sensitivity analysis.

[Download](#)



SWATplus-CUP

SWATplusCUP is a calibration/uncertainty analysis program for SWAT+.

[Download](#)



2w2e Consulting, GmbH, Duebendorf, Switzerland

SWAT-CUP - SWAT Calibration and Uncertainty Analysis Procedures

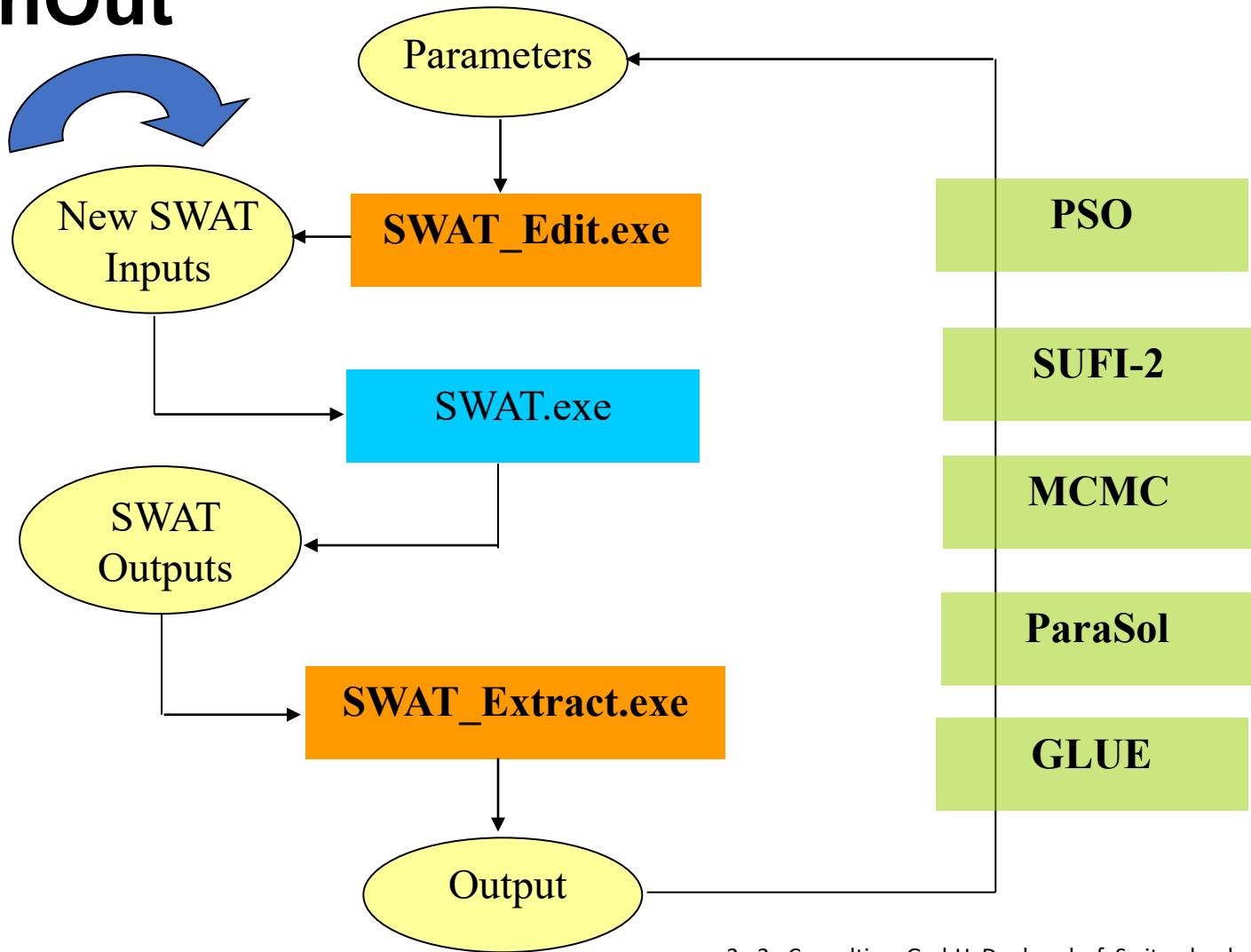
- Calibration
- Validation
- One-at-a-time and global Sensitivity analysis
- Uncertainty analysis
- Visualize the watershed and outlet locations
- Perform parallel processing

Utility programs

- Upstream subbasins
- Make elevation band
- Best management practices
- Make observation files
- Make hourly simulation

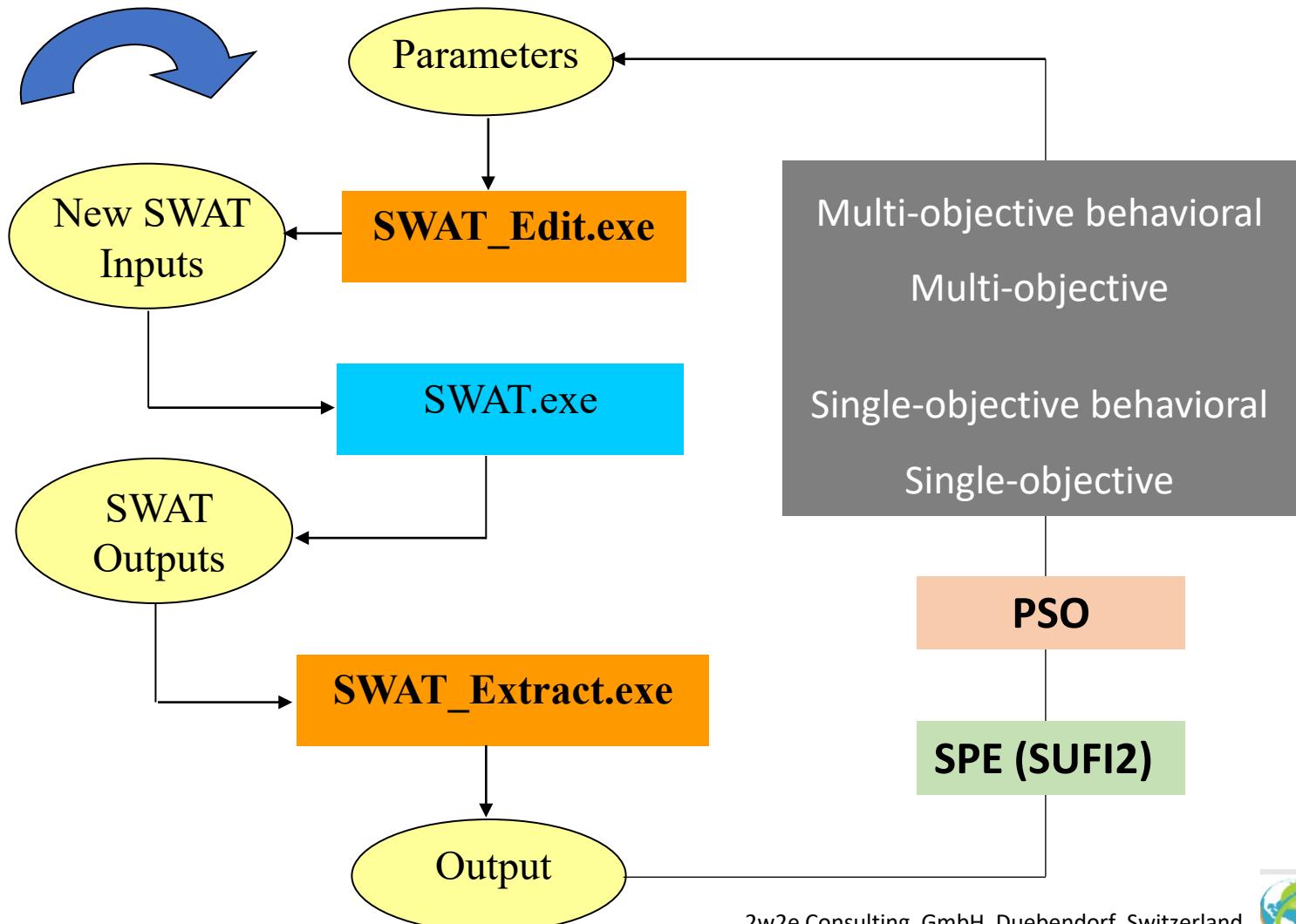


TxtInOut



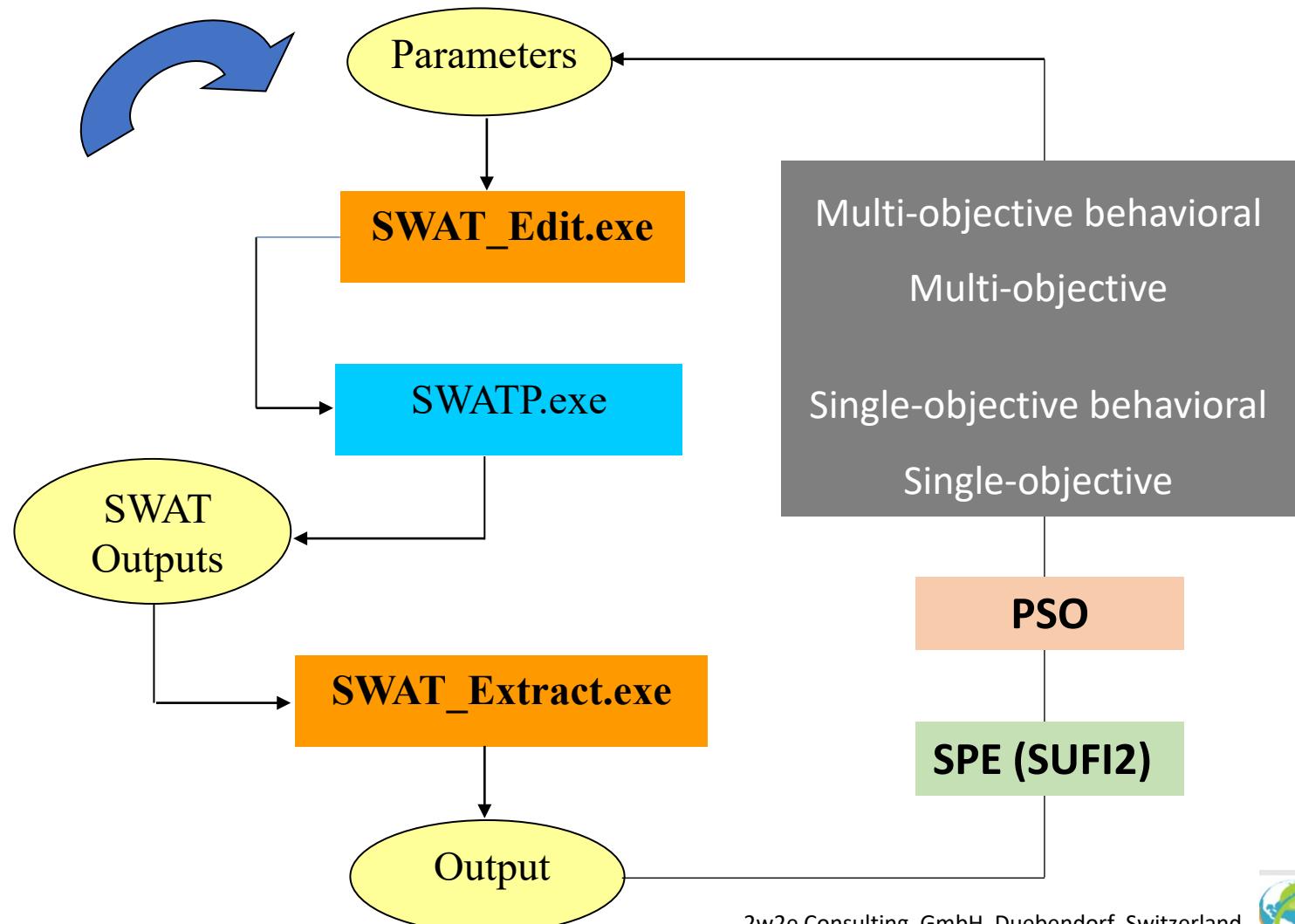
SWATCUP-Premium

TxtInOut



SWATCUP-Plus

TxtInOut

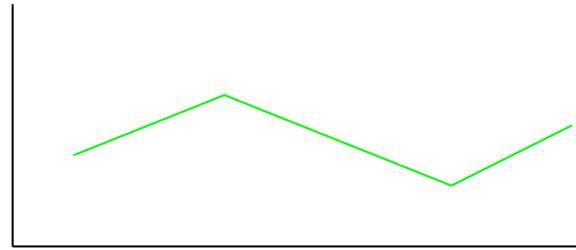


SUFI-2 (SPE)

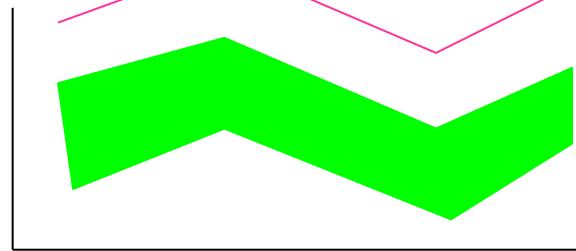
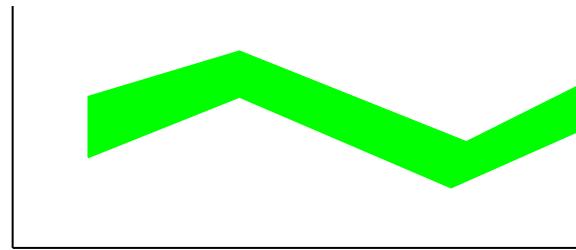
Input



output



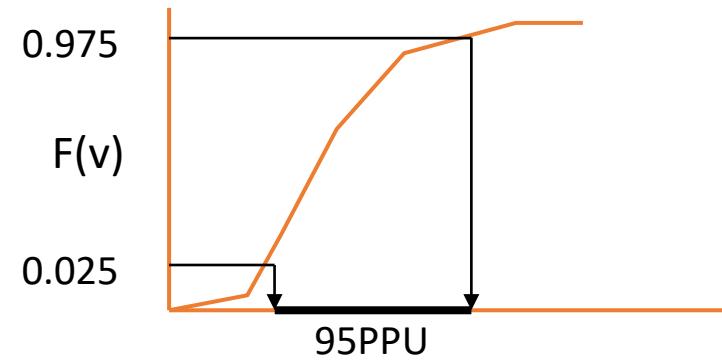
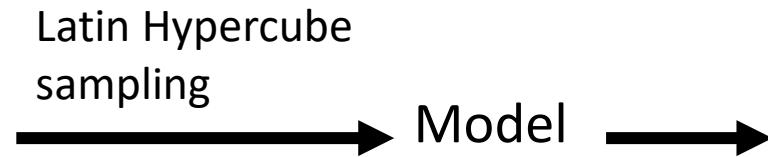
95PPU



Concept

- Combines calibration and uncertainty analysis
- Accounts for all uncertainties combined and maps them onto the parameters
- Parameter uncertainty is depicted as an interval (uniform distribution)
- Output uncertainty is quantified as the 95% prediction uncertainty (95PPU) calculate at the 2.5% and 97.5% levels

parameter
uncertainty



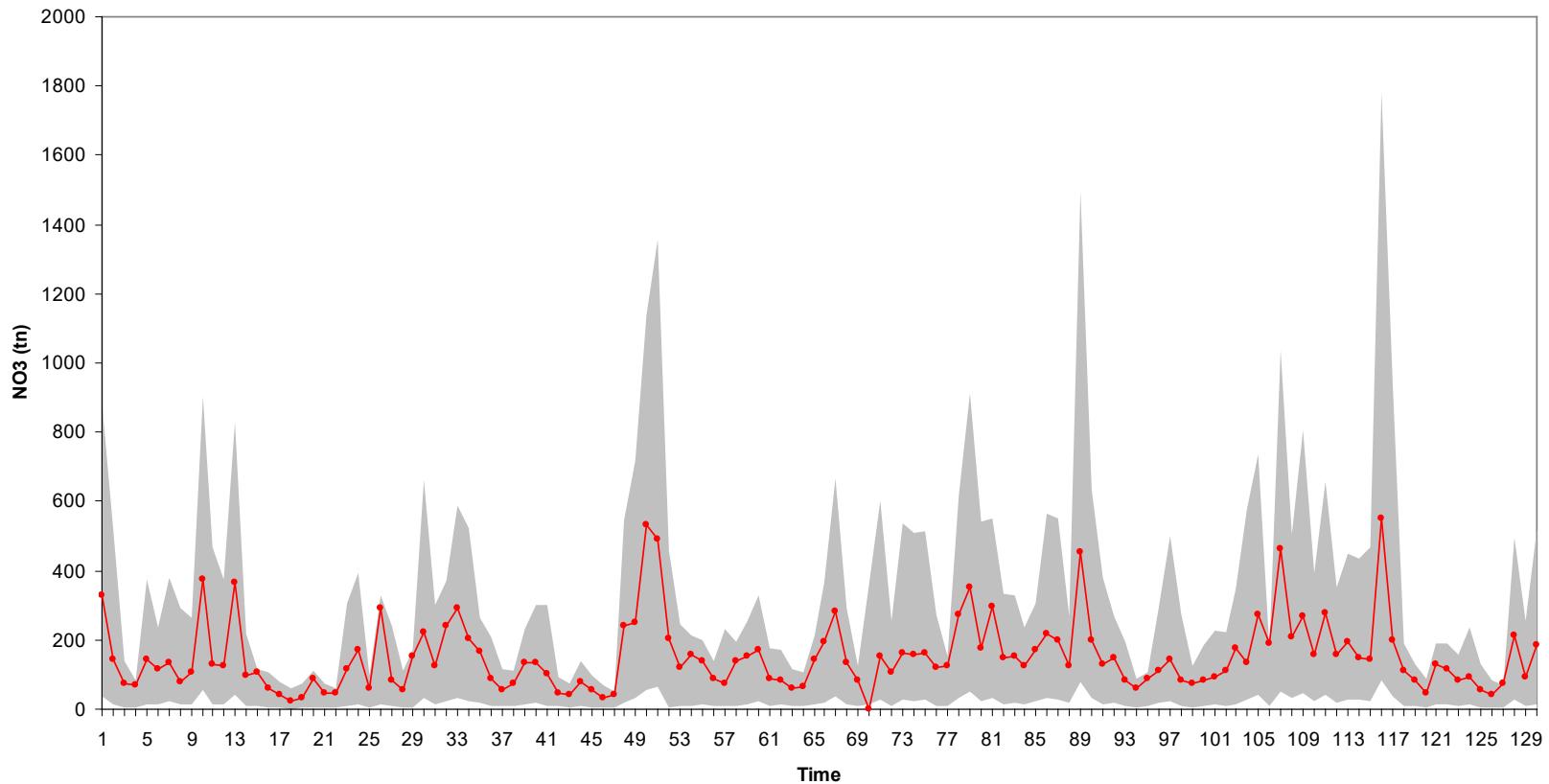
Latin Hypercube (Stratified Sampling) Sampling

