

# Comparison of Optimization Algorithms for the Automatic Calibration of SWAT2000

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# Study Goals

1. Compare optimization algorithms for the efficient and reliable minimization of some single-objective measure of calibration error
  - ◆ present results that are relevant across range of computational scales
2. Create a simple case study that can be easily replicated by future researchers
3. **Motivate some fellow SWAT modellers to try a new algorithm I developed for automatic calibration → GGS algorithm**

# Optimization Algorithms Compared

- ◆ Standard algorithms:
  - Monte Carlo Search or uniform random sampling (**MCS**)
  - Matlab v13 implementation of Nelder-Mead **Simplex** algorithm
- ◆ Population-based evolutionary approaches:
  - Simple Real-valued Genetic Algorithm (**GA**)
  - Shuffled Complex Evolution (**SCE**) algorithm
- ◆ New global optimization method:
  - Global Greedy Search (**GGs**) algorithm

# New Optimization Algorithm – Global Greedy Search (GGS)

- ◆ New heuristic algorithm I developed during my PhD
  - Please note: GGS  $\equiv$  DDS  $\equiv$  GGS  $\equiv$  DDS !!!
- ◆ GGS algorithm development perspective:
  1. Calibration goal is to find a good solution quickly  $\rightarrow$  global optimum is not necessary!
  2. Need better algorithm in higher dimensions, i.e. more than 5 calibration parameters... preferably not limited
  3. Modellers need/prefer an algorithm for calibration that is scaled to operate within their specific case study computational constraints for example:
    - I want an answer tomorrow morning
  4. Keep the algorithm simple

