Co-UDlabs

BUILDING COLLABORATIVE URBAN DRAINAGE RESEARCH LABS COMMUNITIES

Routine Uncertainty Assessment with the Urban Drainage Metrology Toolbox

Webinar, 12 June 2023

Jean-Luc BERTRAND-KRAJEWSKI, Mathieu LEPOT (INSA Lyon)
Francois CLEMENS-MEYER (NTNU, Skillsinmotion)

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement No 101008626

1

nôvatech
L'eau dans la ville | Urban water

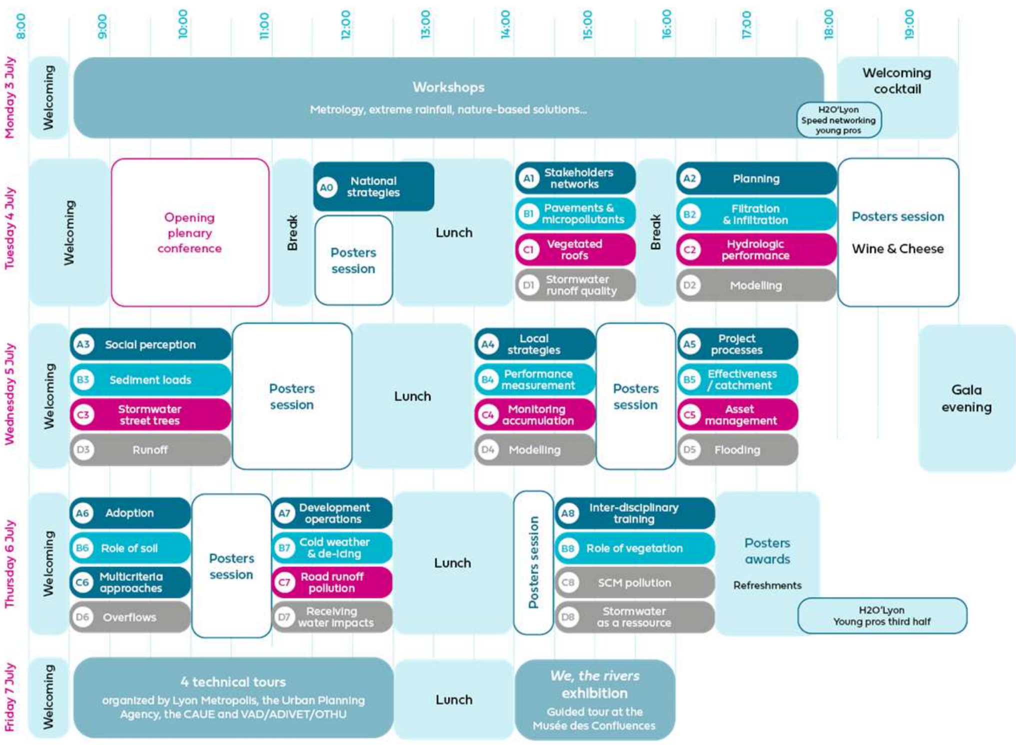
29 countries

220 selected papers

3 days of conference + technical tours & workshops

500 attendees

33 oral sessions &
6 poster sessions

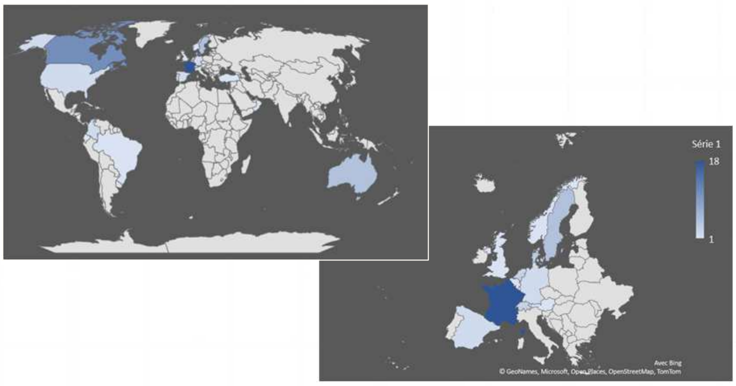


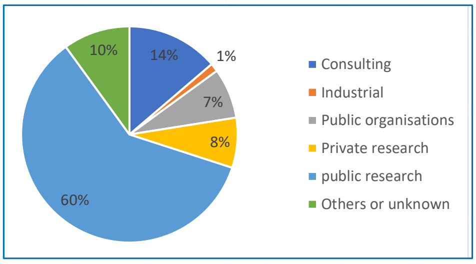
www.novatech2023.org

2

WELCOME!

- 80 registered participants





3

PROGRAMME

- 14:00 Welcome and introduction
- 14:10 Importance of Uncertainty Assessment (UA) in Urban Drainage monitoring (F. Clemens-Meyer)
- 14:30 Basics of UA and brief introduction to the methods applied in the UDMT (J.-L. Bertrand-Krajewski)
- 15:00 Presentation of the UDMT: how it works, user interface, etc. (M. Lepot)
- 15:20 Coffee Break
- 15:35 Examples of UDMT application (J.-L. Bertrand-Krajewski and M. Lepot)
- 16:20 Q&A
- 16:30 Concluding remarks

4

IMPORTANCE OF UNCERTAINTY ASSESSMENT (UA) IN URBAN DRAINAGE MONITORING

F. CLEMENS-MEYER

5

CONTENT

- Why monitor UD systems in the first place?
- Origin of uncertainty/Avoiding systematic errors
- Uncertainty asessement is your friend!
- Concluding remarks

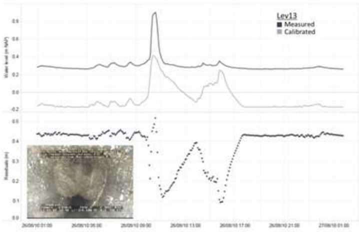
6

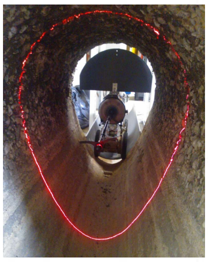
WHY MONITOR UD SYSTEMS?

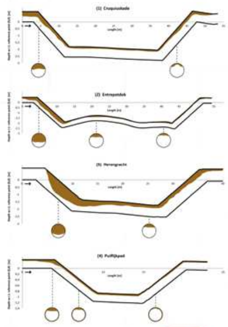
- Actual performance vs design performance (hydraulics, water quality)
- Operation (pump operation, Real Time Control (hydraulics, water quality))
- Impact on environment (receiving surface water bodies, hydraulics +water quality)
- *Technical condition (a.o. CCTV inspection)*

ASSESSING ACTUAL PERFORMANCE

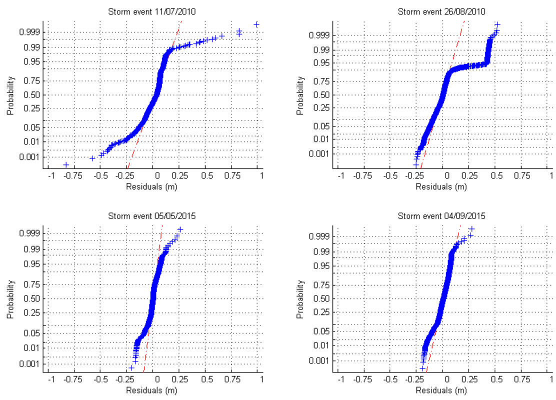
- Protection against flooding/minimising environmental impacts
- Often hydrodynamic models are applied without any validation (compare: in a restaurant the menu is usually not eatable)
- Unexpected issues may influence the actual hydraulic performance that are not taken into account when modelling:

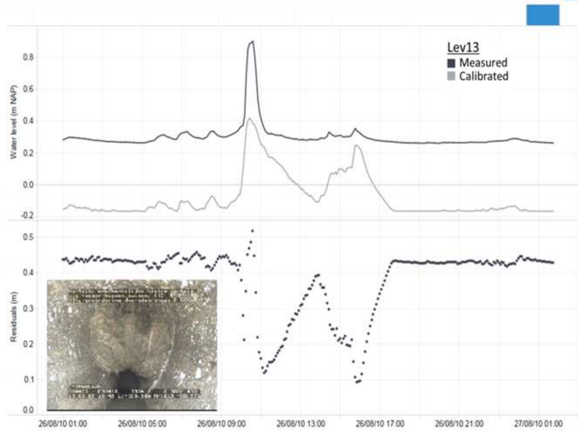




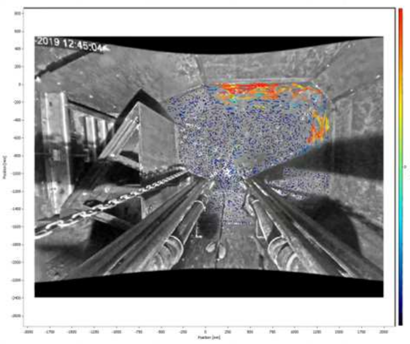


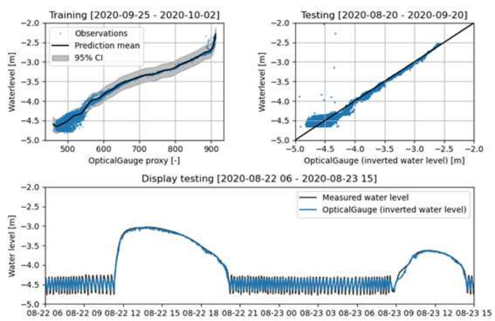
HYDRAULIC FINGERPRINTING



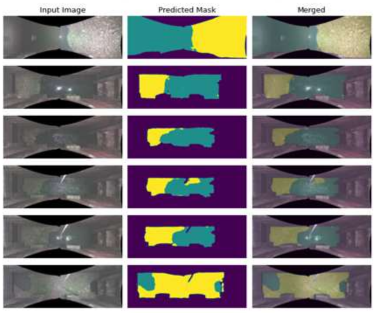


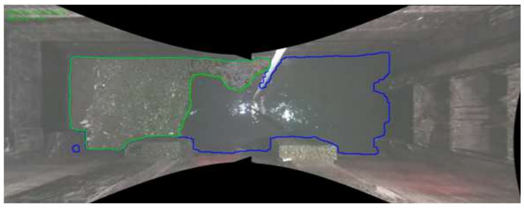
PUMP OPERATION, CHECK ON DESIGN PUMP SUMPS AND WATERLEVEL MEASUREMENT



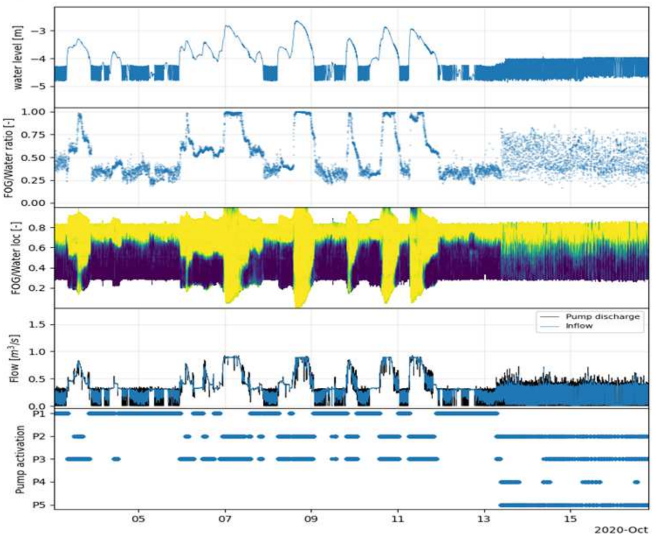


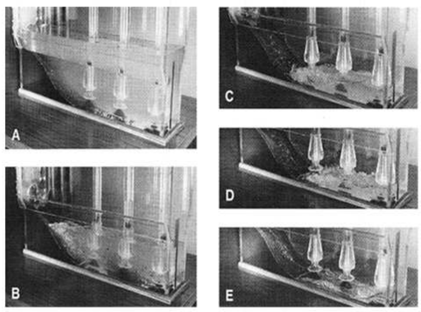
PUMP OPERATION





EFFECT OF PUMP OPERATION ON THE FORMATION OF FOG LAYERS

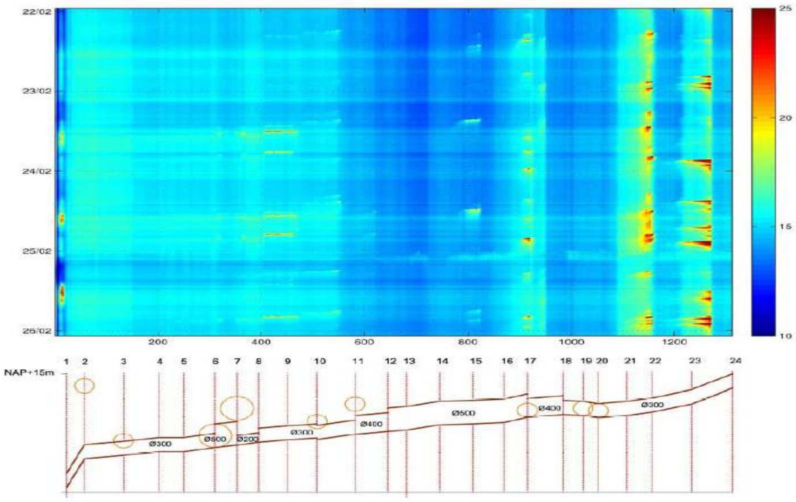




ENVIRONMENTAL IMPACT

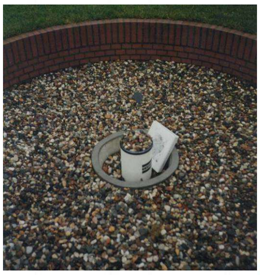
- Monitoring is often related to legislation
- Obviously CSO events serve as **the** default example: monitoring their occurrence can help to identify (and potentially correct for):
  - Design flaws
  - Poor management (e.g. the occurrence of CSO event during dry periods)

ENVIRONMENTAL IMPACT: MONITORING WRONG CONNECTIONS



ORIGIN OF UNCERTAINTY IN MEASUREMENTS

- Many sensoring ***systems*** a sensitive to variations in the conditions in which they operate (e.g. variations in temperature or the presence of EM fields)
- Not to be confused with SYSTEMATIC errors in measurements due to e.g. picking the wrong reference level in waterlevel measurements or setting a wrong scaling factor between e.g. mA and m, these can be avoided by depolying trained personnel



USE THE NOTION OF THE PRESENCE OF UNCERTAINTY TO HAVE CERTAINTY IN MAKING DECISIONS AND AVOIDING (COSTLY) ERRORS

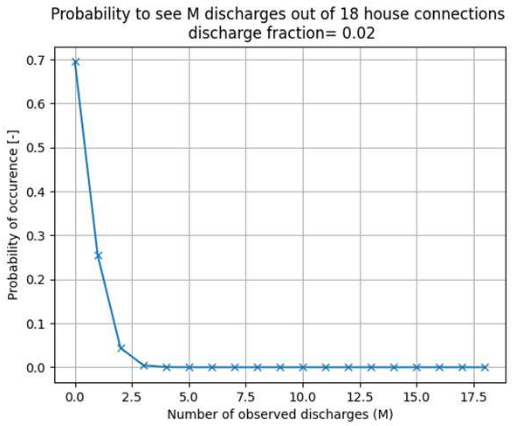
- In legislation: when setting a demand that e.g. the volume of CSO events has to be measured with a maximum uncertainty of 5% is pointless, as this can practically not (or at very high costs only) be realised, feasible would be a 95% uncertainty interval of ~20-25 %.
- Avoid legal discussions when setting norms as much as possible (e.g. when being fined for speeding on the highway, the norm is formulated in such a manner that, in combination with the allowed measuring uncertainty, regular instrument calibration and training of the personnel, the probability that you were ***NOT*** speeding can be neglected (~< 0.05%).
- In redesign: possibly cleaning out sediments and onstacles may increase the actual capacity enough to reduce flooding to within the desired limits, you only know when you measure....
- In interpreting monitoring data and extracting information from them

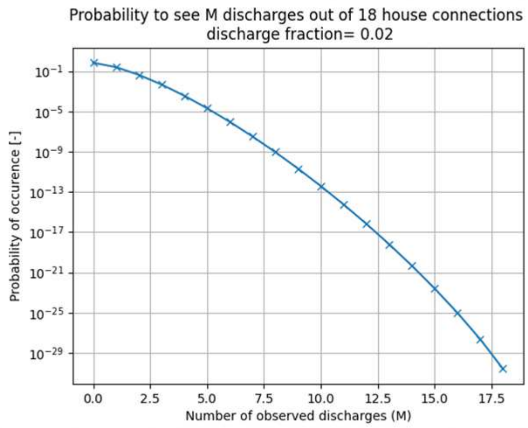
EXAMPLE OF USING THE NOTION OF UNCERTAINTY WHEN INTERPRETING CCTV INFORMATION

- In a lawsuit the question was raised whether or not the groundwater level in a given street was lowered by infiltration of ground water into the sewer system due to neglected maintenance.
- A detailed CCTV inspection had been performed (checked by two independed inspectors, so systematic errors could be excluded).
- No hints for infiltration were observed in the footage alaysed according to the accepted standards(no obvious leaking or displaced joints, no cracks, no holes etc.)
- But during the inspection 15 out of 18 house connections discharged water into the sewer….

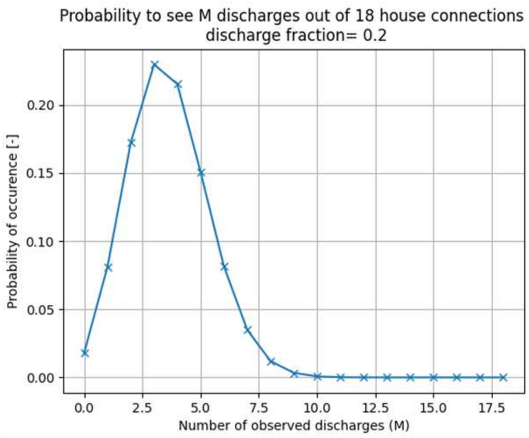
USE OF UNCERTAINTY IN EVALUATING CCTV DATA

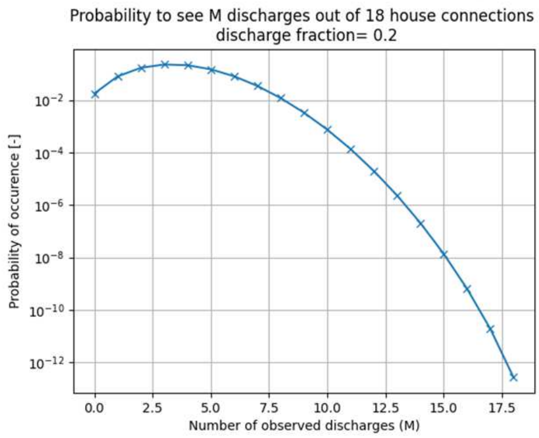
WAS IT REGULAR DISCHARGE OR LEAKAGE?