If you want to make 4 simulations:

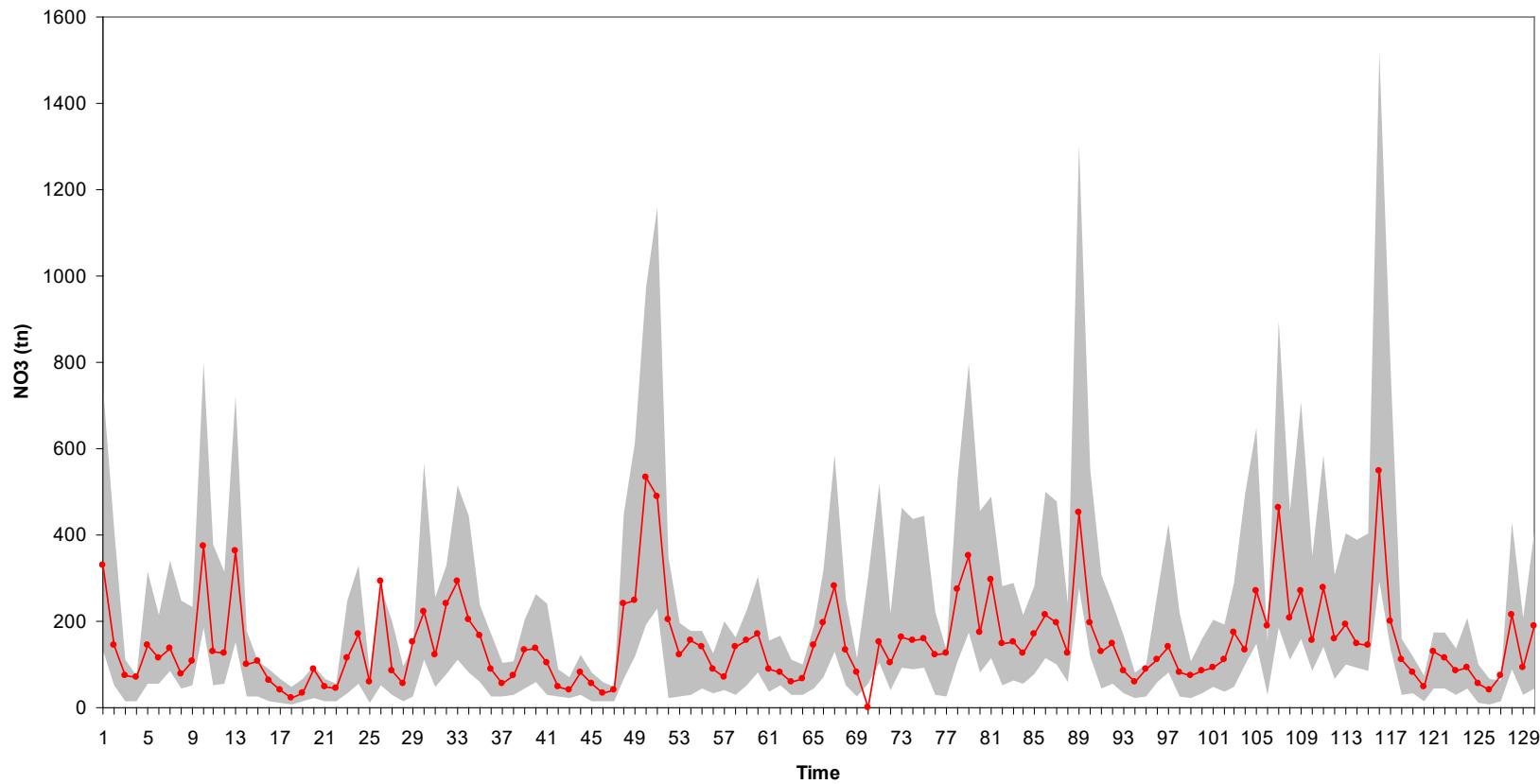


- | | |
|----|---------|
| 1- | 1,3,1,4 |
| 2- | 2,2,3,2 |
| 3- | 4,1,2,3 |
| 4- | 3,4,4,1 |

