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Making uncertainty analysis simple

Luca Vezzaro, Peter-Steen Mikkelsen

DTU Environment
Department of Environmental Engineering

Ana Deletic & David M^cCarthy



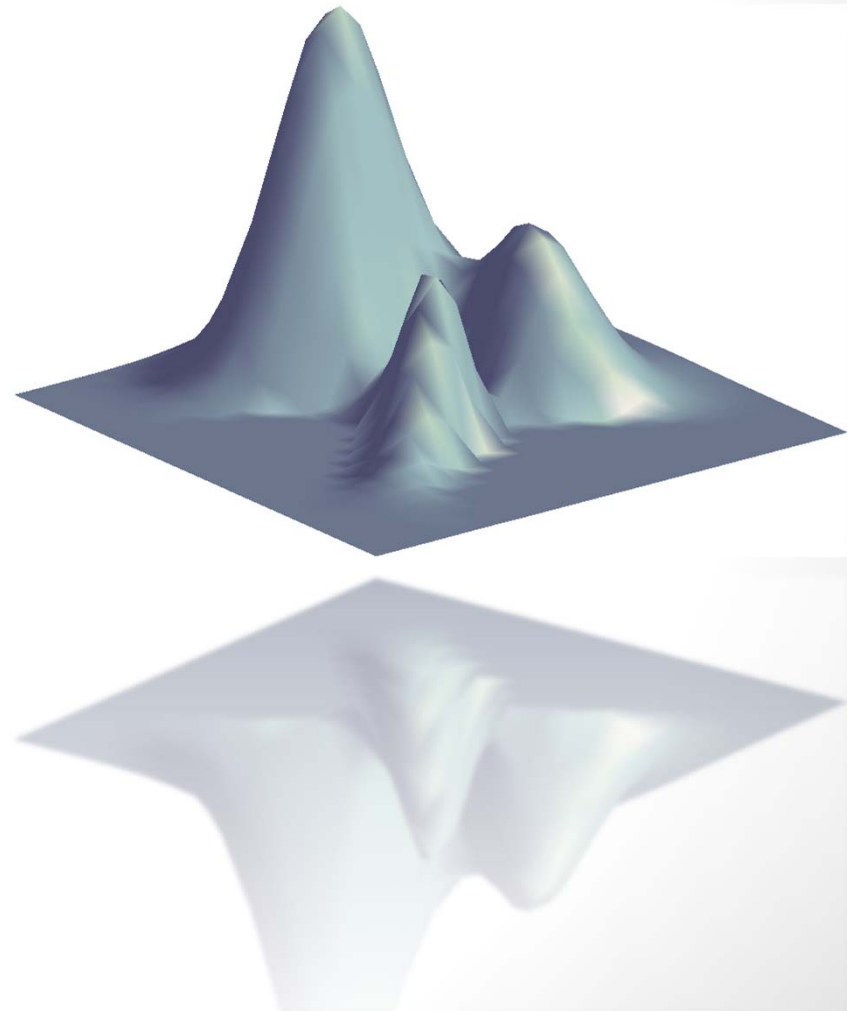
water for liveability



MONASH University

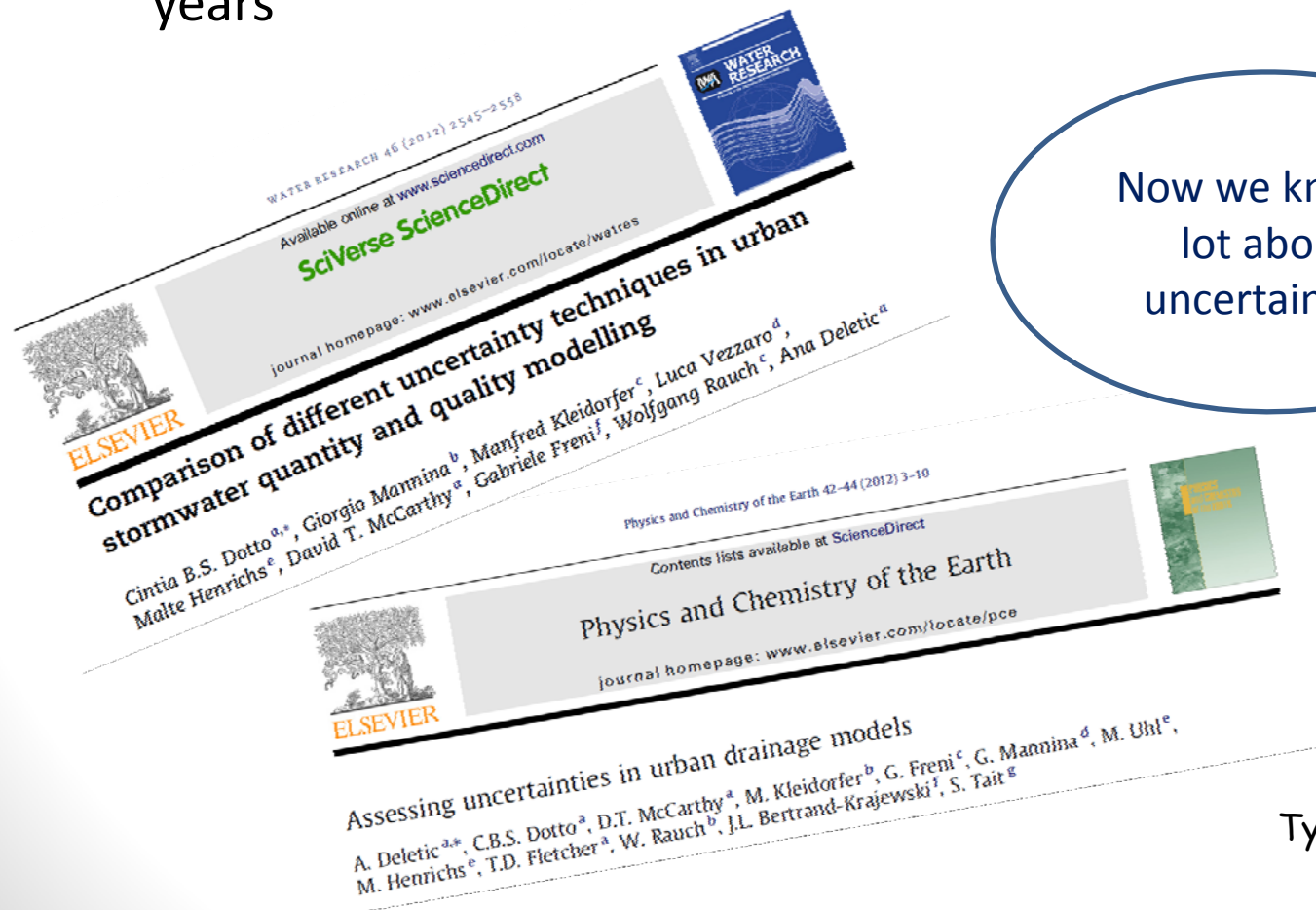
Introduction

- Uncertainty analysis is an important issue in urban drainage modelling
- Everybody agrees on that....



Knowledge on uncertainty is expanding...

- A lot of research in the past decade -> many articles on that
- Main focus of Int. Working Group on Data&Models in the last 5 years



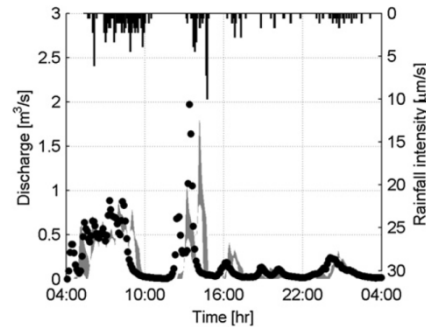
Now we know a lot about uncertainty!!



Typical researcher working with urban drainage models

...but there are still some issues

To create your uncertainty bounds, you can apply a threshold on likelihood of 0.124567



All methods involve a degree of subjectivity