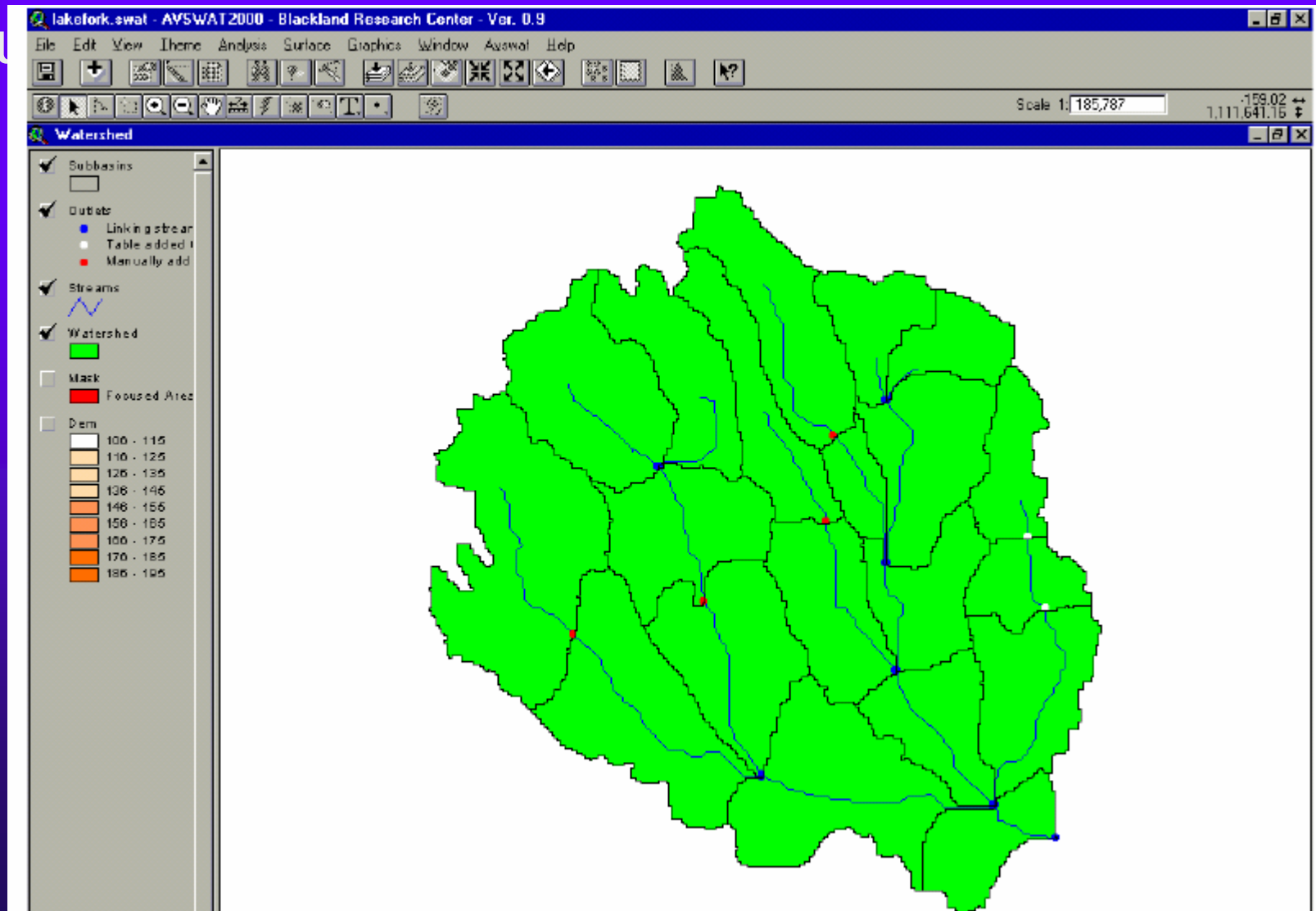
# GGGS Algorithm Description

- ◆ Basic 'Greedy' search strategy:
  1. Initialize starting solution
  2. Perturb current best solution to generate candidate solution
  3. Compare candidate solution to best solution and update best solution if necessary
  4. Repeat from step 2 until stopping criterion met
- ◆ GGS is not population-based
- ◆ GGS is a global search because it can sample candidate solutions from entire search space
- ◆ One GGS algorithm parameter – default of 0.2 used
- ◆ GGS scales search strategy to maximum number of objective function evaluations input by user

# Benchmark Case Study Selection

Select a case study that any researcher can

qu



# Case Study Calibration Formulations

- ◆ Defined two synthetic automatic calibration formulations where measured data created by:
  1. assume default model parameters = true values
  2. run the model & define 2 years of simulation output as the synthetic 'measured data'
- ◆ Parameter ranges from model documentation
- ◆ Formulations defined so as to simplify case study replication & are thus more of a curve-fitting exercise rather than realistic calibration problems

# Case Study Calibration Formulations

## ◆ PROBLEM 1:

- 6 parameter flow calibration
- minimize SSE for monthly flows (min = 0.000)

## ◆ PROBLEM 2:

- 14 parameter simultaneous flow and sediment calibration
- maximize sum of monthly flow and sediment Nash-Sutcliffe efficiencies (max = 2.000)