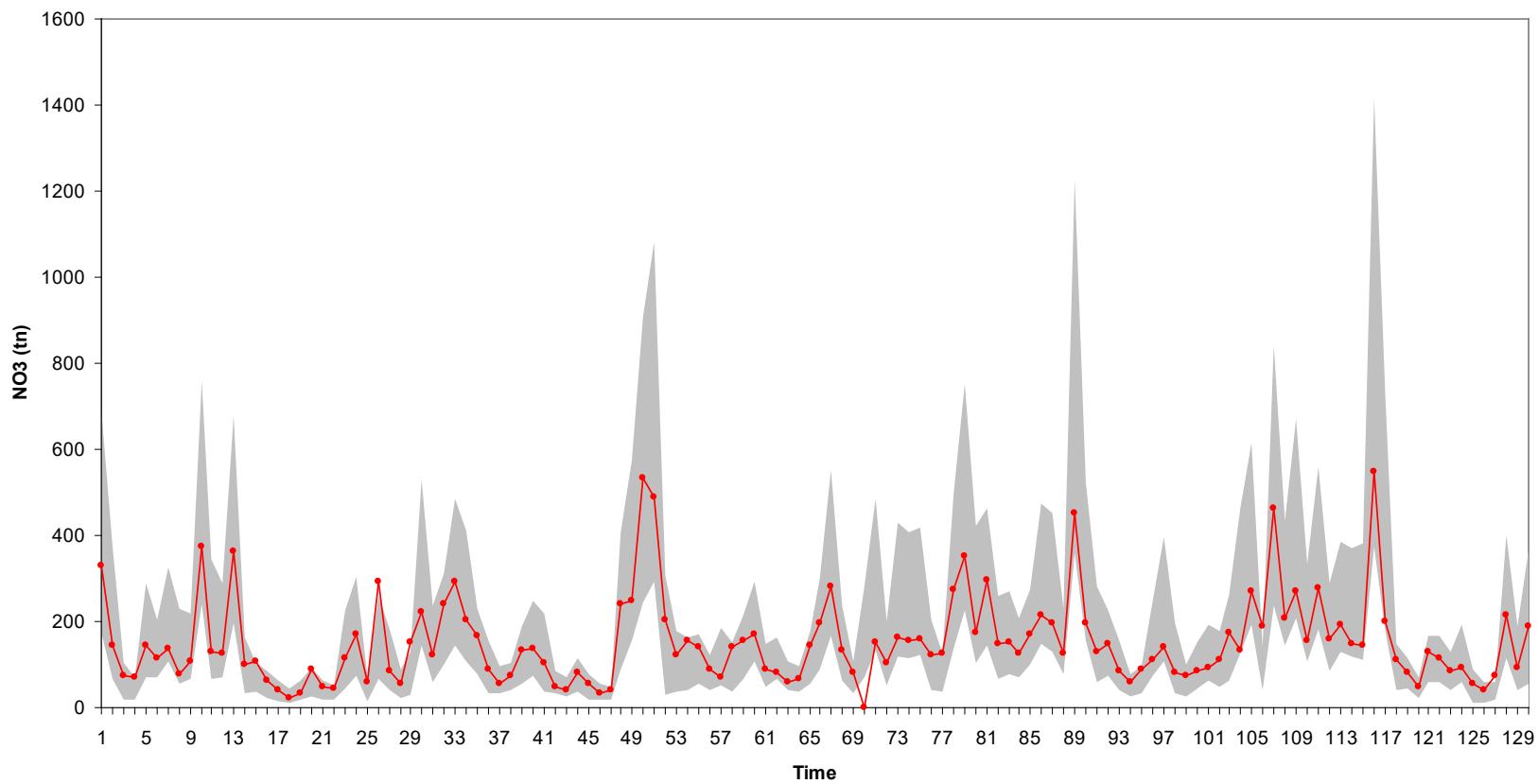
95PPU vs Parameter range



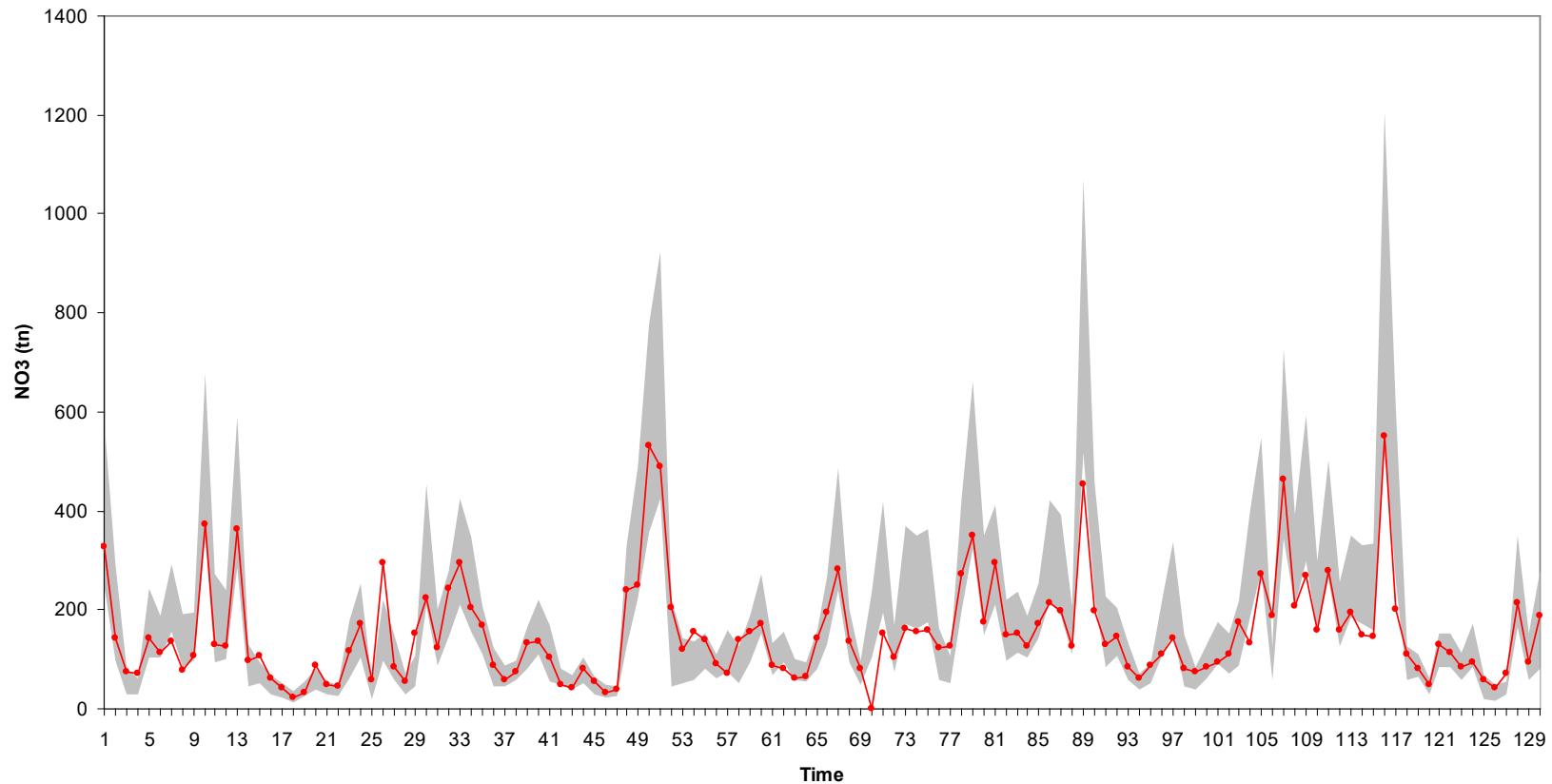
95PPU vs Parameter range



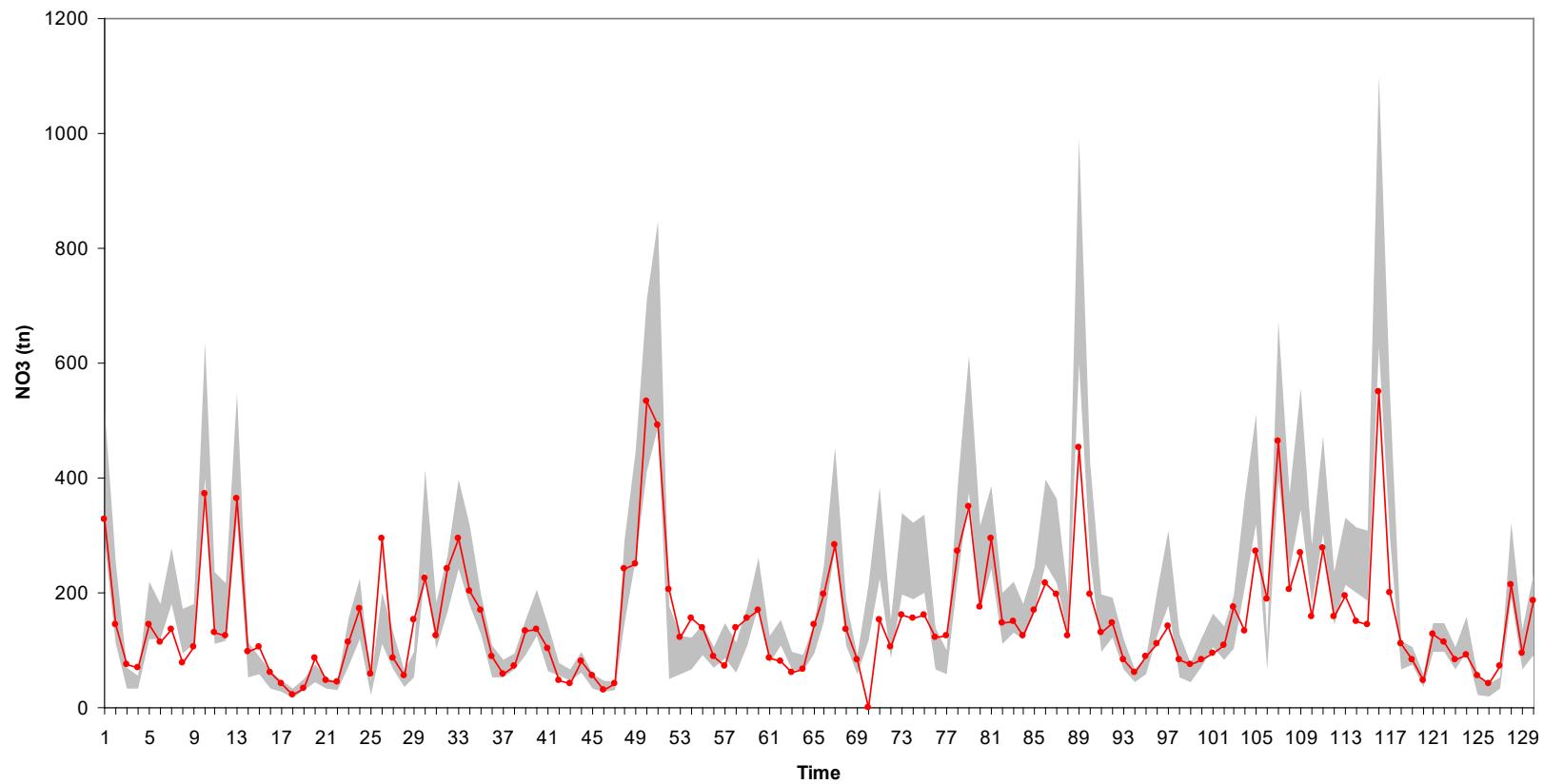
95PPU vs Parameter range



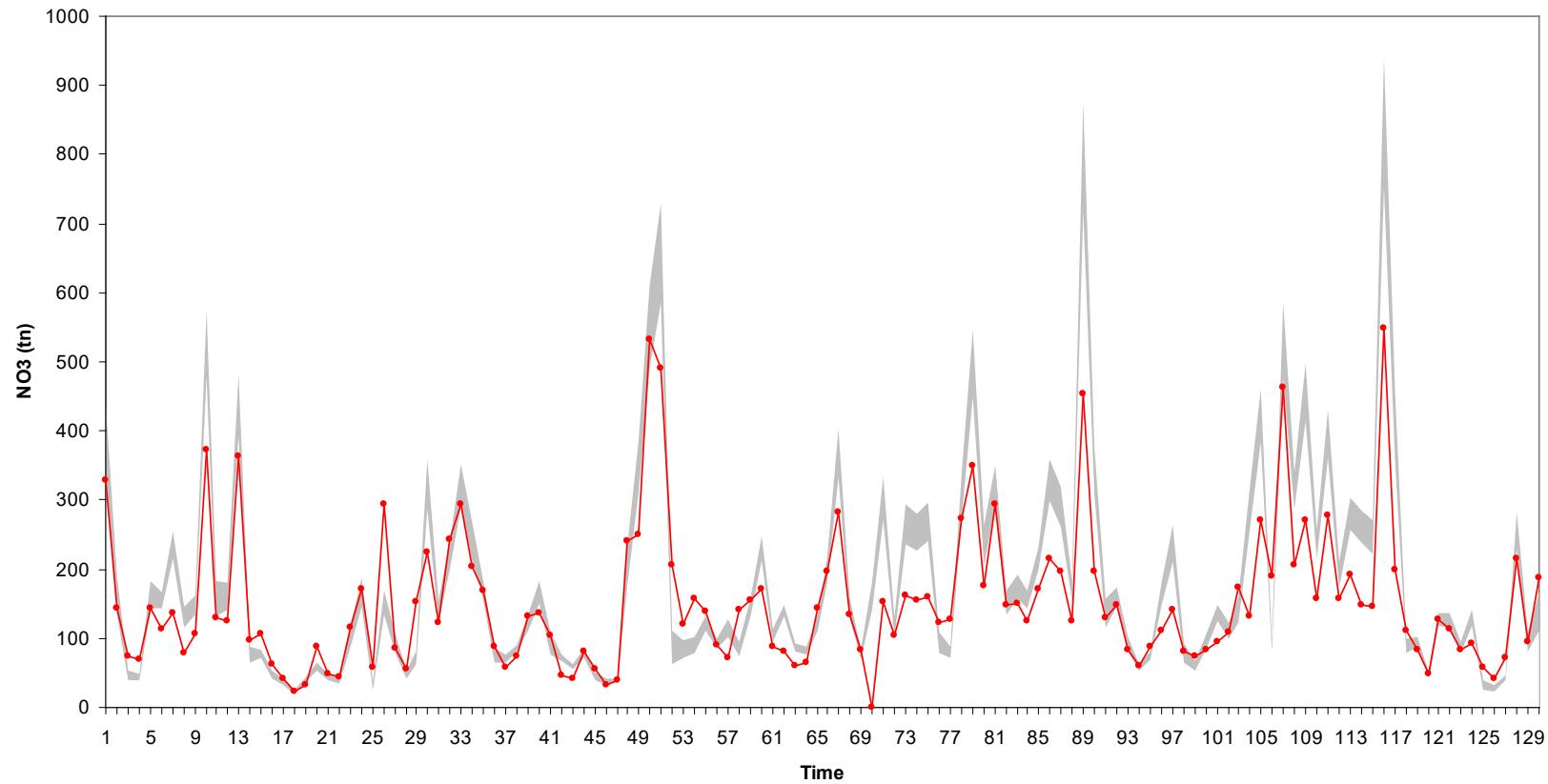
95PPU vs Parameter range



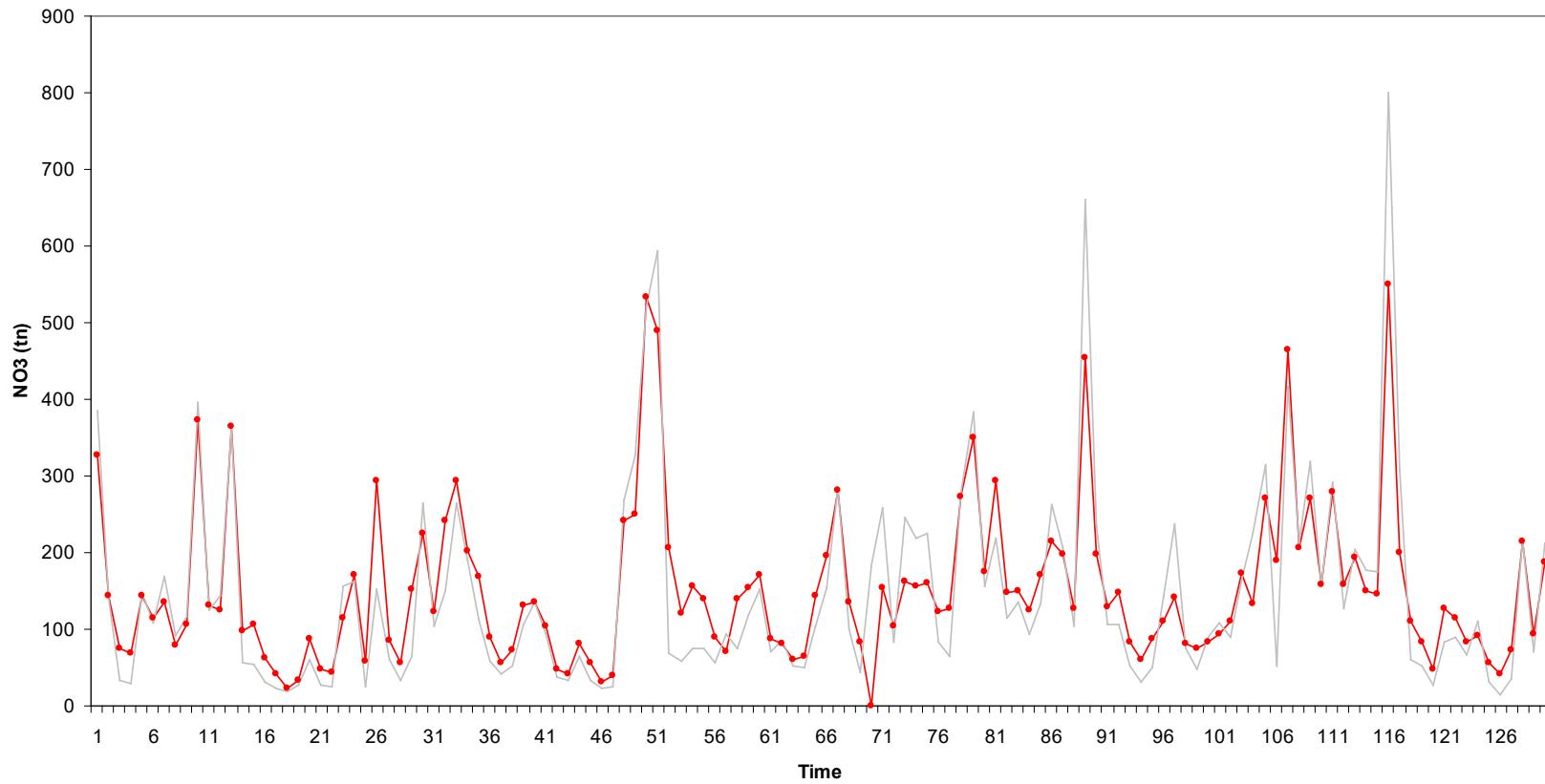
95PPU vs Parameter range



95PPU vs Parameter range



95PPU vs Parameter range



Important to realize that

- Observations reflect the net effect of all the true processes in a watershed
- So, when we calibrate a model based on capturing the observed data, then
- The “calibrated” model accounts for all uncertainties in the model



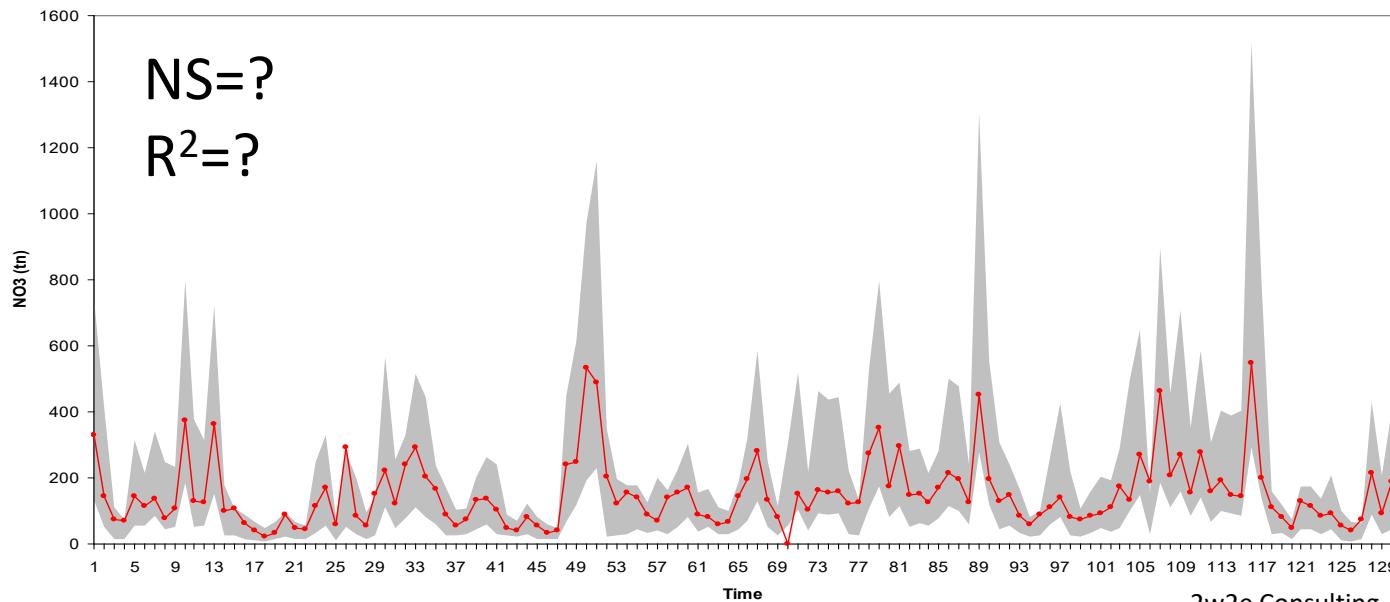
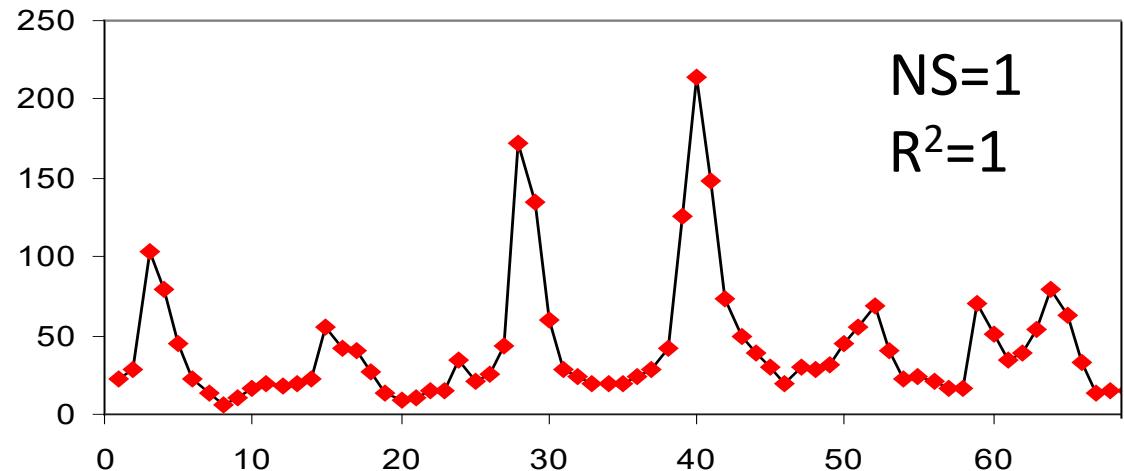
Uncertainty Analysis Definition

- To obtain a range of parameters such that upon propagation the 95PPU brackets “most” of the observed points

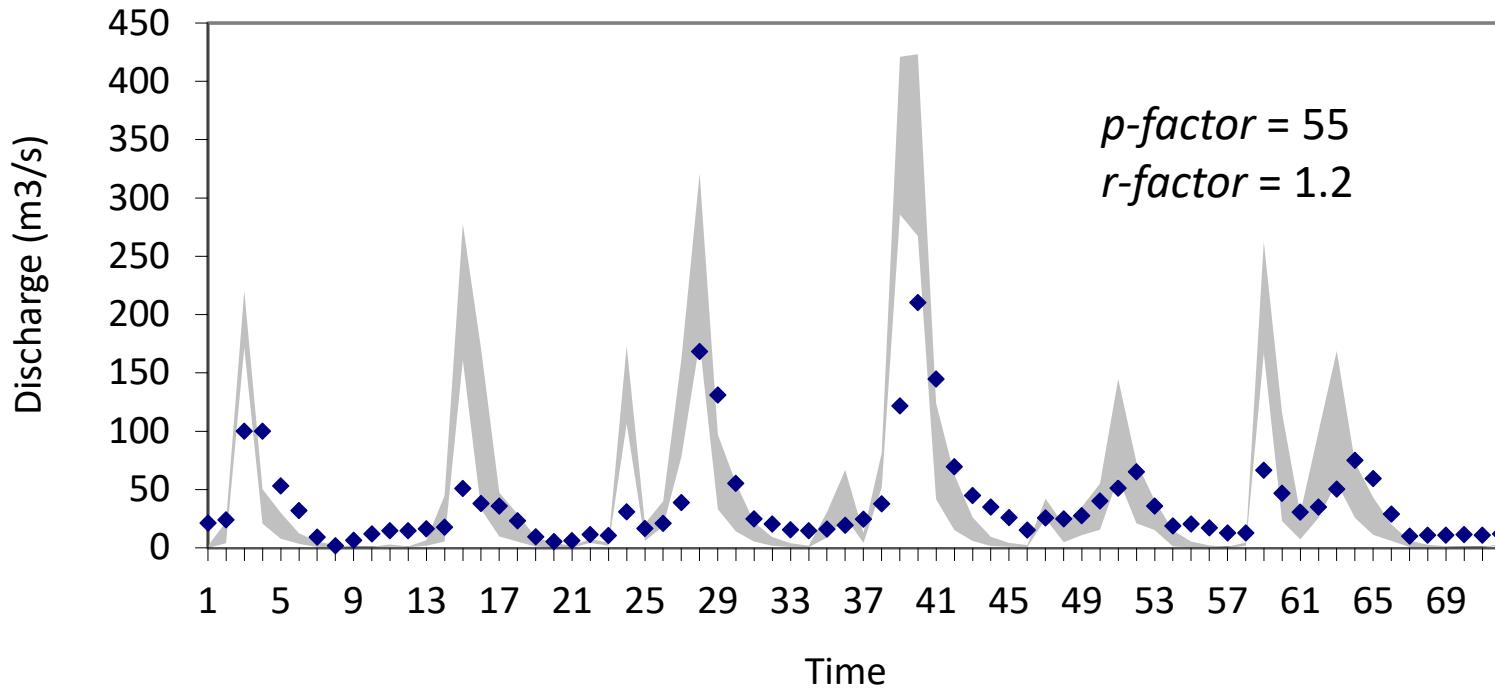


Model uncertainty

Ideal situations



Model uncertainty



p-factor

% observed data bracketed by the 95PPU (→ 1)

r-factor

The ratio of the average distance between the 95PPU band by the standard deviation of the measured data (→ 0)



Calibration rating

- All calibration ratings are subjective
- Trying to reach these subjective values is not justified
- At best they should be used as a very rough guide
- We should just report what we have
- Trying to reach a certain goal makes it very tempting to massage the data to reach that goal

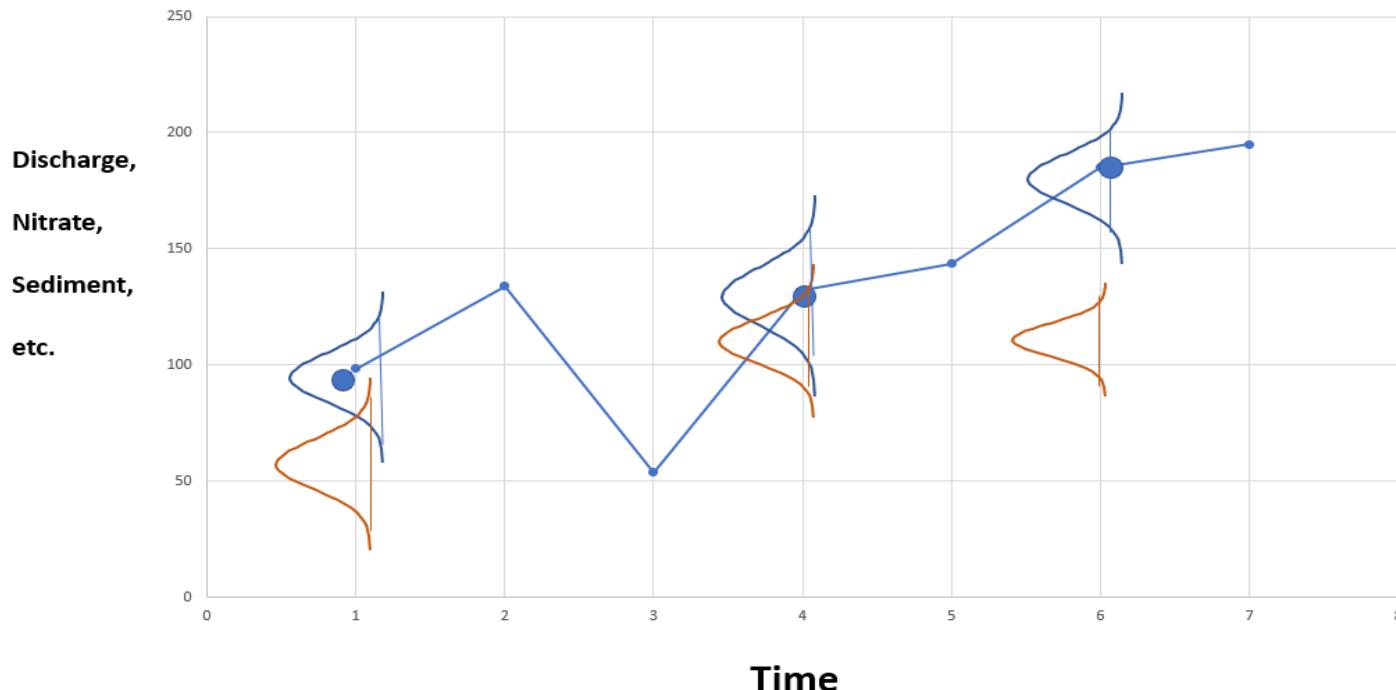
Table 4. General performance ratings for recommended statistics for a monthly time step.

