OpenSense

Short online conference

TEL4RAIN

Microwave link data for urban stormwater management

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VEOLIA

CTU CZECH TECHNICAL UNIVERSITY IN PRAGUE

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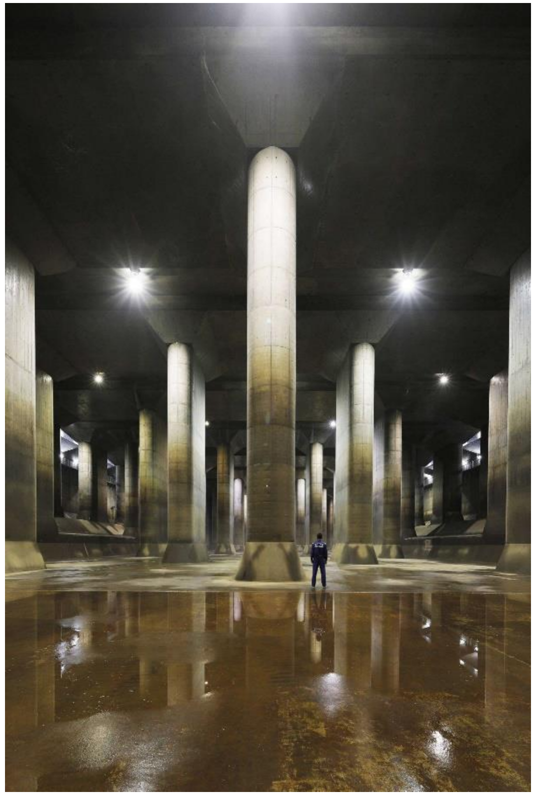
Sewer systems – major step in sanitation

Prague sewer system – old municipal wastewater treatment plant



Tokyo Metropolitan Area Outer Underground Discharge Channel

Limitations of combined sewer systems

Mixing of foul sewage and storm water

Sewage overflow during rainfall (6000 CSO in CZ)

WWTP capacity and treatment efficiency during rainfall

Wastewater treatment plant (Capacity is 2-3 mean daily discharge)

Sewer capacity is limited:
2-5 years rainfall return period

Pluvial flooding in Sweden, 2018

Amplifiers: urbanization, climate change, pharmaceuticals, …

Stormwater management requires rainfall data

In-sewer measures

Catchment measures

Efficient planning and design of in-sewer measures as well as sewer and WWTP operation require drainage models and high-quality rainfall data

Commercial microwave links for urban drainage modelling

Urban catchment characteristics

- High ratio of impervious surfaces
- Drained by sewers with CSOs

↓

- Short time of concentration
- Dynamic response to rainfall space-time variability

↓

- High requirements on rainfall data resolution both in space (1 km^2) and time (1 min)

CML characteristics and potential

Commercial microwave links for urban drainage modelling

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CML characteristics and potential

- Densest in urban catchments
- Δt =< 1 min
- Close-to-ground observations
- Data accessible operationally

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CML characteristics and potential

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- **Completing standard networks for drainage-model calibration**
- **Real-time control of sewer and WWTP, early warning, …**

Main (research) question

What is the potential of CMLs for urban rainfall-runoff modeling and how to properly process CML data?

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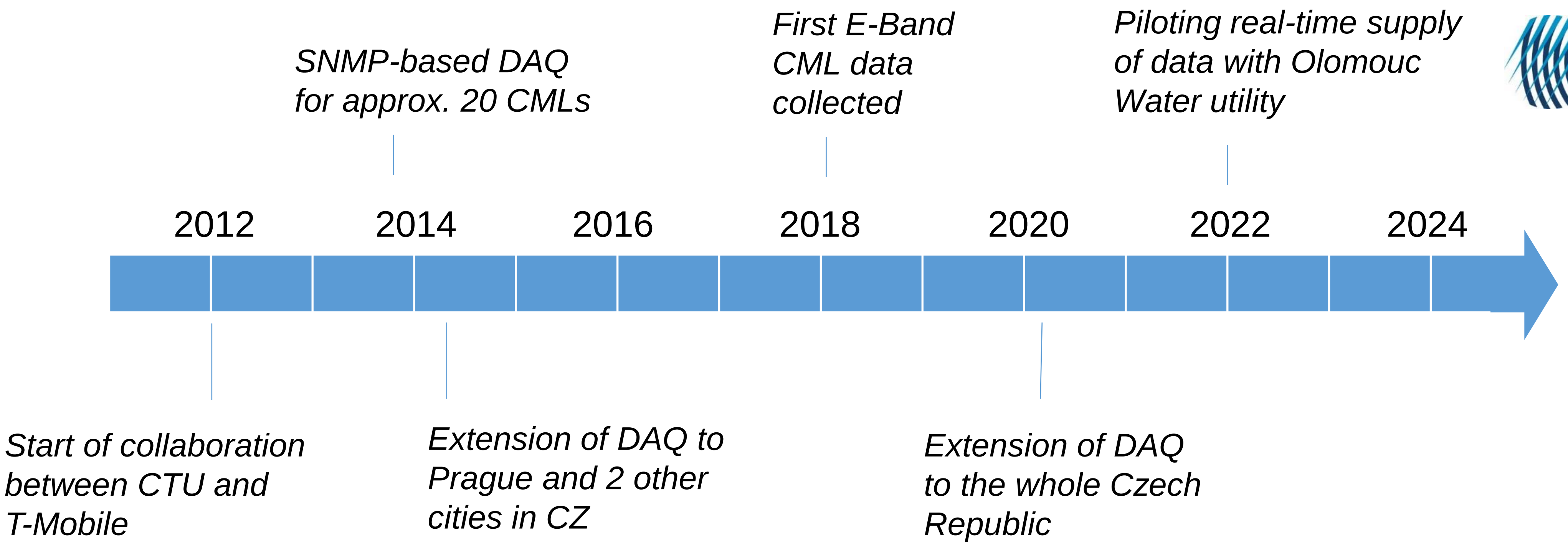
Obtain rainfall information suitable for rainfall-runoff modelling in urban catchments of different sizes from attenuation data of multiple CMLs with different characteristics

Main (research) question

What is the potential of CMLs for urban rainfall-runoff modeling and how to properly process CML data?

Obtain **rainfall information suitable for rainfall-runoff modelling** in **urban catchments of different sizes** from attenuation data of **multiple CMLs with diverse characteristics**

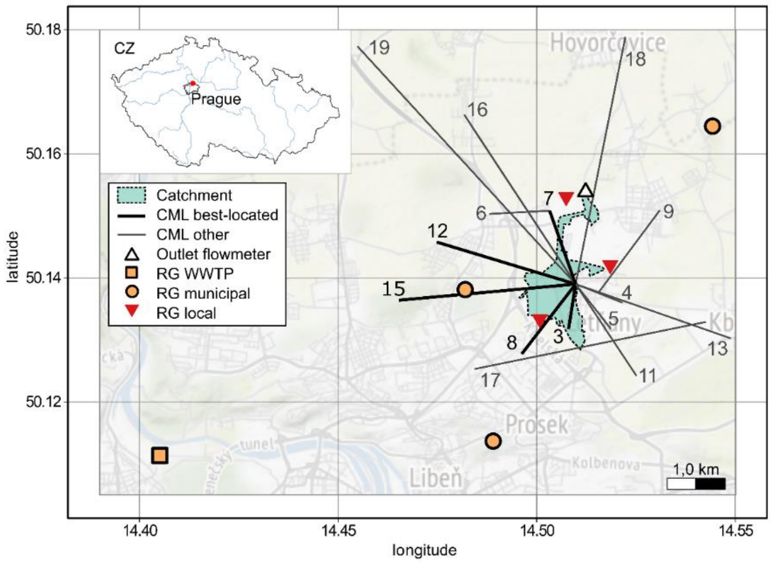
From research towards application



TEL4RAIN

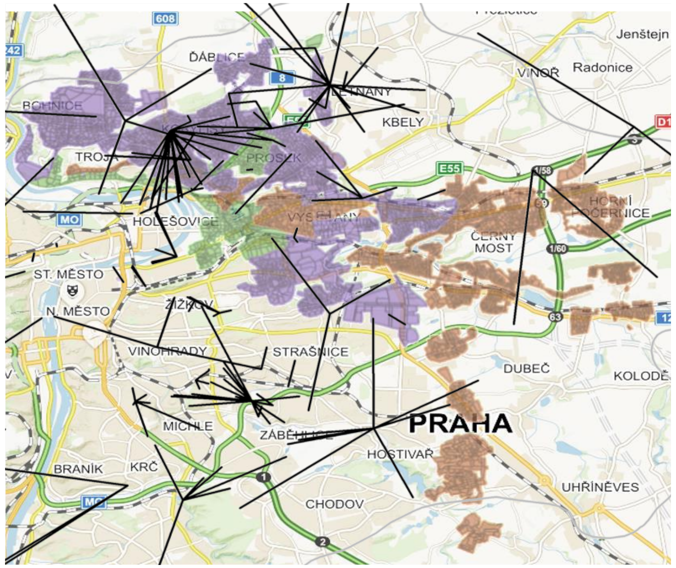
CML & Urban drainage case studies

Prague-Letnany (area 1.3 km²)



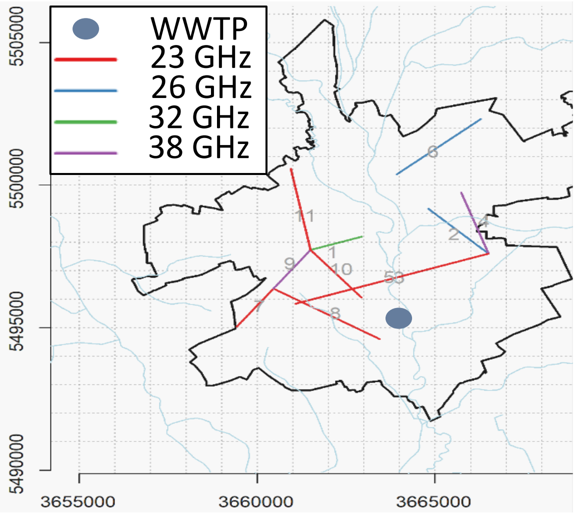
Small (experimental) catchment with most demanding requirements on rainfall data

