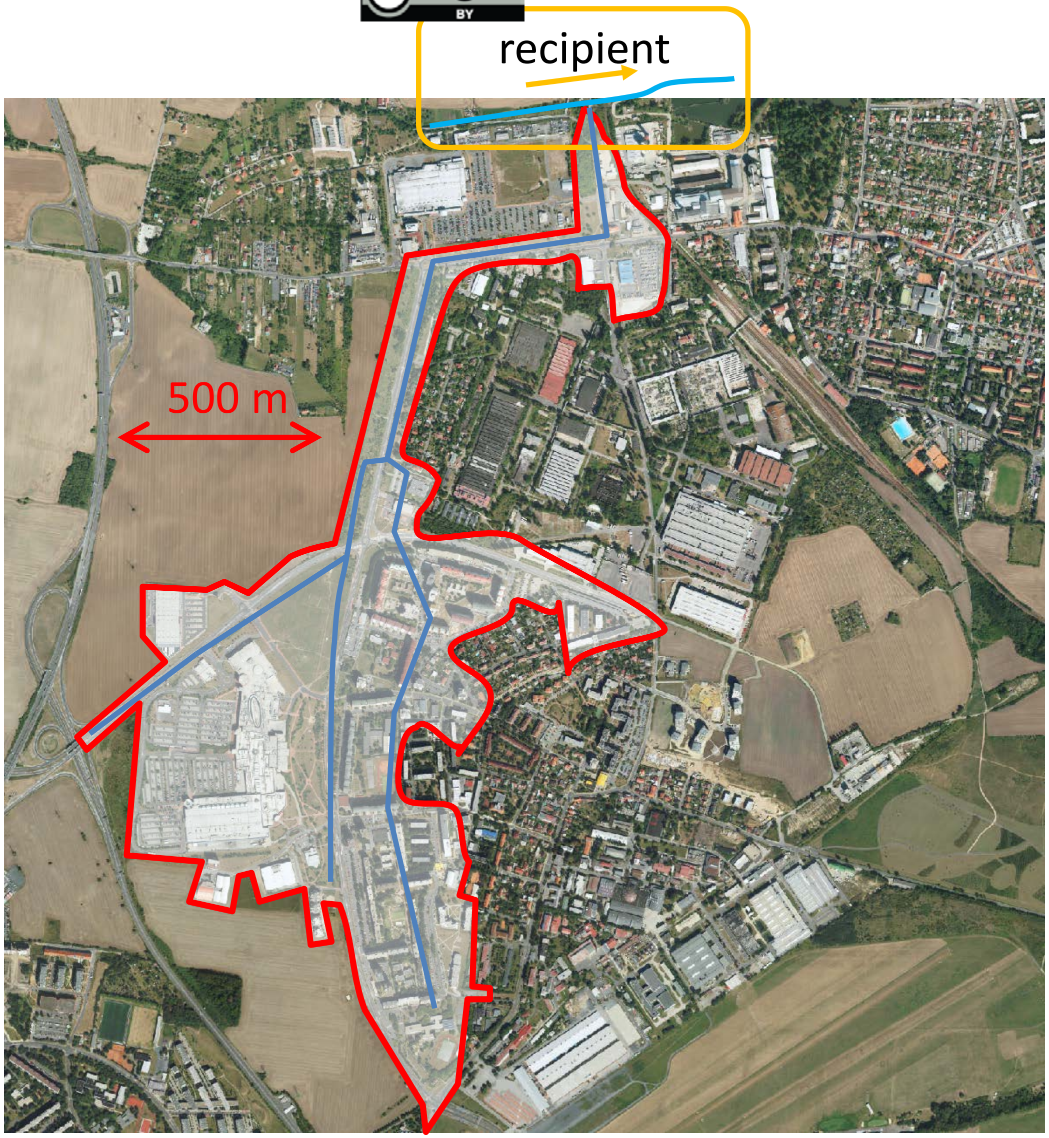
Predicting urban stormwater runoff with quantitative precipitation estimates from commercial microwave links

Jaroslav Pastorek[1] , Martin Fencl[1],
David Stránský[1], Jörg Rieckermann[2], and Vojtěch Bareš[1]

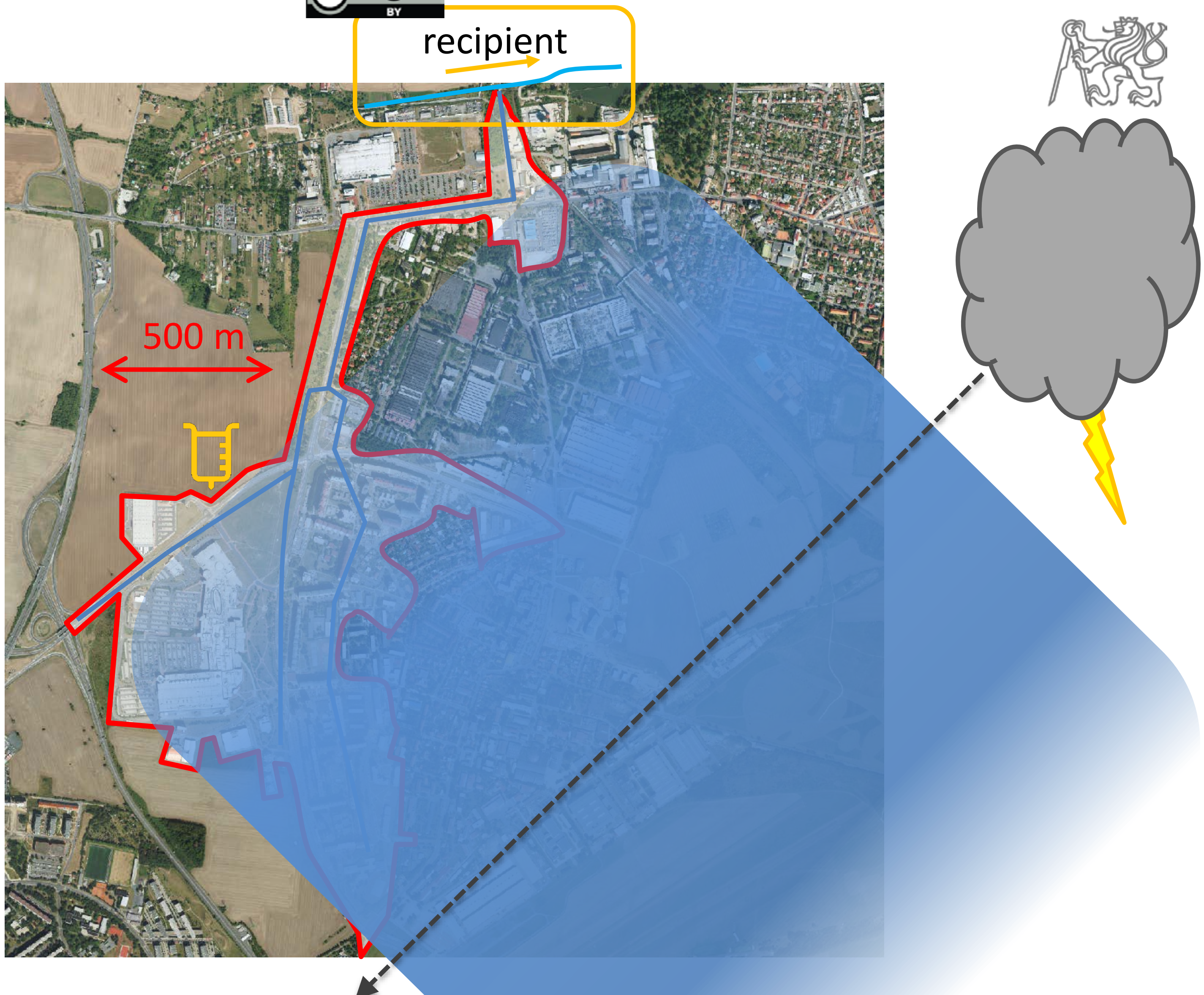
[1] Czech Technical University in Prague, Czech Republic
[2] Eawag, Switzerland

