Assessing the convergence of a Morris-like screening method for a complex environmental model

J. Nossent, O.T. Leta and W. Bauwens

Vrije Universiteit Brussel

Time = Money

Optimizing environmental models

is often very time consuming

Environmental models

Optimization to have good predictions

Difficult due to high number of parameters

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is often very time consuming

Environmental models

Optimization to have good predictions

Difficult due to high number of parameters

Screening sensitivity analysis (SA)

Quick search of parameter importance

Select most important parameters

Dimensionality reduction (Factor Fixing)

Non-converged parameter rankings
lead to loss of model output variability

Quick, but not converged

Mixed parameter rankings

Wrong selection of parameters

Loss of output variance

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We investigated

Convergence of the screening SA

For increasing number of trajectories

Screening methods
are suitable for environmental models

Loss of model variability
due to non-converged parameter rankings

More than 100 trajectories
are required for converged rankings

Screening methods

are suitable for environmental models

Environmental model

SWAT (Soil and Water Assessment Tool)

Rainfall-runoff model

Conceptual, but based on physical processes

Highly nonlinear, nonmonotonic, multimodal

Flow, nitrate, phosphate, sediment,…

Screening methods

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Environmental model

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Case studies: River Kleine Nete (BEL – 40 pars)
River Zenne (BEL – 26 pars)

Screening methods

are suitable for environmental models

Latin-Hypercube – One-factor-at-A-Time

Morris-like screening method

Latin-Hypercube replaces random sampling

Elementary effects

$$EE_i = \left| \frac{100 \cdot \frac{y(\theta_1, \ldots, \theta_i(1+\Delta_i), \ldots, \theta_k) - y(\theta_1, \ldots, \theta_k)}{\left(y(\theta_1, \ldots, \theta_i(1+\Delta_i), \ldots, \theta_k) + y(\theta_1, \ldots, \theta_k)\right)/2}}{\Delta_i} \right|$$

(van Griensven et al., 2006)

Screening methods

are suitable for environmental models

Latin-Hypercube – One-factor-at-A-Time

μ (mean) of elementary effects

Overall effect of the input factor on the output

Unbiased estimator of the distribution of EE’s

σ (stdev) of elementary effects

Uniformity of the effects

Measure for the nonlinearity of the effects

Screening methods
are suitable for environmental models

Limited number of model evaluations

Quantitative parameter rankings

Identify non-influential parameters

Factor fixing = dimensionality reduction

Sometimes fix additional parameters

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Sometimes fix additional parameters

Can be prone to type II errors

Loss of model variability
due to non-converged parameter rankings

a

b

c

d

e

f

Loss of model variability

due to non-converged parameter rankings

a	0.07
b	0.24
c	0.11
d	0.00
e	0.45
f	0.13

Loss of model variability

due to non-converged parameter rankings

a	0.07	e	0.45
b	0.24	b	0.24
c	0.11	f	0.13
d	0.00	c	0.11
e	0.45	a	0.07
f	0.13	d	0.00

Loss of model variability
due to non-converged parameter rankings

e	0.45
b	0.24
f	0.13
c	0.11
a	0.07
d	0.00

Loss of model variability

due to non-converged parameter rankings

e	0.45	e	0.45
b	0.24	b	0.24
f	0.13	a	0.07
c	0.11	c	0.11
a	0.07	f	0.13
d	0.00	d	0.00

Loss of model variability

due to non-converged parameter rankings

e	0.45	e	0.45	e	0.45
b	0.24	b	0.24	a	0.07
f	0.13	a	0.07	c	0.11
c	0.11	c	0.11	f	0.13
a	0.07	f	0.13	b	0.24
d	0.00	d	0.00	d	0.00

Loss of model variability

due to non-converged parameter rankings

e	0.45	e	0.45	e	0.45
b	0.24	b	0.24	a	0.07
f	0.13	a	0.07	c	0.11
c	0.11	c	0.11	f	0.13
a	0.07	f	0.13	b	0.24
d	0.00	d	0.00	d	0.00