Prague – trunk sewer (~30 km²)



Larger catchments with detailed rainfall runoff model

Olomouc (area ~100 km²)

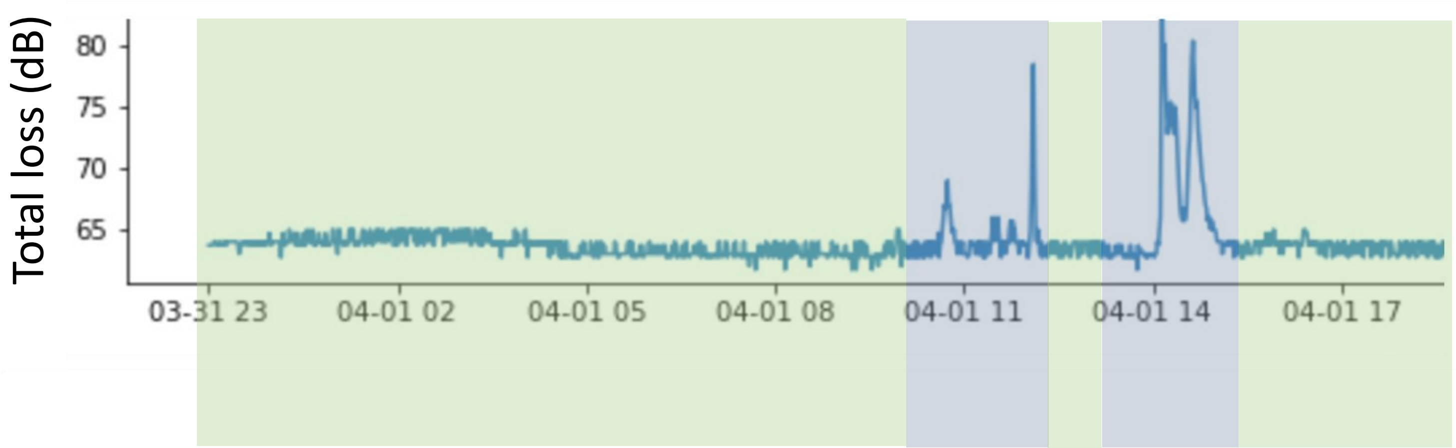


Real-time access to data, operational data-driven modeling

CML rainfall retrieval – wet antenna matters

CML processing chain

CML attenuation data



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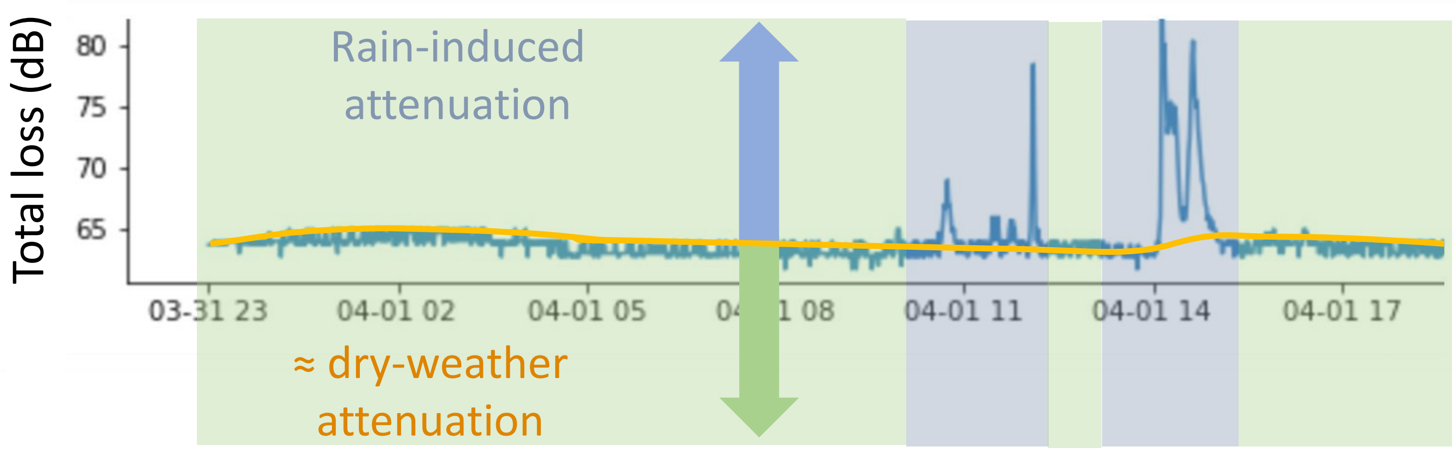
CML processing chain

Baseline identification

CML attenuation data



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Wet antenna correction

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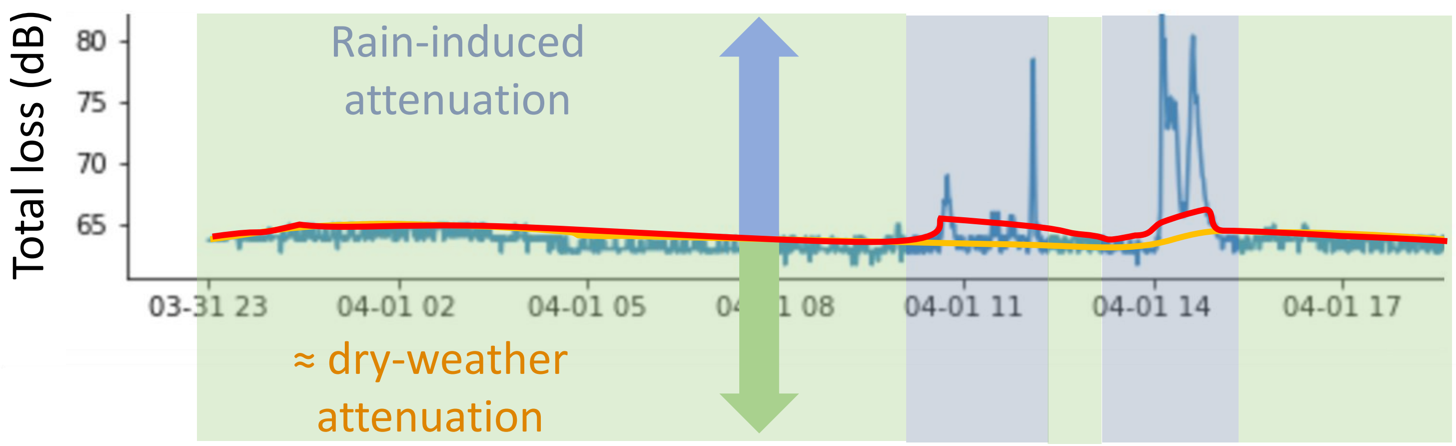