Introduction



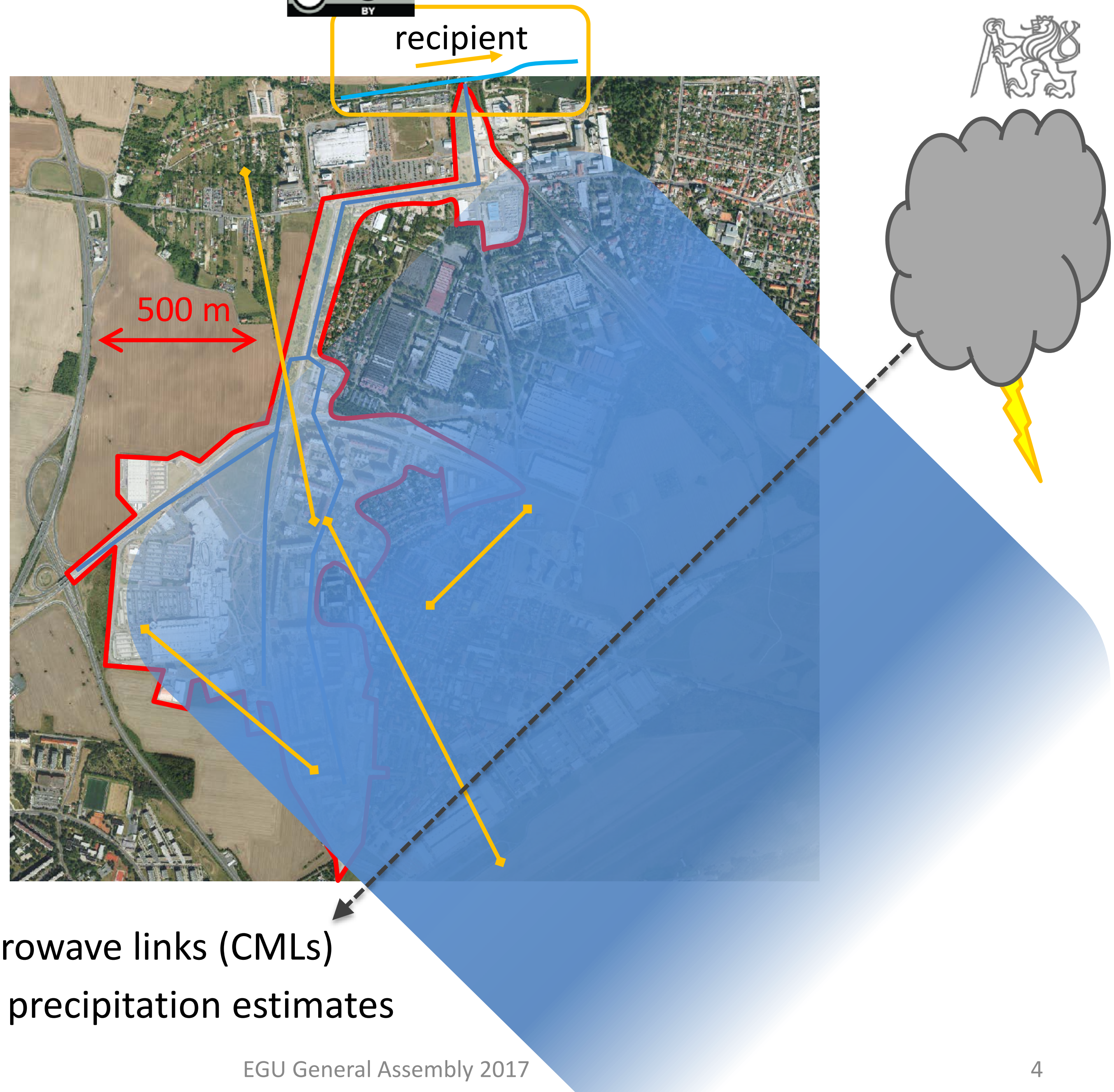
- typical urban catchment with separate sewer system
- very dynamic response

Introduction



- RGs provide point measurements
- obtained spatial information is very limited

Introduction



- commercial microwave links (CMLs)
- path-integrated precipitation estimates

Introduction

- CML data are often highly biased
  - correction method using RG data[1]

[1] Fencl, M., Dohnal, M., Rieckermann, J., and Bareš, V. 2017. **Gauge-adjusted rainfall estimates from commercial microwave links**, *Hydrology and Earth System Sciences* 21, 617-634.

- direct comparison of rainfall data lacks reliable reference

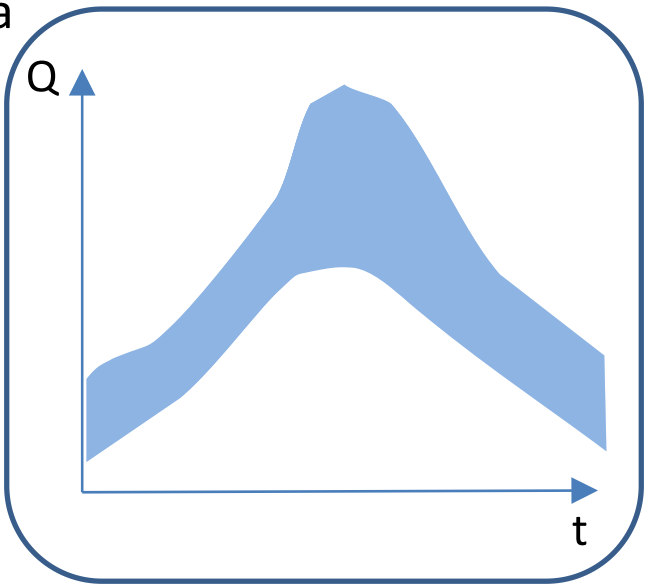
- discharge observations
  - transformed information about rainfall
  - reliable measurements

- can we validate rainfall data using observed discharges as a reference?

Introduction

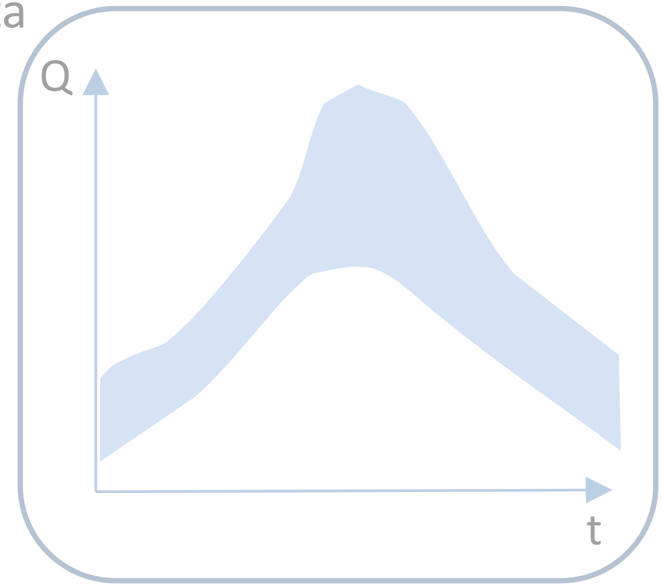
- urban runoff modelling
  - principal application of urban rainfall data
  - introduces additional uncertainties

- uncertainties can be quantified
  - predictions in a form of intervals (bands)
  - not trivial to get them all and correctly



Goal

- urban runoff modelling
  - principal application of urban rainfall data
  - introduces additional uncertainties



- uncertainties can be quantified
  - predictions in a form of intervals (bands)
  - not trivial to get them all and correctly

What is the potential
of precipitation estimates from CMLs
for urban runoff modelling?