Performance Rating	PBIAS (%)				
	RSR	NSE	Streamflow	Sediment	N, P
Very good	$0.00 \leq RSR \leq 0.50$	$0.75 < NSE \leq 1.00$	PBIAS $< \pm 10$	PBIAS $< \pm 15$	PBIAS $< \pm 25$
Good	$0.50 < RSR \leq 0.60$	$0.65 < NSE \leq 0.75$	$\pm 10 \leq PBIAS < \pm 15$	$\pm 15 \leq PBIAS < \pm 30$	$\pm 25 \leq PBIAS < \pm 40$
Satisfactory	$0.60 < RSR \leq 0.70$	$0.50 < NSE \leq 0.65$	$\pm 15 \leq PBIAS < \pm 25$	$\pm 30 \leq PBIAS < \pm 55$	$\pm 40 \leq PBIAS < \pm 70$
Unsatisfactory	RSR > 0.70	$NSE \leq 0.50$	PBIAS $\geq \pm 25$	PBIAS $\geq \pm 55$	PBIAS $\geq \pm 70$

How to work with parameter ranges

1. Comparing two distributions

- Landuse/climate change
- BMPs – terracing, contour farming, filter strips, strip cropping
- Changing fertilizer regime, tillage practice, irrigation, etc.



Z-Score

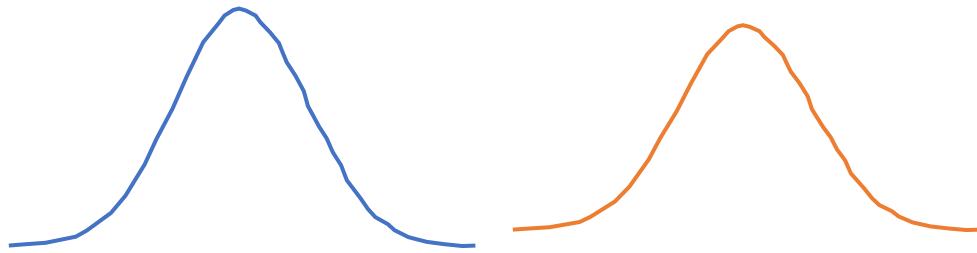
To Compare two samples directly

$$Z_i = \frac{\bar{X}_1 - \bar{X}_2}{\sqrt{\frac{\sigma_1^2 + \sigma_2^2}{n}}}$$

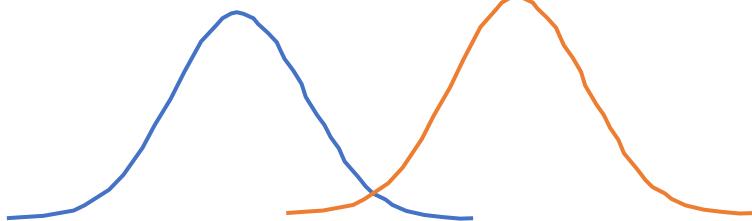
Where:

- \bar{X}_1 is the average of sample one
- \bar{X}_2 is the average of sample two
- σ_1^2 is the variance of sample one
- σ_2^2 is the variance of sample two
- n is the number of simulation
- i is the number of observations

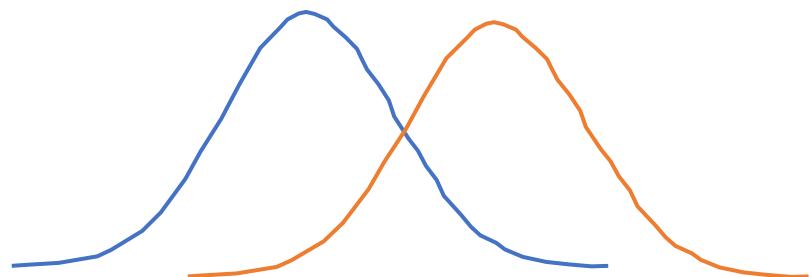




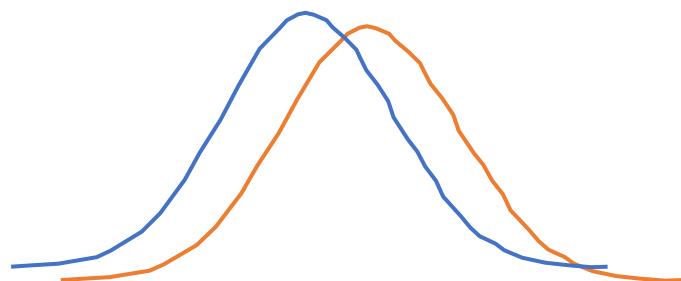
$Z\text{-score} > 3.0$
Highly different



$2.5 < Z\text{-score} < 3.0$
Significantly different



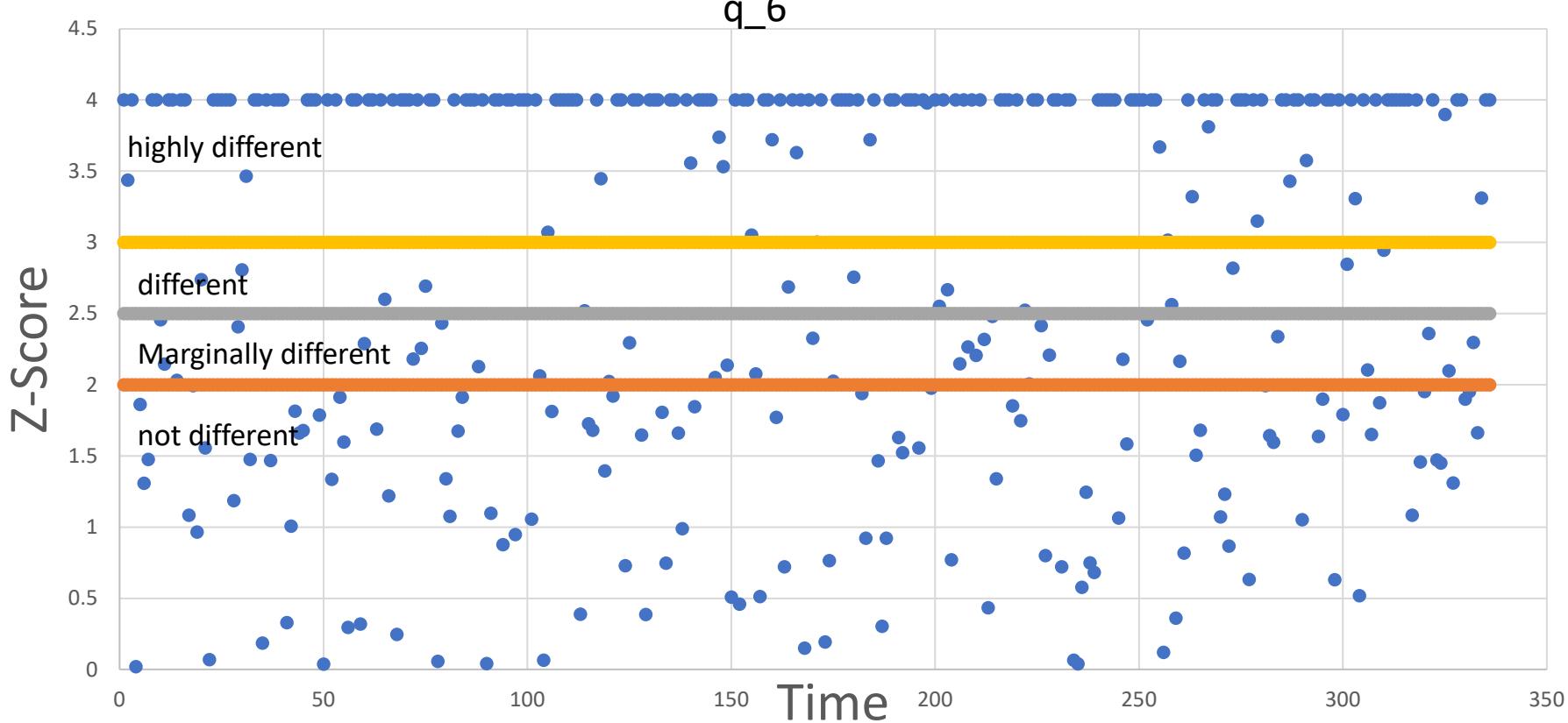
$2.0 < Z\text{-score} < 2.5$
Marginally different



$Z\text{-score} < 2.0$
Not different



q_6



Highly different= 52%

Different = 4%

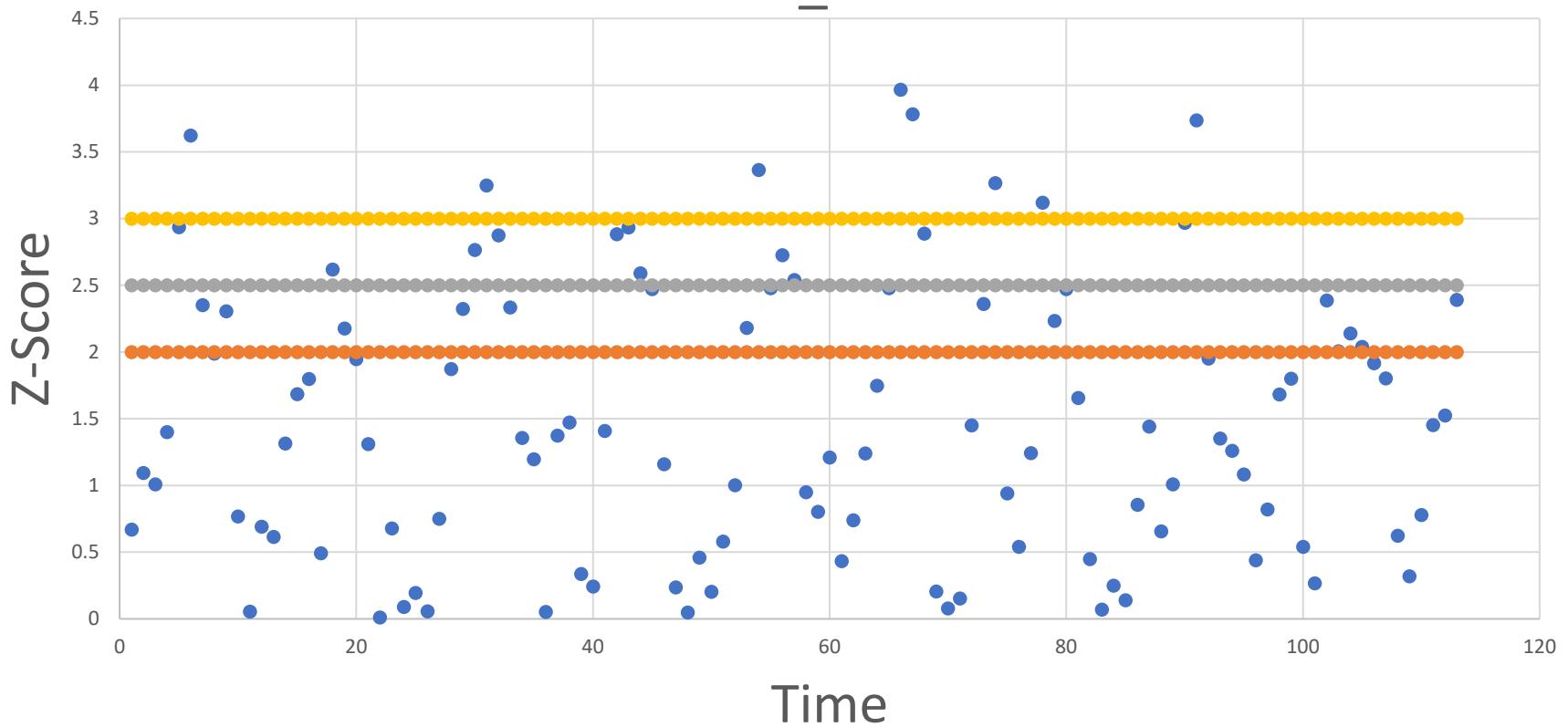
Marginally different= 10%

Not different= 34%

N= 336



NO3_34



Highly different= 7%

Different = 10%

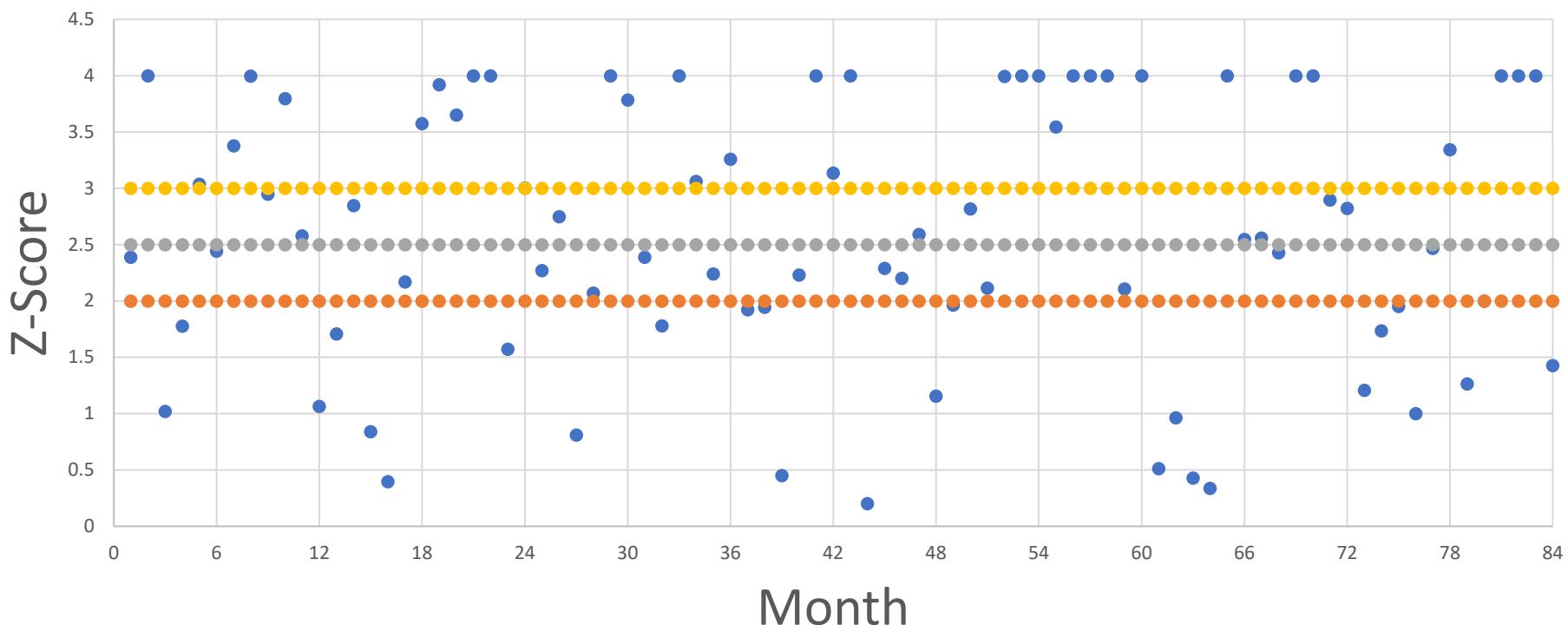
Marginally different = 15%

Not different = 68%

N= 113



NO3_32



Highly different = 40%

Different = 12%

Marginally different = 17%

Not different = 31%

N= 84



Risk analysis

Risk analysis is defined as:

- The assessment of the potential effect of a managerial intervention versus doing nothing

BMP	Effect
Terracing	Decrease soil loss
Contour farming	Reduce runoff
Filter strip	Decrease soil loss
Grade stabilization	Decrease channel slope steepness
Grassed Waterway	Reduce channel erodibility
Streambank stabilization	Decrease movement of TN and TP



Risk analysis

Calculation of Risk:

$$\text{Risk} = \text{Pr(failure)} * \text{Cost(failure)}$$

Pr(failure) = Likelihood of an adverse effect

e.g., passing a threshold of contamination, or soil loss, or runoff, etc.

Cost(failure) = Can be expressed in monetary or health or environmental or uncertainty terms.