Assumptions difficult to express in tangible terms

Threshold of 0.124567?????



Typical practitioner working daily with urban drainage models

...but there are still some issues

My model matches
only 60% of the
observations...



Well, if you knew how
those data were taken...
60% is already a miracle..



Measurement uncertainty is seldom
taken into consideration

Aim & Objectives

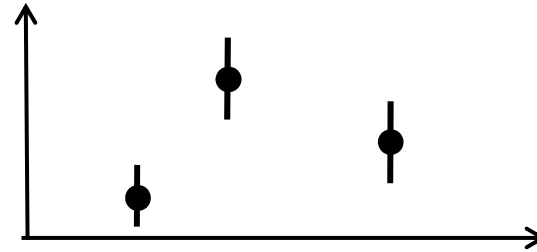
- To make uncertainty analysis simple and understandable
 - Try to reduce the subjectivity of the choices done when running uncertainty analysis
 - Describe the subjective choices in a more tangible manner
 - Introduce a criterion to assess model performance by considering measurement uncertainty
 - Vezzaro-McCarthy Criterion...VMC

Example of Rainfall Runoff model –
predicting flows

Step 1

1

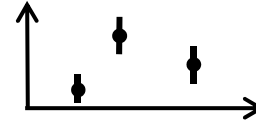
**Define uncertainty
intervals for each
observed datapoint**