Uncertainty analysis

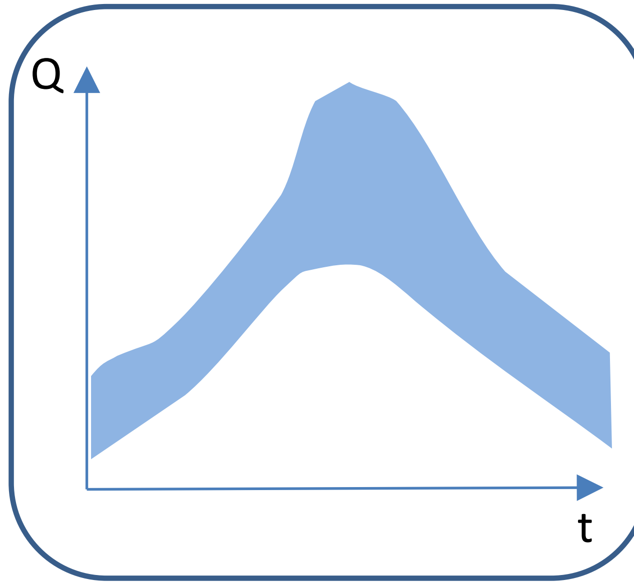
- "total error analysis" method[2]
  - rigorous bayesian inference
  - prior formulation of knowledge necessary

- hydrological model extended with error model

$$Y = y_M + \boxed{B_M} + \boxed{E}$$

"random" errors

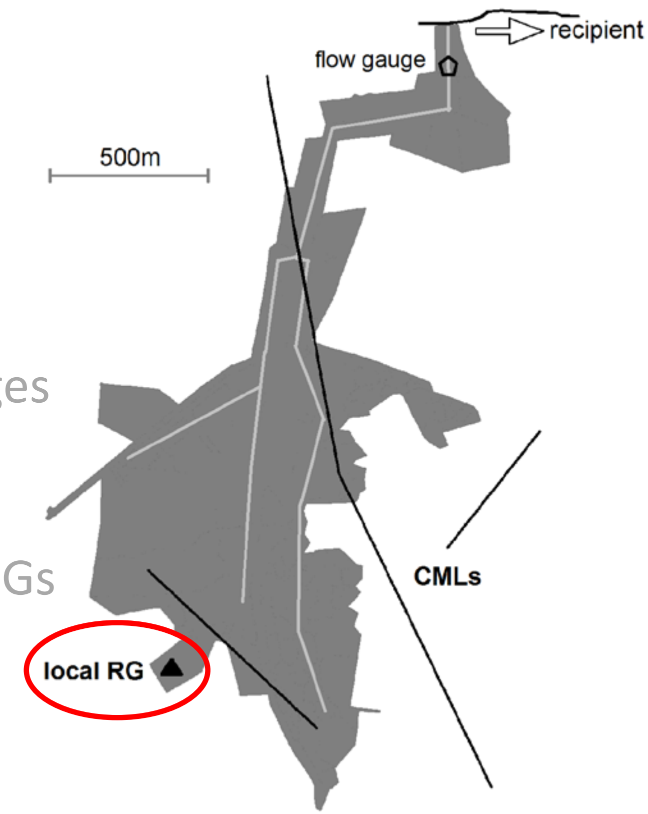
- all principal uncertainty sources considered
  - bias as a stochastic autocorrelated process

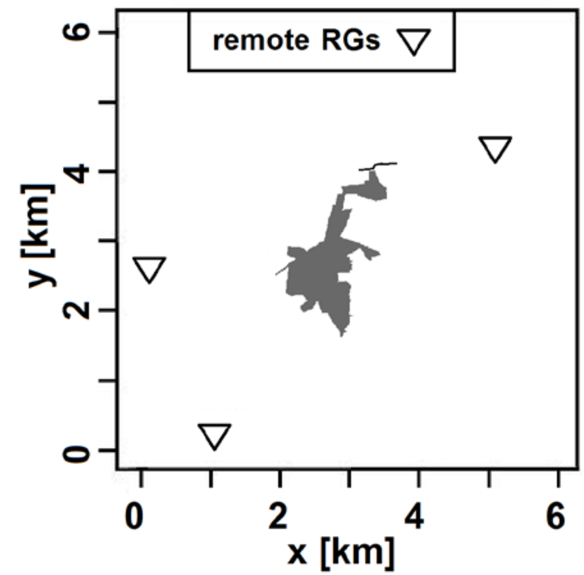


[2] Del Giudice, D., Honti, M., Scheidegger, A., Albert, C., Reichert, P., and Rieckermann, J. 2013. **Improving uncertainty estimation in urban hydrological modeling by statistically describing bias**. *Hydrology and Earth System Sciences* 17, 4209–4225.

Rainfall data

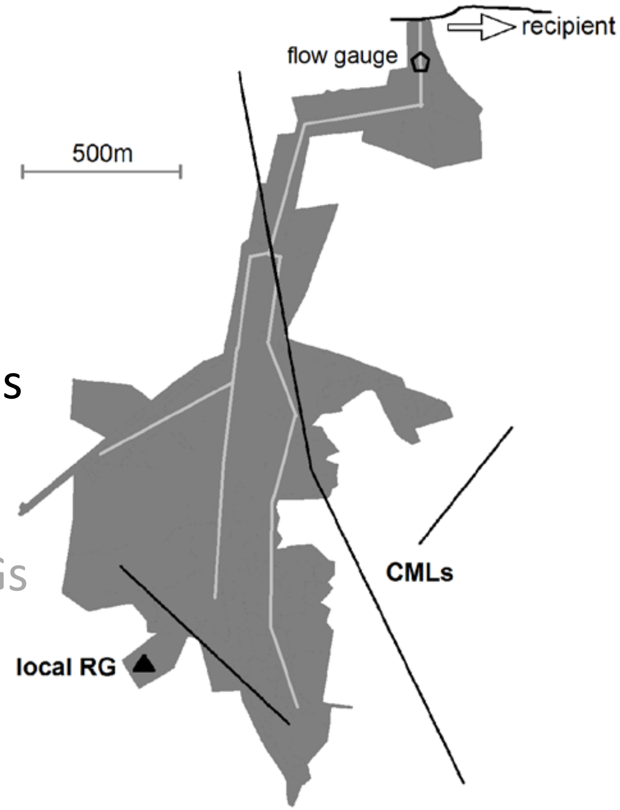
- 3 data sets
  1) 1 local rain gauge
  2) 3 remote rain gauges
  3) CMLs + 3 remote RGs