CML rainfall retrieval – wet antenna matters

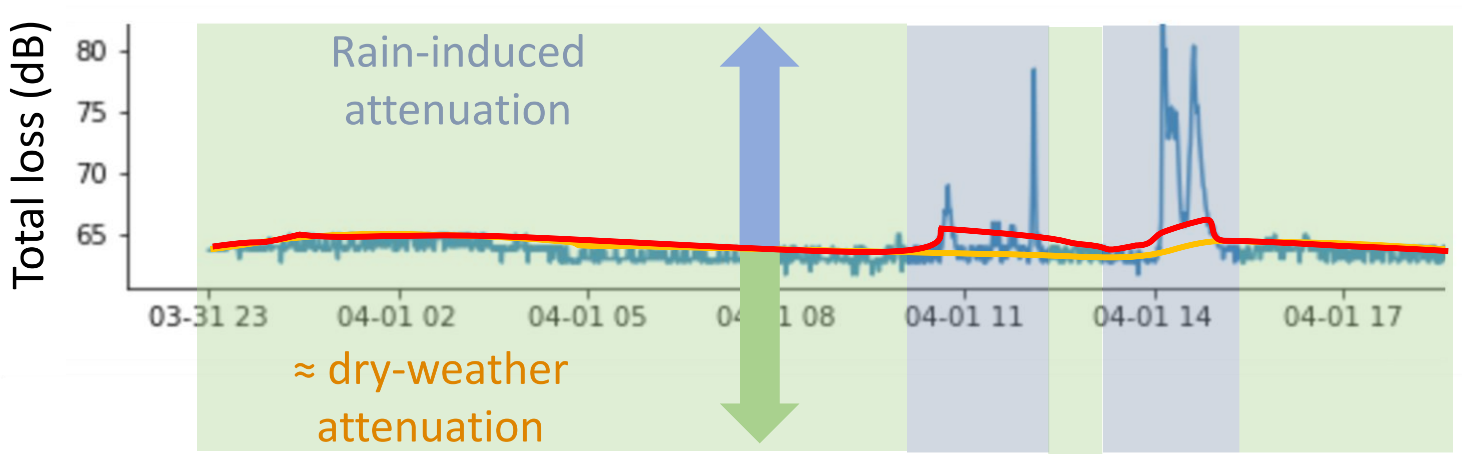
CML processing chain

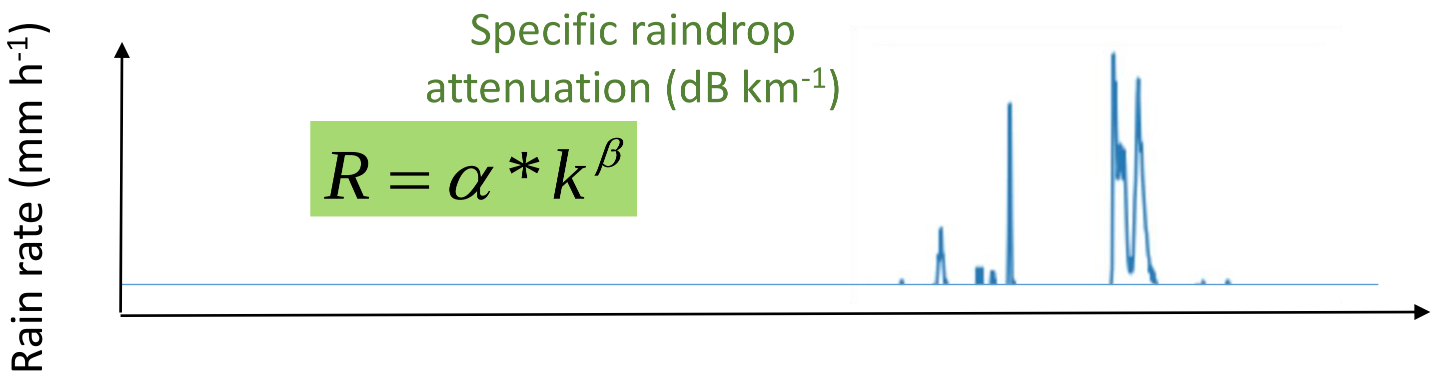
Baseline identification

Wet antenna correction

Raindrop attenuation
to rainfall intensity

CML attenuation data





$$R = \alpha * k^{\beta}$$

CML rainfall retrieval – wet antenna matters

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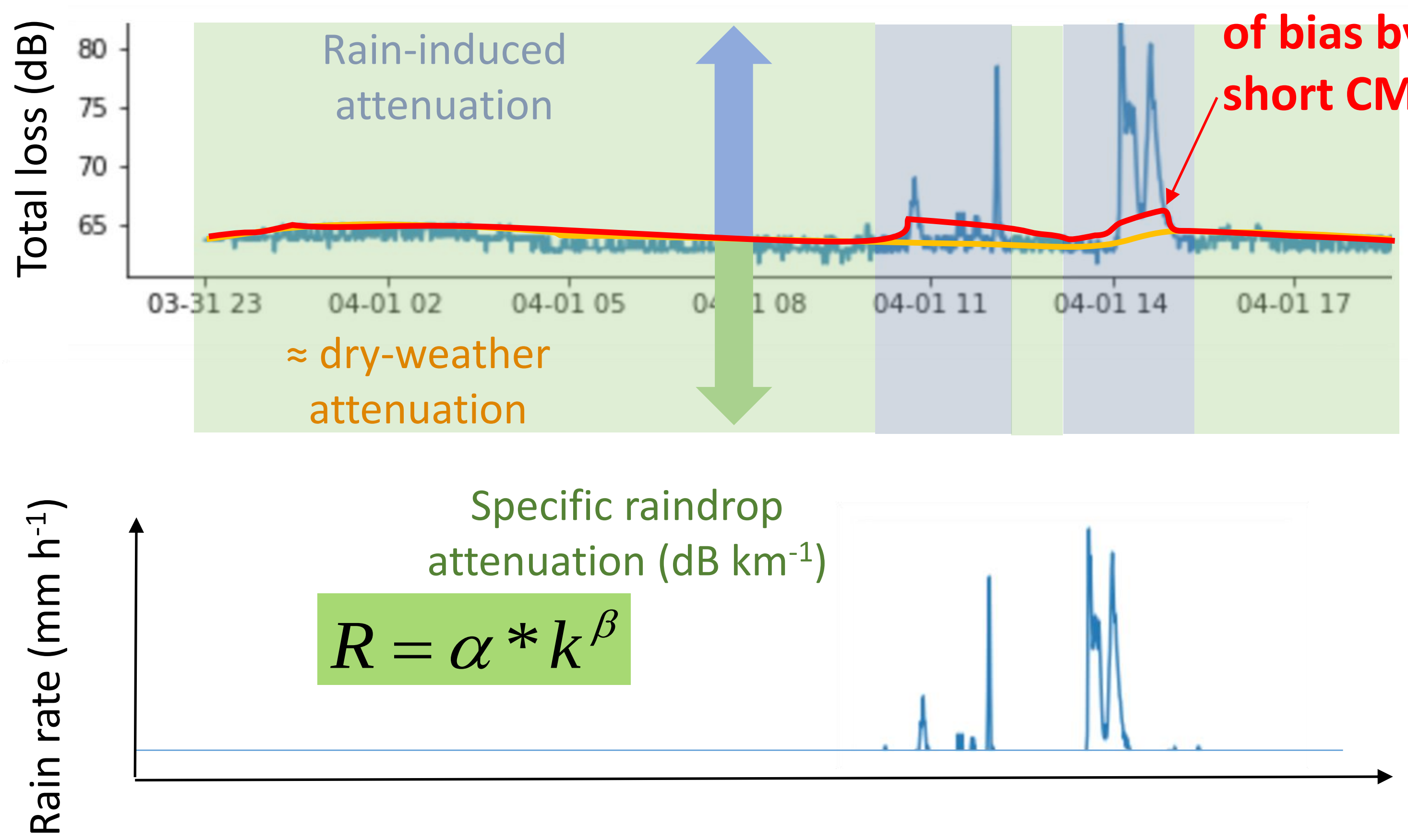
Raindrop attenuation
to rainfall intensity

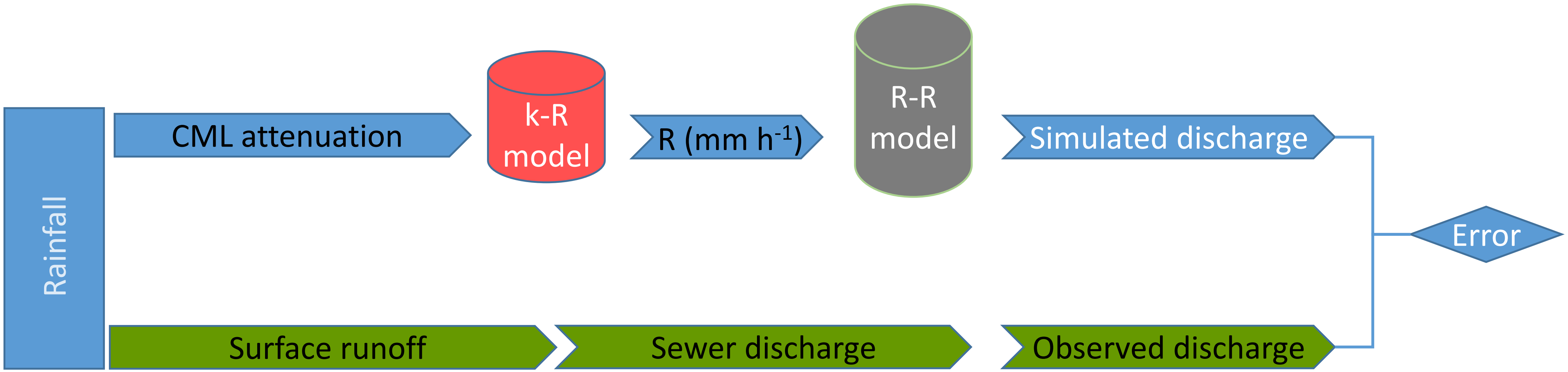
CML attenuation data

major source of bias by short CMLs



Evaluating CML potential for urban drainage modeling

Comparing observed runoff with runoff simulated based on different observation layouts:



Flow at the outlet of a catchment

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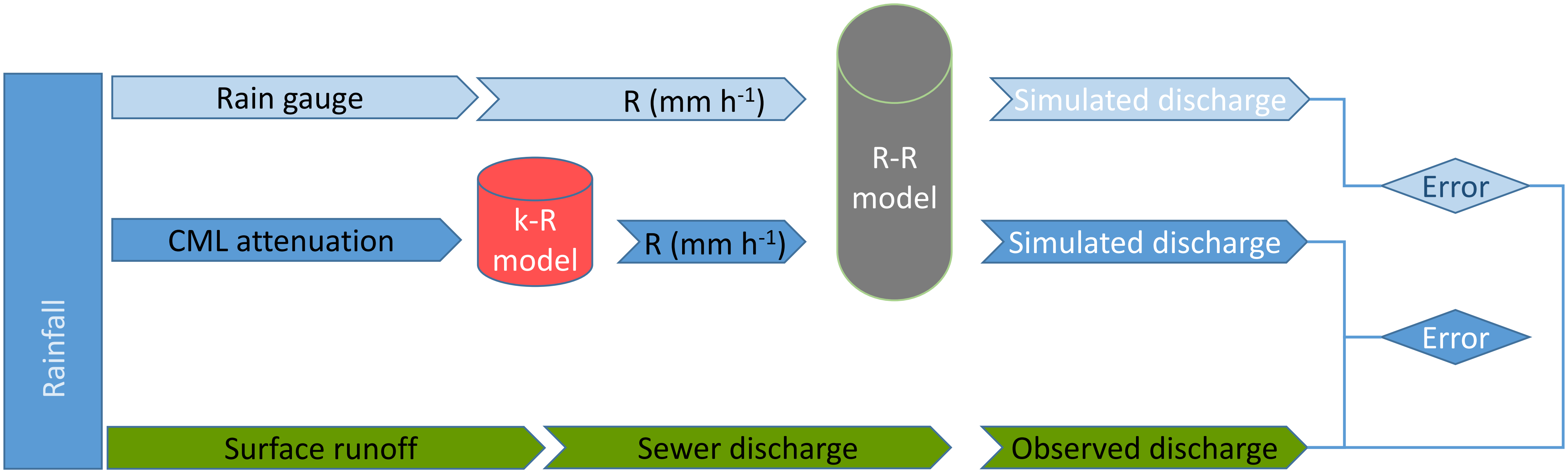
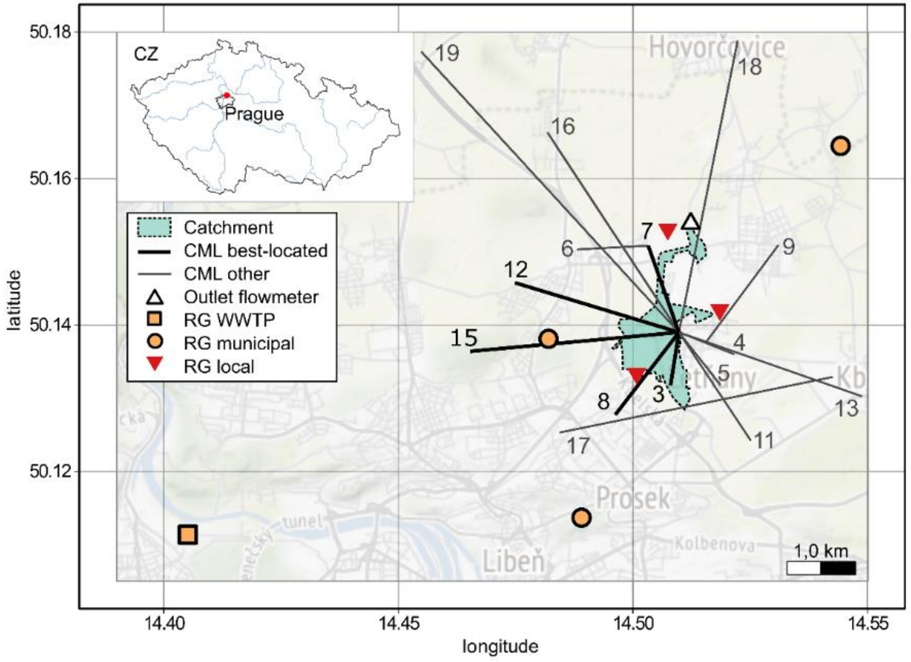