SUPPOSE P=0.2 (SO ~ 5 H/DAY DISCHARGEING)





CONCLUDING REMARKS

- Large scale monitoring has become a possibility over the last decade, due to robust sensor technology, IT technology and the availability of cheap components
- The need for monitoring is increasing as we are faced with changing conditions (climate, increase in urban population), combined with heavier demands this asks for carefull and often costly redesign of existing systems and the evaluation of new concepts being deployed.
- Using the notion of the presence of uncertainty in monitoring data is essential to avoid making wrong decisions in (re)design, operation and law enforcement pertaining to UD systems
- Organisations managing UD systems will need to incorporate the knowledge and the means (personnel) to perform monitoring on the required level. Monitoring is a specalism that asks for attention

21

BASICS OF UA

AND BRIEF INTRODUCTION

TO THE METHODS APPLIED IN THE UDMT

J.-L. BERTRAND-KRAJEWSKI

22

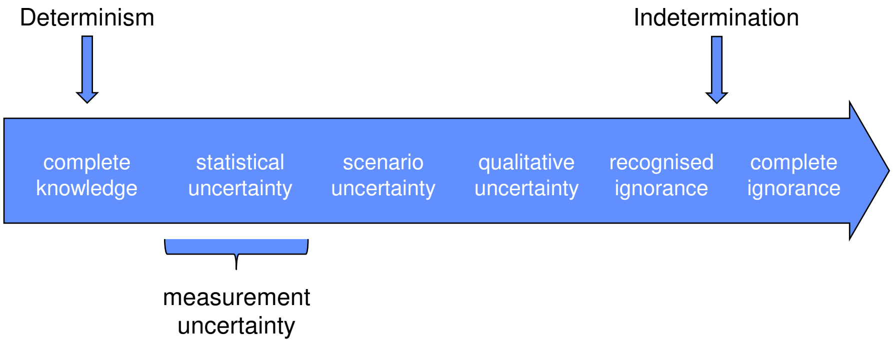
1

[…] so in contemplation,
if we begin with certainties, we shall end in doubts; but if we begin with doubts, and are patient in them, we shall end in certainties.

Francis BACON (1561-1626)
The Advancement of Learning (1605), p. 30 in Ebook PDF version

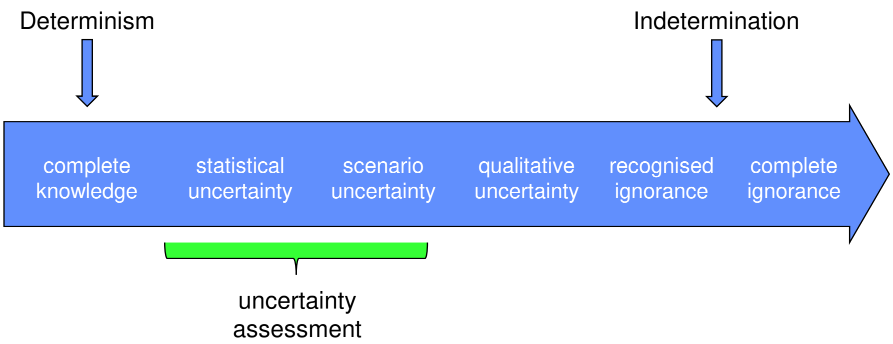
2

UNCERTAINTY



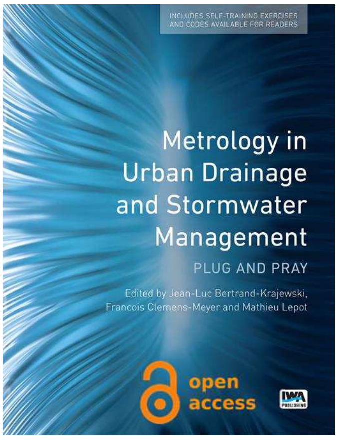
3

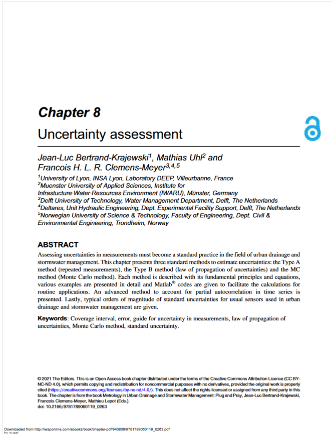
UNCERTAINTY



4

To know more on Uncertainty Assessment




Chapter 8

Uncertainty assessment

Jean-Luc Bertrand-Krajewski[1], Mathias Uhl[2] and Francois H. L. R. Clemens-Meyer[3,4,5]

[1]University of Lyon, INSA Lyon, Laboratory DEEP, Villeurbanne, France
[2]Muenster University of Applied Sciences, Institute for Infrastucture·Water·Resources·Environment (IWARU), Münster, Germany
[3]Delft University of Technology, Water Management Department, Delft, The Netherlands
[4]Deltares, Unit Hydraulic Engineering, Dept. Experimental Facility Support, Delft, The Netherlands
[5]Norwegian University of Science & Technology, Faculty of Engineering, Dept. Civil & Environmental Engineering, Trondheim, Norway

ABSTRACT

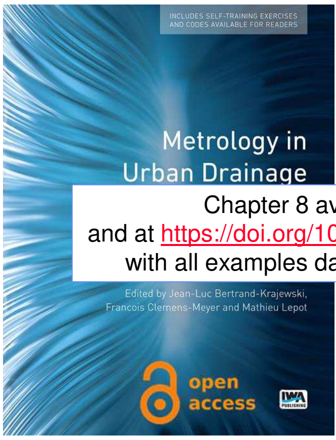
Assessing uncertainties in measurements must become a standard practice in the field of urban drainage and stormwater management. This chapter presents three standard methods to estimate uncertainties: the Type A method (repeated measurements), the Type B method (law of propagation of uncertainties) and the MC method (Monte Carlo method). Each method is described with its fundamental principles and equations, various examples are presented in detail and Matlab® codes are given to facilitate the calculations for routine applications. An advanced method to account for partial autocorrelation in time series is presented. Lastly, typical orders of magnitude of standard uncertainties for usual sensors used in urban drainage and stormwater management are given.

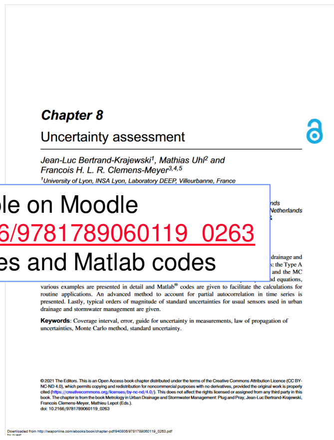
Keywords: Coverage interval, error, guide for uncertainty in measurements, law of propagation of uncertainties, Monte Carlo method, standard uncertainty.

doi: 10.2166/9781789060119_0263

Metrology in Urban Drainage and Stormwater Management: Plug and Pray
Edited by Jean-Luc Bertrand-Krajewski, Francois Clemens-Meyer & Mathieu Lepot
IWA Publishing, London (UK), DOI: https://doi.org/10.2166/9781789060119

To know more on Uncertainty Assessment




Chapter 8

Uncertainty assessment

Jean-Luc Bertrand-Krajewski[1], Mathias Uhl[2] and Francois H. L. R. Clemens-Meyer[3,4,5]
[1]University of Lyon, INSA Lyon, Laboratory DEEP, Villeurbanne, France

Chapter 8 available on Moodle
and at https://doi.org/10.2166/9781789060119_0263
with all examples data files and Matlab codes

Metrology in Urban Drainage and Stormwater Management: Plug and Pray
Edited by Jean-Luc Bertrand-Krajewski, Francois Clemens-Meyer & Mathieu Lepot
IWA Publishing, London (UK), DOI: https://doi.org/10.2166/9781789060119

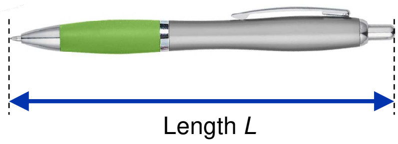
TERMINOLOGY

- VIM : International Vocabulary of Metrology

7

TERMINOLOGY

- **Measurand**
- **True quantity value** : always unknown
- **Measurement result** : L_1 , L_2 , ... L_N
- **Repeatability** : unchanged conditions
- **Reproducibility** : changed conditions