Loss of model variability

due to non-converged parameter rankings

e	0.45	e	0.45	e	0.45
b	0.24	b	0.24	a	0.07
f	0.13	a	0.07	c	0.11
c	0.11	c	0.11	f	0.13
a	0.07	f	0.13	b	0.24
d	0.00	d	0.00	d	0.00

More than 100 trajectories
are required for converged rankings

Increase number of trajectories for SA

Confidence Intervals (CI) for μ and σ

Bootstrapping with resampling

More than 100 trajectories

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Increase number of trajectories for SA

Confidence Intervals (CI) for μ and σ

- Bootstrapping with resampling

If converged

- CI should decrease for increasing # trajectories

More than 100 trajectories

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Increase number of trajectories for SA

Confidence Intervals (CI) for μ and σ

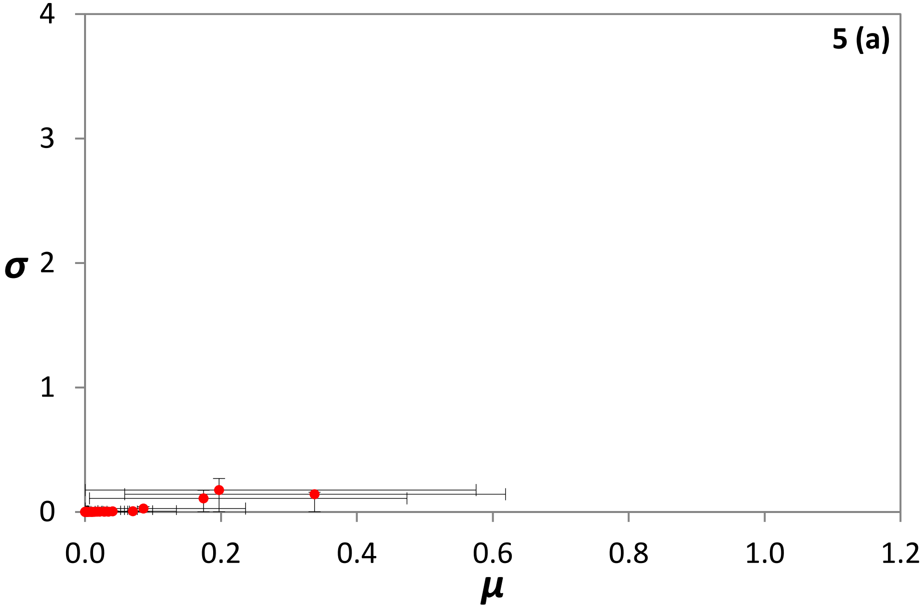
- Bootstrapping with resampling

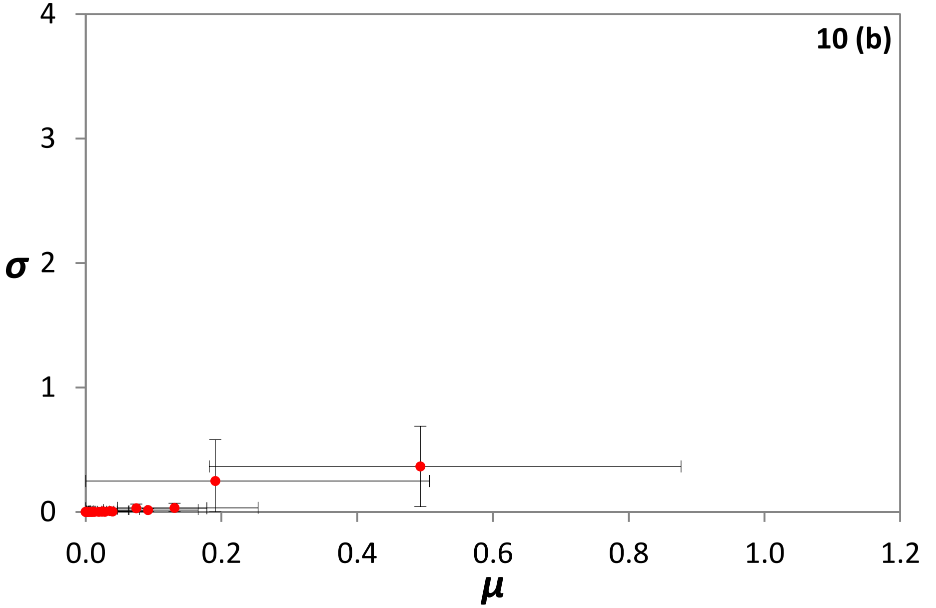
If converged

- CI should decrease for increasing # trajectories
- σ should not increase for increasing # trajectories
  (every EE is a random sample of the distribution of EE's)