Flow at the outlet of a catchment

Potential of CML data alone without fine-tuning



Data

- 19 CMLs (Δt = 1 min), constant WAA
- 3 tipping-bucket rain gauges in the catchment
- 3 municipal tipping-bucket rain gauges outside the catchment (ΔH = 0.1 mm)
- flowmeter, Δt = 2 min
- 2.5 year of data (56 events)

Catchment & model characteristics:

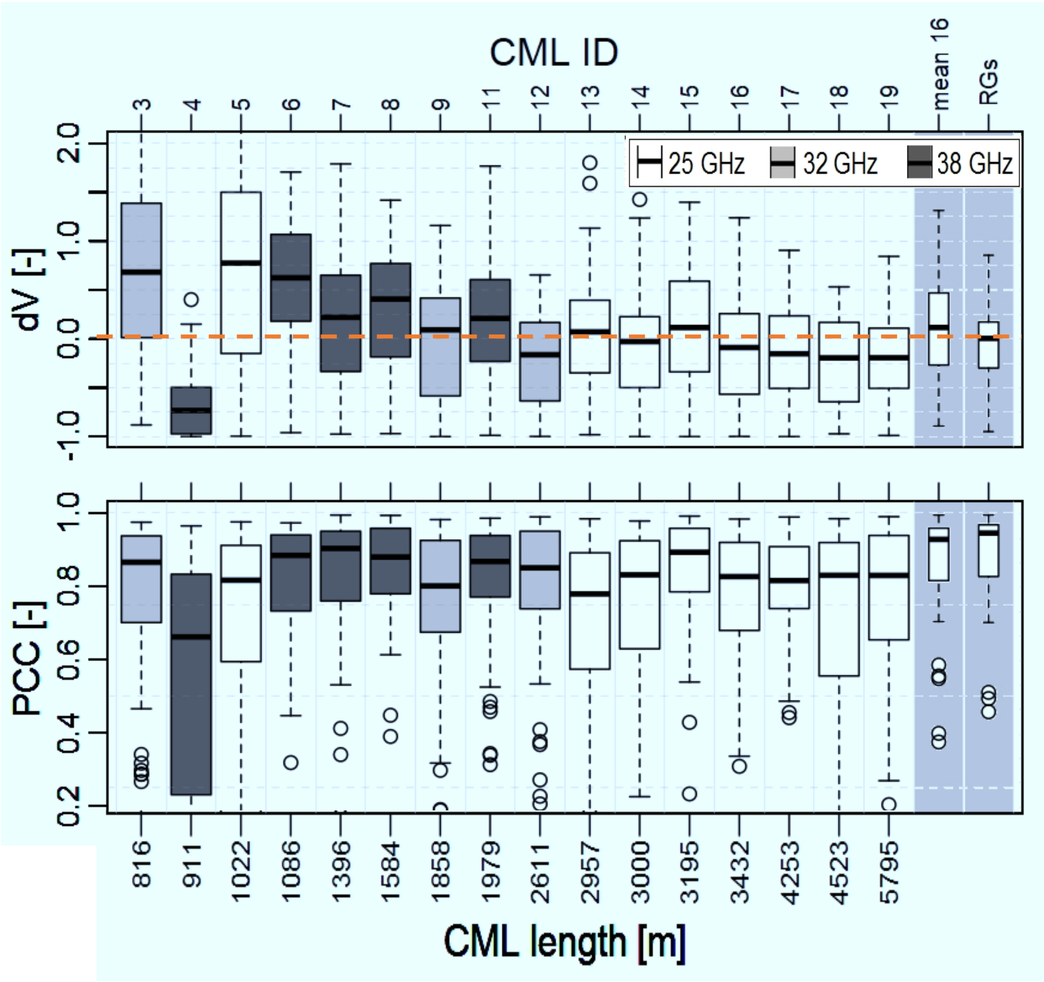
- A = 1.3 km^2, 35 % impervious surfaces
- Lag time between rainfall and runoff peaks approx. 20 min
- EPA-SWMM, hydrodyn. distributed model

Evaluation

- Event-based simulated/observed runoff comparison
  - Error in runoff volume (dV)
  - Correlation (PCC)

Potential of CML data without fine-tuning

Evaluation for all events:

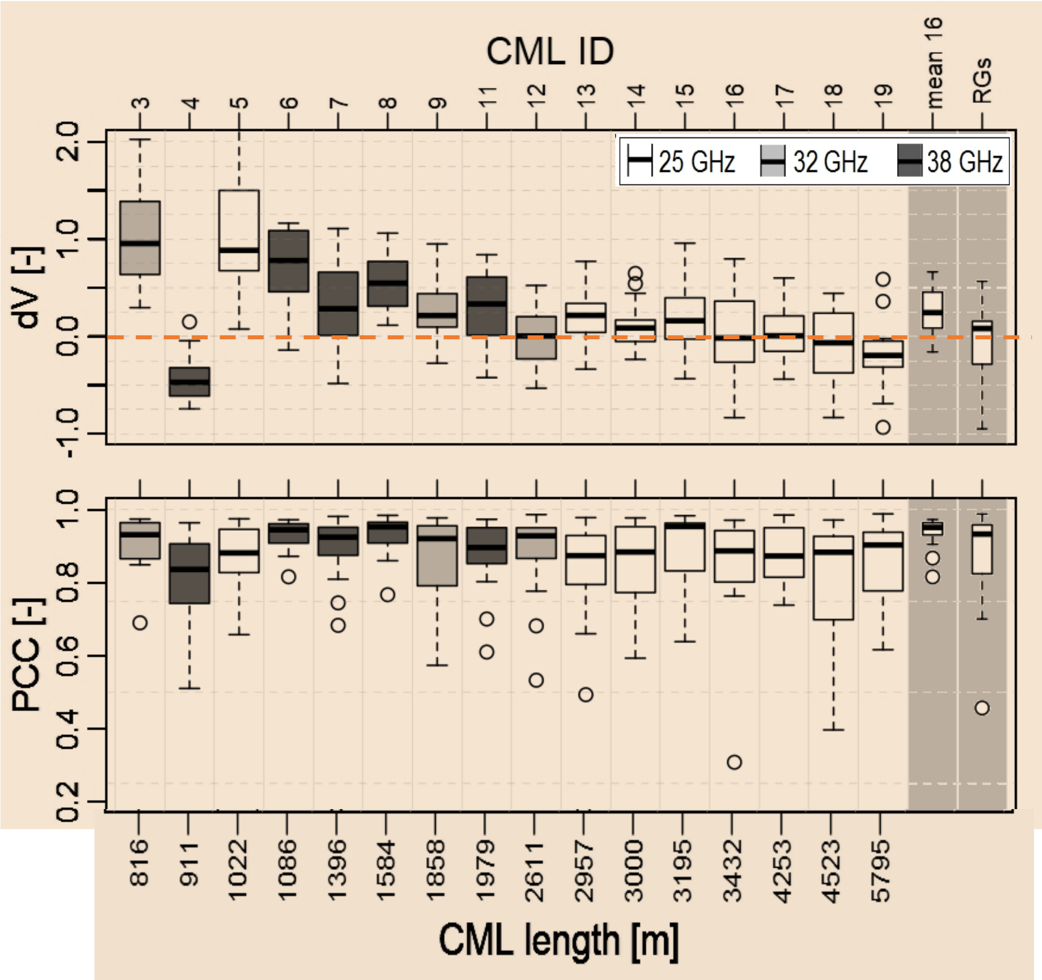


Conclusions:

- Bias decreases with increasing length (sensitivity)
- No clear link between correlation and CML length in overall evaluation
- The best performance is achieved when averaging all CML rain rates

Potential of CML data without fine-tuning

Evaluation for heavy rainfalls (R_{max}>12 mm h^{-1}):



Conclusions:

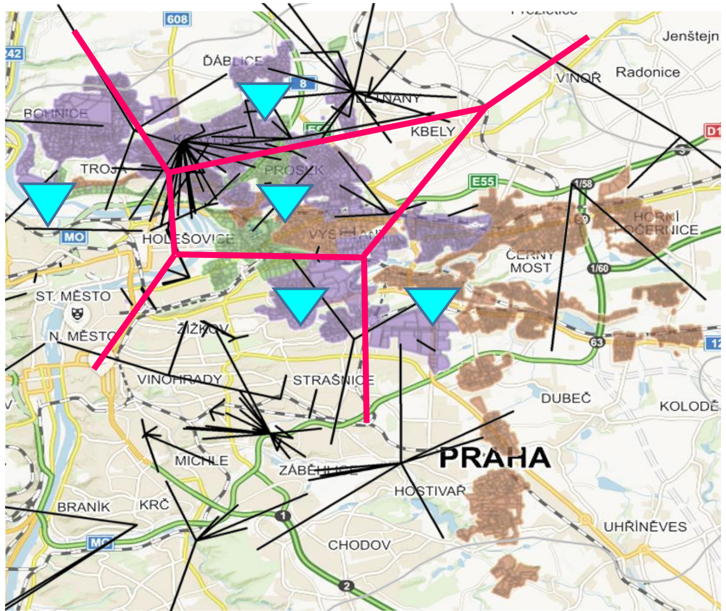
- Bias in simulated runoff decreases with increasing length (sensitivity)
- No clear link between PCC and CML length in overall evaluation
- The best performance is achieved when averaging all CML rain rates

- For heavy rainfalls:
  - Simulated runoff has higher PCC for shorter CMLs
  - Simulation based on all averaged CMLs outperform rain gauges

Potential of CML data without fine-tuning

Case at Prague trunk sewer E,F:

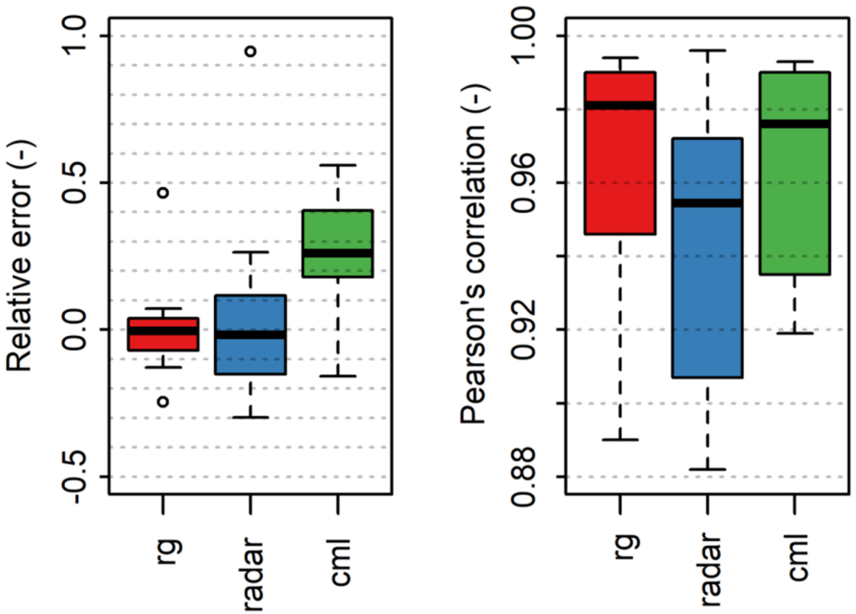
- A ≈ 30 km^2, 24 CSOs
- Lag time between rainfall and runoff peaks approx. 1-2 h
- Mike Urban, hydrodynamic distributed model
- Flow measurements at the outlet (H, Q)



Input data:

- ~100 CMLs, 40 – 45 CMLs inside the catchment
- 5 rain gauges
- Unadjusted radar (CAPPI 2000, 1 x 1 km^2, Δt = 5 min)
- 10 heavy rain events

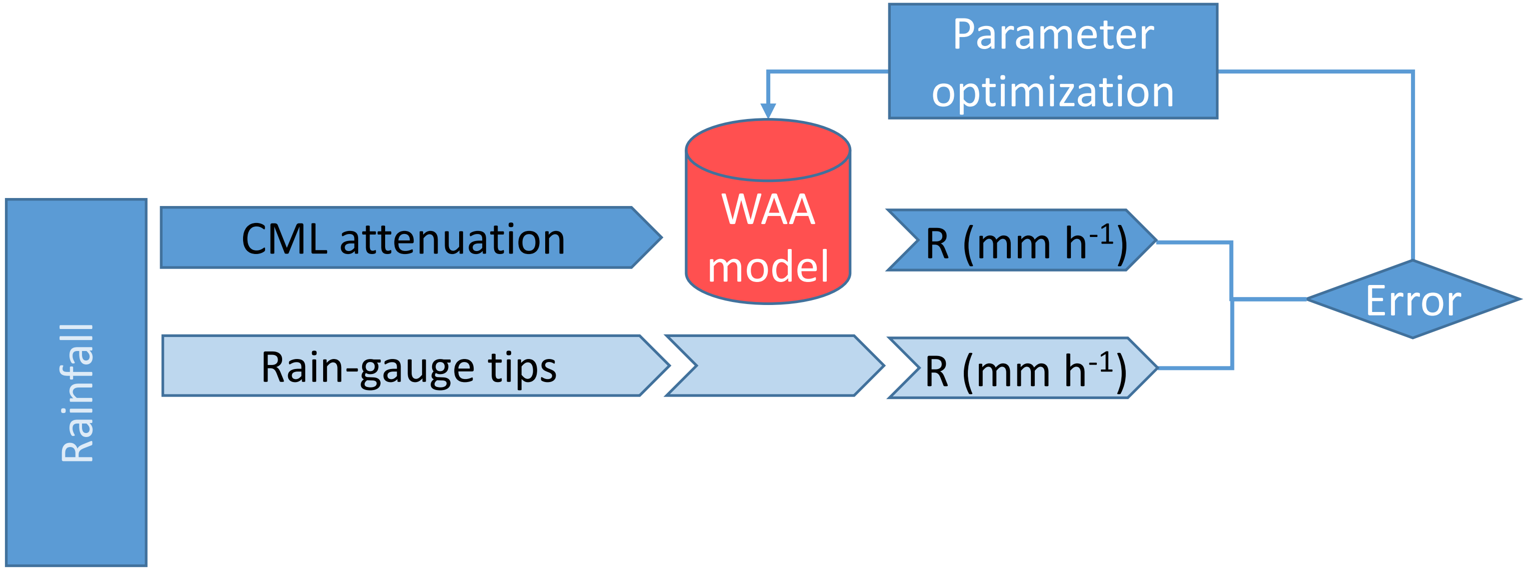
Observed vs. simulated runoff:

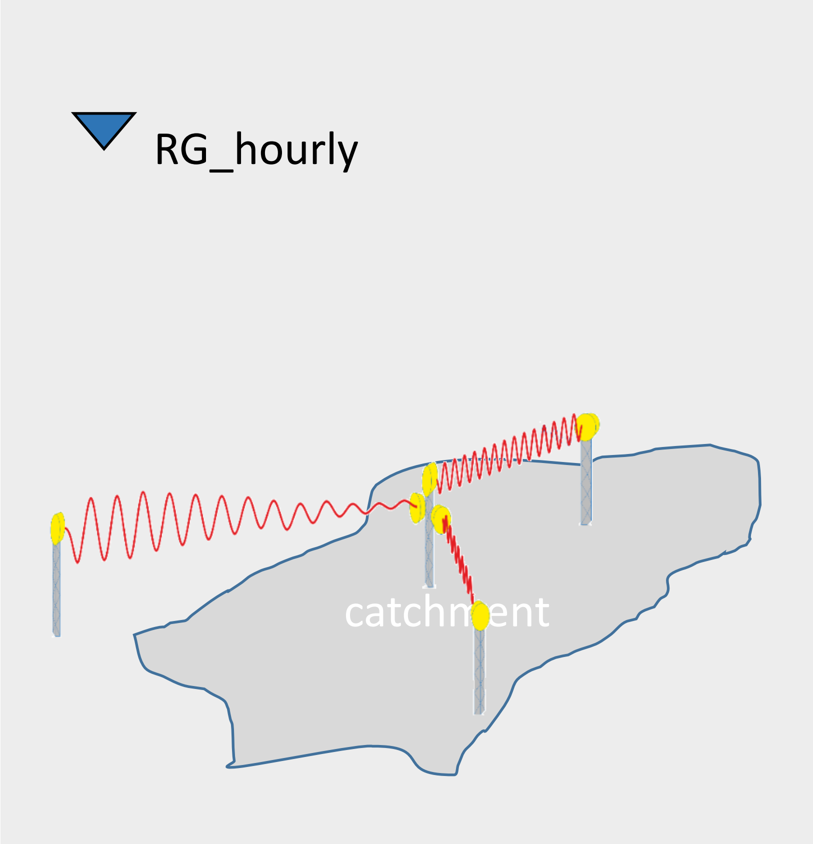


Reducing CML bias with existing standard observations

- How to reduce bias caused by wet antenna attenuation using observations commonly available in urban areas?

Rain-gauge calibration

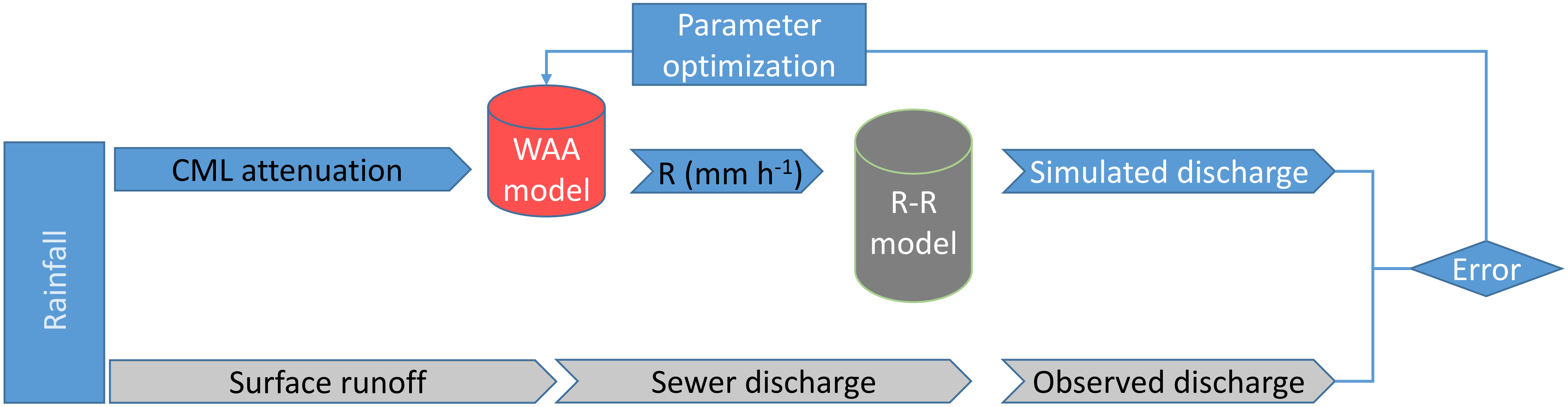




Investigating the potential of CMLs for urban drainage modelling

- How to reduce bias caused by wet antenna attenuation using observations commonly available in urban areas?