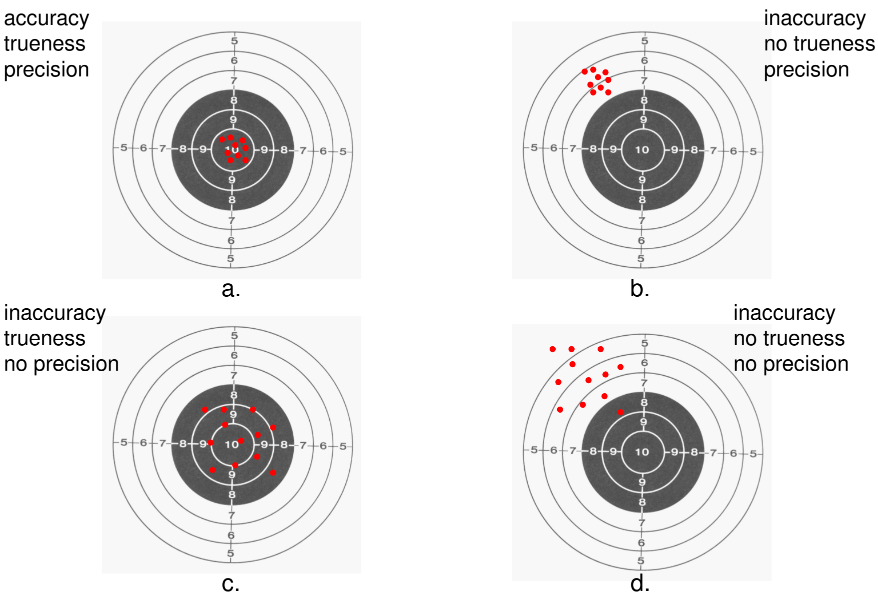


8

TERMINOLOGY

- **Measurement error :**
  measurement result – true or reference value
- **Systematic measurement error**
- **Random measurement error**
- **Measurement accuracy** — closeness of agreement between a **measured quantity value** and a **true quantity value** of a **measurand**
- **Measurement trueness** — closeness of agreement between the average of an infinite number of replicate **measured quantity values** and a **reference quantity value**
- **Measurement precision** — closeness of agreement between **indications** or **measured quantity values** obtained by replicate **measurements** on the same or similar objects under specified conditions

REPEATED MEASUREMENTS



TERMINOLOGY

- **Measurement uncertainty**
  - dispersion of the quantity values being attributed to a measurand
  - probabilistic approach
- **Sources of uncertainty**
  - systematic and random errors due to
    - sensor
    - site
    - user
    - measurement conditions
    - etc…

STANDARD UNCERTAINTY $u(X)$

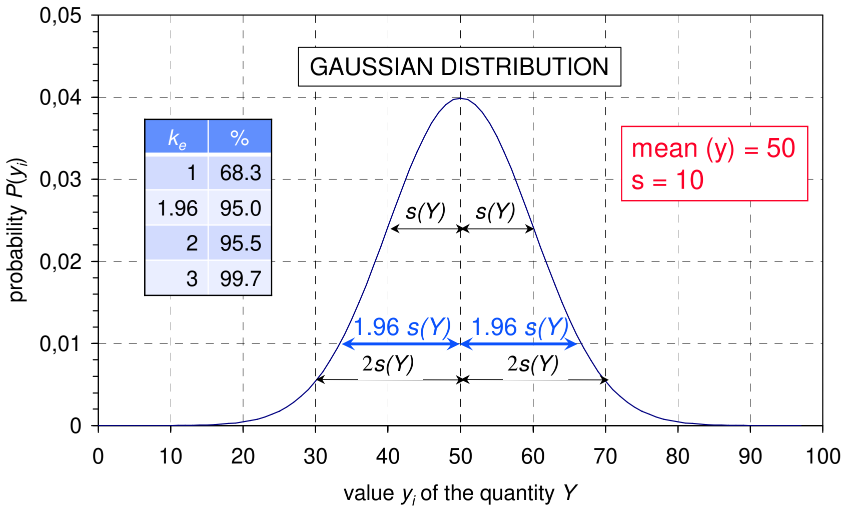
- **hypothesis :** X **random variable**
- x **: measurement result**
- $u(x)$ **: standard uncertainty** ≈ **standard deviation (Type A)**
- $k_e u(x)$ **: enlarged uncertainty,** k_e **enlargement factor**
- $[x - k_e u(x), x + k_e u(x)]$ **: coverage interval**
- $\frac{\Delta x}{x} = \frac{k_e u(x)}{x}$ **: relative enlarged uncertainty**

NORMAL (GAUSSIAN) DISTRIBUTION

Gauss C.F. (1823). *Theoria combinationis observationum erroribus minimis obnoxiae*

13

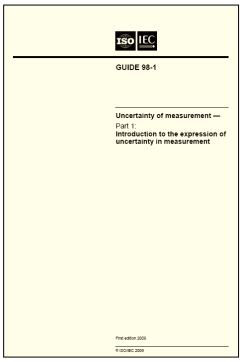
NORMAL (GAUSSIAN) DISTRIBUTION



14

UNCERTAINTY OF MEASUREMENT

- **GUM standards and supplements**
  - ISO/CEI GUIDE 98-1:2009 (Sept. 2009)
  - ISO/CEI GUIDE 98-3/S1:2008 (Dec. 2008)
    ISO/CEI GUIDE 98-3/S1/AC1:2009 (May 2009)


ISO IEC

GUIDE 98-1

Uncertainty of measurement —
Part 1:
Introduction to the expression of uncertainty in measurement

First edition 2009

© ISO/IEC 2009

UNCERTAINTY ASSESSMENT 1/2

- **TYPE A (GUM standard)**
  - repeated measurements
- **TYPE B (GUM standard)**
  - LPU - Law of Propagation of Uncertainties

- **RESULT :** $$Y = \overline{y} \pm k_e u(y)$$
- **if k_e = 1.96 : 95 % coverage interval**

  (k_e = 2 accepted as an approx. for 95 % CI)

UNCERTAINTY ASSESSMENT 2/2

- **Monte Carlo method (MCM)**
  - supplement to GUM
  - reference method

- **RESULT :** $\bar{y}$

  and its 95 % coverage interval

LAW OF PROPAGATION OF UNCERTAINTIES

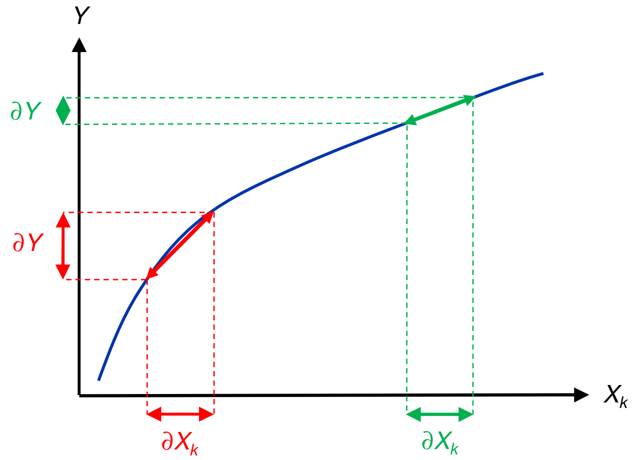
- $Y = f\,(X_1, X_2\,, \ldots X_k\,, \ldots\, X_N)$

- **known** $u(X_k)$

  (calibration, experiments, literature, expertise, etc.)

LAW OF PROPAGATION OF UNCERTAINTIES

$$\partial Y = \partial X_k \times slope$$



LAW OF PROPAGATION OF UNCERTAINTIES

- $Y = f(X_1, X_2, \ldots X_k, \ldots X_N)$
- **known** $u(X_k)$
  (calibration, experiments, literature, expertise, etc.)
- **Law of Propagation of Uncertainties**

$$u(Y)^2 = \sum_{k=1}^{N} u(X_k)^2 \left(\frac{\partial f}{\partial X_k}\right)^2 + 2 \sum_{k=1}^{N-1} \sum_{j=k+1}^{N} r(X_k, X_j)\, u(X_k) u(X_j) \left(\frac{\partial f}{\partial X_k}\right)\left(\frac{\partial f}{\partial X_j}\right)$$

LAW OF PROPAGATION OF UNCERTAINTIES

- ***Y* = *f* (X_1, X_2 , …X_k , … X_N)**
- **X_1, X_2 , …X_k , … X_N shall be independent quantities**
- **No intermediate quantities ► generate covariance**
- ***f* is not the final usual equation, but shall represent the <u>measurement process itself</u>**

$$u(Y)^2 = \sum_{k=1}^{N} u(X_k)^2 \left(\frac{\partial f}{\partial X_k}\right)^2 + 2\sum_{k=1}^{N-1}\sum_{j=k+1}^{N} r(X_k,X_j)\,u(X_k)u(X_j)\left(\frac{\partial f}{\partial X_k}\right)\left(\frac{\partial f}{\partial X_j}\right)$$

LAW OF PROPAGATION OF UNCERTAINTIES

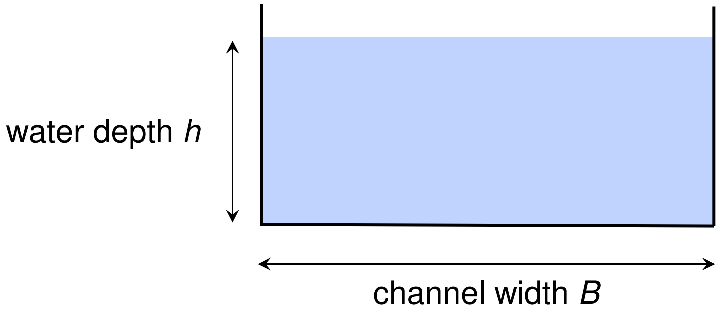
- **Conditions of use**
  - symmetric distributions
  - normal or close to normal distributions
  - 1st order approximation is acceptable (linearity)
- **Watch out for covariances !**
  - covariance of uncertainties
  - covariance of values
  - sometimes difficult to detect and assess
  - possible significant consequences