Example: Terracing

- i-* Estimate the reduction in soil loss at the outlet of a watershed as a result of terracing taking model uncertainty into account
- ii-* Calculate the risk of implementing terracing, i.e., is the cost of saving > the investment



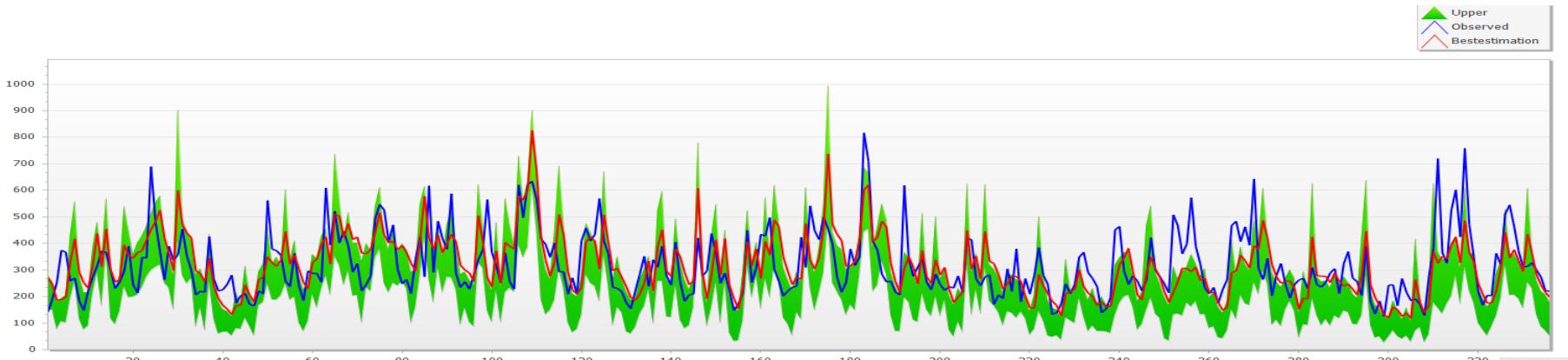
Some typical parameters

Flow	Range		Sediment	Range		Nitrate	Range		total phosphorus	Rage	
r__CN2.mgt	-0.2	0.2	v__PRF_BSN.bsn	0.2	0.25	v__RCN.bsn	1	5	V__PSP.bsn	0.5	0.7
v__ESCO.hru	0.7	0.1	v__SPEXP.bsn	1.3	1.5	v__N_UPDIS.bsn	5	30	V__ERORGp.hru	2	4
v__GWQMN.gw	0.0	1000	v__SPCON.bsn	0.001	0.002	v__SHALLST_N.gw	0	100	V__LAT_ORGP	0	100
v__REVAPMN.gw	0.0	1000	v__CH_COV1.rte	0.12	0.14	v__ERORGn.hru	1	4	V__BC4_BSN.bsn	0.3	0.35
v__GW_REVAP.gw	0.02	0.06	v__CH_COV2.rte	0.2	0.25	v__NPERCO.bsn	0	1	V__RS5.swq	0.05	0.1
r__SOL_AWC().sol	-0.5	0.5	V__ERORGn.hru	2	4	v__LAT_ORGN.gw	0	100	V__USLE_P.mgt	0	1



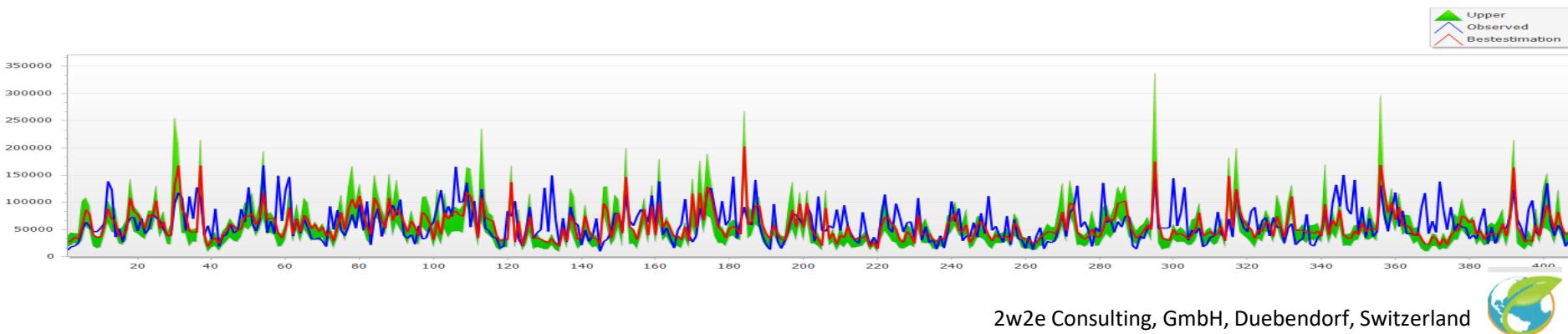
Calibrate for flow

r__CN2.mgt	-0.08927	0.080631
v__ESCO.hru	0.834495	0.934149
r__SOL_AWC().sol	-0.44507	0.03172
r__SOL_K().sol	-2.28205	-1.08942
r__SOL_BD().sol	-0.35689	0.187254
v__ALPHA_BF.gw	0.041521	0.055373
v__GW_DELAY.gw	42.53216	65.54935
v__GW_REVAP.gw	0.056003	0.102077
v__GWQMN.gw	903.2833	1123.265
v__RCHRG_DP.gw	0.519902	0.773894
r__SLSUBBSN.hru	0.119423	0.188895
r__OV_N.hru	-0.33536	-0.11899

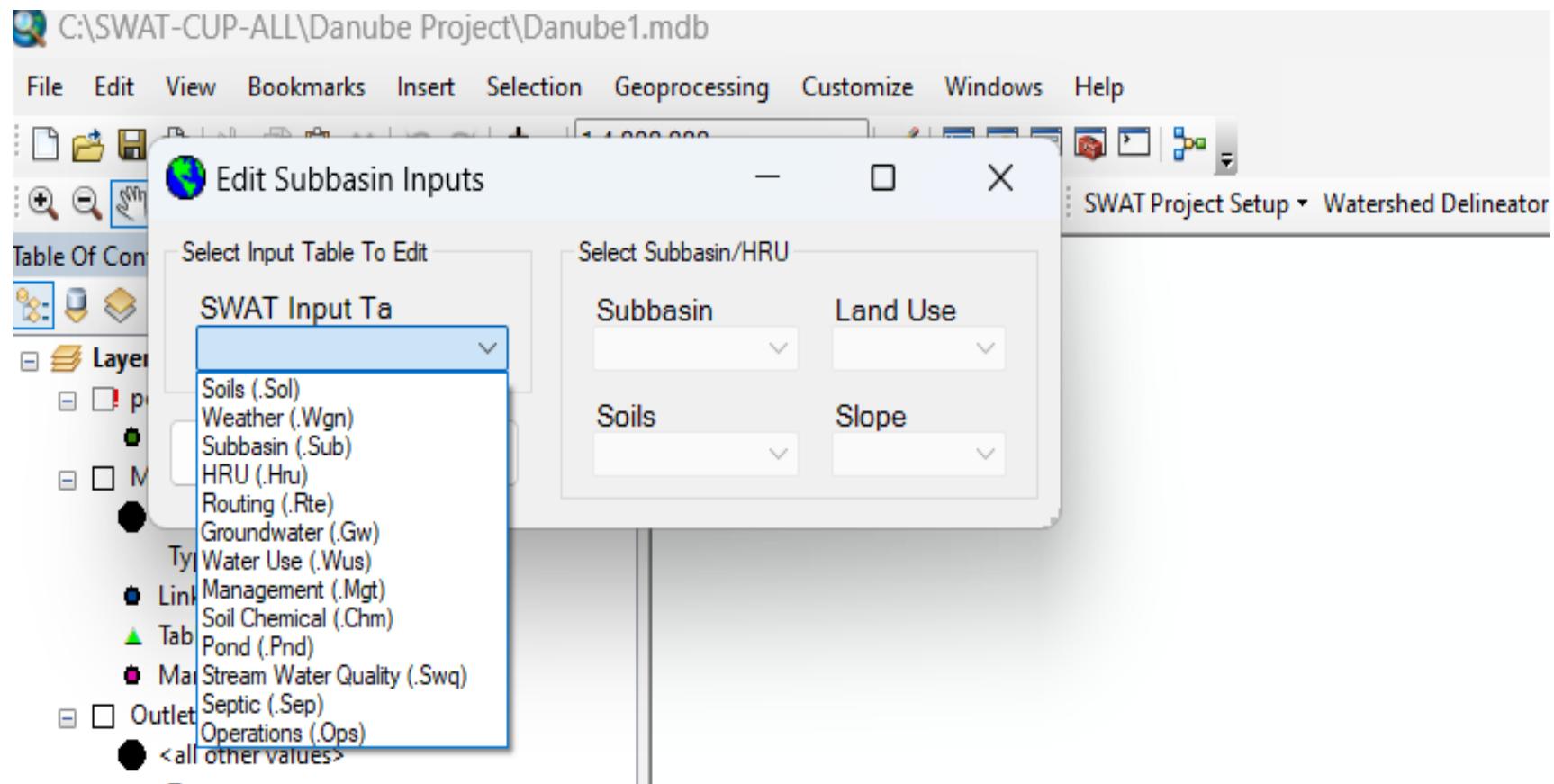


Calibrate for sediment

r__CN2.mgt	-0.08927	0.080631
v__ESCO.hru	0.834495	0.934149
r__SOL_AWC().sol	-0.44507	0.03172
r__SOL_K().sol	-2.28205	-1.08942
r__SOL_BD().sol	-0.35689	0.187254
v__ALPHA_BF.gw	0.041521	0.055373
v__GW_DELAY.gw	42.53216	65.54935
v__GW_REVAP.gw	0.056003	0.102077
v__GWQMN.gw	903.2833	1123.265
v__RCHRG_DP.gw	0.519902	0.773894
r__SLSUBBSN.hru	0.119423	0.188895
r__OV_N.hru	-0.33536	-0.11899
r__PRF_BSN.bsn	-0.77937	-0.46642
r__SPCON.bsn	-0.23262	0.076431
r__SPEXP.bsn	-0.2267	-0.14566
r__CH_COV1.rte	-0.59822	-0.23061
r__CH_COV2.rte	-0.40361	-0.29225
r__USLE_K().sol	0.084748	0.117076
r__USLE_P.mgt	-0.25525	-0.01533



Implement terracing



Make a No_Observed iteration in SWAT-CUP

- File: Extract_rch_No_Obs.def

```
SUFI2          : SWAT-CUP program: SUFI2, SPE, PSO
output.rch      : swat output file name
1              : number of variables to get (such as: discharge, sediment, ET, etc.)
11             : variable column number(s) in the swat output file
R-SED_OUT      : Names of variables

27             : total number of subbasins in the project

1              : number of subbasins to get for the first variable
26             : subbasin numbers for the first variable.

1973           : beginning year of simulation not including the warm-up period
2006           : end year of simulation

2              : time step (1=daily,2=monthly, 3=yearly)

//Remarks
```

- extract_No_Obs_rch.exe

Make a No_Observed iteration in SWAT-CUP

No terracing				Terracing			
Soil loss(tons)	Pr(soil loss)	Cost(Failure)	Risk	Soil loss(tons)	Pr(soil loss)	Cost(Failure)	Risk
53769	0.26	5376877	1410113	24180	0.63	2417951	1523072
115209	0.28	11520891	3190837	60186	0.24	6018561	1445634
176649	0.18	17664903	3203936	96192	0.08	9619171	801594
238089	0.15	23808916	3501315	132198	0.03	13219781	356419
299529	0.07	29952928	2128994	168204	0.00	16820391	82454
360969	0.02	36096941	884736	204210	0.00	20421000	50052
422410	0.01	42240953	621195	240216	0.00	24021609	117754
483850	0.01	48384966	355775	276222	0.00	27622219	67702
545290	0.00	54528981	267301	312228	0.00	31222828	76527
606730	0.01	60672994	594838	348234	0.00	34823438	85352
330249		33024935	1615904	186207		18620695	460656

Cost of failure (soil loss) is \$100/tn

\$ Expected saving due to terracing = $1615904 - 460656 = 1155248$

If cost if terracing is less than 1155248 Then it is worth it!



Response to questions

What you expect to learn – Mathilde Puche

- Selection of relevant parameters to calibrate
- Interpret the final range of parameters
- How to know when a model is calibrated?
- How to use the “calibrated model” to predict flow and make further analyses (climate change impact for example) if the best simulation is not adequate to represent it ?
- Automatization of calibration: is there a way to do it ? (because the procedure explained in the videos is time-consuming when you have to build 20 versions of the model for example).

Selection of relevant parameters to calibrate

Table 1 List of SWAT's parameters that were fitted and their final calibrated values

Variable	Sensitive parameters	Final parameter value
Parameters sensitive to all four variables	<ul style="list-style-type: none"> – snowfall temperature, SFTMP.bsn^a – Melt factor for snow on December 21, SMFMN.bsn – Melt factor for snow on June 21, SMFMX.bsn – Snowmelt base temperature, SMTMP.bsn – Snowmelt temperature lag factor, TIMP.bsn – Baseflow alpha factor, v__ALPHA_BF.gw^c – Groundwater delay time, v__GW_DELAY.gw – Curve number, r__CN2.mgt – Manning's n value for the main channel, v__CH_N2.rte – Effective hyd. cond. in the main channel, v__CH_K2.rte – Soil available water storage capacity, r__SOL_AWC.sol – Soil hydraulic conductivity, r__SOL_K.sol – Soil bulk density, r__SOL_BD.sol – Maximum canopy storage, v__CANMX.hru__AGRR^d – Maximum canopy storage, v__CANMX.hru__FRST – Maximum canopy storage, v__CANMX.hru__PAST 	<ul style="list-style-type: none"> -1.1^b 0.36 2.84 2.8 0.29 [0.17, 0.34] 0.74 [0.085, 0.045] [0.0, 0.3] [4, 14] [-0.17, 0.3] [-0.19, 0.5] [-0.027, 0.3] 2.8 4.8 4.1
Parameters sensitive to sediment only	<ul style="list-style-type: none"> – Sediment routing factor in main channels, v__PRF.bsn – Channel re-entrained exponent parameter v__SPEXP.bsn – Channel re-entrained linear parameter v__SPCON.bsn – Channel erodability factor, v__CH_EROD.rte – Channel cover factor, v__CH_COV.rte 	<ul style="list-style-type: none"> [0.2, 0.25] [1.35, 1.47] [0.001, 0.002] [0.12, 0.14] [0.2, 0.25]
Parameters sensitive to total phosphorus only	<ul style="list-style-type: none"> – Phosphorus availability index, v__PSP.bsn – P enrichment ratio with sediment loading, ERORG.P.hru – Rate constant for mineralization of organic P, BC4.swq – Organic P settling rate, RS5.swq 	<ul style="list-style-type: none"> [0.5, 0.7] [2.0, 4.0] [0.3, 0.5] [0.08, 0.1]
Parameters sensitive to nitrate only	<ul style="list-style-type: none"> – Nitrogen in rain, RCN.bsn – Nitrogen uptake distribution parameter, UBN.bsn – Concentration of NO₃ in groundwater, r__GWNO3.gw – Organic N enrichment for sediment, ERORG.N.hru – Nitrate percolation coefficient, NPERCO.bsn 	<ul style="list-style-type: none"> 1.3 9.4 [-0.3, 0.5] 2.75 0.223
Parameters sensitive to sediment and total phosphorus	<ul style="list-style-type: none"> – support practice factor r__USLE_P.mgt – water erosion factor v__USLE_C.crp__AGRR – water erosion factor v__USLE_C.crp__PAST,ORCD – water erosion factor v__USLE_C.crp__FRST – soil erodability factor, r__USLE_K.sol 	<ul style="list-style-type: none"> [-0.6, -0.1] [0.03, 0.3] [0.07, 0.2] [0.0, 0.1] [-0.19, 0.5]

^a The extension (.bsn) refers to the SWAT file type where the parameter occurs.

^b The fixed values indicate that a parameter was fitted and then fixed.

^c The qualifier (v__) refers to the substitution of a parameter by a value from the given range, while (r__) refers to a relative change in the parameter were the current values is multiplied by 1 plus a factor in the given range.

^d AGRR = agricultural, PAST = pasture, ORCD = orchard, FRST = forest.

Selection of relevant parameters to calibrate

- Base flow too low
- Evapotranspiration too high

GWQMN.gw ↓

GW_REVAP.gw ↓

REVAMPM.gw ↑

Peak flow too low

CN2,mgt ↑

SOL_AWC.sol ↓

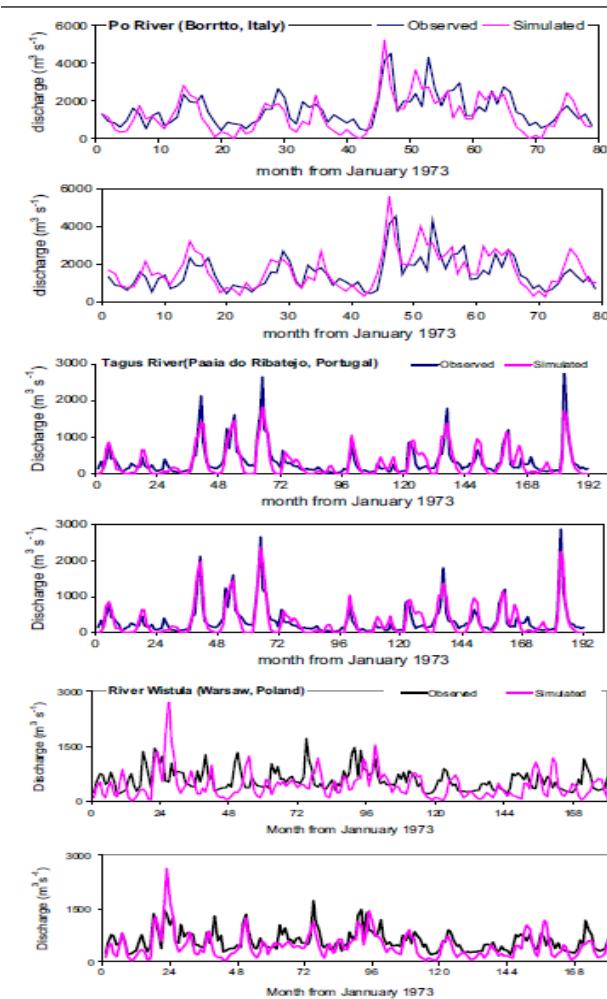
ESOO.hru ↓

Discharge shift to the right

HRU_SLP ↑

OV_N.hru ↓

SLSUBBSN.hru ↓



A continental-scale hydrology and water quality model for Europe:

Calibration and uncertainty of a high-resolution large-scale SWAT model

K.C. Abbaspour et al., Journal of Hydrology 524 (2015) 733–752. <https://doi.org/10.1016/j.jhydrol.2015.03.027>

Selection of relevant parameters to calibrate

Flow	Range		Sediment	Range		Nitrate	Range		total phosphorus	Rage
r__CN2.mgt	-0.2	0.2	v__PRF_BSN.bsn	0.2	0.25	v__RCN.bsn	1	5	V__PSP.bsn	0.5 0.7
v__ESCO.hru	0.7	0.1	v__SPEXP.bsn	1.3	1.5	v__N_UPDIS.bsn	5	30	V__ERORGP.hru	2 4
v__GWQMN.gw	0.0	1000	v__SPCON.bsn	0.001	0.002	v__SHALLST_N.gw	0	100	V__LAT_ORGP	0 100
v__REVAPMN.gw	0.0	1000	v__CH_COV1.rte	0.12	0.14	v__ERORGN.hru	1	4	V__BC4_BSN.bsn	0.3 0.35
v__GW_REVAP.gw	0.02	0.06	v__CH_COV2.rte	0.2	0.25	v__NPERCO.bsn	0	1	V__RS5.swq	0.05 0.1
r__SOL_AWC().sol	-0.5	0.5	V__ERORGN.hru	2	4	v__LAT_ORGN.gw	0	100	V__USLE_P.mgt	0 1

Interpret the final range of parameters

The final parameter ranges are your calibrated parameters. The range shows the uncertainty about them.