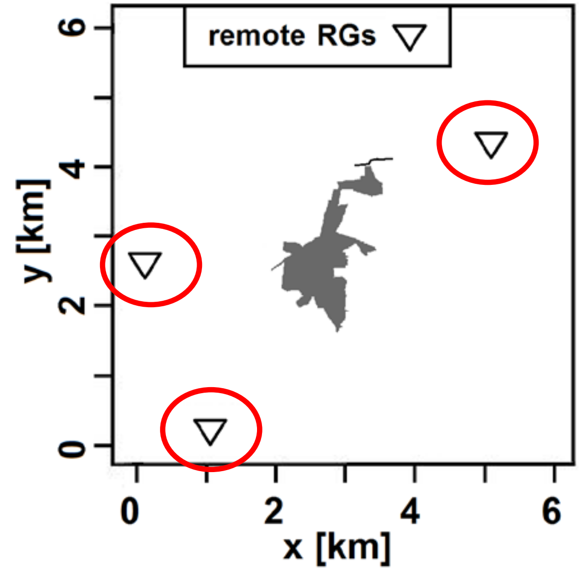




Rainfall data

- 3 data sets
  1) 1 local rain gauge
  2) 3 remote rain gauges
  3) CMLs + 3 remote RGs

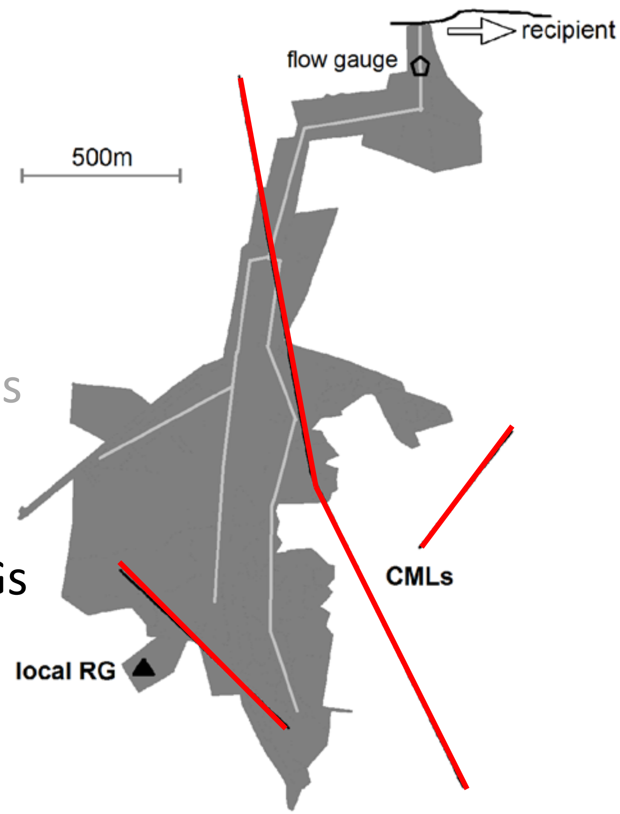


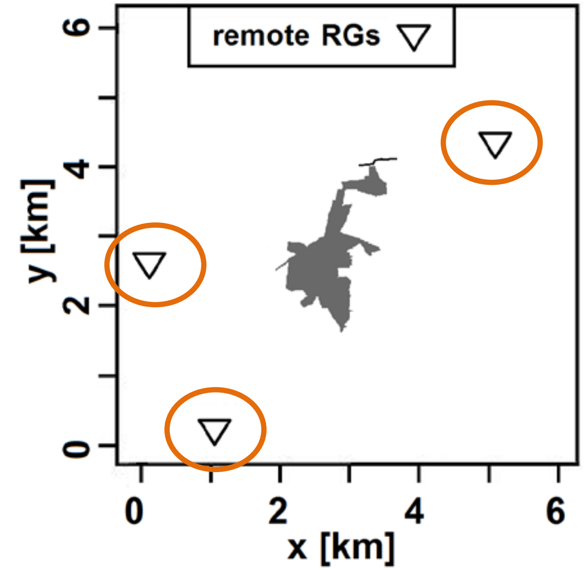


- from a municipal monitoring network

Rainfall data

- 3 data sets
  1) 1 local rain gauge
  2) 3 remote rain gauges
  3) CMLs + 3 remote RGs

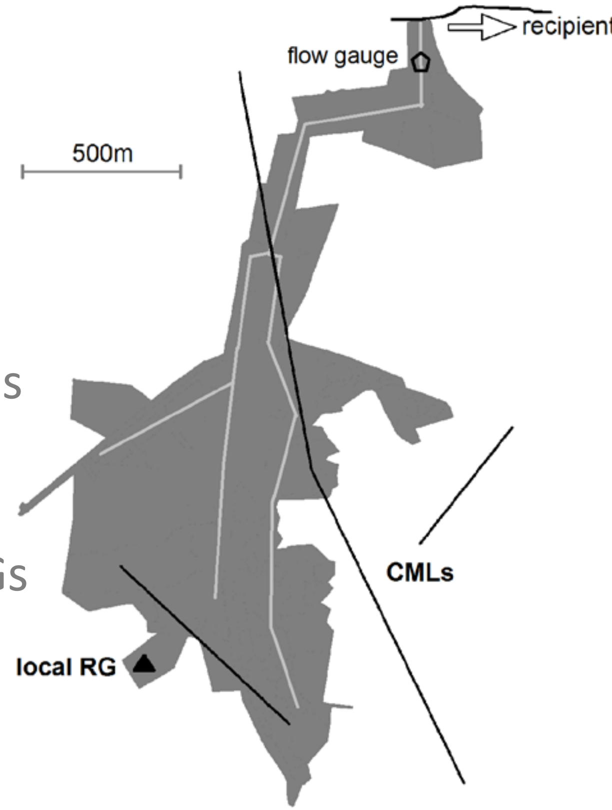


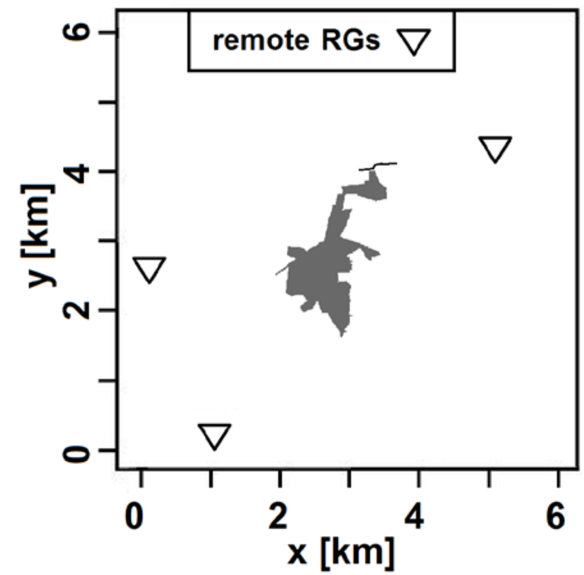


- a combination of the 2 sources
- the adjustment method of Fencl et al. (2017)

Rainfall data

- 3 data sets
  1) 1 local rain gauge
  2) 3 remote rain gauges
  3) CMLs + 3 remote RGs





- areal rainfall
- 15 events from Aug-Oct 2014
- time resolution: 1 min

Implementation

predictions

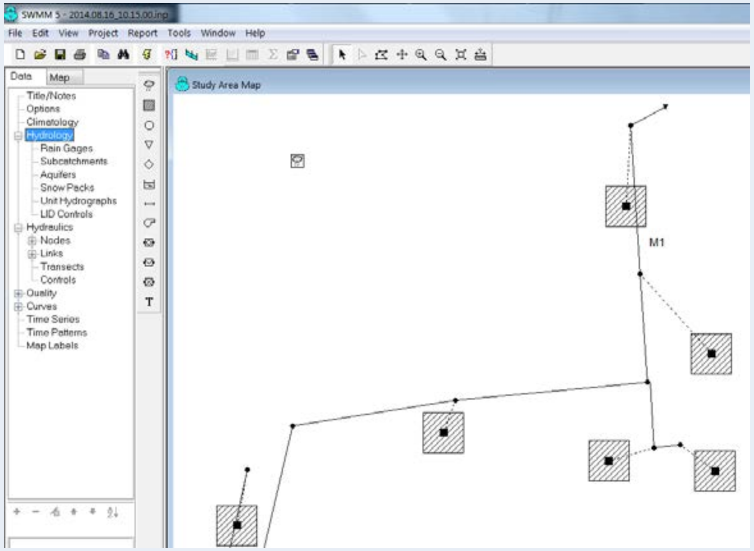
calibration → local RG

calibration → remote RGs

calibration → CMLs + rem. RGs

- 5 events chosen for calibration
  - calibrating the hydrological model and the error model simultaneously
  - using an independent rainfall data set