## ◆ See paper for calibration parameters

## ◆ Objective function definition is application specific and is not trivial to define

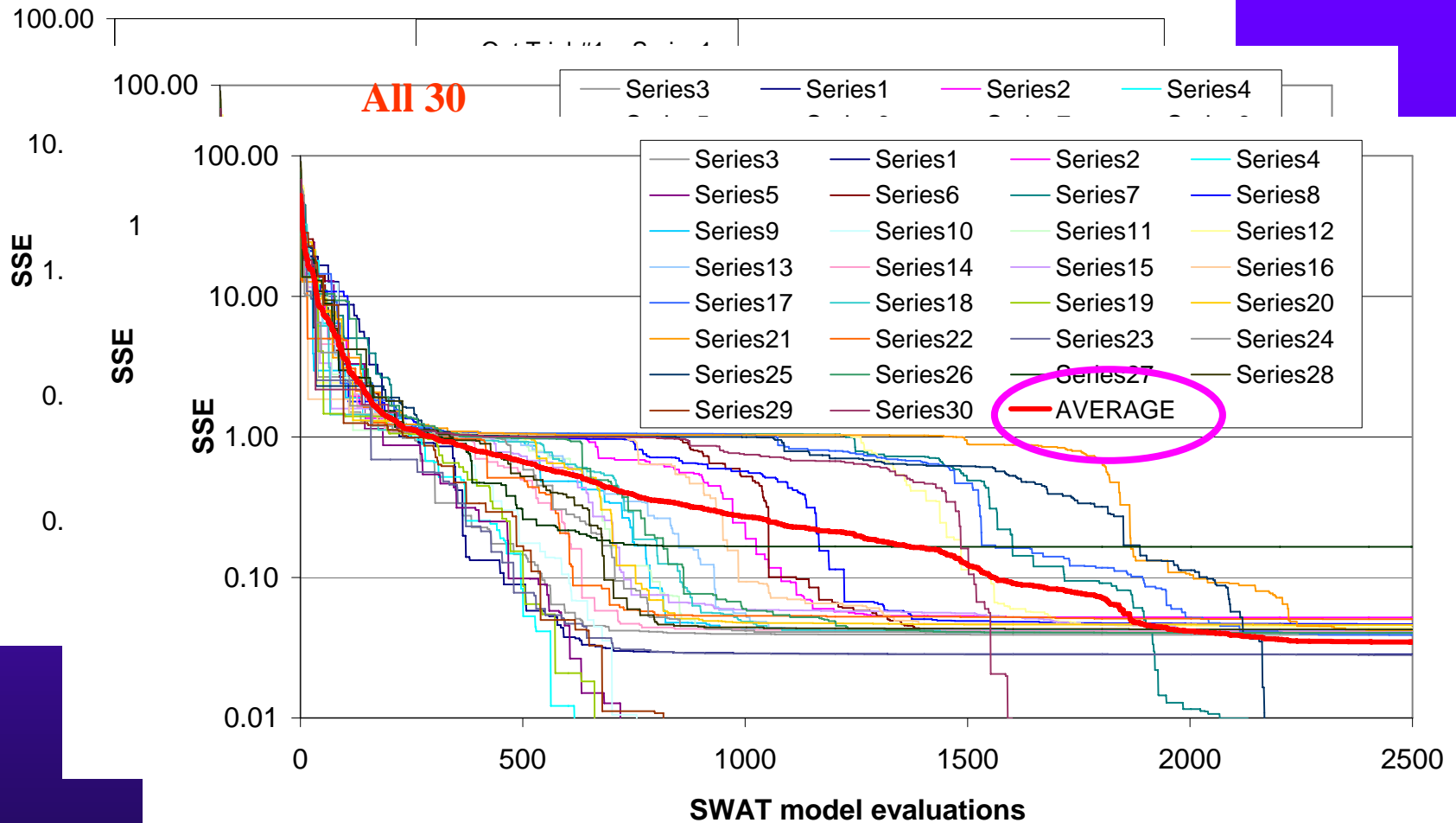


# Optimization Algorithm Comparison

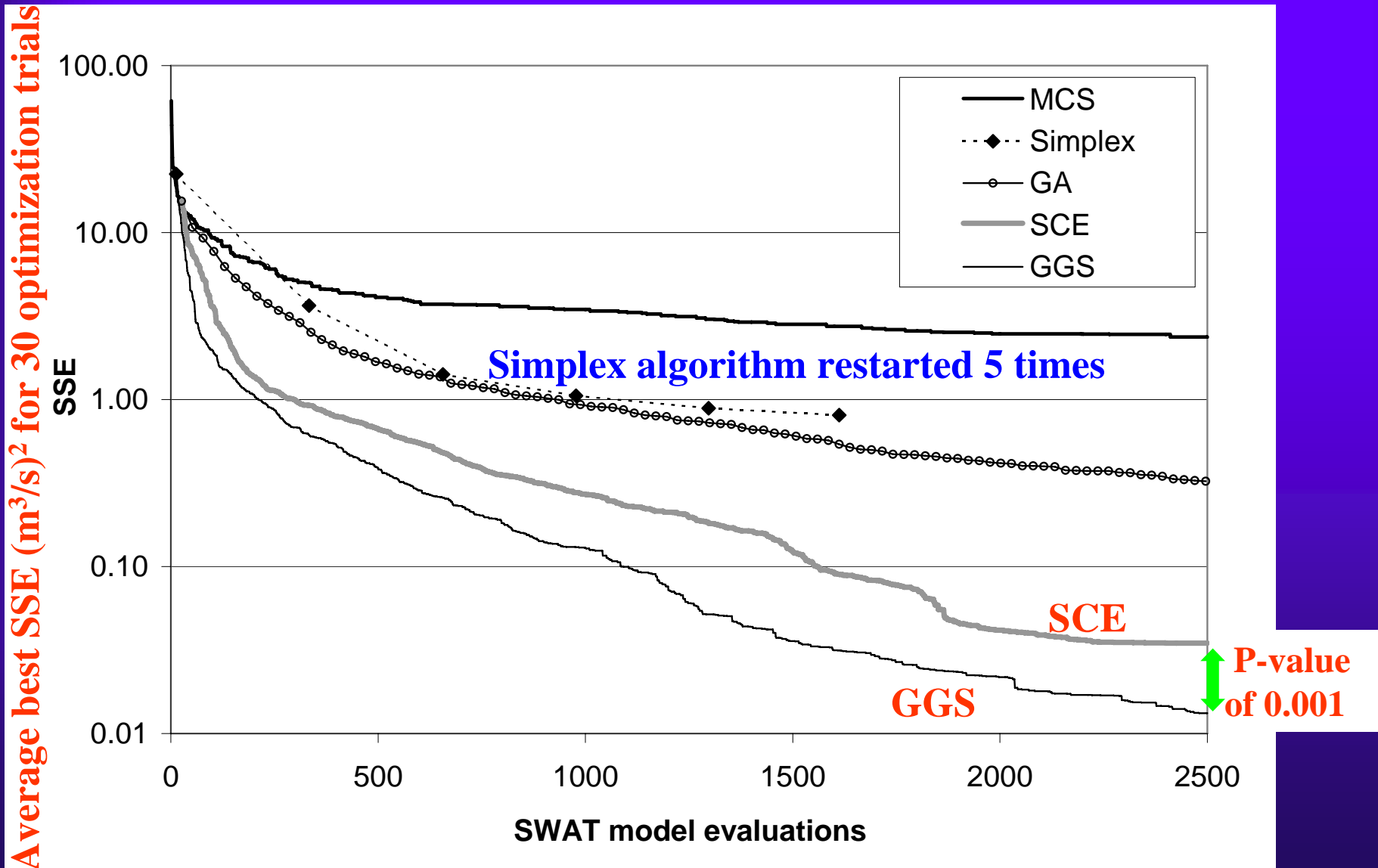
- ◆ Algorithm parameters were not ‘optimized’
- ◆ Instead, algorithm parameters selected based on experience or recommended default values
- ◆ All algorithms solve each of the two problems 30 times (30 optimization trials)
- ◆ Optimization trials use a maximum of:
  - 2500 SWAT model evaluations for 6 variable formulation
  - 6000 SWAT model evaluations for 14 variable formulation
- ◆ All optimization trials initialized to randomly sampled initial solutions (or initial populations)