The ranges must be propagated in all model uses

How to know when a model is calibrated?

Corpus ID: 11879396

Calibration of Hydrologic Models: When is a Model Calibrated?

K. Abbaspour

Published 2005, MODSIM Conference, Melbourne, Australia

Engineering

<https://www.semanticscholar.org/paper/Calibration-of-Hydrologic-Models-%3A-When-is-a-Model-Abbaspour/75ddd759b7bccbfa9207e505205df32519ef557f>

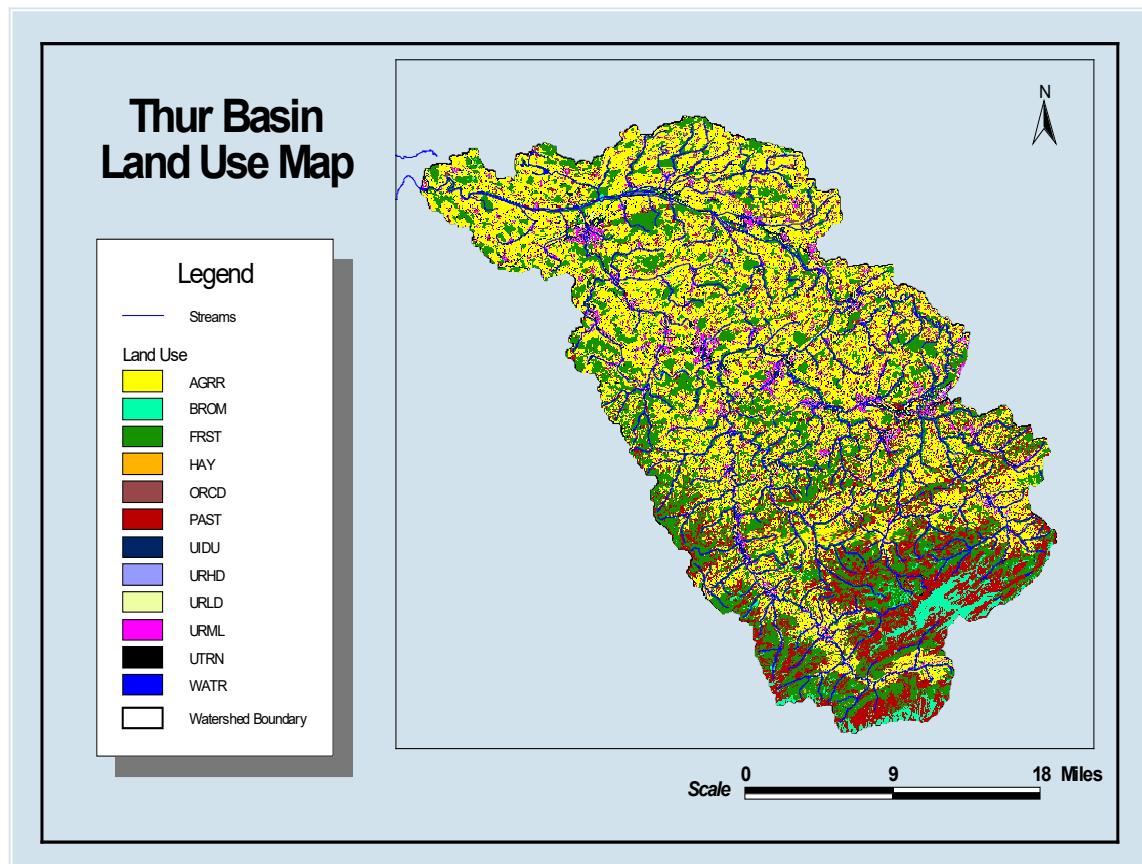
In reality, we will never know!

- But in practice when the next iteration doesn't change the objective function value
- When the next iteration reduces p-factor too much and most of your observed data are not bracketed by 95ppu, which is the simulation result.
- A calibrated model is always conditional and probabilistic (includes uncertainty)
- So, the right question is how to reduce the uncertainty in the calibration of a hydrologic model

Thur Watershed Application - Constraint-optimization

$$g = \frac{1}{\sigma_{Q_m}^2} \sum_{i=1}^{130} (Q_m - Q_s)_i^2 + \frac{1}{\sigma_{S_m}^2} \sum_{i=1}^{130} (S_m - S_s)_i^2 + \frac{1}{\sigma_{N_m}^2} \sum_{i=1}^{130} (N_m - N_s)_i^2 + \frac{1}{\sigma_{P_m}^2} \sum_{i=1}^{130} (P_m - P_s)_i^2$$

$0.1 \leq S_{\text{Forest}} \leq 0.3$
$1.5 \leq S_{\text{Agricultural}} \leq 6$
$2.2 \leq N_{\text{Forest}} \leq 16$
$19 \leq N_{\text{Agricultural}} \leq 47$
$15 \leq N_{\text{Pasture}} \leq 25$
$0.02 \leq P_{\text{Forest}} \leq 0.1$
$0.5 \leq P_{\text{Agricultural}} \leq 2.4$
$0.3 \leq P_{\text{Pasture}} \leq 1.2$



How to use the “calibrated model” to predict flow and make further analyses (climate change impact for example) if the best simulation is not adequate to represent it?

- You always have to propagate the parameter uncertainty
- Show the uncertainty in the output using 95ppu



Example: application to climate change

- Update tmp.tmp and pcp.pcp, update dates in file.cio, and the extract_No_Obs_*.def
- Check the appropriate boxes in SPE_Extract.bat and SPE_No_Obs_Post.bat (uncheck others)
- Run an “iteration” with as many simulations as the final calibration run and all the parameter ranges.
- Run SPE_No_Obs_Post.bat
- In the Outputs/Outputs No Observed see the 95PPU



Automatization of calibration: is there a way to do it? (because the procedure explained in the videos is time-consuming when you have to build 20 versions of the model for example).

The calibration of hydrologic models is time-consuming.

Often it is an iterative process.

However, if you include the correct processes in the model, then you don't need more than 2-3 iterations. So, the idea of looking at the initial simulation can help with including the right processes.

If you have 20 models to calibrate, I suggest

- Make sure the initial model is calibratable,
- Run the SPE (SUFI-2) a couple of iterations with around 200-300 simulations
- Use parallel processing
- Make sure you have a good machine with many CPUs (32) and a large RAM (64 GB)
(can find one for around \$1,800)

(Using the so-called automated programs like PSO, GLUE, ParaSol, etc. will take more runs)



Criterion	GLUE	ParaSol	SUFI-2	Bayesian inference with cont. autoregr. error model	
				MCMC	IS
Goal function	Nash-Sutcliffe	Nash-Sutcliffe	Nash-Sutcliffe	post. prob. density	post. prob. density
a_CN2.mgt	-16.8 (-29.6, -9.8) ¹	-21.0 (-21.9, -20.1)	-26.9 (-30.0, -7.2)	-14.2 (-16.8, -11.6)	-19.60
v_ESCO.hru	0.76 (0.02, 0.97)	0.67 (0.65, 0.69)	0.82 (0.43, 1.0)	0.74 (0.63, 0.75)	0.62
v_EPCO.hru	0.22 (0.04, 0.90)	0.16 (0.13, 0.20)	1 (0.34, 1.0)	0.94 (0.39, 0.98)	0.27
r_SOL_K.sol	-0.16 (-0.36, 0.78)	-0.37 (-0.41, -0.34)	-0.1 (-0.58, 0.34)	-0.29 (-0.31, 0.78)	0.01
a_SOL_AWC.sol	0.11 (0.01, 0.15)	0.07 (0.08, 0.08)	0.07 (0.05, 0.15)	0.12 (0.1, 0.13)	0.05
v_ALPHA_BF.gw	0.12 (0.06, 0.97)	0.12 (0.08, 0.13)	0.51 (0.23, 0.74)	0.14 (0.11, 0.15)	0.91
v_GW_DELAY.gw	159.58 (9.7, 289.3)	107.7 (91.2, 115.2)	190.07 (100.2, 300)	25.5 (17.8, 33.3)	33.15
r_SLSUBBSN.hru	-0.45 (-0.56, 0.46)	-0.59 (-0.60, -0.58)	-0.52 (-0.60, 0.03)	-0.55 (-0.56, 0.15)	0.58
a_CH_K2.rte	78.19 (6.0, 144.8)	35.70 (27.72, 37.67)	83.95 (69.4, 150.0)	78.3 (68.0, 86.2)	147.23
a_OV_N.hru	0.05 (0.00, 0.20)	0.11 (0.07, 0.10)	0.06 (0.00, 0.11)	0.12 (0.00, 0.19)	0.08
$^2\sigma_{\text{dry}}$	-	-	-	0.93 (0.81, 1.10)	0.87
$^2\sigma_{\text{wet}}$	-	-	-	2.81 (2.4, 3.9)	2.30
$^2\tau_{\text{dry}}$	-	-	-	38.13 (29.5, 53.8)	28.47
$^2\tau_{\text{wet}}$	-	-	-	3.42 (2.4, 8.0)	0.92
NS for cal (val)	0.80 (0.78)	0.82 (0.81)	0.80 (0.75)	0.77 (0.77)	0.64 (0.71)
R ² for cal (val)	0.80 (0.84)	0.82 (0.85)	0.81 (0.81)	0.78 (0.81)	0.70 (0.72)

Comparing uncertainty analysis techniques for a SWAT application to the Chaohe Basin in China

Yang et al., 2008: 1-23. <https://doi.org/10.1016/j.jhydrol.2008.05.012>

Uncertainty source	All sources of uncertainty	Parameter uncertainty only	All sources of uncertainty	Parameter uncertainty only	Parameter uncertainty only
Uncertainty described by parameter uncertainty	All sources of uncertainty	Parameter uncertainty only	All sources of uncertainty	Parameter uncertainty only	Parameter uncertainty only
Difficulty of implement.	very easy	easy	easy	more complicated	more complicated
Number of runs	10000	7500	1500 + 1500	5000 + 20'000 + 20'000	100'000

What you expect to learn – Katie Mendoza

- The Latin hypercube sampling
- Using p-factor and r-factor (maybe even Z score) for calibration instead of NS, PBIAS
- What are your thoughts on KGE
- Nitrate calibration (also sediment calibration)
- Validation

Latin Hypercube (Stratified Sampling) Sampling

If you want to make 4 simulations:



- 1- 1,3,1,4
- 2- 2,2,3,2
- 3- 4,1,2,3
- 4- 3,4,4,1

Using p-factor and r-factor (maybe even Z score) for calibration instead of NS, PBIAS

- NS, etc, measure two signals, but we are actually dealing with two distributions
- NS, etc, correspond to one set of parameters. But many sets of parameters can produce statistically similar NSs

What are your thoughts on the Kling-Gupta Efficiency (KGE)

KGE is a statistical metric commonly used as an objective function in hydrological model evaluation.

Maximize:
$$KGE = 1 - \sqrt{(r - 1)^2 + (\alpha - 1)^2 + (\beta - 1)^2}$$

Where $\alpha = \frac{\sigma_s}{\sigma_m}$, and $\beta = \frac{\mu_s}{\mu_m}$, and r = correlation coefficient

- KGE combines multiple aspects of the hydrograph, including the mean, std dev, and correlation into a single metric. This allows for a more holistic assessment of the model's ability to reproduce observed variables.
- KGE is relatively robust to outliers

The Root Mean Square Error Ratio (RSR)

The RSR is a commonly used objective function in hydrological model calibration

Minimize:

$$RSR = \frac{\sqrt{\sum_{i=1}^n (Q_m - Q_s)_i^2}}{\sqrt{\sum_{i=1}^n (Q_{m,i} - \bar{Q}_m)^2}}$$

- RSR is a straightforward and easy-to-understand metric, calculated as the ratio of the root mean square error (RMSE) to the standard deviation of the observed data.
- RSR accounts for the difference between the mean of observed and simulated data and the variability

The percent bias (PBIAS)

PBIAS is a commonly used objective function in hydrological model calibration

Minimize:
$$PBIAS = 100 * \frac{\sum_{i=1}^n (\mathcal{Q}_m - \mathcal{Q}_s)_i}{\sum_{i=1}^n \mathcal{Q}_{m,i}}$$

- PBIAS is a simple and intuitive metric, representing the percentage difference between the observed and simulated values.
- PBIAS is scale-invariant allowing a direct comparison of model performance across different catchments or datasets with varying scales.
- Shows if a model is over or under-estimating. But only accounts for bias and not variability

Sum of Squared Ranks (Average of Rank Squares) (SSQR)

The Sum of Squared Ranks or the Average of Rank Squares (SSQR)

Minimize: $SSQR = \frac{1}{n} \sum_{i=1}^n [Q_{i,m} - Q_{i,s}]^2$

Where i here is the rank of measured and simulated variables.

- By ranking the observations and simulations, SSQR focuses on the relative order or position of the values. It is non-parametric
- SSQR is less sensitive to extreme values or outliers compared to other objective functions that directly consider the differences between observed and simulated values.
- SSQR can be useful in quantifying the performance of a model in capturing the relative severity or intensity of drought and flood events.

Nitrate calibration (also sediment calibration)

- Calibrate flow first
- Add and calibrate nitrate parameters. Keep parameter ranges for flow the same
- Add and calibrate sediment parameters. Keep parameter ranges for flow and nitrate the same
- Add and calibrate phosphor parameters. Keep parameter ranges for flow, nitrate, and sediment the same

Validation

- Use about 1/3 of the data
- Make sure calibration and validation data have similar mean and variances

<https://www.youtube.com/watch?v=7E9qxRzwmV4&t=468s>

SWATCUP-Premium

- SPE Single Objective Function (This is similar to SUFI-2)
- SPE Single Objective Behavioral
- SPE Multiple Objective Function
- SPE Multiple Objective Behavioral

SPE Single Objective Function

- The program SPE Single Objective is like the SUFI-2 program.
- A choice of 11 objective functions can be used to estimate SWAT parameters.
- The approach and input files are the same as what they are for SUFI-2.

SPE Single Objective Behavioral Function

- The program SPE Single Objective Behavioral optimizes the parameters based on a set of behavioral solutions
- The user identifies a behavioral threshold, and optimization method, i.e., $NS>0.7$
- The New_Parameters are calculated based on the behavioral set only
- Therefore, the uncertainty band here is smaller compared to the non-behavioral case

SPE Multiple-Objective Function

- The program SPE Multiple Objective allows the user to build an objective function made up of several objective functions. The program uses the following function as goal function:
- Maximize:
$$\text{multi_goal} = (w_3R_2 + w_5NS + w_6BR2 + w_9KGE + w_{11}MNS) - [w_1MMSE + w_2SMSE + w_4CHI_2 + w_7SSQR + |w_8PBIAS| + w_{10}RSR]$$
- Where wi's are the weights of the corresponding functions.
- An example of a multi-objective function is the following function:
- $\text{Multi_goal} = w_3R_2 + w_5NS - |w_8PBIAS|$

SPE Multiple-Objective Function

16 : number of observed variables

5 : Objective function type,

1=mult,2=sum,3=r2,4=chi2,5=NS,6=br2,7=ssqr,8=PBIAS,9=KGE,10=RSR,11=MNS

0 0 1 0 0.122 0 0 0.0050 0 0 0 :weight of each objective function

-2 : min value of objective function threshold for the behavioral solutions

1 : if objective function is 11=MNS (modified NS), indicate the power, p.