- distributed rainfall-runoff model implemented in EPA SWMM

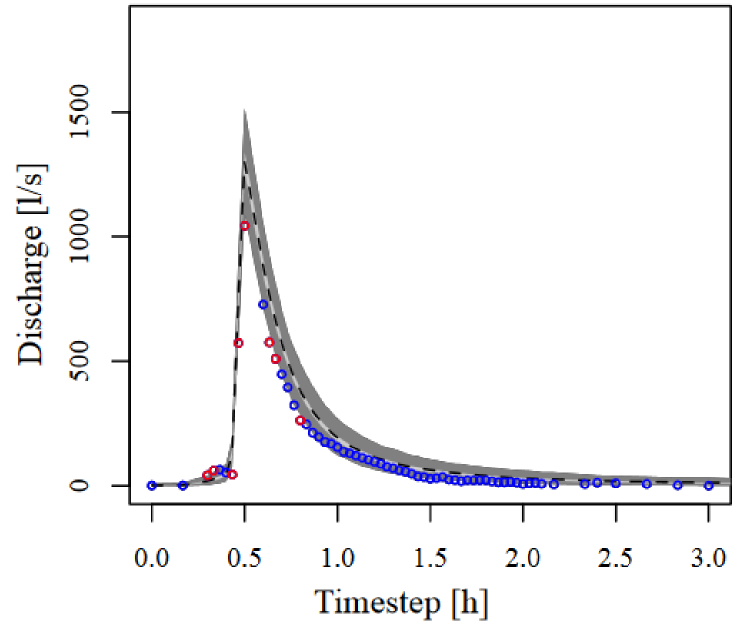


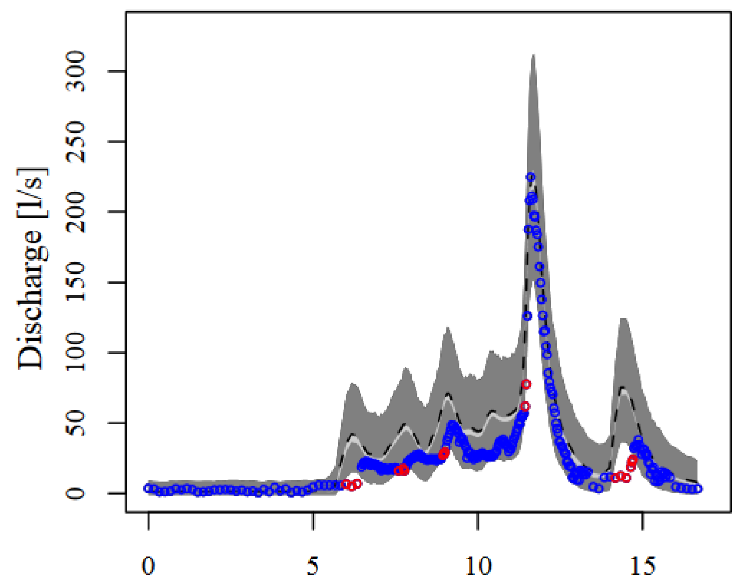
Implementation

predictions

calibration
- local RG
- remote RGs
- CMLs + rem. RGs

- 10 events for predictions
  - 5 heavy rainfalls
  - 5 light rainfalls
- statistical method => many model runs