More than 100 trajectories
are required for converged rankings

The River Kleine Nete – 40 parameter model





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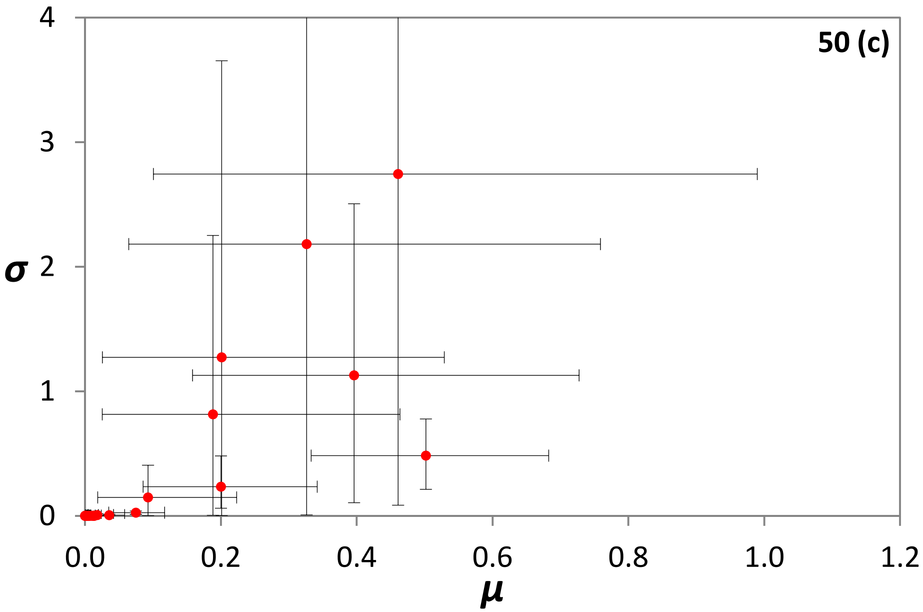