<u>Runoff-based calibration</u>



Rainfall observation layouts used for R-R modeling

Three rainfall observations layouts

A) CMLs (areal rainfall):

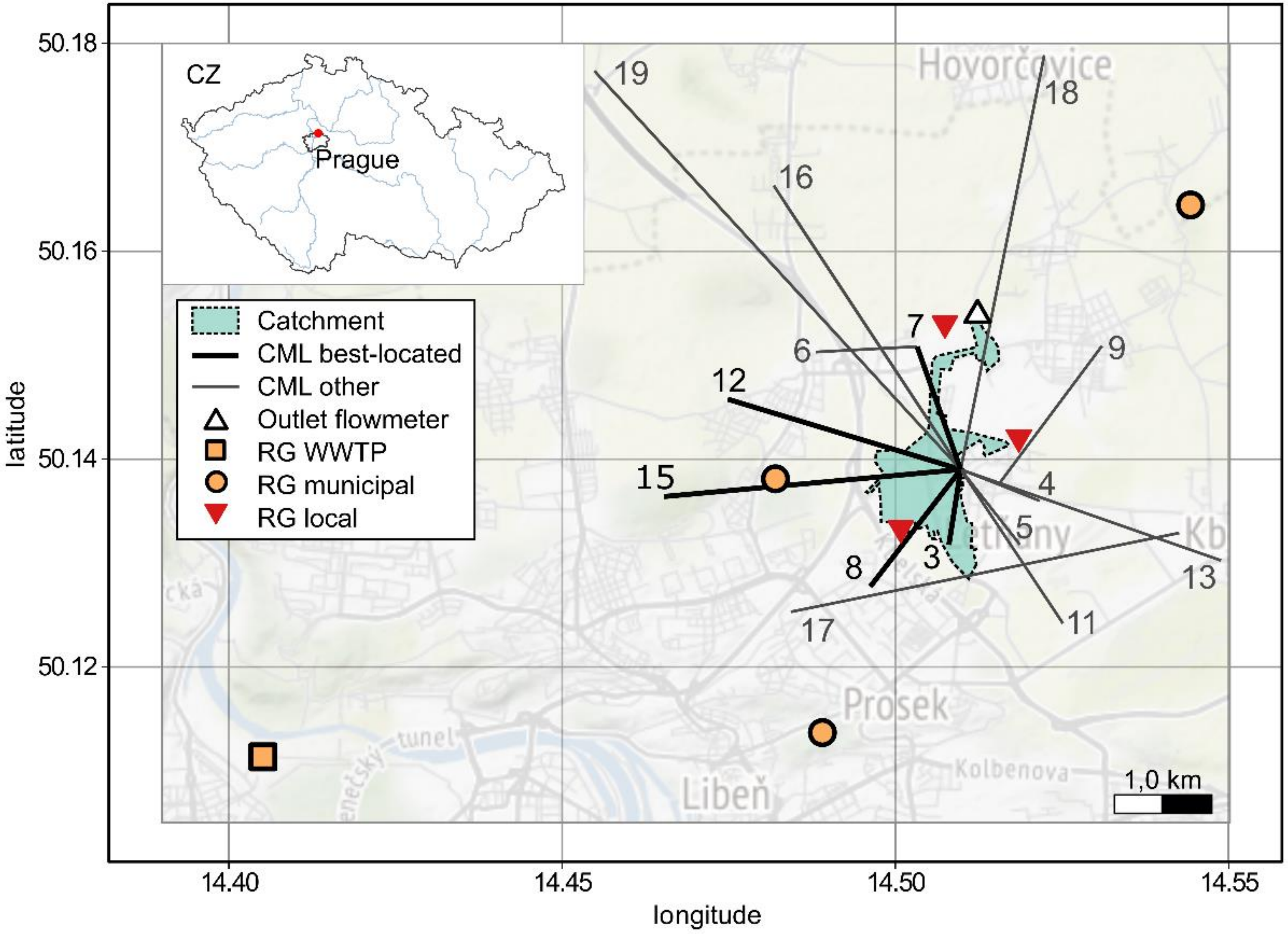
- 1. Optimized to the remote RG
- 2. Optimized to the 3 municipal RGs
- 3. Optimized to the flow data

B) 3 municipal RGs (areal rainfall)

C) 3 benchmark RGs (distributed rainfall)

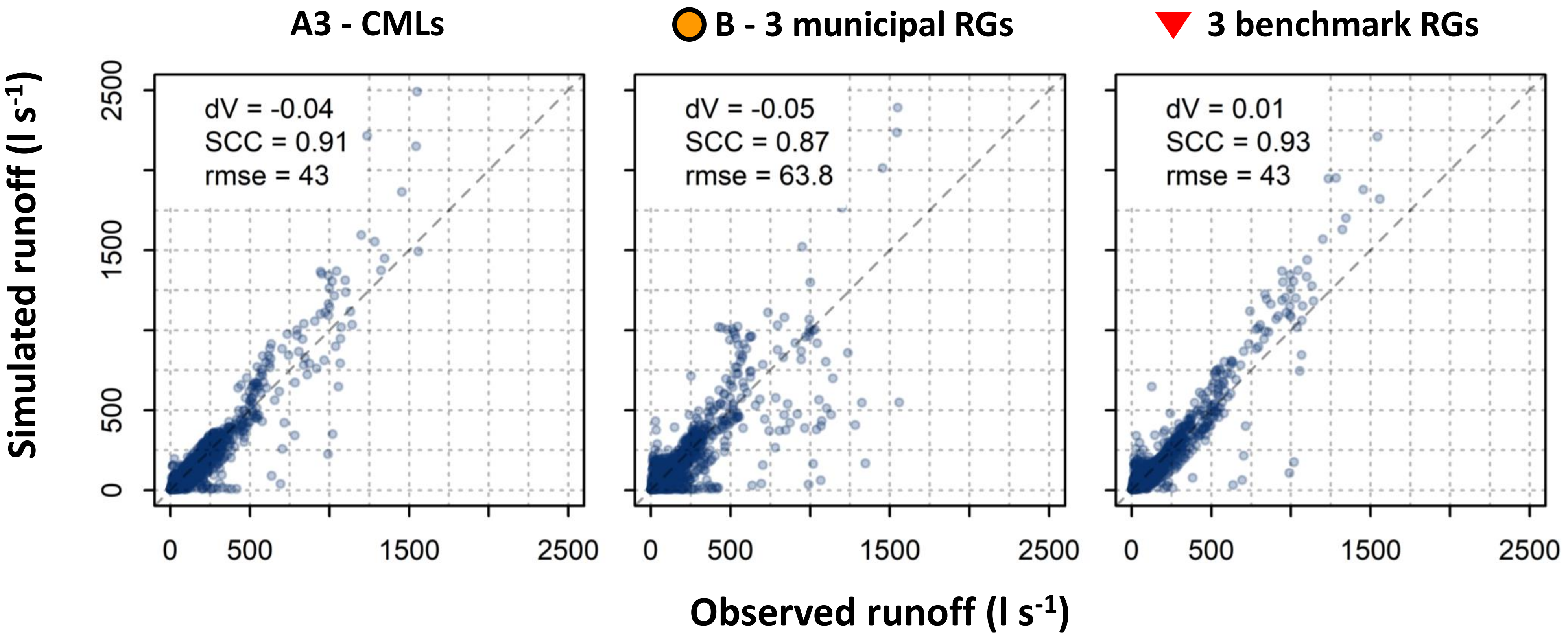
Dataset

- 2.5 years of data
- 23 calibration events
- 23 validation events



Simulated vs. observed runoff from RG and CML layouts

WAA optimized to flow data



Metrics:

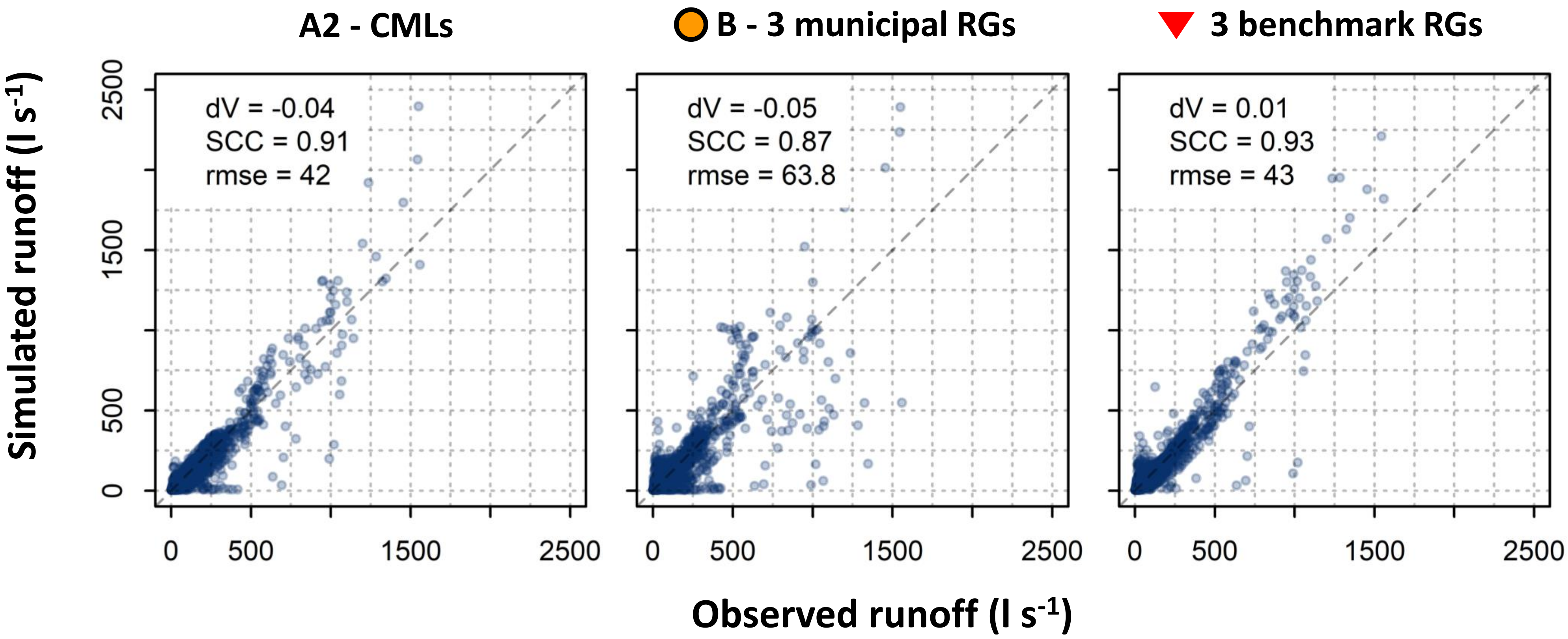
dV – relative error in volume (-)