Step 2

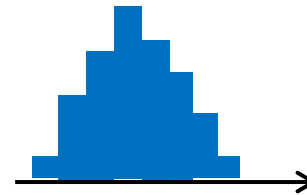
1

Define uncertainty intervals for each observed datapoint



2

Generate N parameter sets



$\Theta_{1,2,\dots,N}$

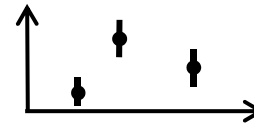
Step 3

1

Define uncertainty intervals for each observed datapoint

2

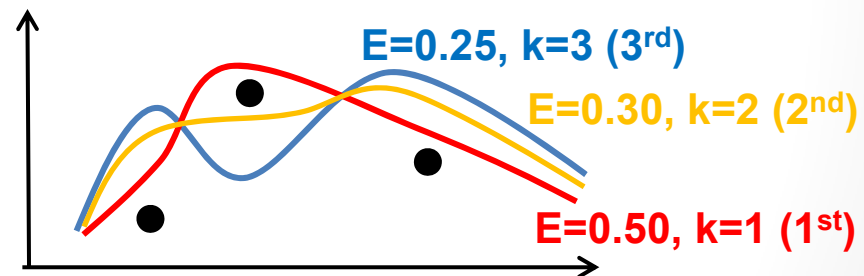
Generate N parameter sets



$\Theta_{1,2,\dots,N}$

3

Run model for N parameter sets and rank them



Step 4

1

Define uncertainty intervals for each observed datapoint

2

Generate N parameter sets

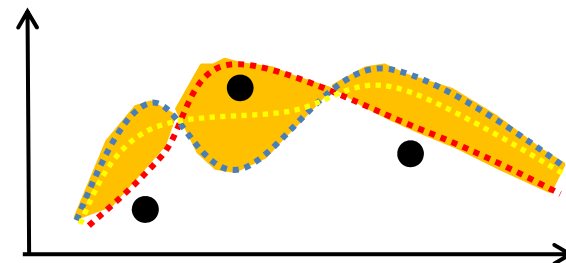
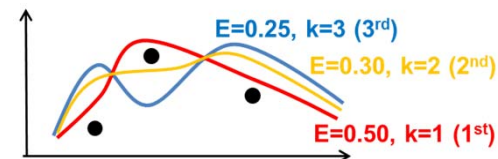
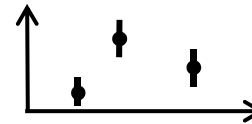
3

Run model for N parameter sets and rank them

4

Estimate model prediction bounds (e.g. $K=3$)

K = number of included ranked simulations in the estimation of the model prediction bounds



Step 5

1

Define uncertainty intervals for each observed datapoint

2

Generate N parameter sets

3

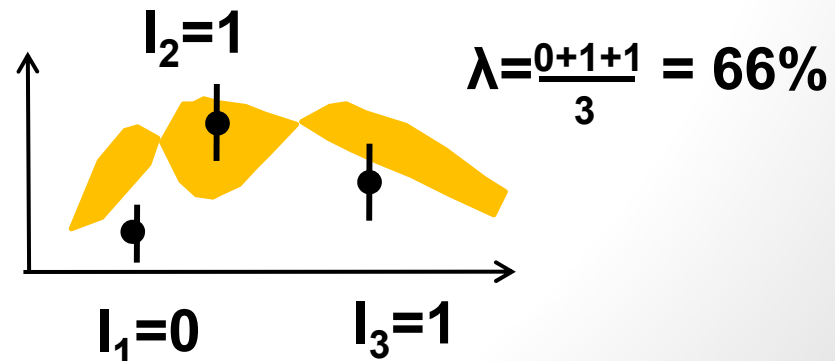
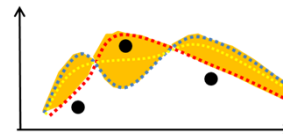
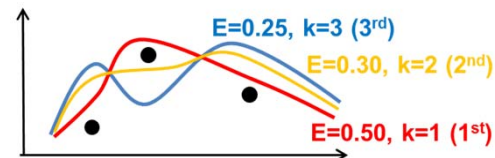
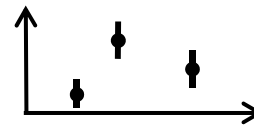
Run model for N parameter sets and rank them

4

Estimate model prediction bounds (e.g. $K=3$)

5

Estimate intersection λ (e.g. for $K=3$, $\lambda=66\%$)