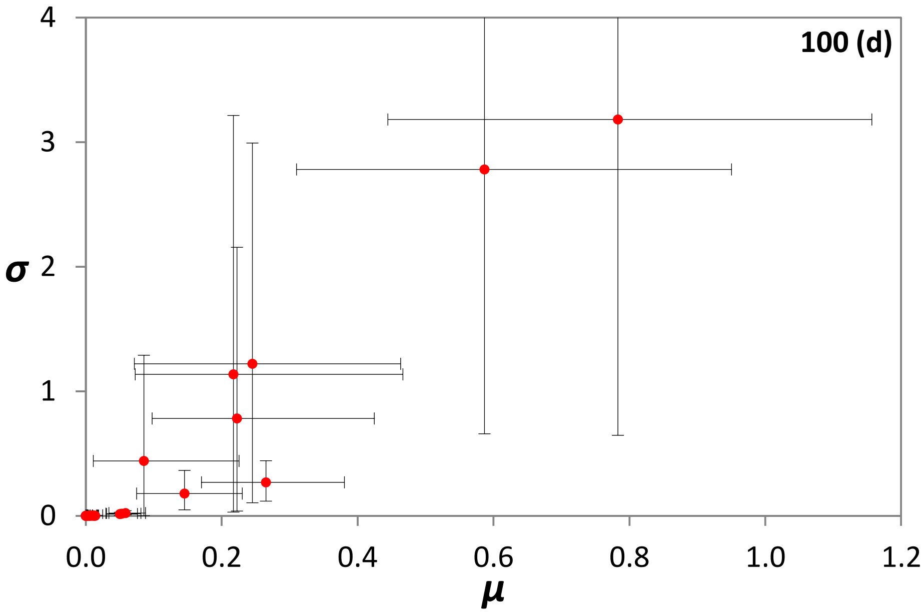

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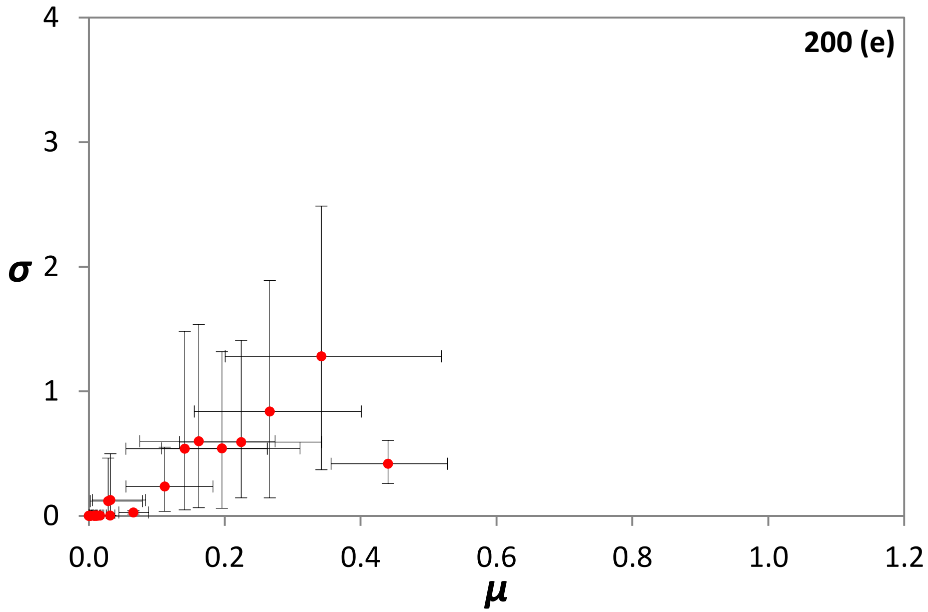

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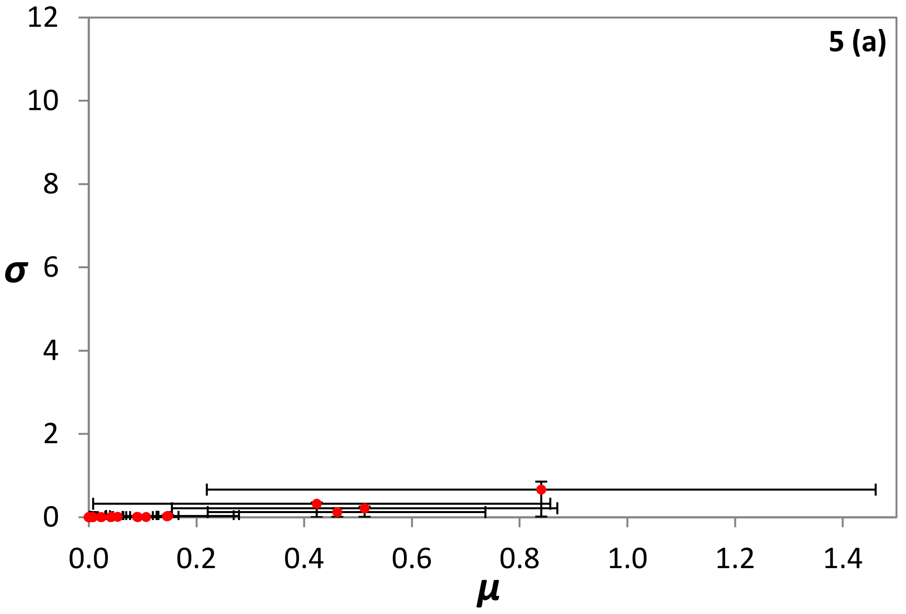
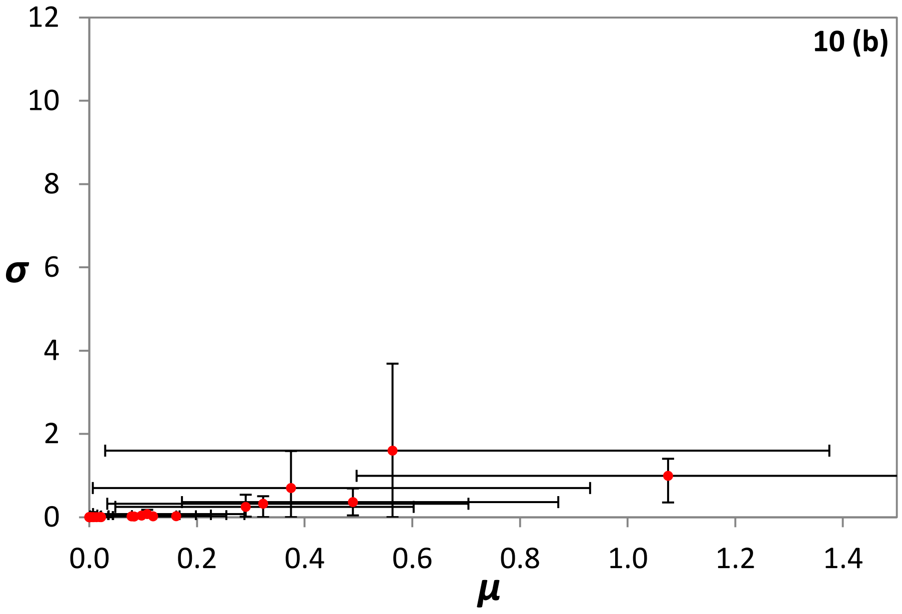
The River Zenne – 26 parameter model