SCC – Spearman correlation coef. (-)

RMSE – root mean square error (l s^{-1})

Simulated vs. observed runoff from RG and CML layouts

WAA optimized to 3 municipal RGs



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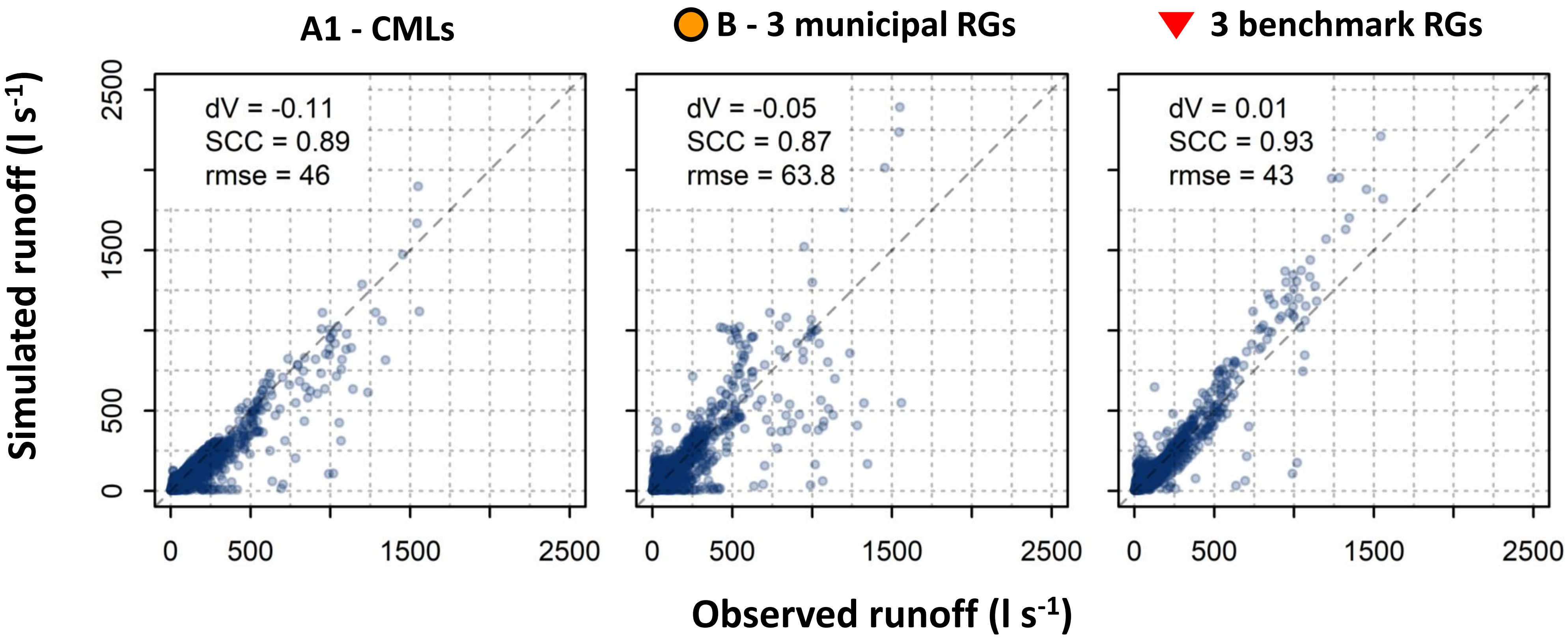
Simulated vs. observed runoff from RG and CML layouts

WAA opt. to the remote RG



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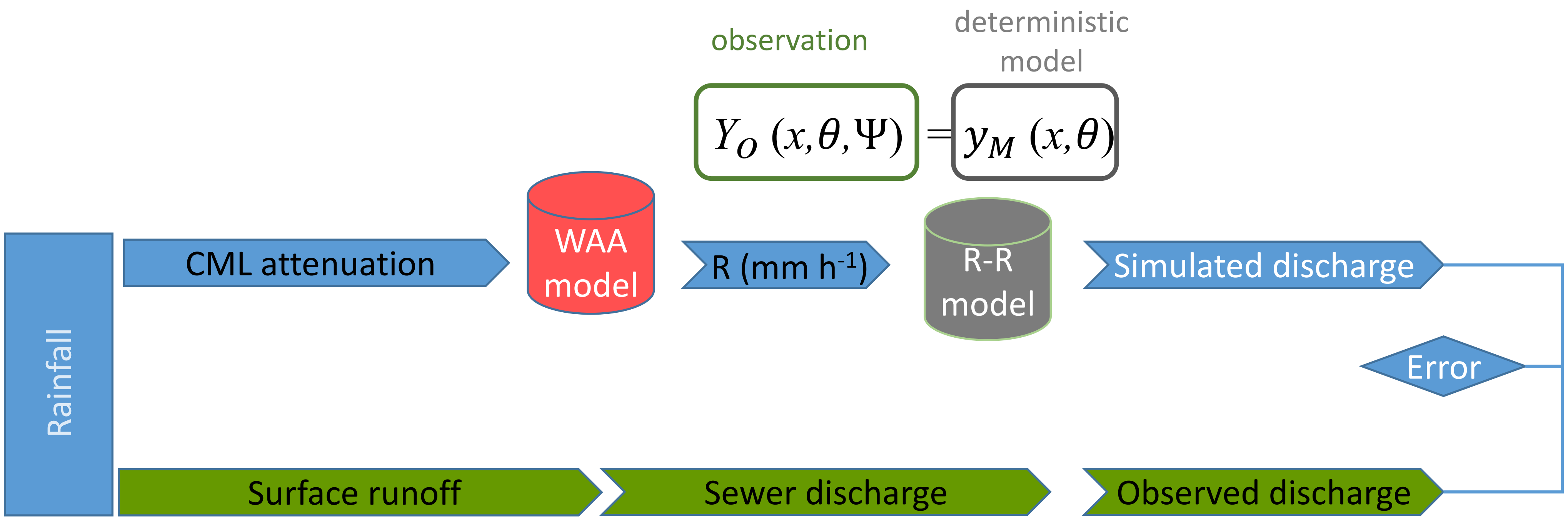
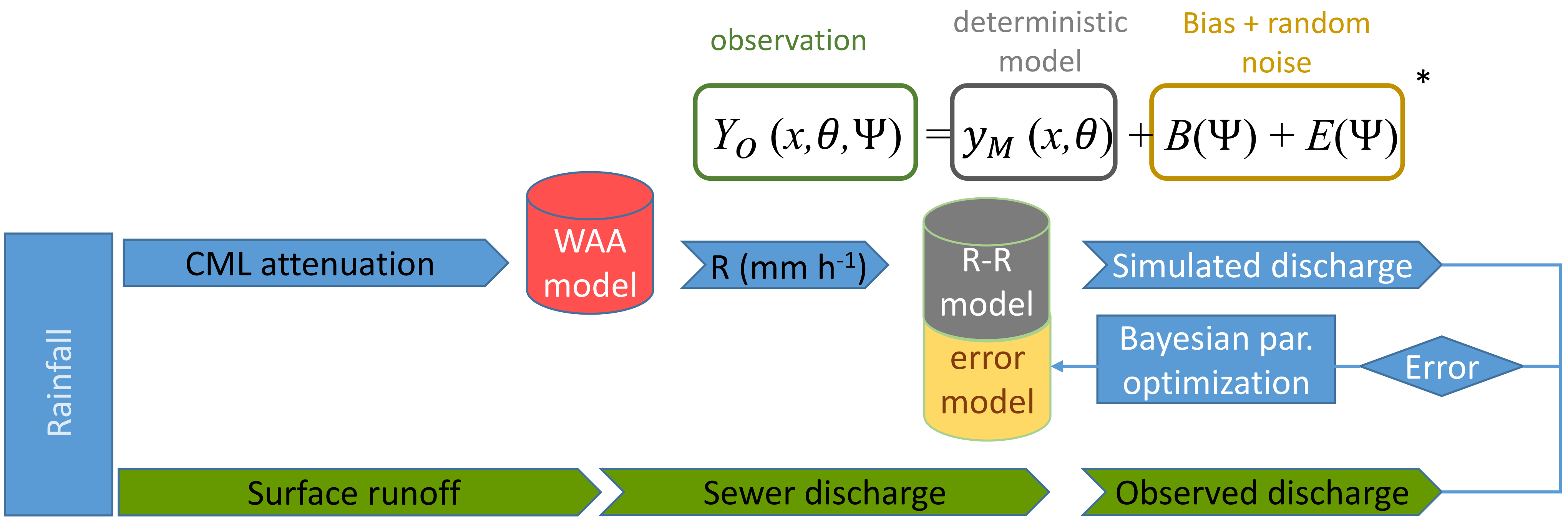
Modeling runoff uncertainty