Step 6

1

Define uncertainty intervals for each observed datapoint

2

Generate N parameter sets

3

Run model for N parameter sets and rank them

4

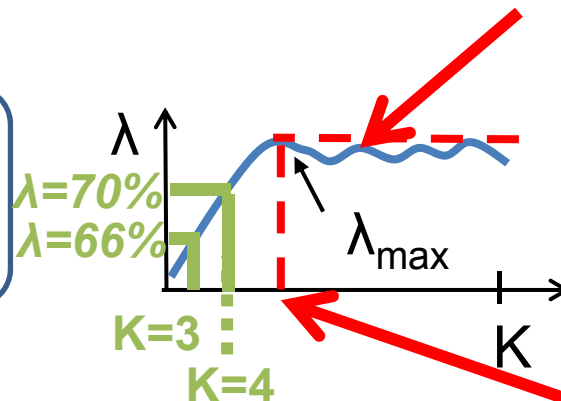
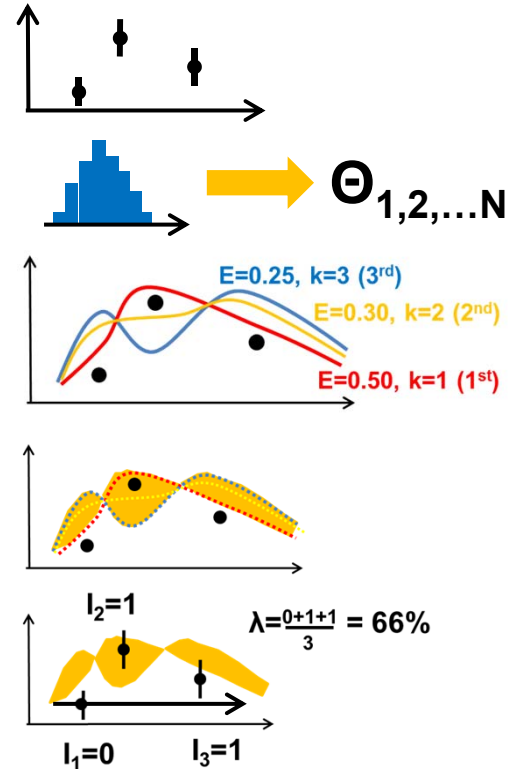
Estimate model prediction bounds (e.g. $K=3$)

5

Estimate intersection λ (e.g. for $K=3$, $\lambda=66\%$)

6

Repeat for $K = 4, 5 \dots N$ (find relationship between λ and K)



K=30
top 30 are the
behavioural
parameter sets

Step 7

1

Define uncertainty intervals for each observed datapoint

2

Generate N parameter sets

3

Run model for N parameter sets and rank them

4

Estimate model prediction bounds (e.g. $K=3$)

5

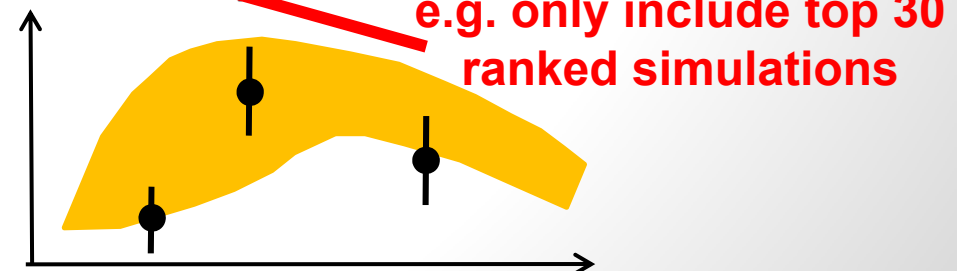
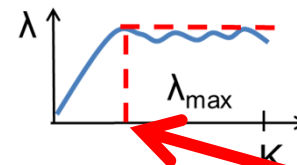
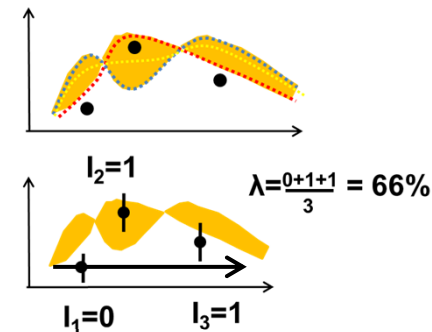
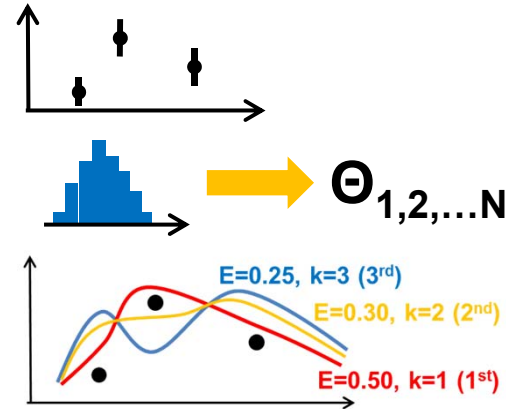
Estimate intersection λ (e.g. for $K=3$, $\lambda=66\%$)

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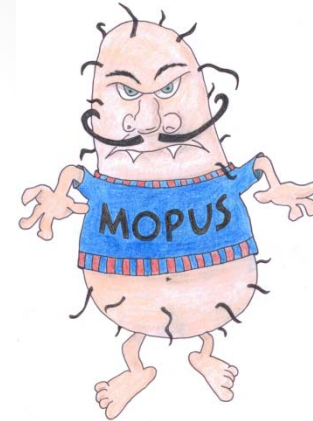
7

Use Step 6 to make a 'less' subjective cut-off and perform uncertainty assessment