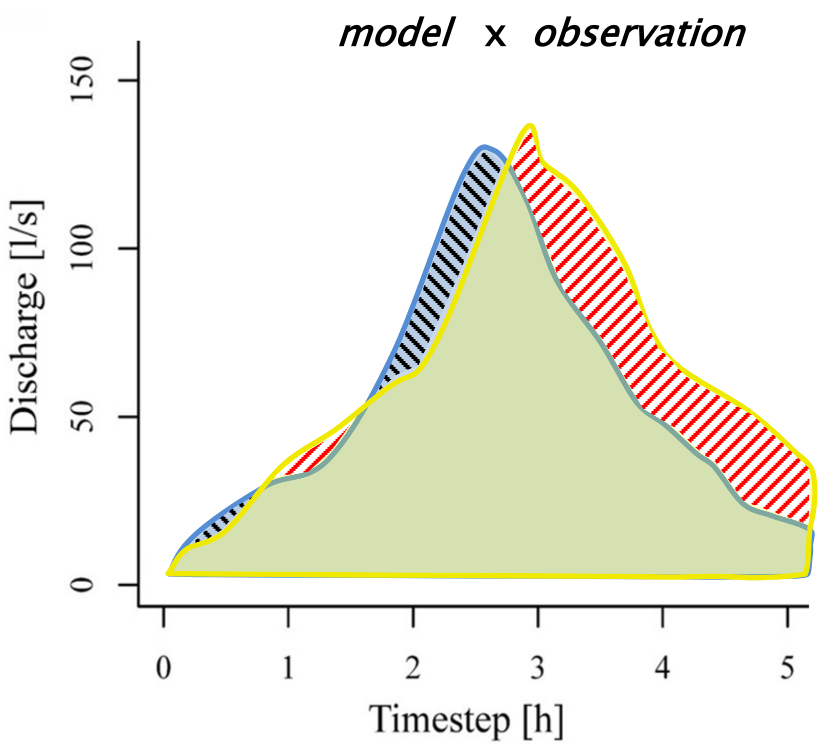




Performance statistics

- the relative error of the total runoff volume

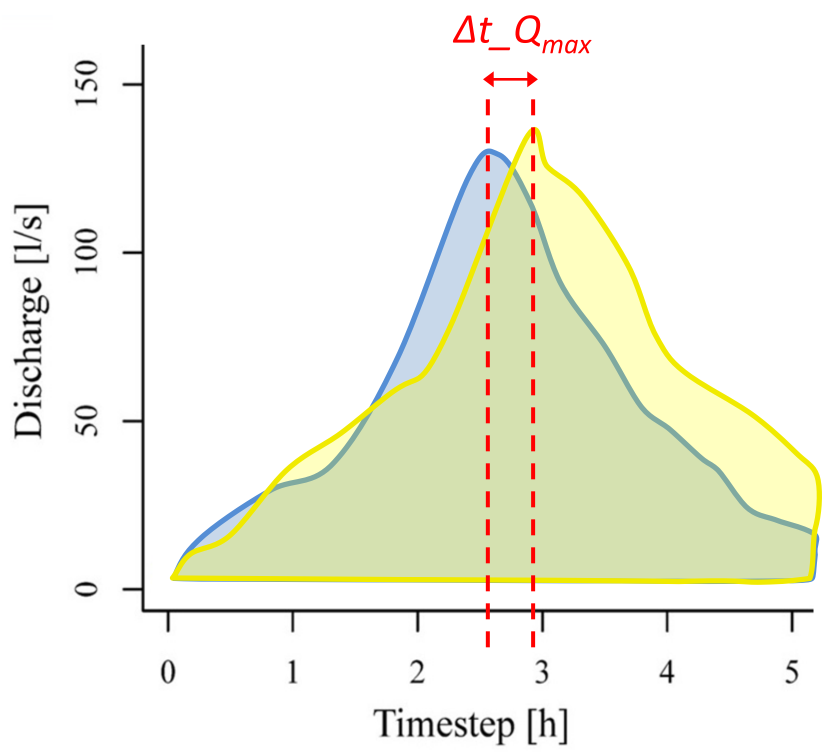
  $dV = (V_m - V_o) / V_o$ *[-]*



Performance statistics

- the time shift of the discharge maximum

  $\Delta t\_Q_{max} = t\_Q_{max,m} - t\_Q_{max,o}$ *[h]*

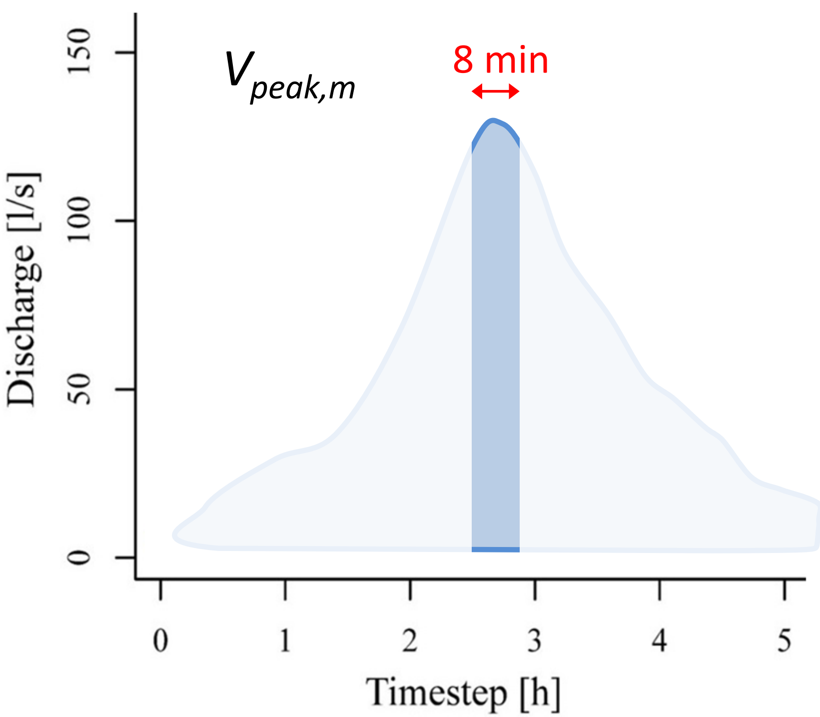


Performance statistics

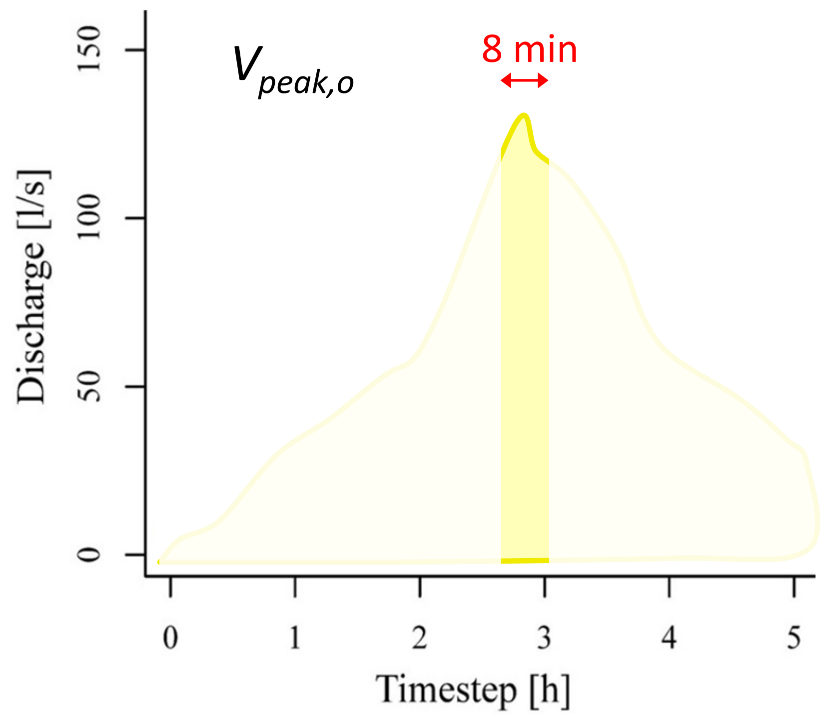
- the relative error of the peak discharges (integrated over 8-min period)

$$dV_{peak} = (V_{peak,m} - V_{peak,o}) / V_{peak,o} \quad [-]$$

model



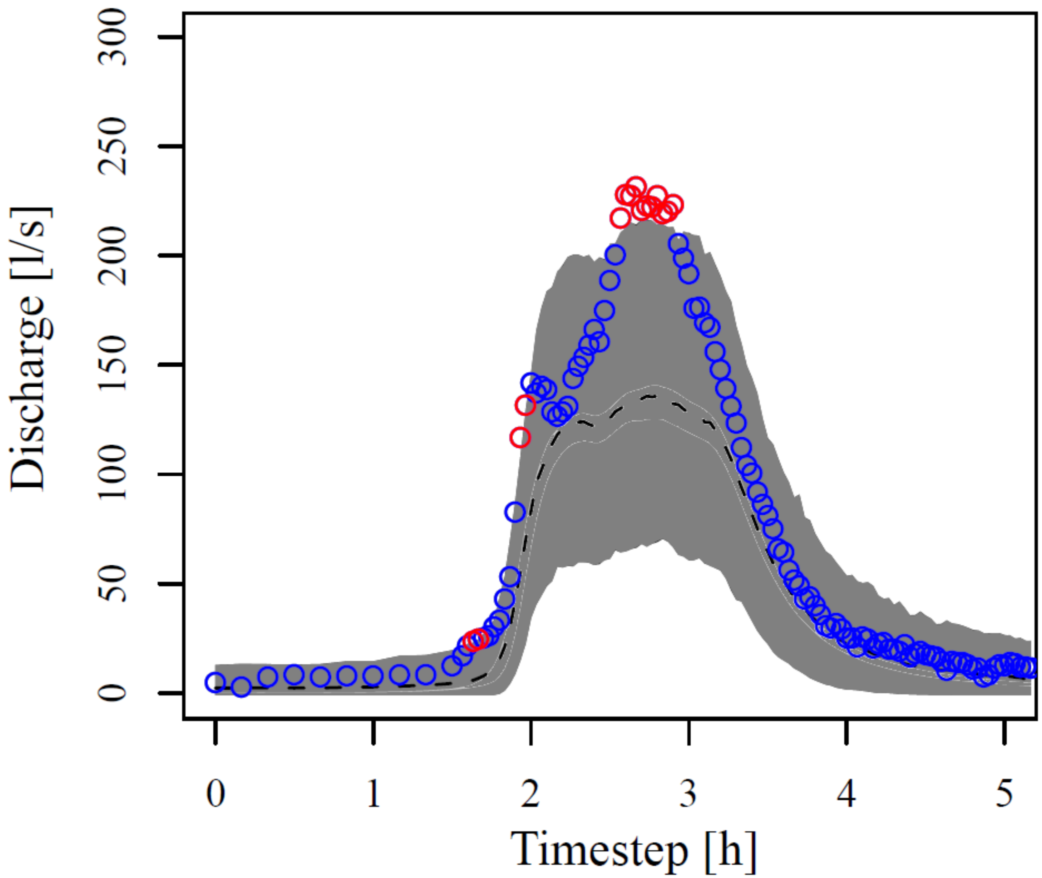
observation



Performance statistics

- the prediction reliability [-]