SPE Multiple-Objective Function Behavioral

Similar to the Single Objective Function, the Multiple-Objective function can also have a threshold to discriminate between simulations

SWAT-CUP videos

<https://www.youtube.com/@2w2e-channel>

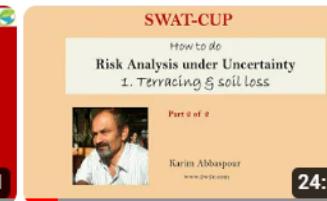
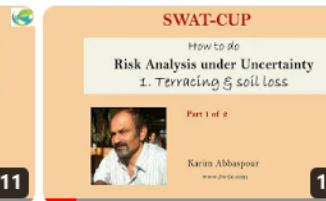
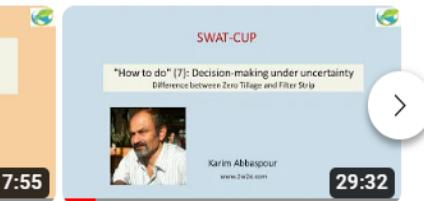
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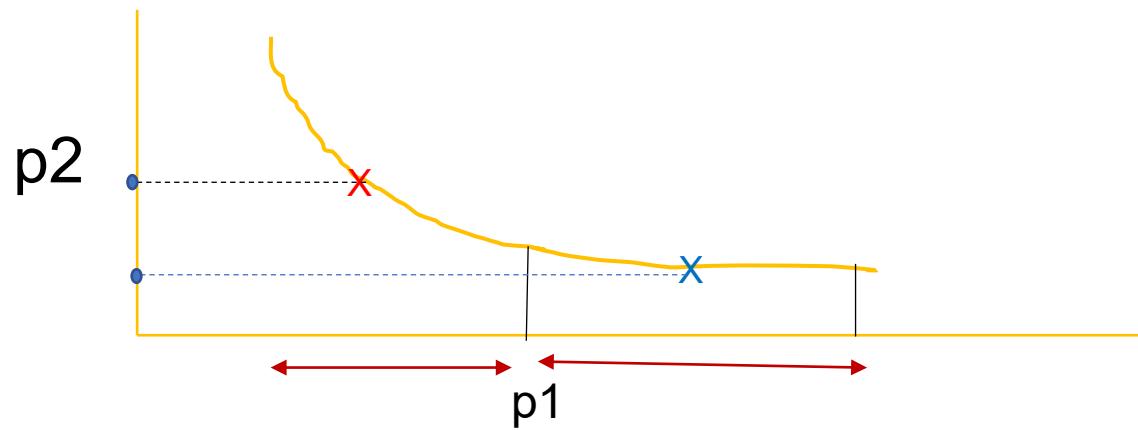
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 <p>SWAT-CUP How to do Design Filter Strip under uncertainty</p> <p>Karim Abbaspour www.2w2e.com</p> <p>20:33</p>	 <p>SWAT-CUP Video Guide Where is everything?</p> <p>Karim Abbaspour www.2w2e.com</p> <p>6:21</p>	 <p>SWAT-CUP How to do Risk Analysis under Uncertainty 1. Terracing & soil loss</p> <p>Karim Abbaspour www.2w2e.com</p> <p>Part 1 of 2</p> <p>24:11</p>	 <p>SWAT-CUP How to do Risk Analysis under Uncertainty 1. Terracing & soil loss</p> <p>Karim Abbaspour www.2w2e.com</p> <p>Part 2 of 2</p> <p>17:55</p>	 <p>SWAT-CUP How to do (7); Decision-making under uncertainty Difference between Zscore and Filter Strip</p> <p>Karim Abbaspour www.2w2e.com</p> <p>29:32</p>
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 2w2e Consulting, GmbH, Duebendorf, Switzerland

4. Sensitivity analysis - one-at-a-time

- Local (one-at-a-time) sensitivity analysis



Licensed SWATCUP Programs from 2w2e Consulting

SWATCUP-2019

- **SUFI2, PSO, GLUE, ParaSol, MCMC**
- Single Objective Function

SWATCUP-Premium

- **SPE (SUFI2), PSO**
- Single-Objective Function,
- Single-Objective Function Behavioral,
- Multi-Objective Function,
- Multi-Objective Function Behavioral

SWATplusCUP

- **SPE (SUFI2), PSO**
- Single-Objective Function,
- Single-Objective Function Behavioral,
- Multi-Objective Function,
- Multi-Objective Function Behavioral



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- Single-Objective Function,
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- Multi-Objective Function,
- Multi-Objective Function Behavioral

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All

Responses:

2022 ▾

2023 ▾

^

Try asking

Is there a protocol for the calibration of SWAT?

What are the sensitive parameters to flow and sediment?

What are the advancements of glaciers in SWAT modeling?

How is snowmelt handled in SWAT program?

What are the advancements of glaciers in SWAT modeling?

Ask

Q: Is there a calibration protocol for swat?

2000

The calibration of the SWAT (Soil and Water Assessment Tool) **model involves an iterative, trial-and-error process**, often supported by automated parameter estimation tools like **PEST (Parameter ESTimation)**. The calibration process aims to adjust model parameters so that the model's simulated outputs closely match observed data. Key steps in the SWAT model calibration protocol typically include:

1. Selection of Calibration Parameters: Identify sensitive parameters that significantly influence the model's output. These parameters can include, but are not limited to, surface runoff, groundwater recharge, soil properties, and crop growth parameters.
2. Collection of Observed Data: Gather observed data for comparison with model simulations. This data can include streamflow measurements, groundwater levels, and water quality data from the watershed being modeled.
3. Initial Parameter Estimation: Set initial values for the calibration parameters based on literature, field measurements, or expert judgment.
4. Model Runs and Sensitivity Analysis: Perform initial model runs and conduct sensitivity analysis to determine the influence of each parameter on model outputs. This helps in focusing calibration efforts on the most influential parameters.
5. Calibration Process: Adjust the parameters iteratively to minimize the difference between the observed and simulated data. This process can be manual (trial-and-error) or automated using software like PEST.
6. Model Evaluation: Assess the model's performance using statistical measures such as the Nash-Sutcliffe efficiency, RMSE (Root Mean Square Error), and others to quantify the goodness-of-fit between observed and simulated data.
7. Validation: After calibration, validate the model using a different dataset from the calibration period to test the model's predictive capability.
8. Refinement and Uncertainty Analysis: Refine the model as necessary based on validation results and perform uncertainty analysis to understand the confidence in model predictions.

The SWAT model's user manual and scientific literature provide detailed guidance on the calibration process, including recommended practices for parameter sensitivity analysis, calibration, validation, and uncertainty assessment. It's also important to leverage the SWAT community forums and resources for specific advice and best practices tailored to individual projects.

Q: Is there a calibration protocol for swat?

2023

Yes, there is a **calibration protocol** for the Soil and Water Assessment Tool (SWAT) model. The calibration of SWAT models is a critical step to ensure that the model accurately represents the physical processes occurring within a watershed. The calibration process involves adjusting model parameters within their plausible ranges until the model outputs closely match observed data for variables such as streamflow, sediment load, nutrient concentrations, etc.

A general approach to SWAT model calibration includes the following steps:

1. Pre-Calibration Input Data and Model Structure Improvement: Before calibration, it's essential to build the SWAT model using the best available data and knowledge. This includes selecting the most appropriate datasets for soil, land use, climate, etc., and ensuring the model structure accurately represents the watershed's physical characteristics. It's important to test different datasets and choose the best ones to proceed with. The initial model performance should not be drastically different from measured data; otherwise, calibration might be of little help. Including as many relevant processes in the model as possible is crucial at this stage.

2. Sensitivity Analysis: Conducting a sensitivity analysis to identify which parameters significantly influence model outputs. This helps focus the calibration efforts on the most influential parameters.

3. Calibration Process: Adjusting the sensitive parameters identified in the sensitivity analysis to minimize the difference between the model's simulated outputs and observed data. This often involves using an optimization algorithm or manual adjustments based on expert knowledge.

4. Validation: After calibration, the model is validated with a different dataset (not used in the calibration) to ensure that the calibrated model can accurately predict watershed behavior under different conditions.

5. Uncertainty Analysis: Finally, conducting an uncertainty analysis is important to understand the confidence in the model predictions and the impact of parameter uncertainties on model outputs.

The calibration process can be supported by tools such as **SWAT-CUP** (SWAT Calibration and Uncertainty Programs), which facilitates the calibration and uncertainty analysis of SWAT models. SWAT-CUP uses various algorithms, including Sequential Uncertainty Fitting (SUFI-2), to automate the calibration process and quantify uncertainties.

Reference:

- Abbaspour, K.C., Vagheli, S., Srinivasan, R., "A Guideline for Successful Calibration and Uncertainty Analysis for Soil and Water Assessment: A Review of Papers from the 2016 International SWAT Conference"; Page: 10.0; URL: [\[ref\]](#)

Year Published: 2018.0; Title: A Guideline for Successful Calibration and Uncertainty Analysis for Soil and Water Assessment: A Review of Papers from the 2016 International SWAT Conference.

Q: What are the advancements in glaciers-SWAT modeling?

2000

There is not enough info to answer the question.

2001

The Soil and Water Assessment Tool (SWAT) is a comprehensive model developed to predict the impact of land management practices on water, sediment, and agricultural chemical yields in large, complex watersheds with varying soils, land use, and management conditions over long periods of time. While SWAT is extensively used for hydrological and agricultural applications, including the assessment of climate change impacts on water resources, its direct application to modeling glacier dynamics or advancements is not explicitly detailed in the provided references.

The primary focus of SWAT, as described in the inputs, is on simulating the hydrologic cycle, soil moisture, runoff, evapotranspiration, and the impact of land use changes on water quality and quantity. It incorporates algorithms for hydrology, weather, soil processes, plant growth, and land management practices. Modifications to the model have been made to account for the effects of changing atmospheric CO₂ on evapotranspiration and radiation use efficiency, and it has been linked to Geographic Information Systems (GIS) for setting watershed boundaries and extracting necessary input variables from digital databases. SWAT has been applied in various studies to evaluate the impact of potential climate change on streamflow, water quality, and water yield in different regions, including the Missouri River Basin and the Black Hills of South Dakota, USA.

However, the specific modeling of glaciers, including their advancements or retreats, typically requires specialized glaciological models or the integration of SWAT with other models that can simulate glacier dynamics. Some studies might use SWAT in conjunction with Regional Climate Models (RegCM) or other hydrological models that include glacier melt as a component of the hydrology to assess the impact of climate change on water resources in glacier-fed river basins. These applications would involve using SWAT to simulate downstream hydrological processes while relying on other models or data sources to account for glacier mass balance and dynamics.

Q: What are the advancements for glaciers-SWAT modeling? 2020

The advancements in glaciers-SWAT (Soil and Water Assessment Tool) modeling have been significant, focusing on improving the accuracy and comprehensiveness of simulations related to glacier dynamics, snowmelt, and their hydrological impacts. Key advancements include:

1. Integration of Enhanced Snowmelt and Glacier Melt Modules: Modifications to the SWAT model have been made to better simulate the processes of snowmelt and glacier melt. For instance, Duan et al. (2020) introduced an improved SWAT model that incorporates modified snow melting and flood processes, significantly enhancing the model's ability to simulate ice and snow runoff in mountainous terrains like the Kunlun Mountains, China. This includes adjustments for accumulated temperature effects on precipitation form, aiming to improve the temporal accuracy of flooding simulations in alpine regions ([Duan et al., 2020](#)).
2. High-Resolution Temporal Simulation Capabilities: Efforts have been made to simulate hydrological processes at a sub-daily scale, addressing the need for high temporal resolution in areas with significant ice and snow melt. This is crucial for accurately simulating flood events in glacier-fed river basins ([Duan et al., 2019](#)).
3. Inclusion of Remote Sensing Data: The use of remote sensing data to enhance SWAT modeling of glacier and snow-covered areas has been a significant advancement. This includes the use of MODIS imagery for snow cover assessment and the integration of snow water equivalent data to improve snowmelt runoff predictions ([Grusson et al., 2015](#)).
4. Multi-Objective Calibration and Validation: The application of multi-objective calibration techniques using remote sensing products has improved the reliability of SWAT predictions in snow-dominated regions. This approach allows for a more comprehensive evaluation of model performance across different hydrological components ([Liu et al., 2020](#)).
5. Improved Representation of Glacier Dynamics: While traditional SWAT applications focused more on snowmelt, recent advancements have aimed at incorporating glacier dynamics into the model. This includes the simulation of glacier area changes over time and their impact on runoff ([Qi et al., 2017](#)).
6. Climate Change Impact Assessment: SWAT models have been increasingly used to assess the impacts of climate change on glacier melt and snowmelt processes, providing valuable insights into future water availability and management strategies in glacier-fed basins ([Khadka et al., 2014; Zhang et al., 2015](#)).

These advancements reflect ongoing efforts to enhance the SWAT model's capabilities in simulating complex hydrological processes in glacierized and snow-dominated catchments. The integration of improved snow and ice melt algorithms, high-resolution temporal simulation capabilities, and the use of remote sensing data are key factors contributing to the model's enhanced performance in these challenging environments.

References:

- Duan, Y., Liu, T., Meng, F., Luo, M., Frankl, A., De Maeyer, P., Bao, A., Kurban, A., & Feng, X. (2020). Accurate Simulation of Ice and Snow Runoff for the Mountainous Terrain of the Kunlun Mountains, China. *Remote Sensing*, 12(179); URL: [\[ref\]](#)
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; Year Published: 2020.
- Qi, J., Li, S., Jamieson, R., Hebb, D., Xing, Z., & Meng, F.-R. (2017). Modifying SWAT with an energy balance module to simulate snowmelt for maritime regions. *Environmental Model & Software*, 93, 146–160; Year Published: 2017. [\[ref\]](#)
- Khadka, D., Babel, M.S., Shrestha, S., & Tripathi, N.K. (2014). Climate change impact on glacier and snow melt and runoff in Tamakoshi basin in the Hindu Kush Himalayan (HKH) region. *Journal of Hydrology*, 511, 49–60; Year Published: 2014. [\[ref\]](#)
- Zhang, Y., Su, F., Hao, Z., Xu, C., Yu, Z., Wang, L., & Tong, K. (2015). Impact of projected climate change on the hydrology in the headwaters of the Yellow River basin. *Hydrological Processes*, 29, 4379–4397; Year Published: 2015. [\[ref\]](#)

Q: what are swat's applications in climate change studies?

2000

The Soil and Water Assessment Tool (SWAT) is a comprehensive, river basin or watershed scale model developed by the US Department of Agriculture, Agricultural Research Service. It is designed to predict the impact of land-management practices on water, sediment, and agricultural chemical yields in large, complex watersheds with varying soils, land use, and management conditions over long periods of time. SWAT's applications in climate change and land-use change studies are extensive due to its ability to simulate long-term impacts using readily available inputs and its computational efficiency. Here are some of the key applications:

1. Assessing Climate Change Impacts: SWAT can be used to evaluate the effects of climate change on water resources by simulating how changes in temperature, precipitation patterns, and CO₂ concentrations affect evapotranspiration, soil moisture, and runoff. This helps in understanding potential future changes in water availability, flood risks, and drought occurrences within a watershed.
2. Evaluating Land-use Change Scenarios: The model can simulate the effects of various land-use changes, such as deforestation, urbanization, or changes in agricultural practices, on water quality and quantity. This is crucial for assessing the impacts of land-use planning and policy decisions on watershed hydrology and for developing strategies to mitigate adverse effects.
3. Water Quality Management: SWAT is capable of simulating the transport of sediments, nutrients, and pesticides across a watershed, making it a valuable tool for assessing the impacts of land-use and climate change on water quality. This can inform the development of management practices aimed at reducing pollution loads in rivers and lakes.
4. Integrated Water Resources Management (IWRM): By providing a holistic view of the watershed, SWAT supports IWRM approaches that consider the interconnections between land use, water use, and water quality under changing climatic conditions. This facilitates the development of sustainable water management strategies that balance human needs with environmental protection.
5. Agricultural Practices and Policy Evaluation: SWAT can evaluate the effectiveness of various agricultural practices (e.g., conservation tillage, nutrient management) in reducing runoff and improving water quality. It also helps in assessing the potential impacts of agricultural policies on water resources under future climate scenarios.
6. Hydrological Modeling and Prediction: SWAT's ability to simulate daily time steps over long periods makes it suitable for hydrological predictions under changing climate and land-use conditions. This includes forecasting streamflow, analyzing flood risks, and assessing the sustainability of water resources for future demands.
7. Ecosystem Services Assessment: The model can be used to assess how changes in climate and land use affect ecosystem services related to water, such as habitat provision, water purification, and flood regulation. This is important for conservation planning and for valuing the benefits provided by ecosystems. (**In-house knowledge of gpt-4**).

Q: what are swat's applications in climate change/landuse change studies?

2001

1. Climate Change Impact Assessment: SWAT has been used to simulate the hydrological response to climate change scenarios, including changes in precipitation, temperature, and CO₂ levels. For instance, the study by Fontaine et al. (2001) utilized SWAT to model the hydrology of the Spring Creek basin in the Black Hills of South Dakota, USA, and simulate the impact of potential climate change. The study found that increased temperature led to a decrease in water yield, while increased precipitation and CO₂ levels caused an increase in water yield. The model demonstrated that increased atmospheric CO₂ could dampen water yield loss due to increased temperature or decreased precipitation alone;

Reference:

- URL: [\[ref\]](#)

2. Evaluating Water Quality Impacts of Land Use Change: SWAT has been adapted to study the water quality impacts associated with land use conversion, such as converting farmland and forests to turfgrass. This involves modeling the relative changes in water quality associated with different land use scenarios, demonstrating SWAT's capability in assessing the environmental impacts of land use changes;

Reference:

- URL: [\[ref\]](#)

3. Water Yield Analysis under Climate Change Scenarios: SWAT has been modified to incorporate data from Regional Climate Models (RegCM) to analyze climate change impacts on basin water yields, such as in the Missouri River Basin. This showcases SWAT's utility in large-scale hydrologic modeling to assess the impacts of climate change on agricultural productivity and water resources;

Reference:

- URL: [\[ref\]](#)

- Year Published: 2001

- Title: Impacts of climate change on Missouri River Basin water yield.

Q: what are swat's applications in climate change/landuse change studies?