More than 100 trajectories
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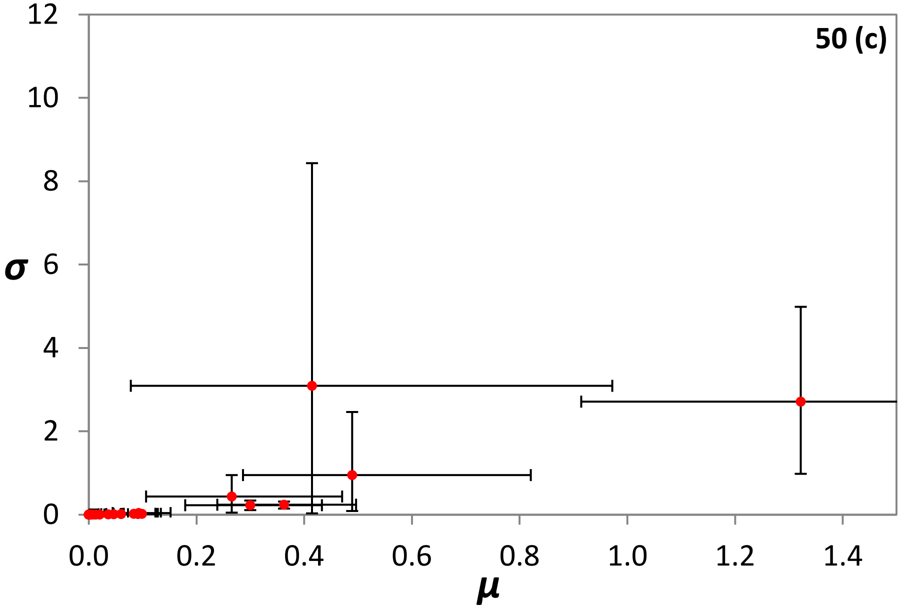
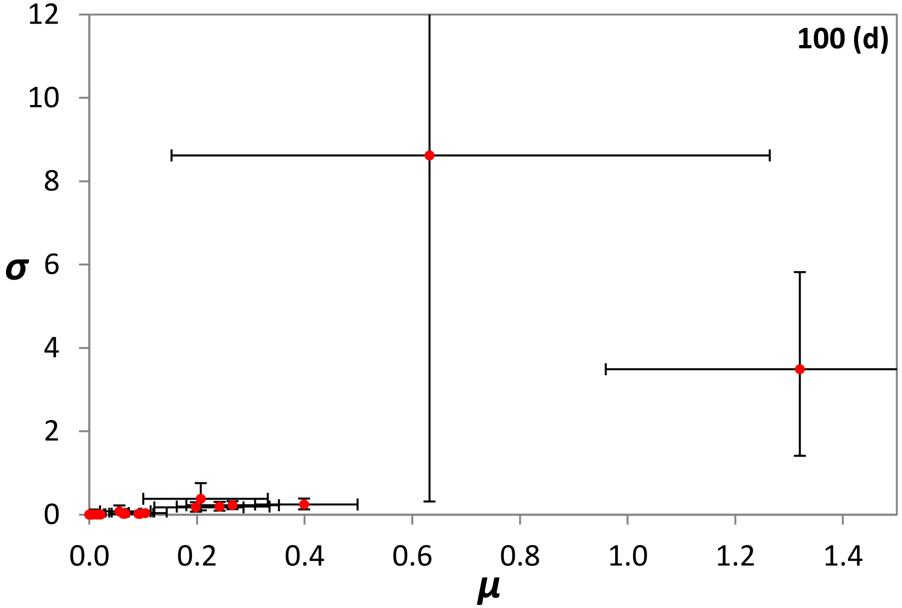
The River Zenne – 26 parameter model