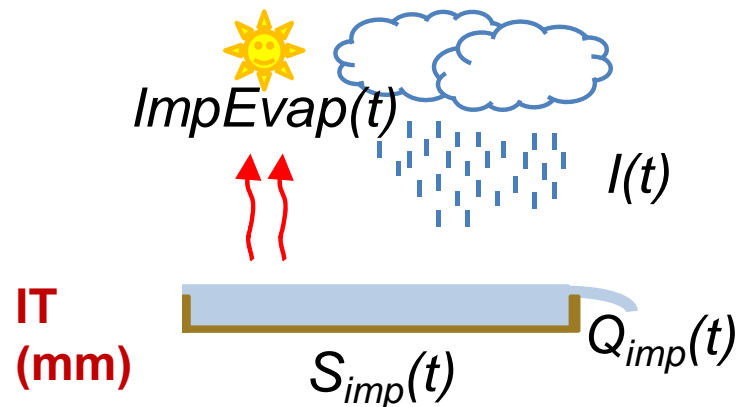


Case-study

- MOPUS Rainfall-Runoff model



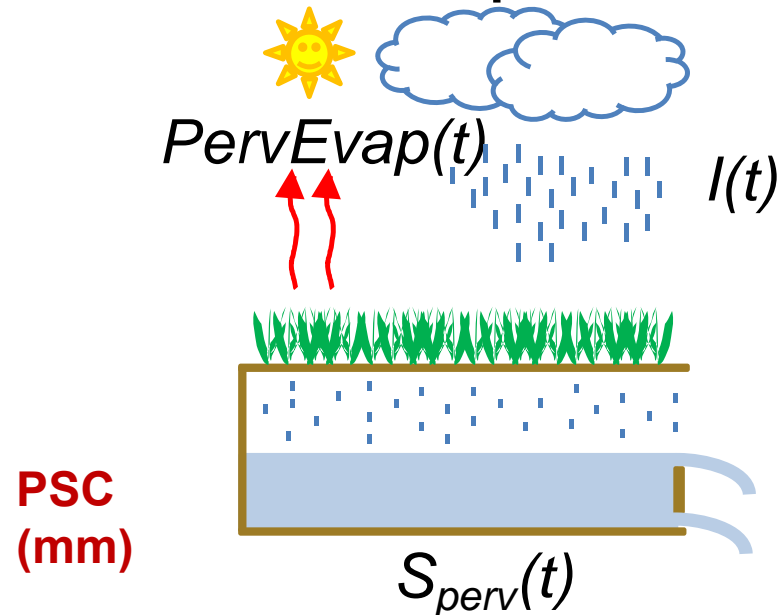
Impervious component



6 Parameters

1. IMP - Imperviousness
2. IT - Impervious store cap.
3. PSC - Pervious store capacity
4. k - Routing coefficient
5. m - Routing exponent
6. TOC

Pervious component



$$Q(t) = k \cdot \text{RoutingStore}^m$$

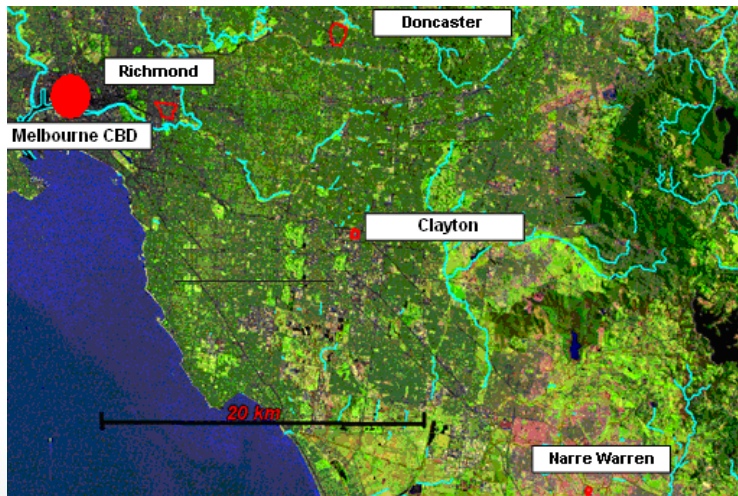
$$Q_{\text{outlet}}(t) = Q(t - \text{TOC})$$

Case-study



- Clayton catchment; 2 years of continuous flow and rainfall

Land use	Light -industrial
Area	28 ha
Total imperviousness	80%
Catchment slope	1%
Rainfall gauge distance from outlet	300 m
Range of event rainfall totals	2.0 – 25.4 mm
Number of rainfall events	108



Case-study

1

Define uncertainty intervals for each observed datapoint

2

Generate N parameter sets

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Run model for N parameter sets and rank them

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Estimate model prediction bounds (e.g. $K=3$)