# Evaluating Average Algorithm Convergence Performance

Best SSE found so far

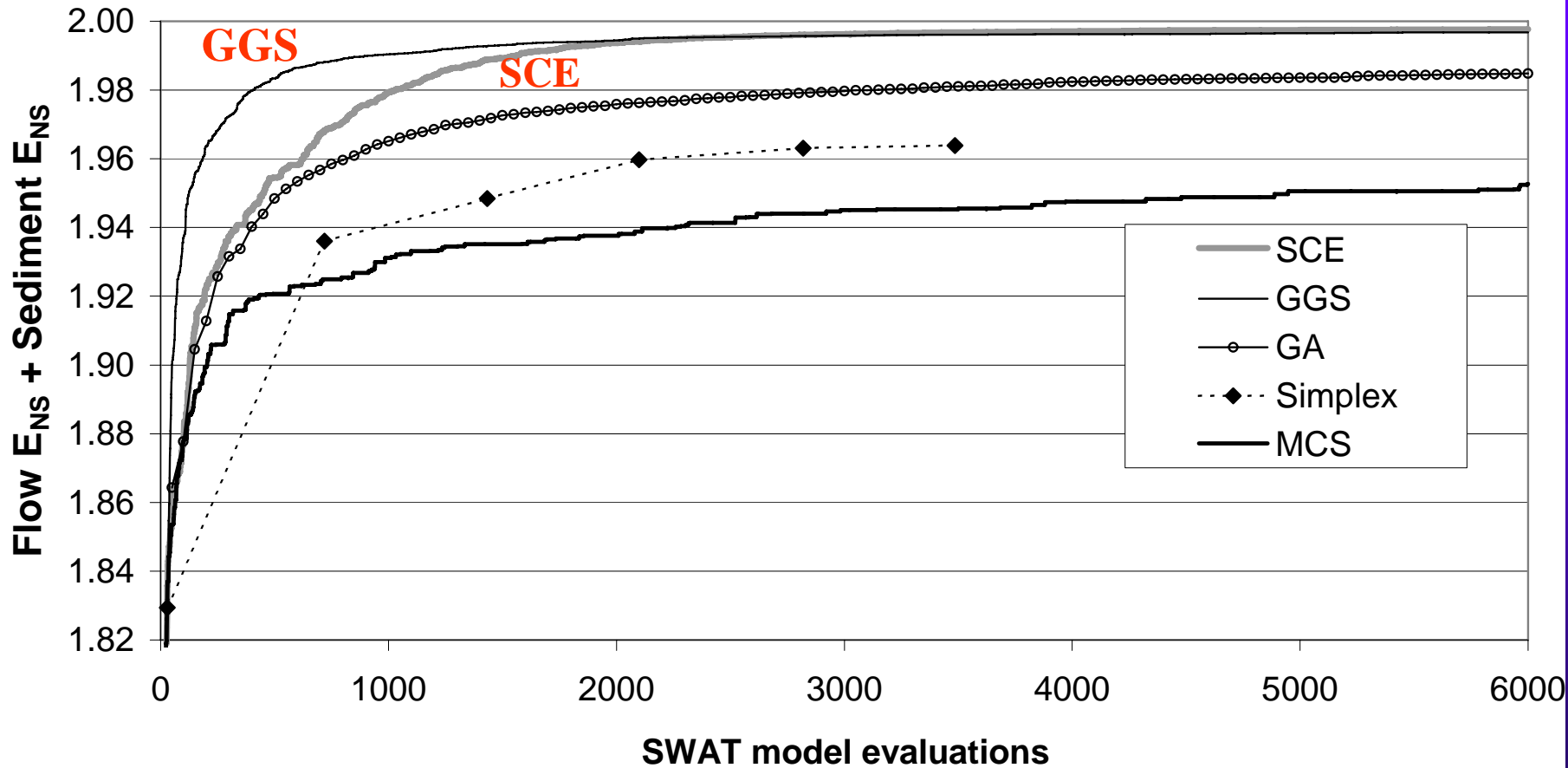


# Comparison Results for Problem 1: 6 Parameter Flow Calibration



# Comparison Results for Problem 2: 14 Parameter Flow & Sediment Calibration

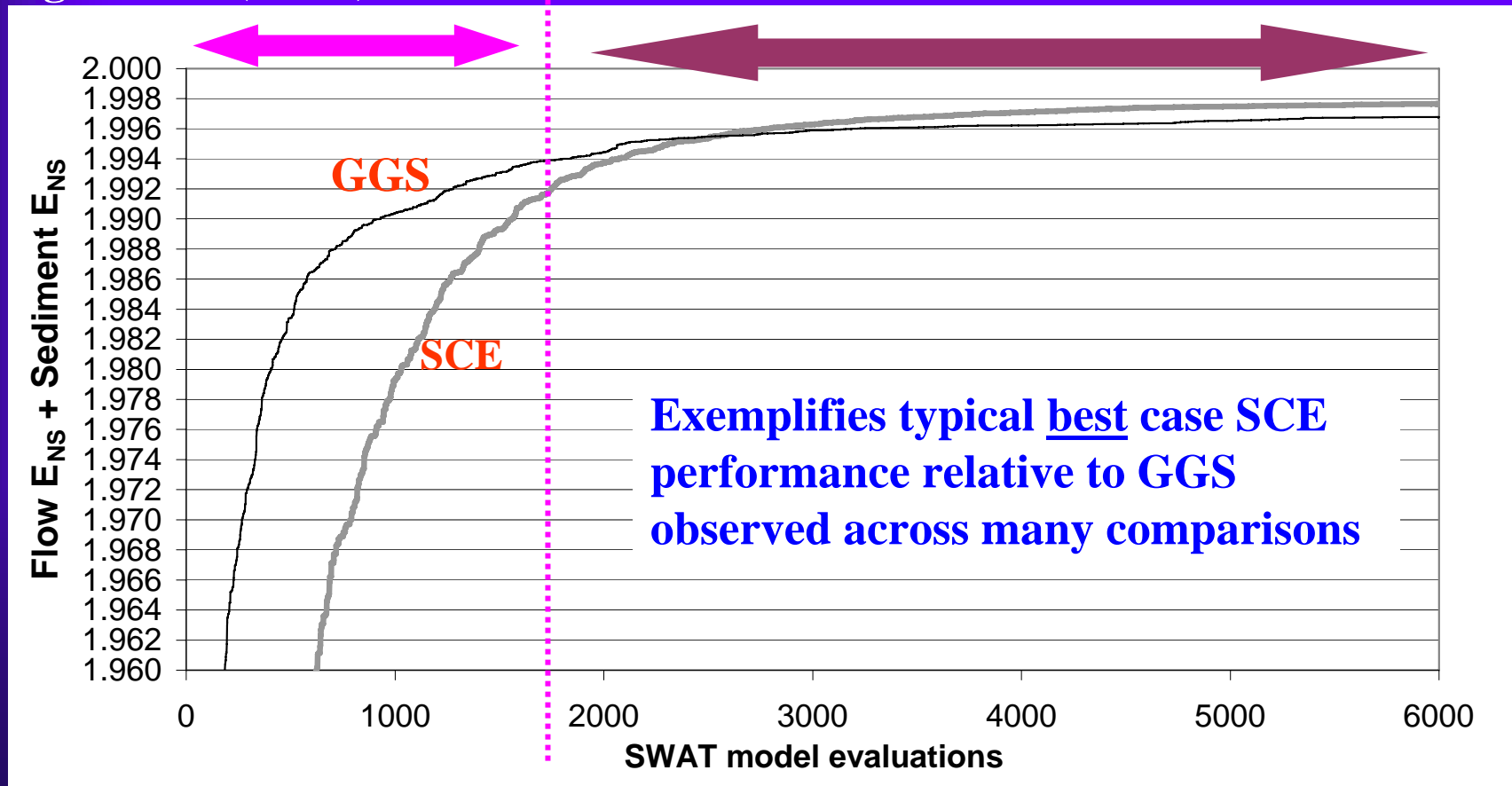
Average best for 30 optimization trials



# Problem 2 Results: Focus on SCE versus GGS

GGS improvement over SCE is more(?) practically significant (~0.02)

Algorithm differences not practically significant (e.g. < 0.002 difference)



# Highlight Additional Results on REAL Calibration Case Study:

## Watershed Modeling of the Cannonsville Basin using SWAT2000:

### Model Development, Calibration and Validation for the Prediction of Flow, Sediment and Phosphorus Transport to the Cannonsville Reservoir

Version 1.0

Technical Report  
School of Civil and Environmental Engineering  
Cornell University

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#### Project Administered by:

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1) The Delaware County Board of Supervisors with funds provided by the US Environmental Protection Agency through the New York State Department of Environmental Conservation and 2) funds from Cornell University.