  (fraction of the flow observations falling into the predicted interval)



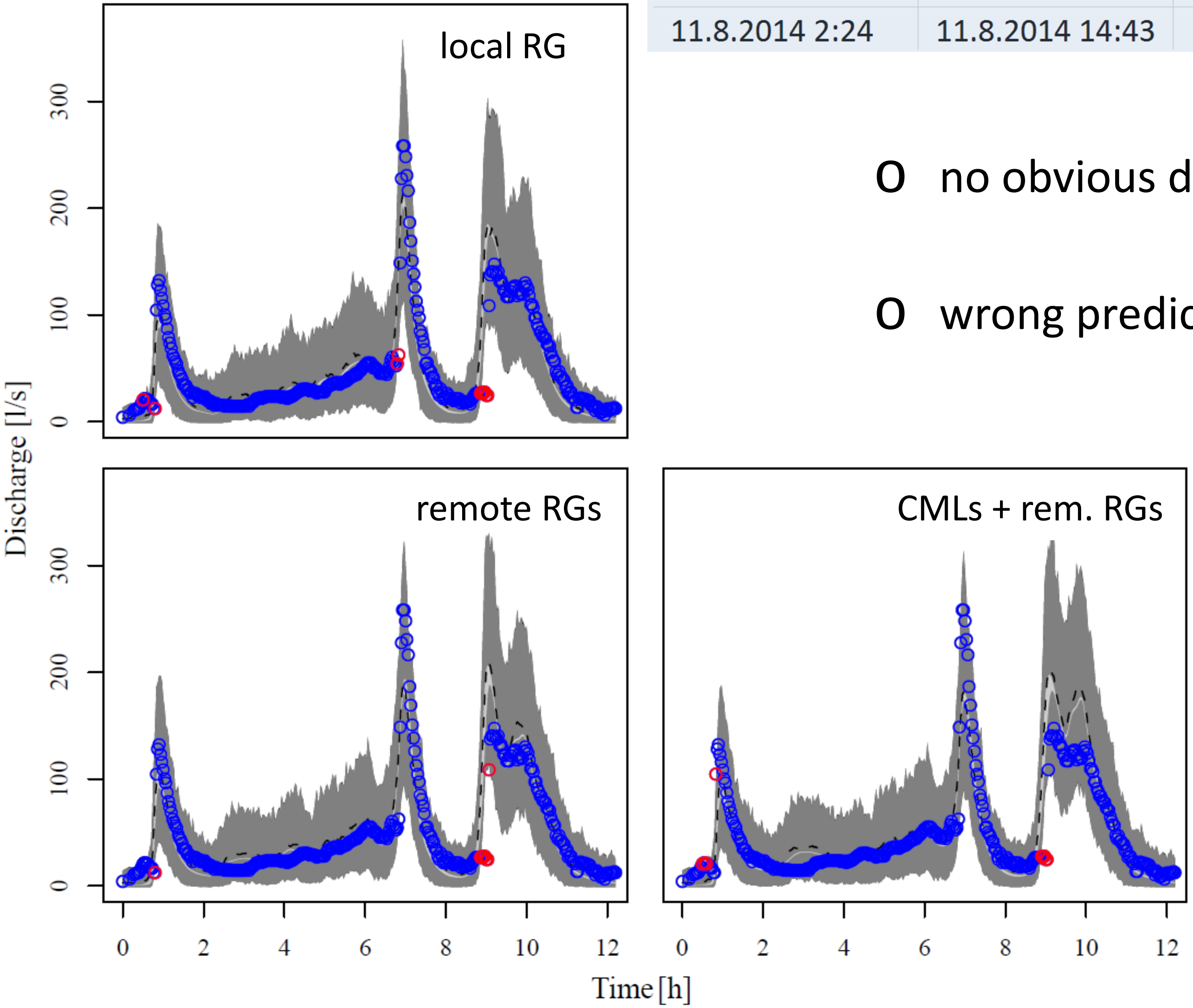
$$\frac{\sum \text{blue circles}}{\sum \text{all circles}}$$

Results

- example of a light event

start	end	length [min]	depth [mm]	Rmax [mm/h]	Rmax10 [mm/h]
11.8.2014 2:24	11.8.2014 14:43	739	7.8	6.0	4.3

- no obvious difference
- wrong predictions for rising limbs



Results

- light events summary *(all light events and all model runs)*

  - the relative error of the total runoff volume

	local RG	remote RGs	CML + rem. RGs
E(dV)	−0.089	−0.163	−0.065
sd(dV)	0.222	0.294	0.292

  - the prediction reliability

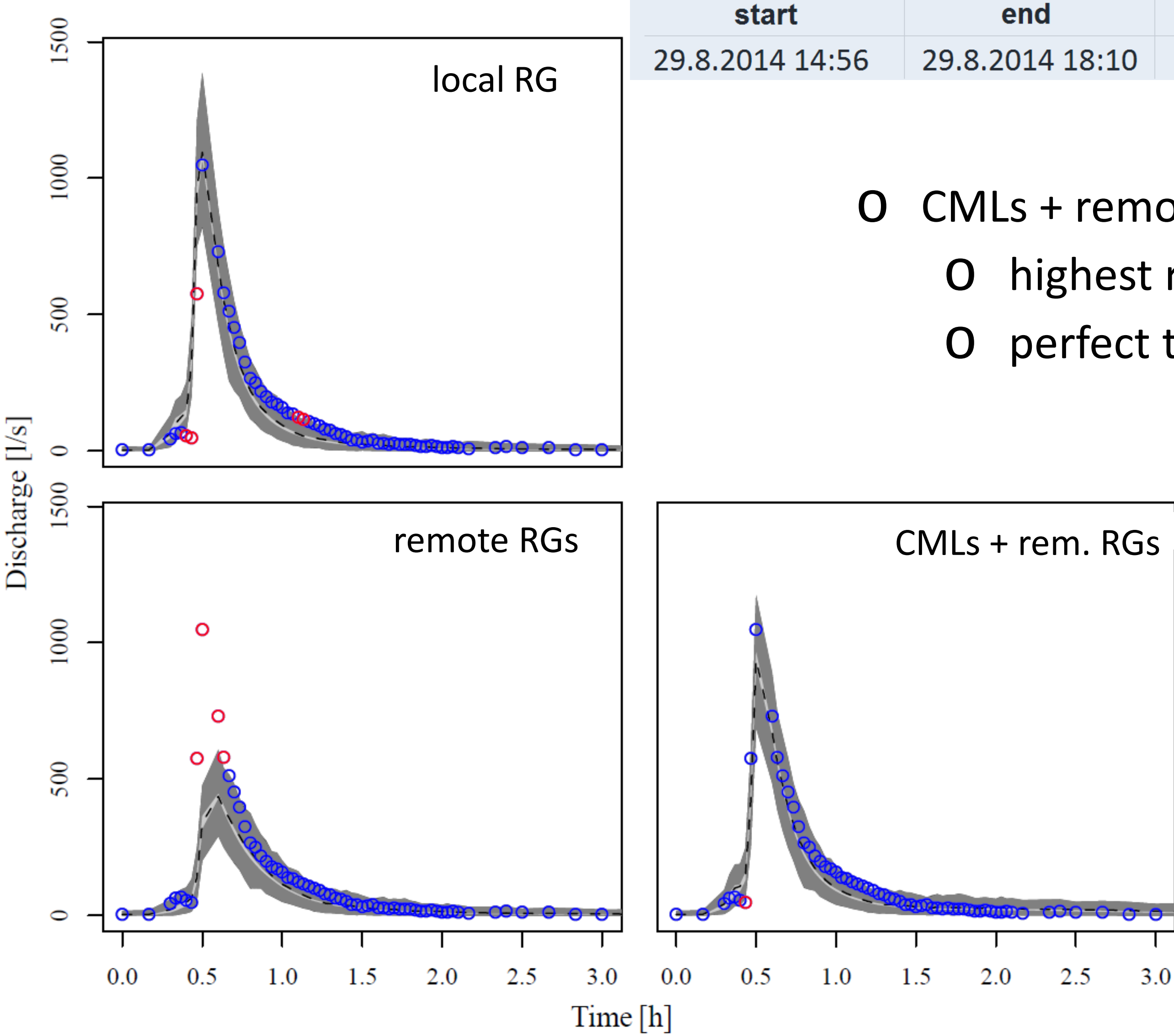
	local RG	remote RGs	CML + rem. RGs
reliab	0.97	0.905	0.932