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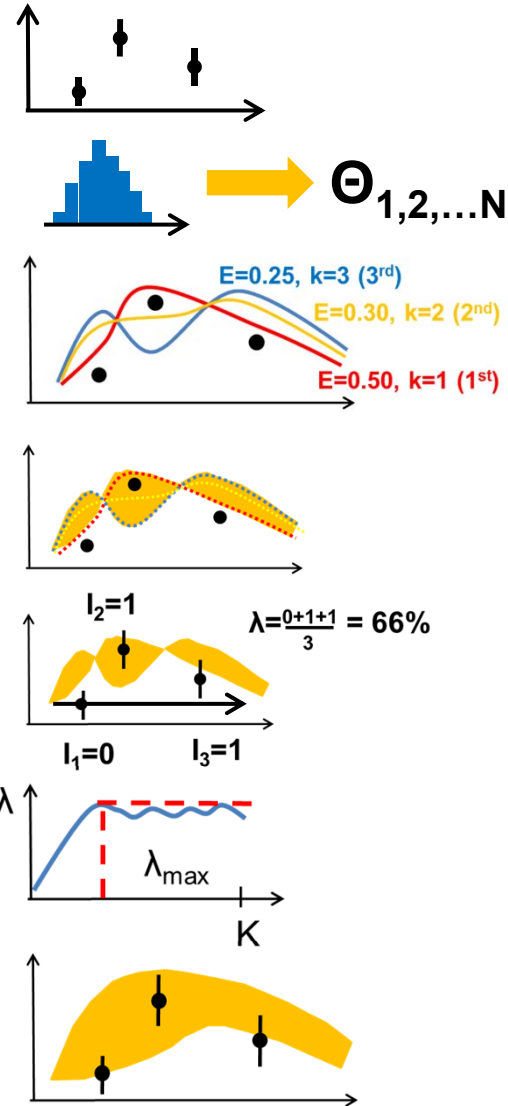
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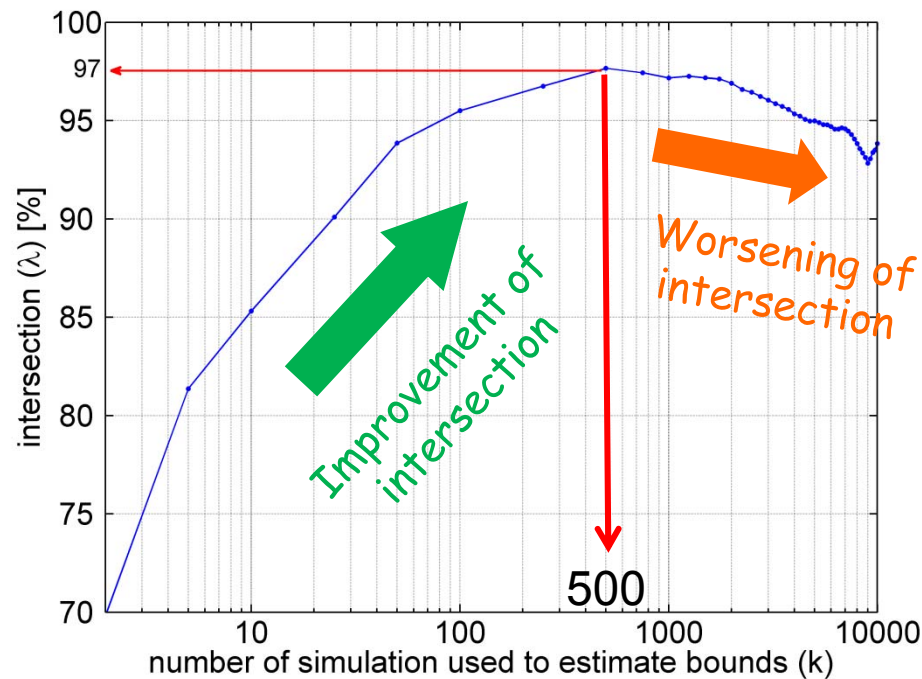
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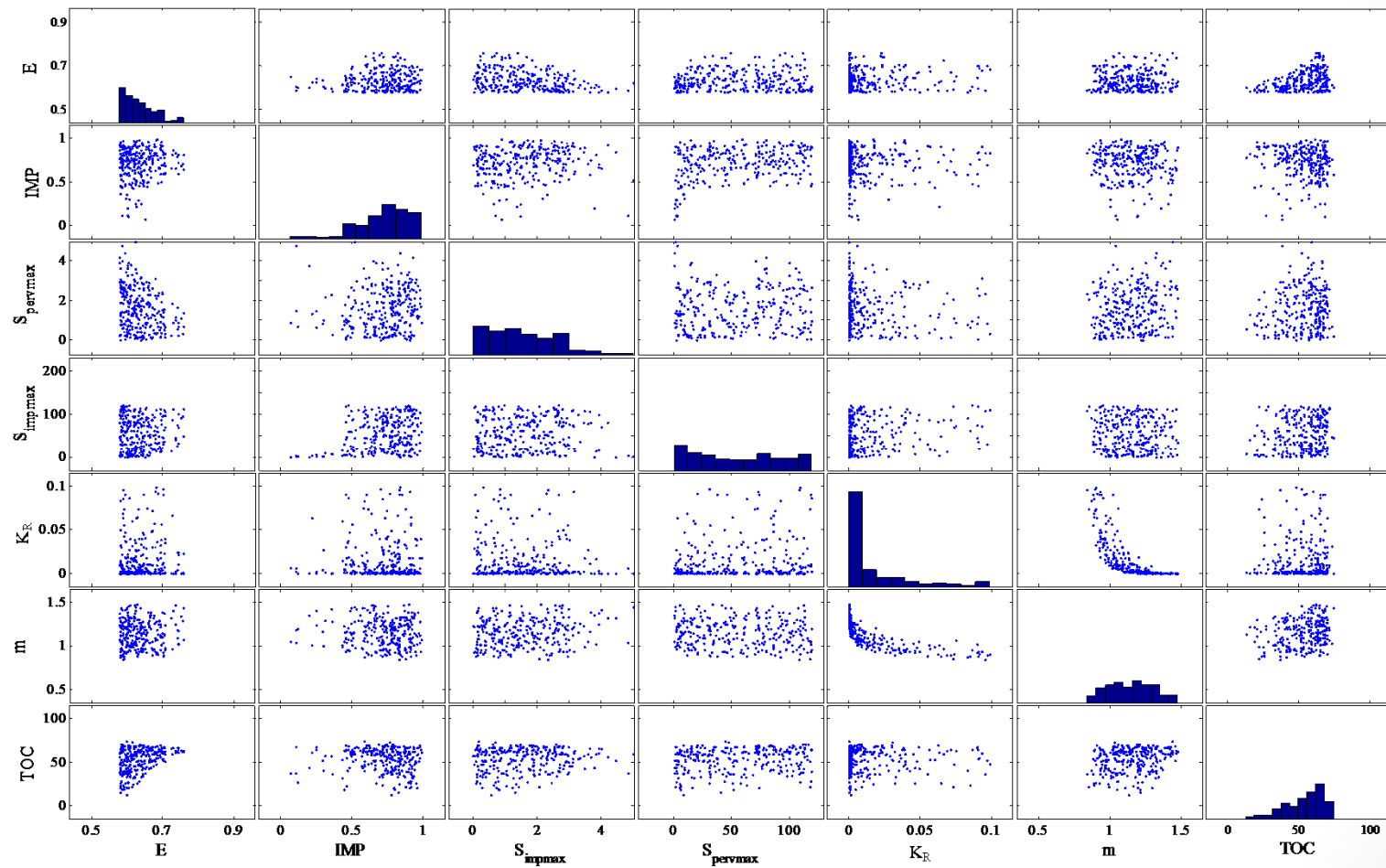