EXAMPLE 1: RECTANGULAR CHANNEL

B = 1.50 m
h = 0.62 m
U = 0.38 m/s

Q = 0.35 m^3/s

$$Q = S(h)U = BhU$$



EXAMPLE 1

$$Q = S(h)U = BhU$$

$$u(Q)^2 = u(B)^2\left(\frac{\partial Q}{\partial B}\right)^2 + u(h)^2\left(\frac{\partial Q}{\partial h}\right)^2 + u(U)^2\left(\frac{\partial Q}{\partial U}\right)^2$$

$$u(Q)^2 = u(B)^2(hU)^2 + u(h)^2(BU)^2 + u(U)^2(Bh)^2$$

EXAMPLE 1

- **TYPE B**
- $u(B)$ = 0.002 m
  $u(h)$ = 0.003 m
  $u(U)$ = 0.04 m/s
- $u(Q) = 0.0372\ m^3/s$
- $Q = 0.35 \pm k_e\ u(Q)$
- $Q = 0.35 \pm 0.05\ m^3/s$
- $\Delta Q/Q = 20.7\ \%$

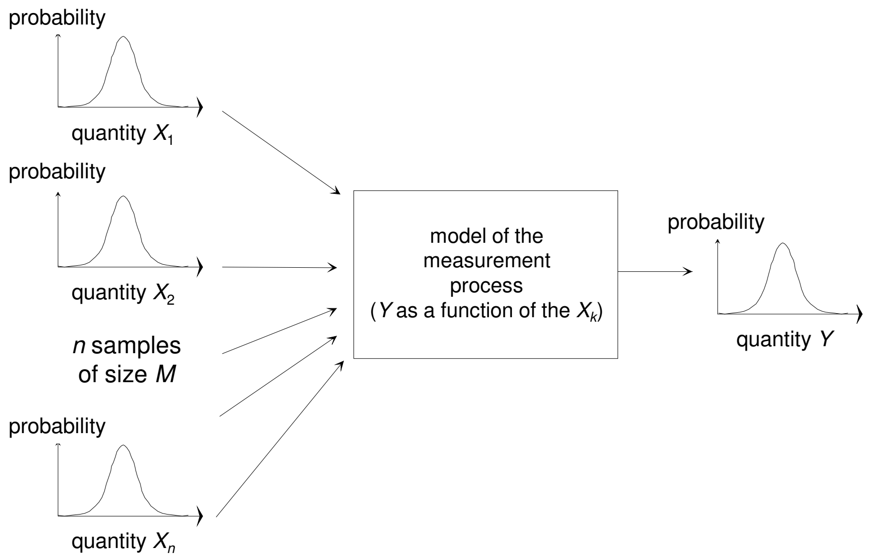
25

MONTE CARLO METHOD

- **ISO/CEI GUIDE 98-3/S1:2008 (Dec. 2008)**
  ISO/CEI GUIDE 98-3/S1/AC1:2009 (May 2009)
- **Simulating M times the measurement process with samples of size M of the quantities X_k**
- **Analysing the M values of Y**
  - mean value of Y
  - minimum 95 % coverage interval (sorting percentiles 0-95 to 5-100)

26

MONTE-CARLO METHOD

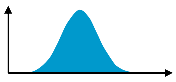


MONTE-CARLO METHOD

Sample for X_1	Sample for X_2	···	Sample for X_i	···	Sample for X_N	$f(X_1,X_2,\ldots X_i,\ldots X_N)$	Sample for Y
$x_{1,1}$	$x_{2,1}$		$x_{i,1}$		$x_{N,1}$	→	y_1
$x_{1,2}$	$x_{2,2}$		$x_{i,2}$		$x_{N,2}$	→	y_2
$x_{1,3}$	$x_{2,3}$		$x_{i,3}$		$x_{N,3}$	→	y_3
.	.		.		.		.
.	.		.		.		.
.	.		.		.		.
$x_{1,r}$	$x_{2,r}$		$x_{i,r}$		$x_{N,r}$	→	y_r
.	.		.		.		.
.	.		.		.		.
.	.		.		.		.
$x_{1,M}$	$x_{2,M}$		$x_{i,M}$		$x_{N,M}$	→	y_M

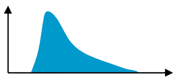
DISTRIBUTIONS OF THE X_k

- **Normal distribution $\mathcal{N}(\mu,\sigma)$**

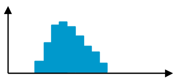


- **Uniform distribution $U(a,b)$**

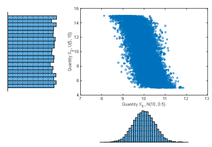
- **Other theoretical distributions**



- **Empirical distributions**



- **Independence or covariance of the X_k**



29

SIZE *M*

- **Simple approach : $M = 10^6$**
- **Iterative approach (standard) : M such that the boundaries of the 95 % coverage interval are stabilised with a given tolerance defined by the user.**
  Sub-samples of size 10^4

30

EFFECT OF *M*

- **WARNING : ORDERS OF MAGNITUDE ONLY !!**
  To be checked case by case
- **Convergence of Y_{mean} :** **log M = 2 to 3**
- **Convergence of $s(Y)$:** **log M = 3 to 5**
- **Convergence of IC95 boundaries :** **log M = 4 to 6**

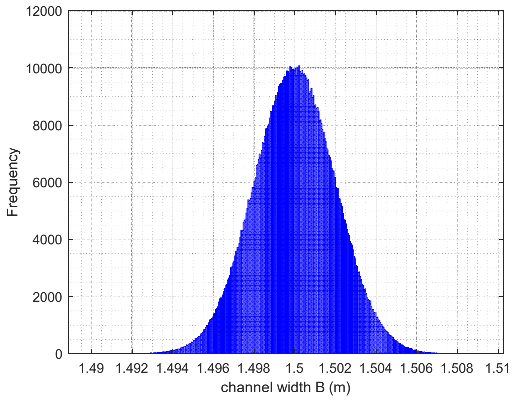
EXAMPLE 1

- **Matlab demo, $M = 10^6$**
  - code

```
B = 1.50 + 0.002*randn(1e6,1);
h = 0.62 + 0.003*randn(1e6,1);
U = 0.38 + 0.04*randn(1e6,1);
Q = B.*h.*U;
mean(Q)
std(Q)
IC95min(Q)
```

EXAMPLE 1

- **Sample of *B* : 10^6 values**



20 first values :

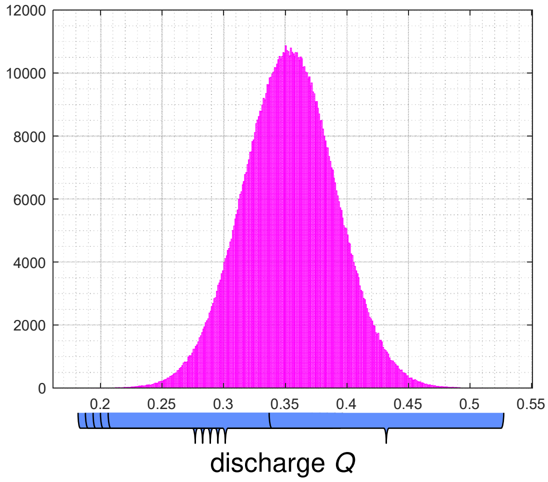
1.5010
1.5036
1.4954
1.5017
1.5006
1.4973
1.4991
1.5006
1.5071
1.5055
1.4973
1.5060
1.5014
1.4998
1.5014
1.4995
1.4997
1.5029
1.5028
1.5028
.....

33

EXAMPLE 1

mean = 0.3534 m^3/s
std. dev. = 0.0372 m^3/s
IC95mini = [0.2802, 0.4263] m^3/s

IC95mini



34

EXAMPLE 1

TYPE B

- $u(B)$ = 0.002 m
  $u(h)$ = 0.003 m
  $u(U)$ = 0.04 m/s
- $u(Q)$ = 0.0372 m^3/s
- $Q = 0.3534 \pm k_e\, u(Q)$
  = [0.2804, 0.4264]
- $Q = 0.35 \pm 0.05$ m^3/s
- $\Delta Q/Q$ = 20.7 %

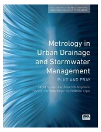
MONTE-CARLO

- $M = 10^6$
- mean (Q) = 0.3534 m^3/s
- [0.2802, 0.4263]

35

TYPE B or MONTE CARLO ?

