

Hydrological Application of OS Data: The Lambro Catchment Case Study

Greta Cazzaniga¹, Andrijana Todorovic², Cristina Deidda³, Carlo De Michele⁴, Roberto Nebuloni⁵

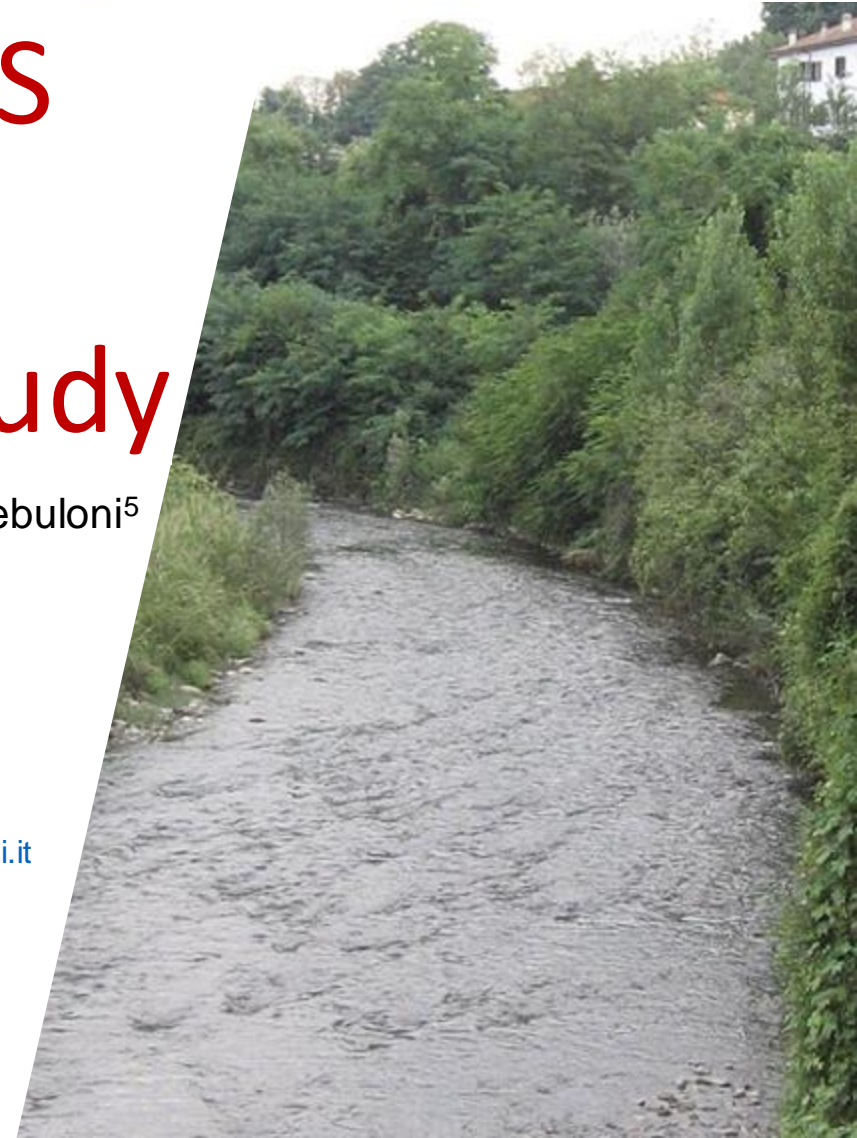
(1) Université Paris Saclay, Laboratoire des Sciences du Climat et de l'Environnement, Gif-sur-Yvette, France; greta.cazzaniga@lsce.ipsl.fr

(2) University of Belgrade, Faculty of Civil Engineering, Belgrade, Serbia; atodorovic@grf.bg.ac.rs

(3) Vrije Universiteit Brussel, Department of Water and Climate, Brussel, Belgium; cristina.deidda@vub.be

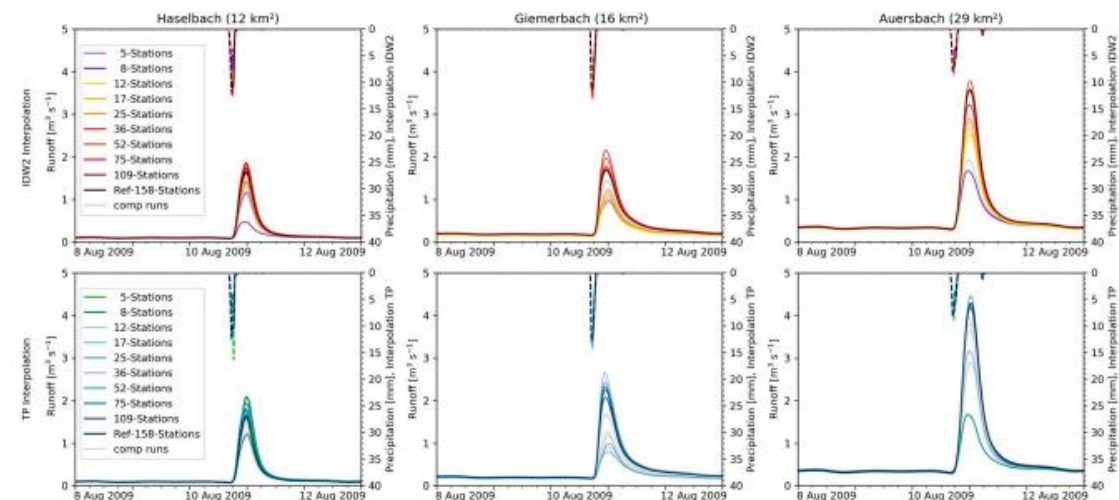
(4) Politecnico di Milano, Department of Civil and Environmental Engineering, Milano, Italy; carlo.demichele@polimi.it