Results – cut off threshold



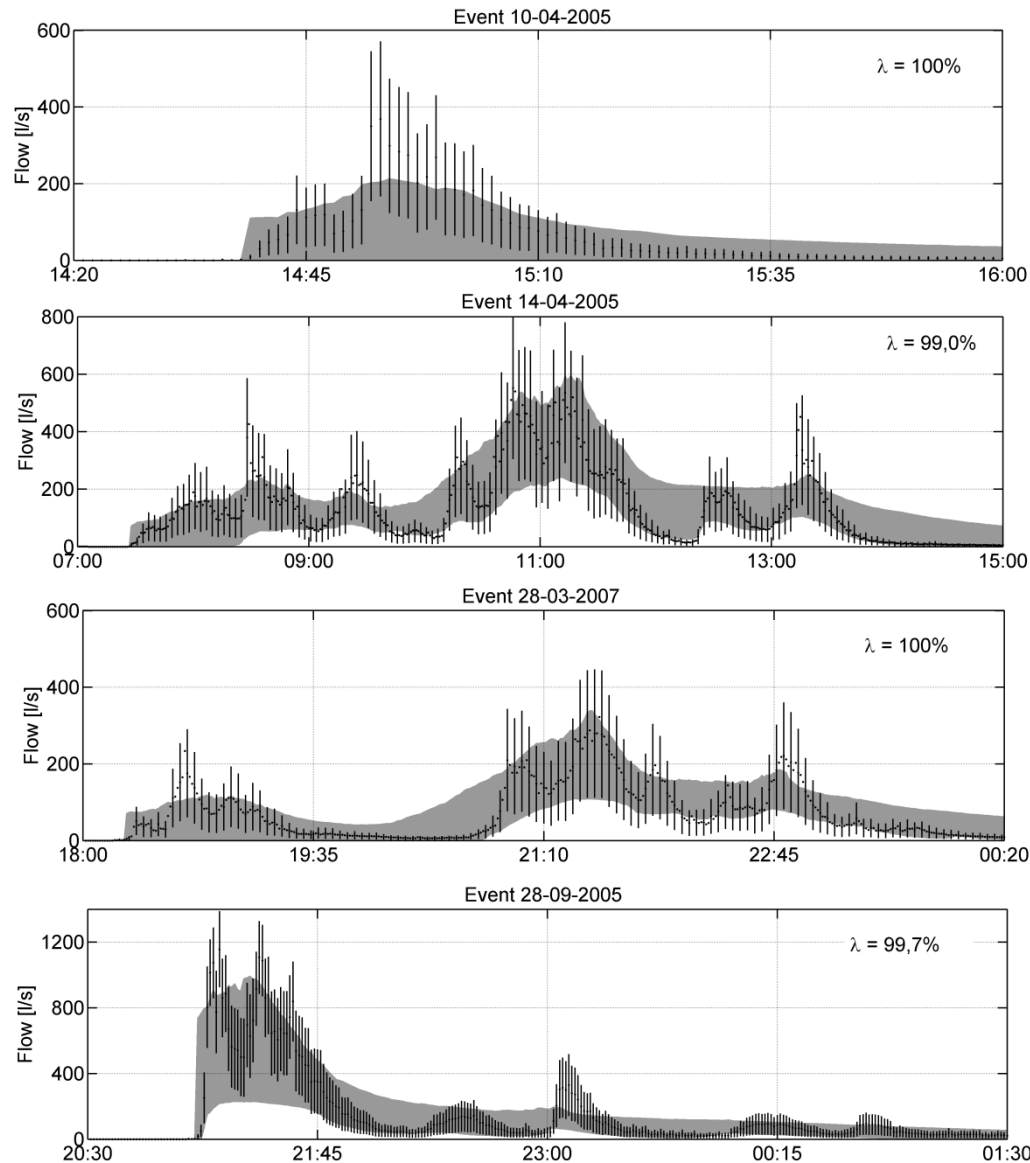
- Not possible to cover all observations - ?
- Max. intersection of 97% (top 500 parameter sets)
- Performance not linearly proportional to number of parameter sets