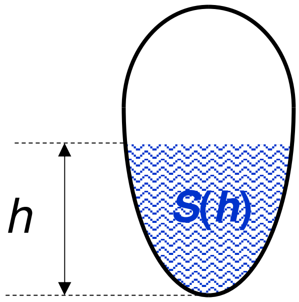
- **Reference : Monte Carlo**
- **If the following assumptions are verified**
  - linear process
  - normal or symmetric distributions
  - 1st order approximation is acceptable
  - close results with MCM

  then type B can be applied (cf. example)
- **More details in** 

36

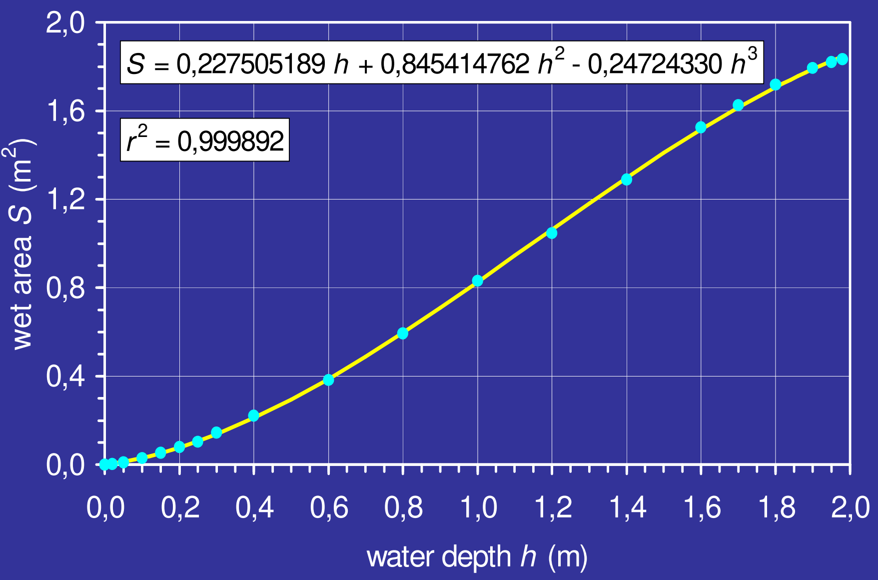
T200 EGG-SHAPE SEWER

- ***Q* = *S*(*h*)*U***

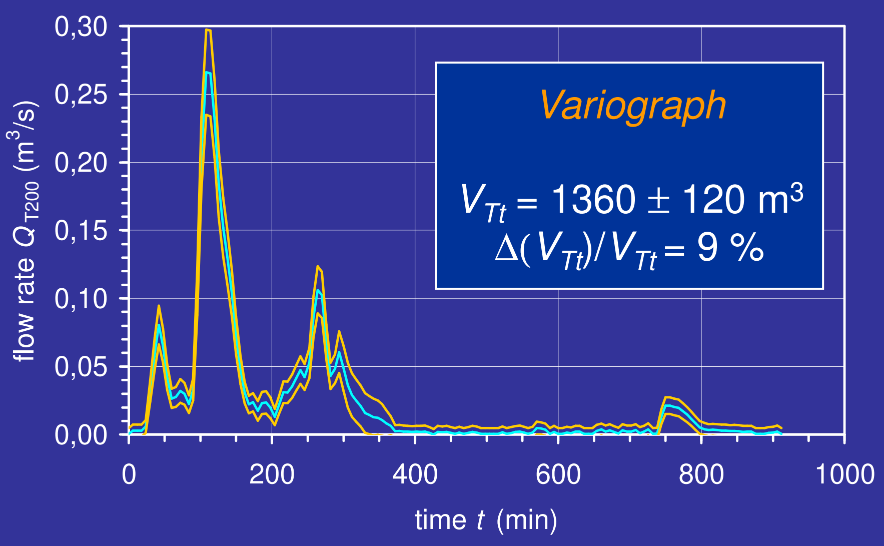


- **3 sources of uncertainty:**
  - $u(h)$ = 5 mm
  - $u(U)$ = 0,1 m/s
  - $u(S)$ = ?

T200 FUNCTION *S*(*h*)



HYDROGRAPH T200 on 28 March 1995



39

40

PRESENTATION OF THE UDMT

M. LEPOT

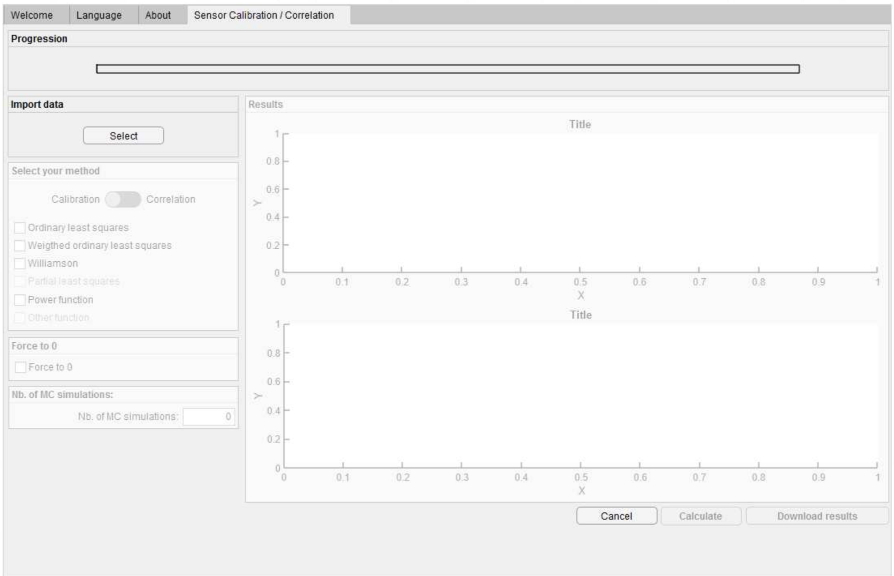
25

A FREE TOOLBOX FOR EVERYONE

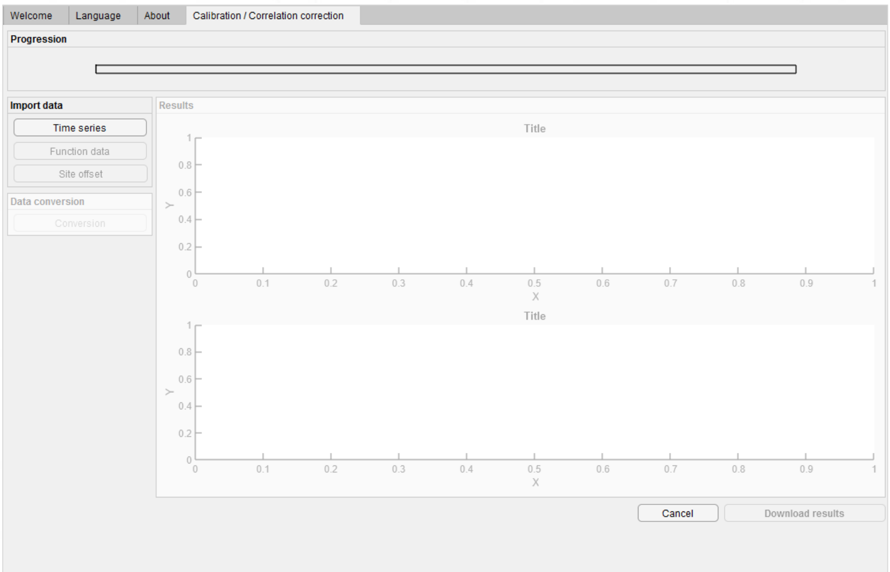
- A free WebApp accessible by everyone (on- and off-line)
- Adress : www.coudlabs.alisonen.com
- User manual, training files and offline version* available
- For the moment : in English, French and Spanish (other langages possible in the near future if needed)
- Both versions regulary updated, in a transparent manner
- CSV file required, according to template described in the user manual
- Comments, remarks and suggestions/ to be sent at UrbanDrainageMetrologyToolbox@gmail.com