#### The appropriate reference for this report is:

Tolson, B. A. and Shoemaker, C. A. (2004). Watershed modeling of the Cannonsville Basin using SWAT2000: Model development, calibration and validation for the prediction of flow, sediment and phosphorus transport to the Cannonsville Reservoir. Version 1.0. Technical Report, School of Civil and Environmental Engineering, Cornell University. 159 pp.  
<http://techreports.library.cornell.edu:8081/Dienst/UI/1.0/Display/cul.wat/2004-2>

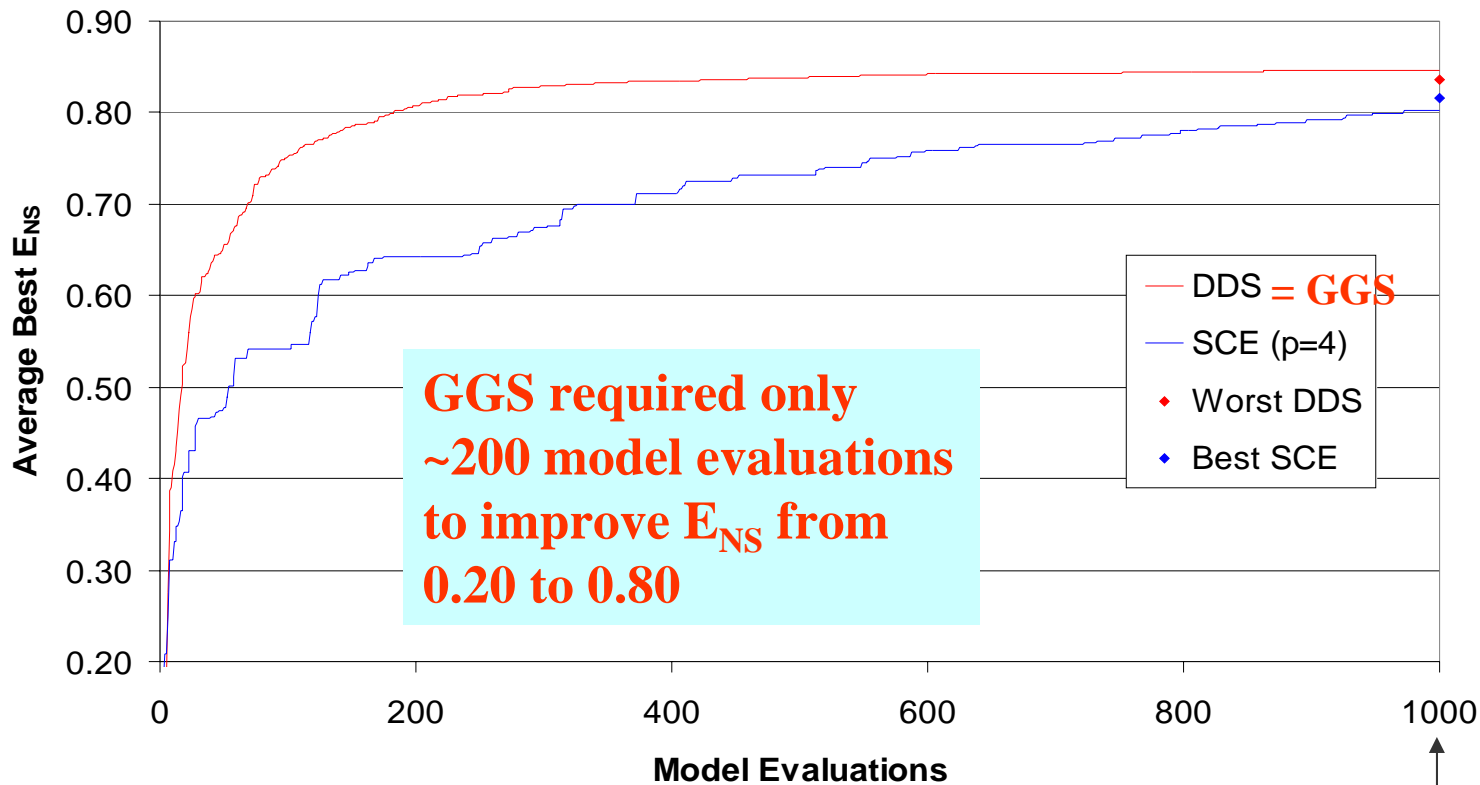
→ following results  
NOT in the conference  
paper  
... shown because they  
are much more  
interesting!