2021

The Soil and Water Assessment Tool (SWAT) has been extensively applied in various studies to assess the impacts of climate change and land use change on water resources, hydrology, and agriculture. Here are some of the key applications of SWAT in climate change and land use change studies:

1. Climate Change Impact on Water Resources: SWAT has been used to evaluate the potential future climatic changes and their effects on water resources management, water access, and agriculture. For instance, studies have utilized SWAT to understand the impacts of various climatic change scenarios on water resources in the Nzoia catchment, Kenya, and the River Mitano basin, Uganda, highlighting the importance of precipitation-evaporation balance and the sensitivity of projected streamflow to rainfall and temperature variations in regions like the Dinder River Basin, Sudan, and the Keleta River watershed in Ethiopia (Reference: A Review of SWAT Model Application in Africa; Page: 7; URL: [\[ref\]](#); Year Published: 2021).
2. Assessment of Land Use Change Impacts: SWAT has been applied to determine the effects of land use and climate changes on streamflow and sediment concentration, as seen in the Purna River basin, India. This includes evaluating the impacts of conventional agricultural land-use types on direct flows compared to those dominated by pasture and integrated rainwater harvesting land-use types (Reference: Improvement of the ESA CCI Land cover maps for water balance analysis in tropical regions: A case study in the Muda River Basin, Malaysia; Page: 13; URL: [\[ref\]](#); Year Published: 2021).
3. Hydrological Responses to Climate Changes: SWAT has been employed to assess hydrological responses to climate changes in various regions, including the evaluation of climate change impact on the hydrology of the Himalayan River Basin and the assessment of the impact of climate change on surface hydrological processes using SWAT in cases like the Omo-Gibe river basin, Ethiopia (Reference: Evaluating watershed hydrological responses to climate changes at Hangar Watershed, Ethiopia; Page: 14; URL: [\[ref\]](#); Year Published: 2021).
4. Simulation of Hydrological Processes Influencing Water Supplies: SWAT has been used to simulate ecohydrological processes influencing water supplies in watersheds, such as the Tuul River watershed in Mongolia, demonstrating SWAT's capability in predicting streamflow upstream of dams and assessing the impact of land use spatial resolution on model performance (Reference: Simulation of ecohydrological processes influencing water supplies in the Tuul River watershed of Mongolia; Page: 14; URL: [\[ref\]](#); Year Published: 2021).

Q: Summarize all swat-modflow applications?

2000

The SWAT-MODFLOW integrated modeling approach has been applied in various case studies to address complex watershed and groundwater management issues. These applications demonstrate the versatility and practicality of combining SWAT (Soil and Water Assessment Tool) and MODFLOW (Modular Finite-Difference Ground-Water Flow Model) for comprehensive water resources management. The key applications summarized from the provided references include:

1. Rattlesnake Creek Basin, South-Central Kansas: This application focused on developing a comprehensive, long-term management strategy to address water problems such as groundwater declines and surface-water depletions. The integrated model was used to evaluate various management strategies and enforce water-rights conditions to optimize the use of available water resources. The model allowed for a complete analysis of the land-based hydrologic cycle, predicting the impact of management changes on total water supplies and evaluating the impacts of land use, irrigation development, and climate change on both surface- and ground-water resources ([Sophocleous et al., 2000](#)).
2. Lower Republican River Basin: This application explored alternative conceptual models of spatial heterogeneity related to the presence or absence of an underlying aquifer with shallow or deep-water tables. The SWAT-MODFLOW integration demonstrated methods for coupling separately executed simulations using successive approximation, particularly focusing on shallow groundwater interactions with the overlying soil profile ([Sophocleous et al., 2000](#)).
3. Wet Walnut Creek Basin: Instead of using SWAT as the watershed simulator, this application employed POTYLD, a simpler code, linked to MODFLOW with little additional effort using the existing SWAT-MODFLOW linkage structure. This case study clarified the effects of watershed structures and irrigation water-use on stream yield, showing that the impact of watershed structures on stream yield was relatively small compared to the substantial effect of irrigation water use on streamflow ([Sophocleous et al., 2000](#)).

These applications underscore the integrated model's ability to handle stream-aquifer interactions, distributed well withdrawals, and multiple land uses effectively. They also highlight the importance of model calibration, the use of readily available data, and the need for models that are both comprehensive and practical for real-world, basin-wide management applications. The SWAT-MODFLOW integration enhances model calibration and reliability of model results, providing a valuable tool for water resource managers and decision-makers ([Sophocleous et al., 2000](#)).

References:

- [Sophocleous et al., 2000. "Methodology and application of combined watershed and ground-water models in Kansas."](#)
[Journal of Hydrology, 236\(2000\), 185–201; URL: \[ref\]](#)

Year Published: 2000.

Q: Summarize all swat-modflow applications?

2008

The SWAT-MODFLOW integrated model has been applied in various studies to address complex hydrological and environmental issues across different geographical locations and scales. Here's a summary of its applications based on the provided references:

1. **Musimcheon Basin, Korea:** The integrated SWAT-MODFLOW model was successfully applied to the Musimcheon Basin in Korea, demonstrating its capability to simulate the spatio-temporal distribution of **groundwater recharge rates, aquifer evapotranspiration, and groundwater levels**. It also enabled the interaction between the saturated aquifer and channel reaches to be considered, showcasing the model's utility in understanding river-aquifer interactions and groundwater dynamics within a watershed (Kim et al., 2008).
2. **Estancia Basin:** The model was used in combination with SWAT runoff results and previous estimates of groundwater flow to assess the hydrological balance of the Estancia Basin. This application employed the MODFLOW-LAK2 package to evaluate modern hydrological conditions, illustrating the model's versatility in integrating surface water and groundwater components to assess basin-scale hydrology (Kim et al., 2008).
3. **Bonello Coastal Basin, Northern Italy:** Galbiati et al. (2006) presented the application of the SWAT model, linked with MODFLOW, to the Bonello coastal basin. This application was successful in predicting water and nutrient leaching from the surface to the aquifer, groundwater dynamics, aquifer interactions with the stream system, and surface water and nutrient fluxes at the watershed outlet. This demonstrates the model's effectiveness in addressing diffuse pollution and nutrient transport in coastal areas (Kim et al., 2008).
4. **Rattlesnake Creek Basin, South-Central Kansas:** An interface between SWAT and MODFLOW, called SWAT-MOD, was developed for the Rattlesnake Creek basin. This system is capable of simulating the flow of surface water, groundwater, and stream-aquifer interactions on a continuous basis, highlighting the model's applicability in drought impact analyses and integrated water resource management (Kim et al., 2008).
5. **Vergara Basin, Chile:** The SWAT model's application for the Vergara basin confirmed its usefulness in making preliminary assessments of the potential impacts of land-use and climate changes on basin hydrology. This application underscores the model's potential in regions with limited data availability and its ability to provide valuable insights into hydrological processes under changing environmental conditions (Stehr et al., 2008).
6. **General Applications:** The SWAT-MODFLOW model has been extensively tested for hydrologic modeling at different spatial scales, including agricultural fields in southern Quebec, watersheds in Kentucky and Maryland, and the Bosque River watershed. These applications demonstrate the model's broad utility in hydrological modeling, including water discharge, groundwater dynamics, soil moisture, and nutrient transport across diverse landscapes (Zhang et al., 2008).

Q: What are the areas of SWAT-Modflow applications?

2023

The Soil and Water Assessment Tool (SWAT) has been extensively applied in various studies to address a wide range of topics related to hydrology and water management. When coupled with MODFLOW, a model for simulating groundwater flow, SWAT can provide a comprehensive understanding of both surface and groundwater systems. Based on the provided references, here is a summary of SWAT-MODFLOW applications across the specified topics:

1. Water Availability and Management: SWAT-MODFLOW has been utilized to develop decision-aiding methodologies for agricultural groundwater management, demonstrating its capability to estimate groundwater recharge rates and test groundwater management scenarios (**Pisinaras et al., 2013**).

2. Groundwater and Surface Water Interactions: The coupling of SWAT with MODFLOW and MT3DMS has offered a comprehensive view of urban water systems, detailing spatial and temporal settings and demonstrating the benefits of integrated hydrologic modeling in understanding the interactions between surface water and groundwater (**Eshtawi et al., 2016**).

3. Climate Change Impacts: The integration of SWAT with other models like GROWA and FEFLOW has been used to analyze nitrate contaminant vulnerability under climate change scenarios, indicating the potential of SWAT-MODFLOW to assess climate change impacts on hydrological processes and water quality (**Uhan et al., 2011**).

4. Urban Water Management: Eshtawi et al. (2016) demonstrated the application of SWAT-MODFLOW for urban water management by quantifying interactions between surface and groundwater in quantity and quality under expanding urbanization, highlighting its utility in urban water system assessments.

5. Pollution and Water Quality: The sequential coupling of SWAT, MODFLOW, and MT3DMS has been applied to simulate the effects of land use and climate change on recharge, pumping, and groundwater levels, including nitrate content, showcasing the model's ability to address pollution and water quality issues (**Pulido-Velazquez et al., 2015**).

6. Hydrological Processes and Geochemistry: The combination of SWAT with GROWA and FEFLOW for nitrate contaminant vulnerability analysis in the Lower Savinja Valley (Slovenia) exemplifies the use of SWAT-MODFLOW in understanding hydrological processes and geochemistry, particularly in identifying nitrate-vulnerable zones (**Uhan et al., 2011**).

Q: which parameters in swat govern surface runoff and infiltration?

2023

In the SWAT model, surface runoff is primarily governed by the CN2 parameter, which is the SCS runoff curve number for moisture condition II. The larger the value of CN2, the less permeable the underlying surface is, thus generating more runoff. Infiltration is influenced by several parameters, including the SOL_AWC (available water content of the soil) and SOL_K (hydraulic conductivity of the soil). SOL_AWC affects the soil water-holding capacity, which in turn influences how much water can infiltrate into the soil before runoff occurs. SOL_K regulates lateral flow and infiltration through the soil profile. Additionally, the Green and Ampt infiltration method, if used instead of the SCS Curve Number method, directly models infiltration but is less commonly applied in SWAT due to its complexity and data requirements.

Reference:

- Kumar et al., 2023; Page: 8; URL: [\[ref\]](#)

Title: Assessing the synergic effect of land use and climate change on the upper Betwa River catchment in Central India under present, past, and future climate scenarios;

- Liu et al., 2023; Page: 4; URL: [\[ref\]](#)

Title: Impacts of land use/cover change on water balance by using the SWAT model in a typical loess hilly watershed of China;

- Anteneh et al., 2023; Page: 8; URL: [\[ref\]](#)

Title: Modeling runoff-sediment influx responses to alternative BMP interventions in the Gojeb watershed, Ethiopia, using the SWAT hydrological model.

Q: what are the sensitive parameters to flow and sediment transport?

2000

The sensitive parameters affecting stream yield and groundwater recharge, which in turn influence groundwater levels, include watershed-related parameters such as the **NRCS runoff curve number**, **soil properties** (particularly available water capacity), **crop type**, and **land use characteristics** (especially irrigated area and water use). These parameters were found to be more sensitive than aquifer and stream hydrogeologic properties, such as aquifer hydraulic conductivity and storativity, and streambed hydraulic conductivity. Among the hydrogeologic parameters, aquifer hydraulic conductivity and storativity were identified as more sensitive than streambed hydraulic properties. This sensitivity analysis suggests that adjustments to watershed-related parameters, particularly runoff curve number and, secondarily, plant stress factor or soil moisture threshold value to trigger irrigation, are crucial during model calibration to produce relatively low errors in streamflows and groundwater levels. The calibration process also involved adjusting aquifer hydraulic conductivity within expected limits and optimizing aquifer storativity for transient conditions to minimize groundwater-level residuals for predevelopment (steady-state) conditions;

Reference: 2000-Sophocleous-et-al.pdf; **Page:** 9; **URL:** [ref]

Year Published: 2000; **Title:** Methodology and application of combined watershed and.

Q: what are the sensitive parameters to flow and sediment transport?

2021

1. Flow:

- Initial curve number for moisture condition II (CN2)
- Saturated hydraulic conductivity (SOL_K)
- Average slope steepness (HRU_SLP)
- Maximum canopy storage (CANMX)
- Average slope length (SLSUBBSN)
- Groundwater delay (GW_DELAY)
- Manning's "n" value for overland flow (OV_N)
- Effective hydraulic conductivity of the main channel alluvium (CH_K2)
- Bank storage factor (ALPHA_BNK)
- Available water capacity of the soil (SOL_AWC)
- Groundwater "revap" rate (GW_REVAP)
- Deep aquifer percolation factor (RCHRG_DP)

2. Sediment Transport:

- USLE equation support practice factor (USLE_P)
- Soil erodibility factor (USLE_K)
- Sediment concentration in lateral and groundwater flow (LAT_SED)
- Channel erodibility factor (CH_EROD)
- Linear and exponential factors for channel sediment routing (SPCON, SPEXP)
- Channel cover factor (CH_COV)
- Erodibility of channels (CH_COV1, CH_COV2)

These parameters were identified through sensitivity analyses in various studies, indicating their significant influence on the simulation of flow and sediment transport in different watersheds. The sensitivity of these parameters can vary based on regional characteristics, model setup, and specific hydrological and sediment transport processes being modeled.

References:

- Zhang et al., 2020; Page: 2; URL: [ref]

Title: Emission estimation and fate modelling of three typical pesticides in Dongjiang River basin, China. (SWATCUP)

- Du et al., 2020; Page: 6; URL: [ref]

Title: Hydro-climate and biogeochemical processes control watershed organic carbon inflows: Development of an in-stream organic carbon module coupled with a process-based hydrologic model.

- Ouallali et al., 2020; Page: 10; URL: [ref]

Title: Hydrological foretelling uncertainty evaluation of water balance components and sediments yield using a multi-variable optimization approach in an external Rif's catchment. Morocco. (SWATCUP)

- Mauri et al., 2020; Page: 4; URL: [ref]

Title: Hydrosedimentological modeling in a headwater basin in Southeast Brazil. (SWATCUP)

- Sinha et al., 2020; Page: 8; URL: [ref]

Title: Assessing the impacts of historical and future land use and climate change on the streamflow and sediment yield of a tropical mountainous river basin in South India. (SWATCUP)

- Dibaba et al., 2021 Prioritization of Sub-Watersheds to Sediment Yield and Evaluation of Best Management Practices in Highland Ethiopia, Finchaa Catchment; Page: 8; URL: [\[ref\]](#) (SWATCUP)

- Tesema et al., 2020; Page: 7; URL: [ref]

Title: Sediment Yield Estimation and Effect of Management Options on Sediment Yield of Kesem Dam Watershed, Awash Basin, Ethiopia. (SWATCUP)

Gashaw et al., 2021. Evaluating the Effectiveness of Best Management Practices On Soil Erosion Reduction Using the SWAT Model: for the Case of Gumara Watershed, Abbay (Upper Blue Nile) Basin; Page: 9; URL: [ref] (SWATCUP)

A Topical Analysis of the Evolution of the SWAT Applications Since 2000

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Abstract

The Soil and Water Assessment Tool (SWAT) has significantly advanced the modeling of water resources and nonpoint-source pollution in large river basins. Developed over three decades by the USDA Agricultural Research Service (ARS), SWAT's origins trace back to foundational models like CREAMS, GLEAMS, and EPIC. These models set the stage for SWAT's direct predecessor, SWRRB. SWAT, introduced in the early 1990s, represented a major leap in simulating management impacts on water and sediment movement in ungauged rural basins. It integrated enhanced components such as groundwater return flow, reservoir storage, crop growth modeling, and sediment transport calculations. The combination of SWRRB and the ROTO model enabled large-scale simulations, paving the way for SWAT's comprehensive watershed analysis approach. SWAT has continually evolved, incorporating in-stream kinetic routines from the QUAL2E model and a broad range of management practice simulations. This evolution demonstrates SWAT's commitment to robustly evaluating the effects of various management strategies on water resources and pollution, addressing complex environmental challenges. Globally, SWAT has been extensively applied across North America, Europe, Africa, and Asia. In the U.S., it plays a crucial role in TMDL assessments and conservation practice evaluations. In Europe, it supports the EU Water Framework Directive, among other initiatives. Its applications in Africa, China, India, South Korea, and Iran showcase its versatility in tackling hydrological and water quality issues, including climate change impacts and watershed management. SWAT's continuous development, including its latest versions, SWAT2019 and SWAT+, along with extensive documentation and support, underscores its importance in environmental research and management. SWAT's ability to simulate complex watershed interactions, incorporating processes like weather, hydrology, soil properties, plant growth, and land management, makes it an indispensable tool for scientists, policymakers, and environmental managers worldwide. In the current study, we follow the topical development of SWAT in various applications since 2000, highlighting its continuous advancements and broadening scope.

A comparison of Earlier SWAT and Later SWAT

2000-2004:

- Model Capabilities and Focus

Primarily on basic hydrological processes

- Technological Integration

With GIS was a significant advancement; however, the interface was less user-friendly and limited in capacity

- Application

Focused on agricultural watersheds, mainly in the United States

- Data and Computational Resources

Applications constrained in size and complexity. Data resolution and availability were also lower.

2019-2023

- Advanced Model Capabilities

Nutrient cycling, climate change impacts, more accurate representation surface-groundwater interactions. SWAT+ and other versions offer enhanced flexibility and precision.

- Broader Application Scope

Global applications, Beyond agriculture, Global water security issues. There's a stronger focus on integrated water resources management and climate change adaptation.

- Technological Advancements

Integration with high-resolution remote sensing data, climate models, and much improved computational power. User interfaces like QSWAT have made the tool more accessible and user-friendly.

- Community and Collaboration

The SWAT user community has grown, fostering collaboration and the exchange of best practices through conferences and workshops. This has led to more standardized practices and enhanced model performance through shared knowledge.