26

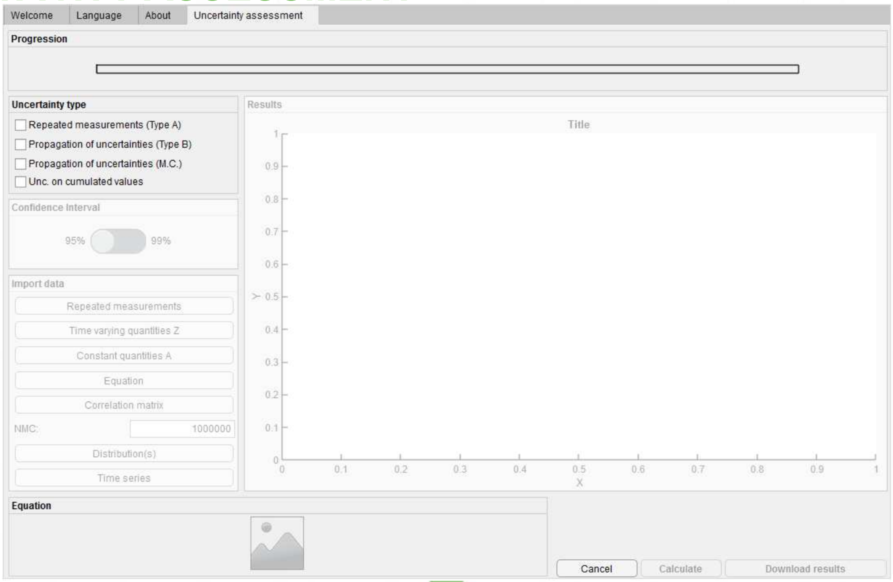
SENSOR CALIBRATION / CORRELATION



CALIBRATION / CORRELATION CORRECTION

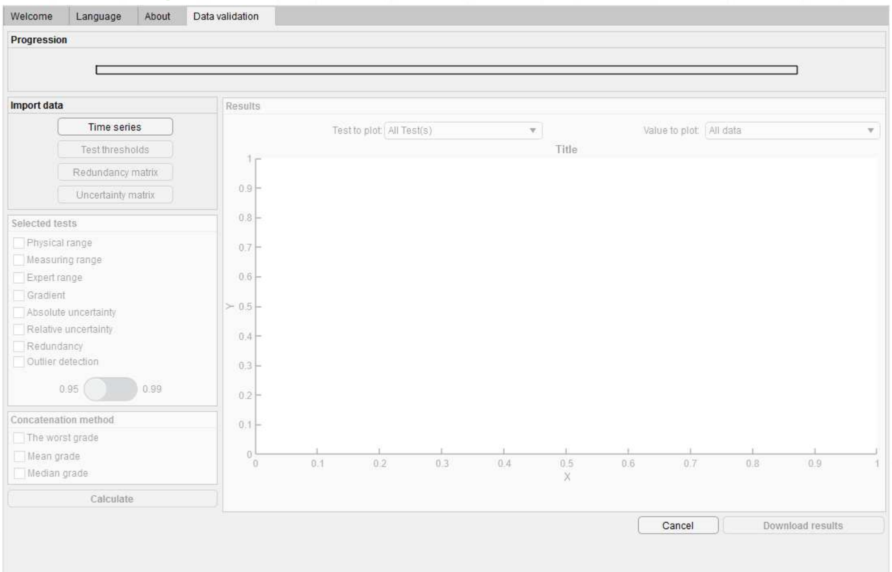


UNCERTAINTY ASSESSMENT



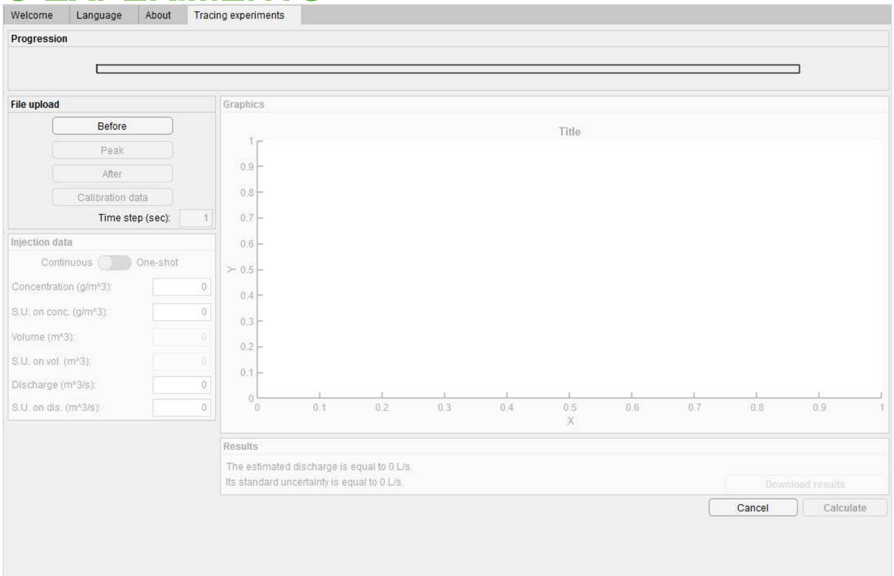
27

DATA VALIDATION



28

TRACING EXPERIMENTS



Co-UDlabs

BUILDING COLLABORATIVE URBAN DRAINAGE RESEARCH LABS COMMUNITIES

Routine Uncertainty Assessment with the Urban Drainage Metrology Toolbox

Webinar, 12 June 2023

Jean-Luc BERTRAND-KRAJEWSKI, Mathieu LEPOT (INSA Lyon)
Francois CLEMENS (NTNU, Skillsinmotion)

EXAMPLES OF APPLICATION OF THE UDMT

J.-L. BERTRAND-KRAJEWSKI, M. LEPOT

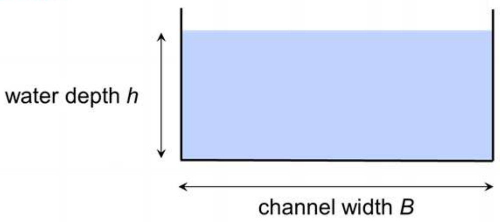
RECTANGULAR CHANNEL WITH UDMT

- Same case as earlier

B = 1.50 m
h = 0.62 m
U = 0.38 m/s

Q = 0.35 m³/s

$$Q = S(h)U = BhU$$



TYPE B

- $u(B)$ = 0.002 m
  $u(h)$ = 0.003 m
  $u(U)$ = 0.04 m/s
- $u(Q)$ = 0.0372 m³/s
- $Q = 0.3534 \pm k_e\, u(Q)$
  = [0.2804, 0.4264]
- Q = 0.35 ± 0.05 m³/s
- $\Delta Q/Q$ = 20.7 %

MONTE-CARLO

- $M = 10^6$
- mean (Q) = 0.3534 m³/s
- [0.2802, 0.4263]

RECTANGULAR CHANNEL WITH UDMT

- UDMT inputs : csv files, with specified format requirements (see user manual)
- For Type B method
  - *Z* file : quantities varying with time, e.g. *h*, *U*, *pH*, *Tu*, etc.
  - *A* file : constant quantities, e.g. channel width, pipe diameter, roughness, etc.
  - equation file : function $f(X_1, X_2, \dots X_N)$ with X_k and $u(X_k)$ given in Z or A files
  - correlation file : correlation matrix of X_k quantities
- For Monte Carlo method
  - *M* : size of samples
  - distributions file : matrix indicating the samples distributions
    1 = Gaussian, 2 = uniform

33

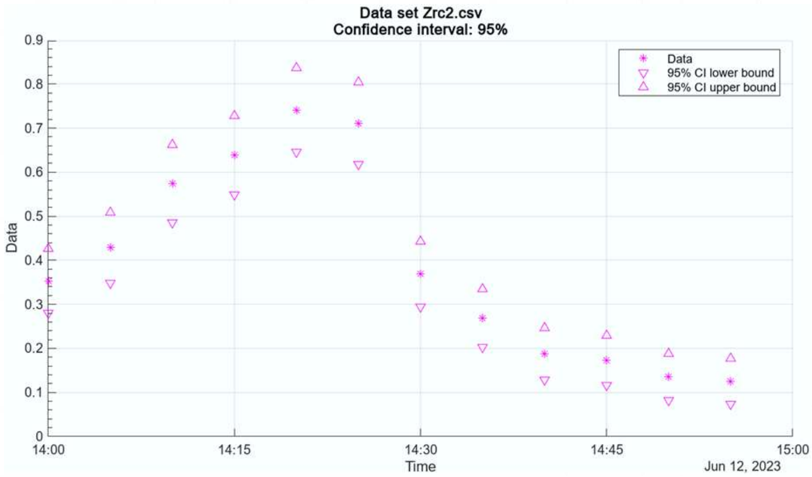
RECTANGULAR CHANNEL WITH UDMT

- check csv files
- on-line demo

34

RECTANGULAR CHANNEL WITH UDMT : TIME SERIES

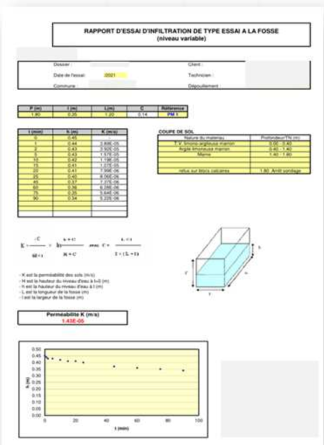
- Zfile = Zrc2
- on-line demo



INFILTRATION WITH UDMT

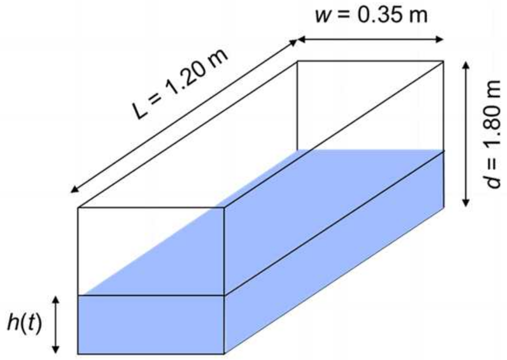
- ***In situ*** **infiltration measurement > estimate** K_s **(m/s)**

  (real case taken from a consulting company report)


RAPPORT D'ESSAI D'INFILTRATION DE TYPE ESSAI A LA FOSSE
(niveau variable)