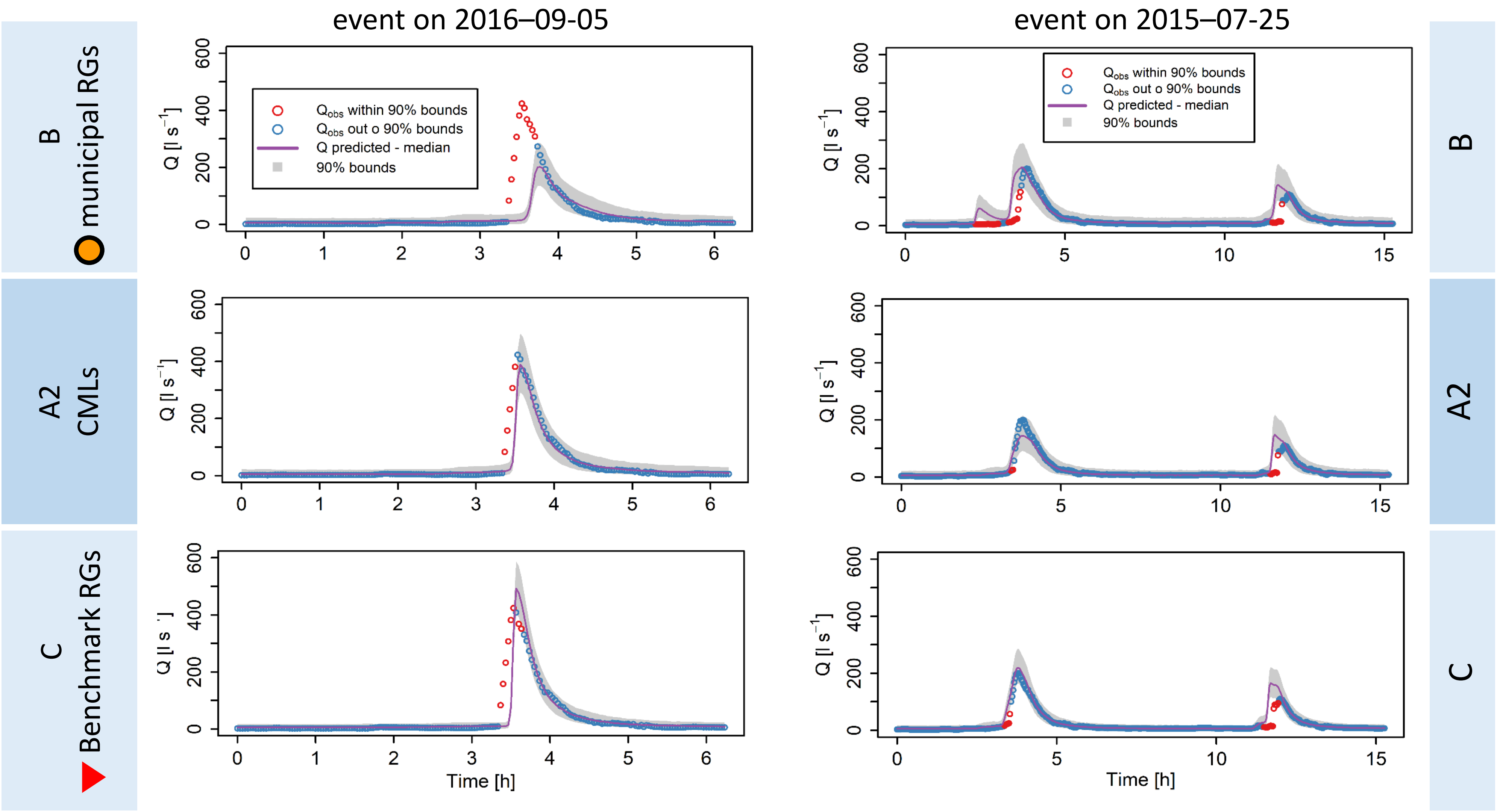
Modeling runoff uncertainty



- Use calibration events to infer posterior distributions of error model parameters using MCMC method
- During validation generate from multivariate distribution of error model paramerers ensemble of 2000 realizations and calculate 90% uncertainty bands

*Reichert, P. & Schuwirth, N. (2012). Linking statistical bias description to multiobjective model calibration. *Water Res. Research*, 48.

Simulated vs. observed runoff from RG and CML layouts



Case-study conclusions

- CMLs can provide precise discharge predictions when calibrated using existing runoff data or rain gauges (even when they are far away)
- Runoff model can be extended by an error model and provide reliable uncertainty estimates

CMLs can conveniently complement existing observation networks and improve runoff simulations of existing calibrated urban-drainage models

Commerccial microwave links – Case study Olomouc

Can the operational CML attenuation data be used directly for modelling the rainfall runoff (inflow to the WWTP)?

i.e. without conversion to rainfall intensity

Assess the potential of CMLs for operational (real-time) modelling of the inflow to the Olomouc WWTP

CML data were delivered operationally to Olomouc water utility during the year 2022

Material

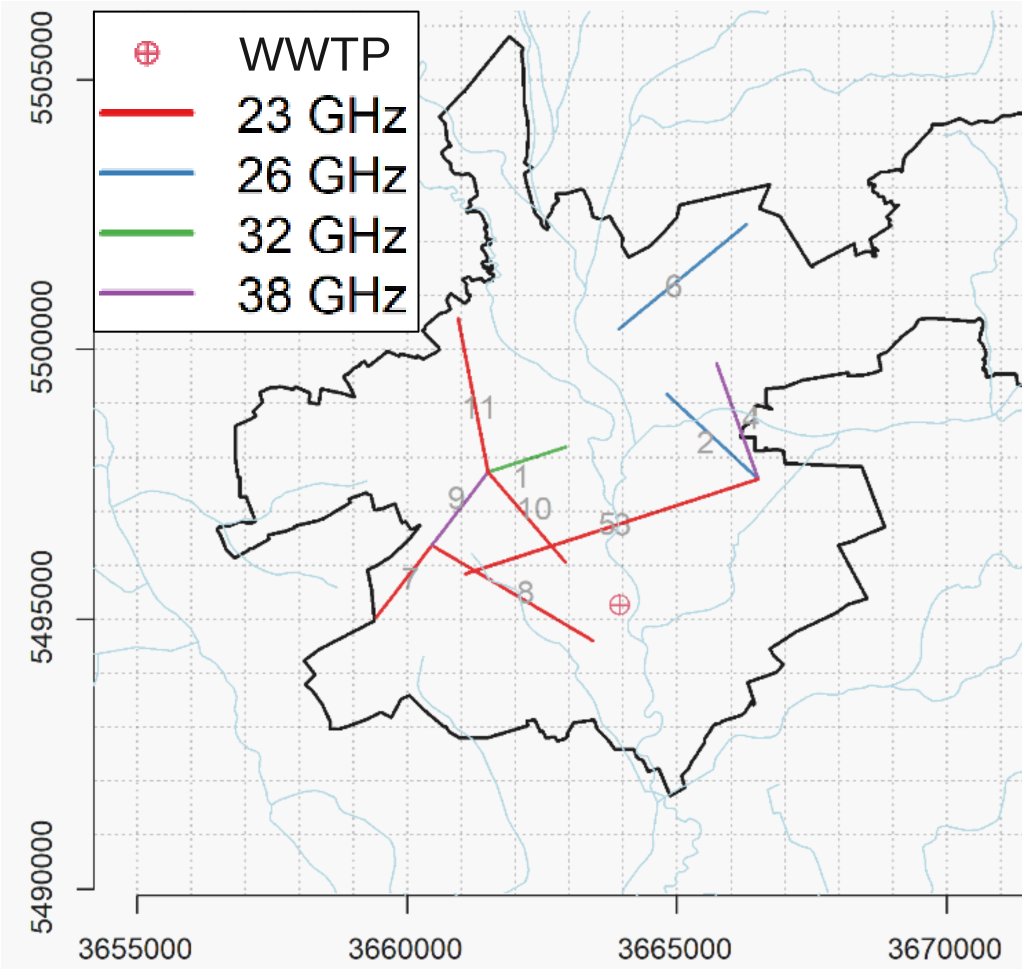
CML data available online

- 12 Ericsson MINILINK CMLs
- frequency 23-38 GHz
- time step 1 min

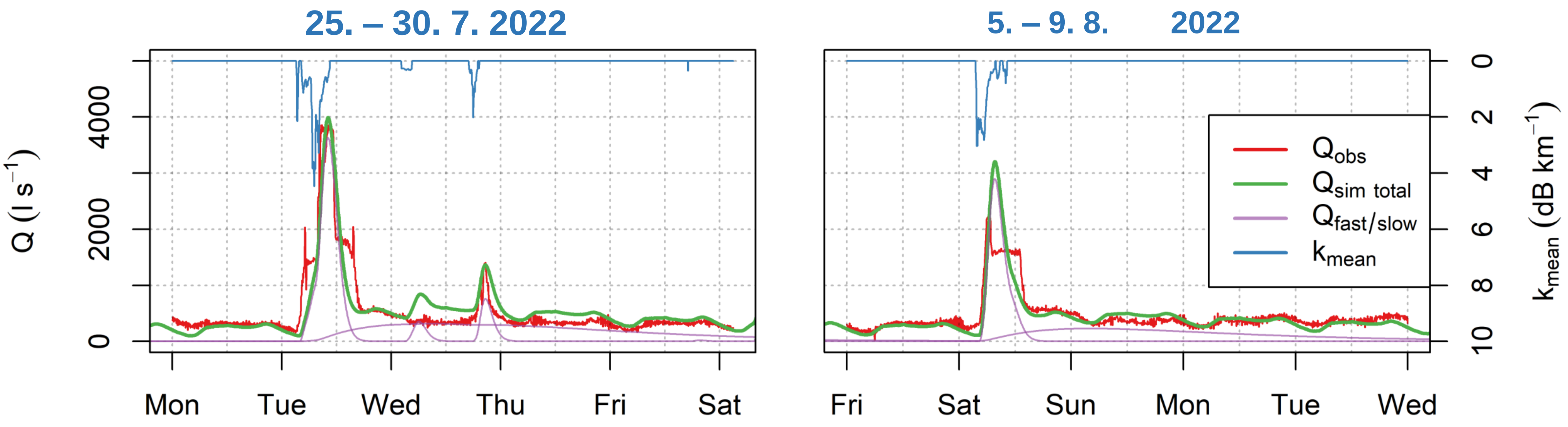
Flow data

- Trunk sewer before the inflow to WWTP
- Ultrasonic area-velocity flow meter
- Time step 30 s

Custom-made data-driven attenuation-runoff model



Model performance



Model reproduces well

- Beginning of rainfall runoff
- Timing of peak runoff
- Slow runoff after rainfall events

Case-study conclusions

The simulated flow rates are well correlated with the measurements (r = 0.75) and with no systematic bias

Systematic errors of CMLs are effectively compensated by optimizing the parameters of the conceptual rainfall-runoff model

CMLs have considerable potential for operational runoff modeling in the closing profile of a large urban catchment

Business model is missing to ensure sustainable long-term data availability

Lessons learned - outlook

- CML-based runoff simulations capture very well rainfall temporal dynamics but are often biased
- Existing observations can be conveniently used to calibrate a WAA model and thus eliminate the bias even by relatively short CMLs
- Real-time CML rainfall data can be conveniently used as an input for data-driven rainfall-runoff models
- Water utilities require high (and long-term) data availability -> business models are missing

Further research concentrates on:

- Data-driven rainfall-runoff modeling, automated quality-control algorithms, rainfall spatial reconstruction at small-scale, methods for merging CMLs with other (OS) observations

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