- CMLs + remote RGs:
  - *dV* – as good as others
  - *reliab* – better than distant RGs alone

Results

- example of a heavy event #1

start	end	length [min]	depth [mm]	Rmax [mm/h]	Rmax10 [mm/h]
29.8.2014 14:56	29.8.2014 18:10	194	4.0	26.9	17.9

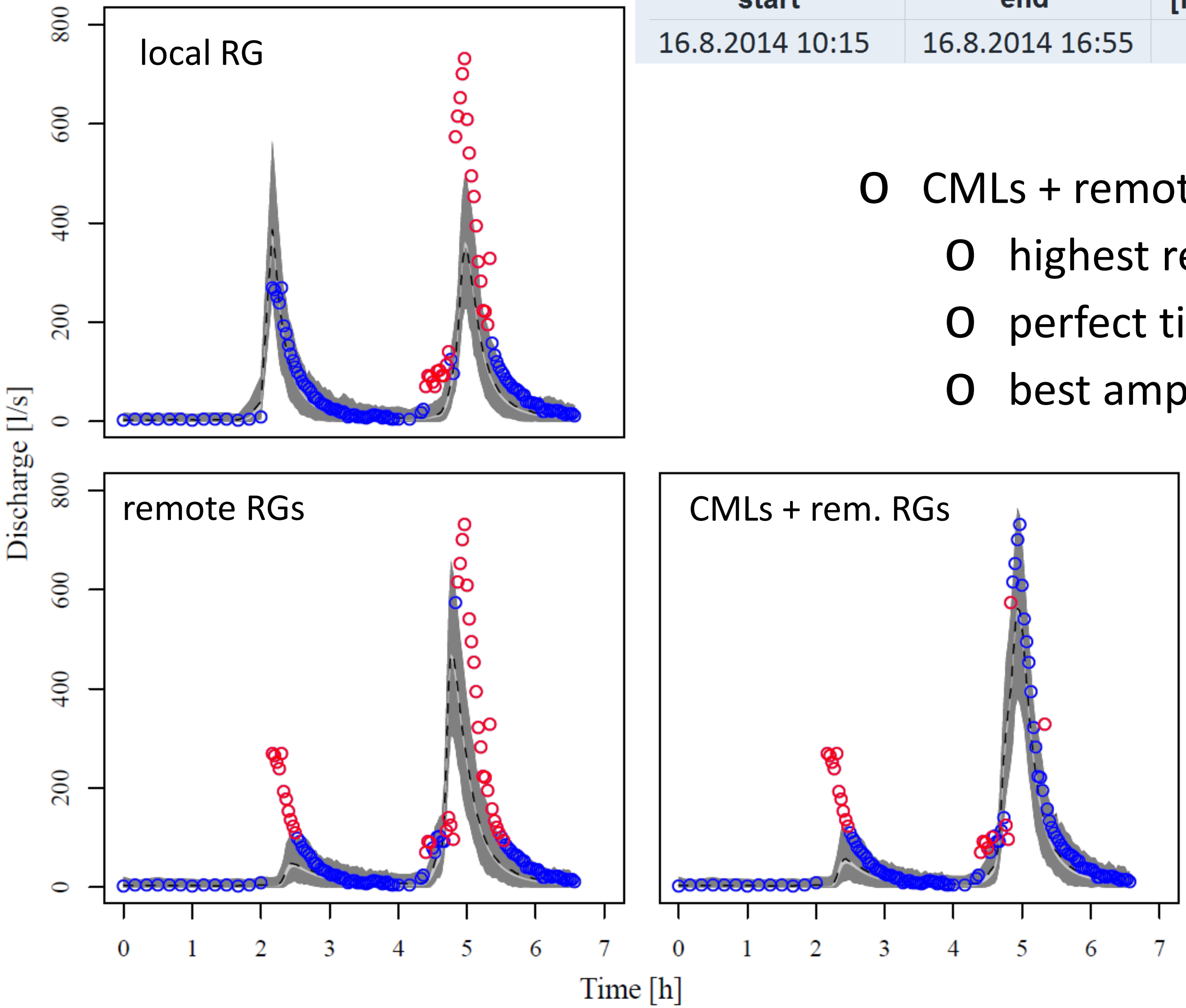


- CMLs + remote RGs:
  - highest reliability
  - perfect timing of the maximum

Results

- example of a heavy event #2

start	end	length [min]	depth [mm]	Rmax [mm/h]	Rmax10 [mm/h]
16.8.2014 10:15	16.8.2014 16:55	400	6.8	26.8	15.0



- CMLs + remote RGs:
  - highest reliability
  - perfect timing of the maximum
  - best amplitude of the maximum

Results

- heavy events summary *(all heavy events and all model runs)*

	local RG	remote RGs	CML + rem.RGs
E(dV)	−0.182	−0.202	−0.114
sd(dV)	0.158	0.226	0.183
E(dVpeak)	0.177	−0.047	−0.001
sd(dVpeak)	0.52	0.457	0.19
E(shift(Qmax))	−0.231	0.087	0.086
sd(shift(Qmax))	0.904	0.177	0.134
reliab	0.856	0.842	0.863

- CMLs + remote RGs
  - best values for all statistics
  - especially for maximum-related statistics

Conclusions

What is the potential
of precipitation estimates from CML
for urban runoff modelling?

- light events
  - the same quality level as rain gauges
  - higher reliability of predictions than remote RGs alone

- heavy events
  - systematically better than remote RGs alone, not worse than a local RG
  - for extraordinarily spatially variable events better than a local RG

Conclusions

What is the potential
of precipitation estimates from CMLs
for urban runoff modelling?

Invitation:

Fencl, M., Dohnal, M., and Bareš, V.
Real-time adjusting of rainfall estimates
from commercial microwave links

- light events
  - the same quality level as rain gauges
  - higher reliability of predictions than remote RGs alone

- heavy events
  - systematically better than remote RGs alone, not worse than a local RG
  - for extraordinarily spatially variable events better than a local RG

enabled by:

VEOLIA
PVS PRAŽSKÁ VODOHOSPODÁŘSKÁ SPOLEČNOST a.s.
T · ·
GAČR CZECH SCIENCE FOUNDATION