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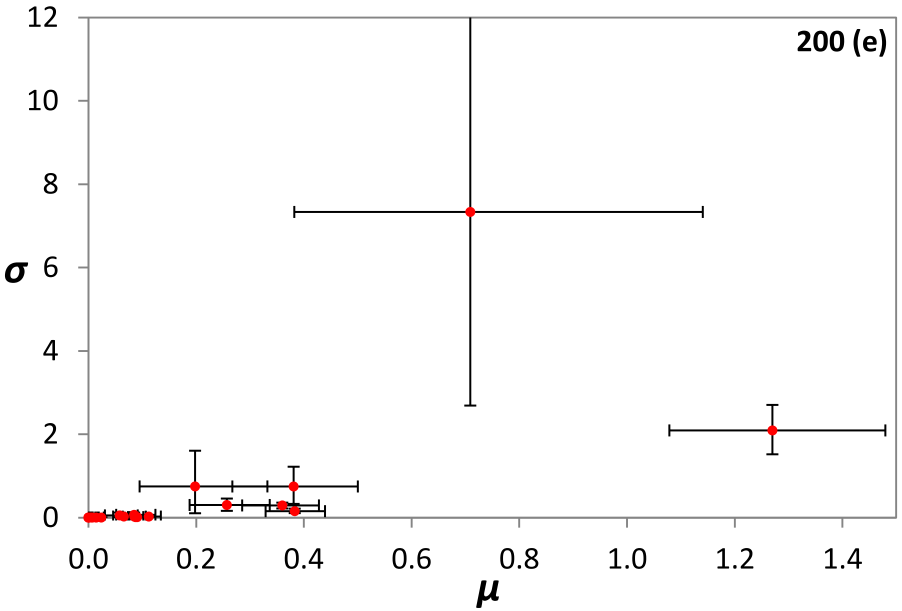
The River Zenne – 26 parameter model