# Highlight Comparative Algorithm Performance on REAL Case Study 1

Daily flow calibration for 1200 km<sup>2</sup> watershed, 758 HRUs, 5 yr simulation, 14 calibration parameters

Average best daily NS for 10 opt. trials



**GGs required only  
~200 model evaluations  
to improve  $E_{NS}$  from  
0.20 to 0.80**

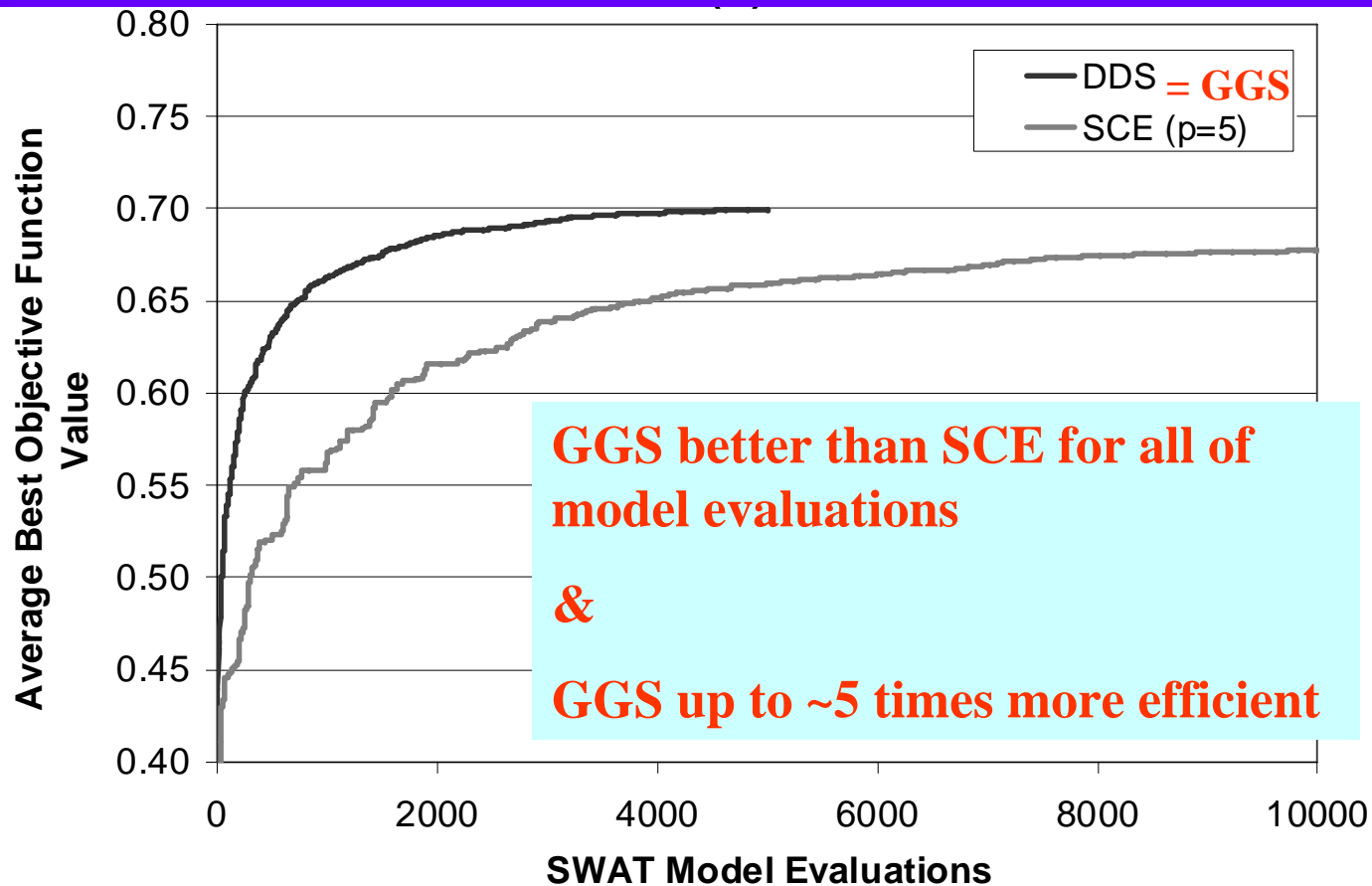
- DDS = **GGs**
- SCE (p=4)
- ◆ Worst DDS
- ◆ Best SCE