INFILTRATION WITH UDMT

- Open trench infiltration experiment



$$K_s(t) = \frac{-C}{t} Log\left(\frac{h(t)+C}{h_0+C}\right)$$

with

$$C = \frac{S}{P_h} = \frac{Lw}{2(L+w)}$$

INFILTRATION WITH UDMT

time (min)	time (s)	h_m	L_m	w_m	S_m2	Ph_m	C_m	K_m_per_s
0	0	0.45	1.2	0.35	0.42	3.1	0.1355	---
1	60	0.44						3.8901E-05
2	120	0.43						3.9242E-05
5	300	0.43						1.5697E-05
10	600	0.42						1.1877E-05
15	900	0.41						1.0653E-05
20	1200	0.41						7.9896E-06
25	1500	0.4						8.0629E-06
45	2700	0.37						7.3725E-06
60	3600	0.36						6.2813E-06
75	4500	0.35						5.6389E-06
90	5400	0.34						5.2213E-06

INFILTRATION WITH UDMT

time (min)	time (s)	h_m	L_m	w_m	S_m2	Ph_m	C_m	K_m_per_s
0	0	0.45	1.2	0.35	0.42	3.1	0.1355	---
1	60	0.44						3.8901E-05
2	120	0.43						3.9242E-05
5	300	0.43						1.5697E-05
10	600	0.42						1.1877E-05
15	900	0.41						1.0653E-05
20	1200	0.41						7.9896E-06
25	1500	0.4						8.0629E-06
45	2700	0.37						7.3725E-06
60	3600	0.36						6.2813E-06
75	4500	0.35						5.6389E-06
90	5400	0.34						5.2213E-06
							mean Ks	1.4267E-05

INFILTRATION WITH UDMT

- **Application of type B method**
  - Rewrite the measurement process equation

$$K_s(t) = \frac{-C}{t} Log\left(\frac{h(t)+C}{h_0+C}\right) \quad \text{with} \quad C = \frac{S}{P_h} = \frac{Lw}{2(L+w)}$$

$$K_s(t) = \frac{-Lw}{2(L+w)t} Log\left(\frac{h(t)+\frac{Lw}{2(L+w)}}{h_0+\frac{Lw}{2(L+w)}}\right)$$

```
eq='-L.*w/2./(L+w)./t.*log((h+L.*w/2./(L+w))./(h0+L.*w/2./(L+w)))'
```

INFILTRATION WITH UDMT

- **Application of type B method**
  - Initial hypotheses for UA
    - $u(L) = u(w) = 0.005$ m
    - $u(h) = u(h_0) = 0.0025$ m
    - $u(t) = 0.1$ s
  - Prepare data
    - *Z* timetable for quantities possibly changing with time
      `Zinfil.csv`
    - *A* timetable for constant quantities
      `Ainfil.csv`

INFILTRATION WITH UDMT

- **Application of type B method**
  - Data Z (values changing with time)

```
>> Z=readtimetable('Zinfil.csv','Delimiter',';')
Z =
  11×4 timetable
           Time              t_s     ut_s     h_m      uh_m
    ____________________    ____     ____     ____    ______
    06-Jul-2022 08:01:00      60     0.1      0.44    0.0025
    06-Jul-2022 08:02:00     120     0.1      0.43    0.0025
    06-Jul-2022 08:05:00     300     0.1      0.43    0.0025
    06-Jul-2022 08:10:00     600     0.1      0.42    0.0025
    06-Jul-2022 08:15:00     900     0.1      0.41    0.0025
    06-Jul-2022 08:20:00    1200     0.1      0.41    0.0025
    06-Jul-2022 08:25:00    1500     0.1       0.4    0.0025
    06-Jul-2022 08:45:00    2700     0.1      0.37    0.0025
    06-Jul-2022 09:00:00    3600     0.1      0.36    0.0025
    06-Jul-2022 09:15:00    4500     0.1      0.35    0.0025
    06-Jul-2022 09:30:00    5400     0.1      0.34    0.0025
```

INFILTRATION WITH UDMT

- **Application of type B method**
  - Data A (constant values)

```
>> A=readtimetable('Ainfil.csv','Delimiter',';')
A =
  1×6 timetable
          Time               L_m      uL_m      w_m      uw_m      h0_m      uh0_m
    ____________________    ___     _____     ____     _____     ____     ______
    06-Jul-2022 08:00:00    1.2     0.005     0.35     0.005     0.45     0.0025
```


INFILTRATION WITH UDMT

- **Application of type B method**
  - Set
    - alpha = 0.95 (level of coverage interval)
    - Correlation matrix
      initial hypothesis: no correlation between quantities

```
MatCor =
     1     0     0     0     0
     0     1     0     0     0
     0     0     1     0     0
     0     0     0     1     0
     0     0     0     0     1
```

INFILTRATION WITH UDMT : ON-LINE DEMO

- **Application of type B method**

```
Ks =
   1.0e-04 *
    0.3890    0.1376    0.1193    0.6587
    0.3924    0.0695    0.2562    0.5286
    0.1570    0.0278    0.1025    0.2114
    0.1188    0.0140    0.0912    0.1463
    0.1065    0.0095    0.0880    0.1251
    0.0799    0.0071    0.0660    0.0938
    0.0806    0.0058    0.0694    0.0919
    0.0737    0.0033    0.0672    0.0803
    0.0628    0.0025    0.0578    0.0678
    0.0564    0.0021    0.0523    0.0604
    0.0522    0.0018    0.0488    0.0556
```

K_{si} $u(K_{si})$ $K_{si,\,low}$ $K_{si,\,high}$

95 % coverage interval

INFILTRATION WITH UDMT

- **Final value of K_s**
  - mean value

    $\overline{K_s}$ = mean(Ks(:,1)) = 0.1427 E-4 m/s ✓

  - uncertainty in mean value

    $u(\overline{K_s})$ = mean(Ks(:,2)) = 0.0255 E-4 m/s ?

K_s values are autocorrelated

INFILTRATION WITH UDMT : VARIOGRAPH DEMO

- Partial correlation: variograph approach

Ksbar =
1.0e-04 *

0.14266	Mean value
0.01435	No correlation
0.02553	Full correlation
0.02294	Variograph method

- $\overline{K_s}$ 95% coverage interval

= [0.0977, 0.1876] E-4 m/s

UNCERTAINTY ASSESSMENT IN THE UDMT

- Uncertainties are systematically estimated with the UDMT
  - in measurements
  - in sensor calibration functions
  - in sensor correlation functions
  - in tracing experiments

TRACER EXPERIMENTS

✦ One injection, several measurements

TRACER EXPERIMENTS

✦ A classical mass balance

$$M_{INJ} = M_{MEAS}$$

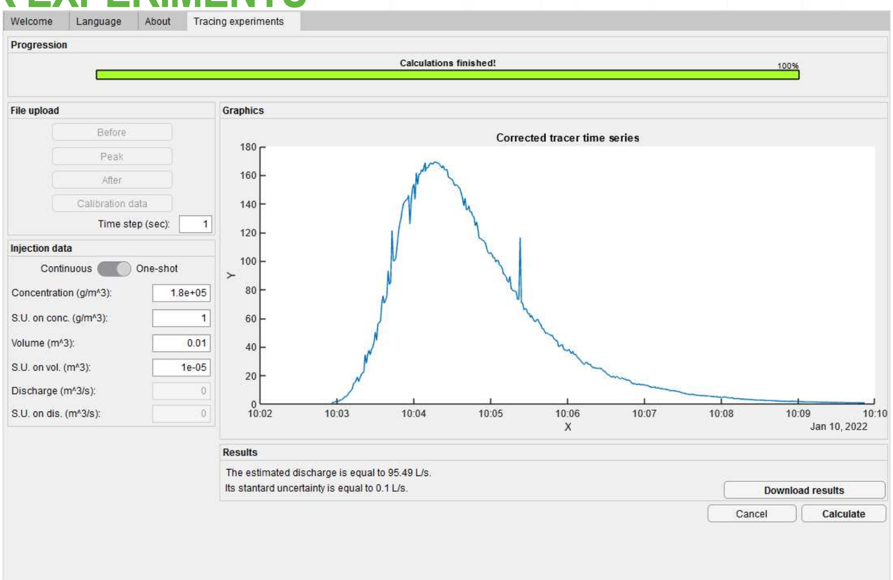
✦ Leading to …

$$Q = \frac{C_{INJ} \times V_{INJ}}{\sum_{i=start}^{end} C_{MEAS}(i) \times dt}$$

TRACER EXPERIMENTS

- Steps
  - Correlation between [Salt] and conductivity
  - Run the Tracing experiments tool
    - Input data: *Before.csv*, *Peak.csv*, *After.csv* and *TE-ConductivityvsSaltconcentration_Function-Data.csv*
    - Injection data: *One-Shot*, $C_{INJ} = 180\ 000\ g/m^3$, $u(C_{INJ}) = 1\ g/m^3$, $V_{INJ} = 0.01\ m^3$, $u(V_{INJ}) = 10^{-5}\ m^3$

TRACER EXPERIMENTS



Q = 95.49 L/s
u(Q) = 0.1 L/s

QUESTIONS & ANSWERS

J.-L. BERTRAND-KRAJEWSKI, M. LEPOT,
F. CLEMENS-MEYER

53

CONCLUSION

J.-L. BERTRAND-KRAJEWSKI, M. LEPOT,
F. CLEMENS-MEYER

54

FOLLOW THE Co-UDlabs PROJECT UPDATES

Sign for our news and newsletter

https://co-udlabs.eu/contact/

Social Media

https://www.linkedin.com/company/co-udlabs-project/

https://twitter.com/CoUDlabs

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement No 101008626