More than 100 trajectories
are required for converged rankings

The River Zenne – 26 parameter model

5 non-influential parameters

Already identified with standard sample size

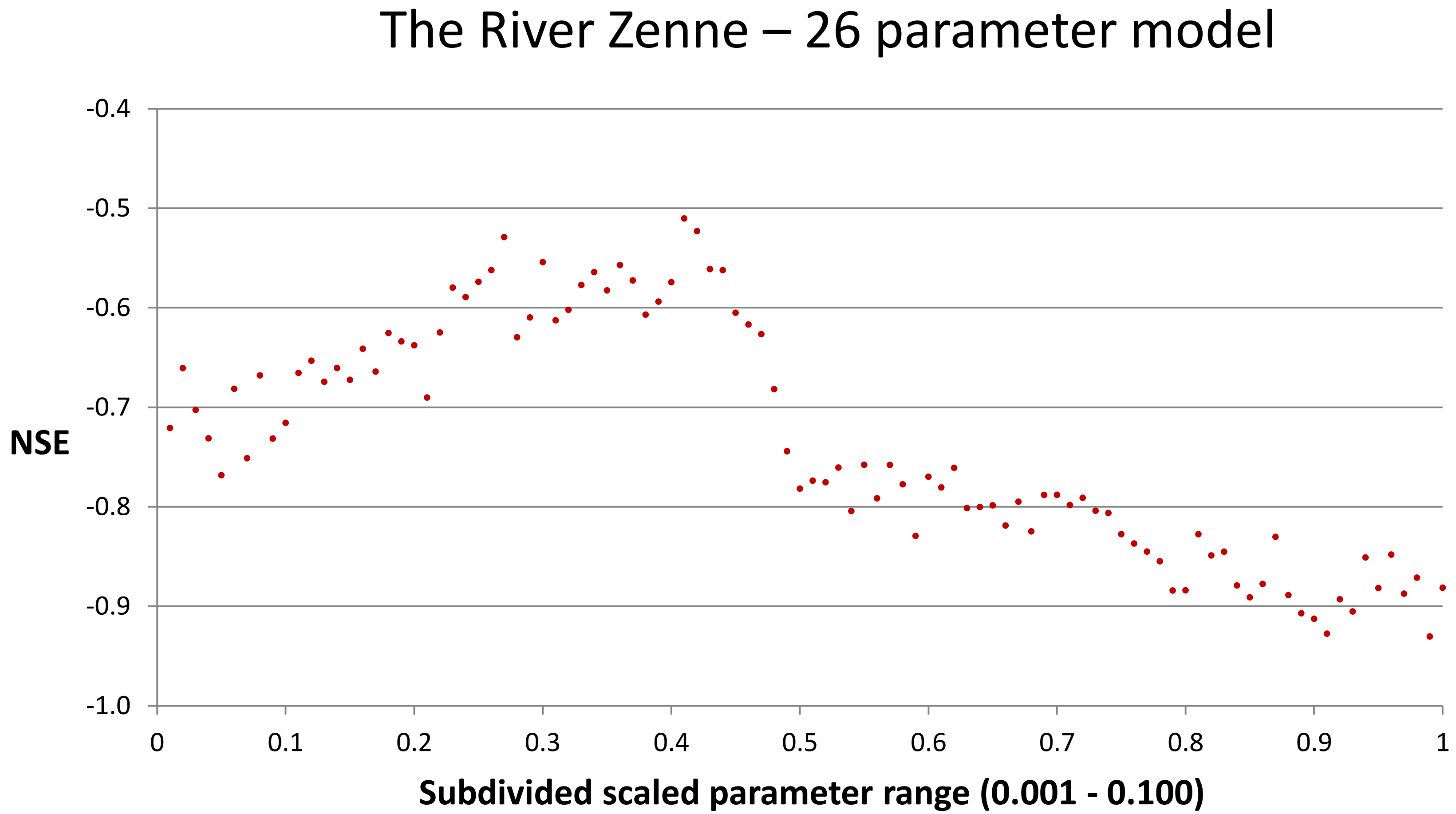
Limited type II error

Parameter Ch_N (channel conductivity)

	5	10	50	100	200
rank	11	4	3	2	2
μ	4.20E-02	3.75E-01	4.14E-01	6.32E-01	7.09E-01

More than 100 trajectories

are required for converged rankings



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Conclusions

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make a correct selection of parameters

reduce the dimensionality
with least loss of model variability

Conclusions

100 trajectories are required to

achieve converged parameter rankings

become more resilient to type II errors

make a correct selection of parameters

reduce the dimensionality
with least loss of model variability

achieve better predictions

Investing time (more trajectories)

presently costs you money

Investing time (more trajectories)

presently costs you money

but gives you profit in future
(reduced loss of variability)

Jiri Nossent
Dept. of Hydrology and Hydraulic Engineering

jnossent@vub.ac.be

Vrije Universiteit Brussel