**~2 days serial  
PC time**

# Highlight Comparative Algorithm Performance on REAL Case Study 2

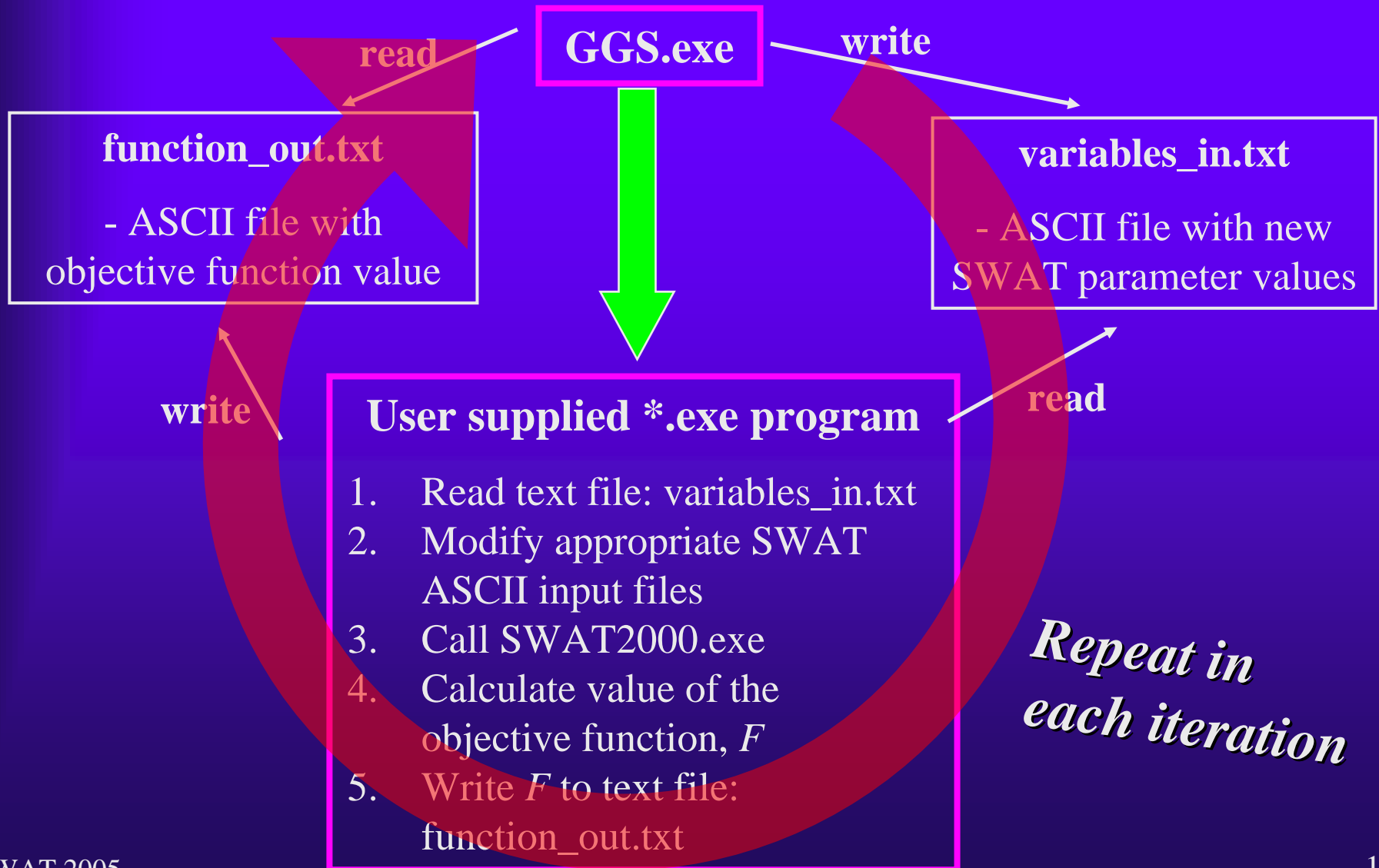
Simultaneous daily flow, sediment and total P calibration for 40 km<sup>2</sup> watershed (Town Brook), 30 HRUs, 3 yr simulation, 26 calibration parameters

Average best “weighted” NS for 10 trials





# GGGS Program Framework Currently Available – email: [btolson@uwaterloo.ca](mailto:btolson@uwaterloo.ca)



# GGG Program Availability

- ◆ Only available as a compiled executable program
- ◆ Requires Matlab .dll library installation (simple)
- ◆ In your email, let me know if you will run algorithm on PC with Matlab v13 or v14
- ◆ Matlab source code will be available as soon as journal paper accepted
- ◆ Working on incorporation into released version of SWAT2005
- ◆ Very easy to recode in programming language of your choice... as soon as journal publication comes out!

# Conclusions

1. GGS algorithm a promising alternative to SCE that is available by contacting me
2. Two benchmark case studies available for automatic calibration algorithm testing (available by contacting me OR my website: <http://www.civil.uwaterloo.ca/btolson>)
3. Robust algorithm comparisons need to present convergence speed to ‘good’ solutions

# “Future” Work

1. GGS applications to efficient sensitivity and uncertainty analysis
2. Parallel computing version of GGS

QUESTIONS...?

THANKS