Results – Parameter distributions



- Flat distribution????

Results – Uncertainty bounds

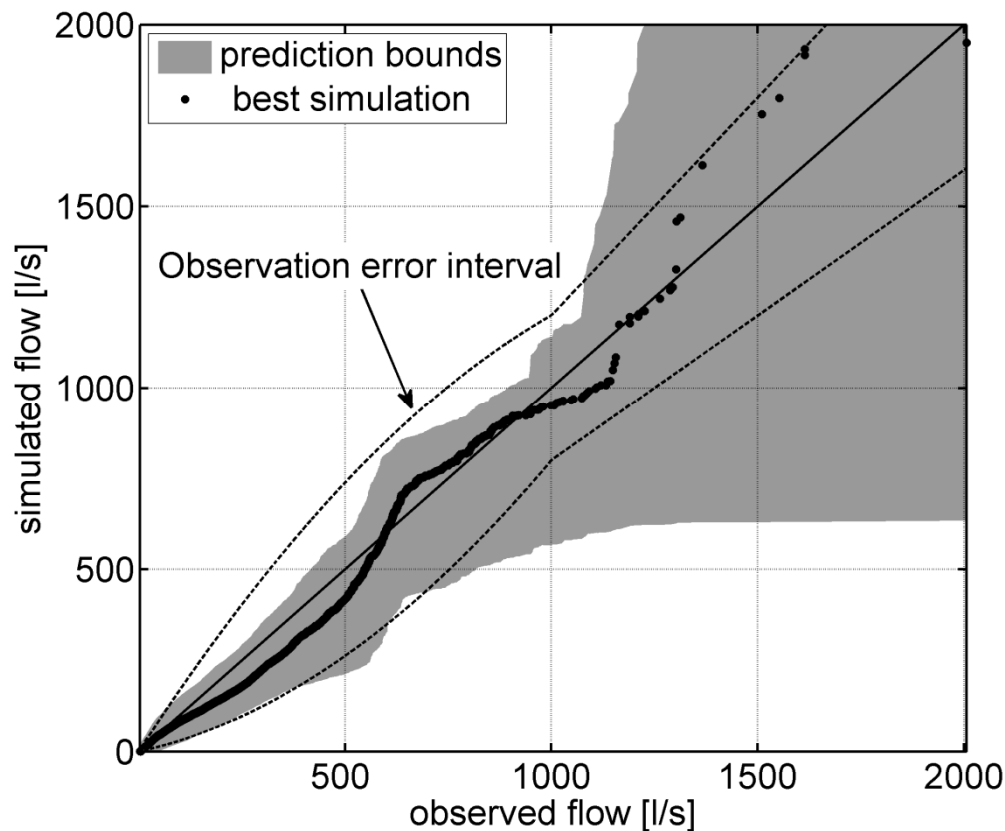


- Good intersection between uncertainty bounds and measurement bounds

Now I get it!!!!...97% intersection between model and measurement bounds



Results – Uncertainty bounds



- Low flows: model uncertainty lower than measurements'
- Above 750 l/s: model uncertainty explodes
- 99% observations below 750 l/s

Conclusions

- A new approach to conduct uncertainty analysis
- Subjectivity is reduced by proposing a tangible criterion
- Measurement uncertainty is taken into account
- Wider application of uncertainty analysis in the "real world" (hopefully)

We love the VMC!



Future work

- Validation
- More catchments
- Water quality model
- Input uncertainty (e.g. time displacement in rainfall)
- Exposure of the proposed method to "real practitioners"