(5) IEIIT, Consiglio Nazionale delle Ricerche, Milano, Italy; roberto.nebuloni@ieiit.cnr.it



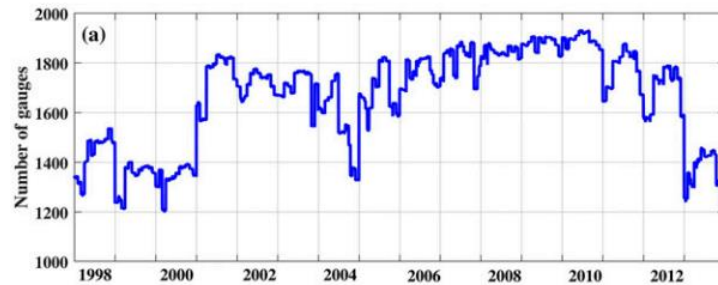
Hydrological modelling

- Hydrological (rainfall-runoff) models are essential for sustainable water resources management
 - Estimation of values of hydrological variables (e.g., flows at ungauged sites, or flows in the future, i.e., streamflow forecasting)
 - Analyses of various scenarios
- Rainfall data is of utmost importance for hydrological modelling
 - Information on rain depth, rainfall dynamics and its spatial variability are needed



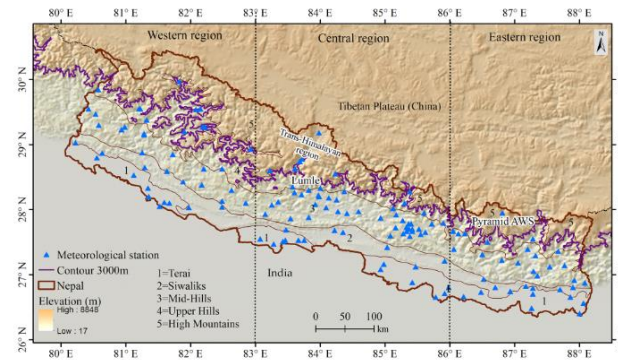
Rainfall data in hydrological modelling

- Rainfall data are traditionally being obtained from the raingauges
 - Rain gauge observations are affected by the wind, the number of the gauges can decrease over time, majority of gauges are located at lower elevation...



Prakash et al., 2019

https://journals.ametsoc.org/downloadpdf/view/journals/hydr/20/5/jhm-d-18-0161_1.pdf



Sharma et al., 2020

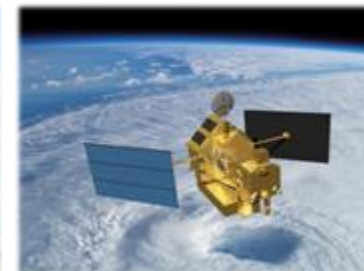
<https://doi.org/10.1029/2020EA001315>



Dhurmea et al., 2009

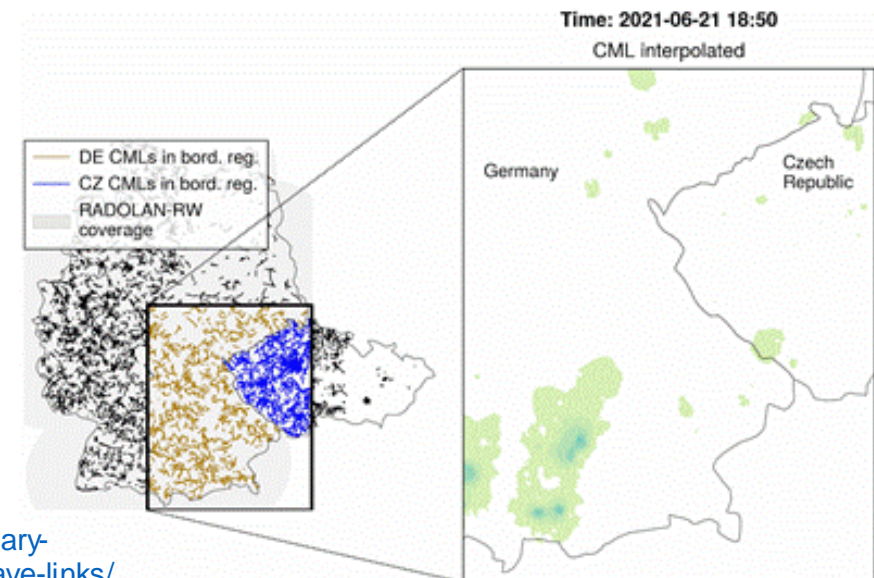
Conference: 3rd Research Week 2009-2010, International Conference, University of Mauritius

- Recent tendencies to use radar- or satellite rainfall data
 - Indirect rainfall observations



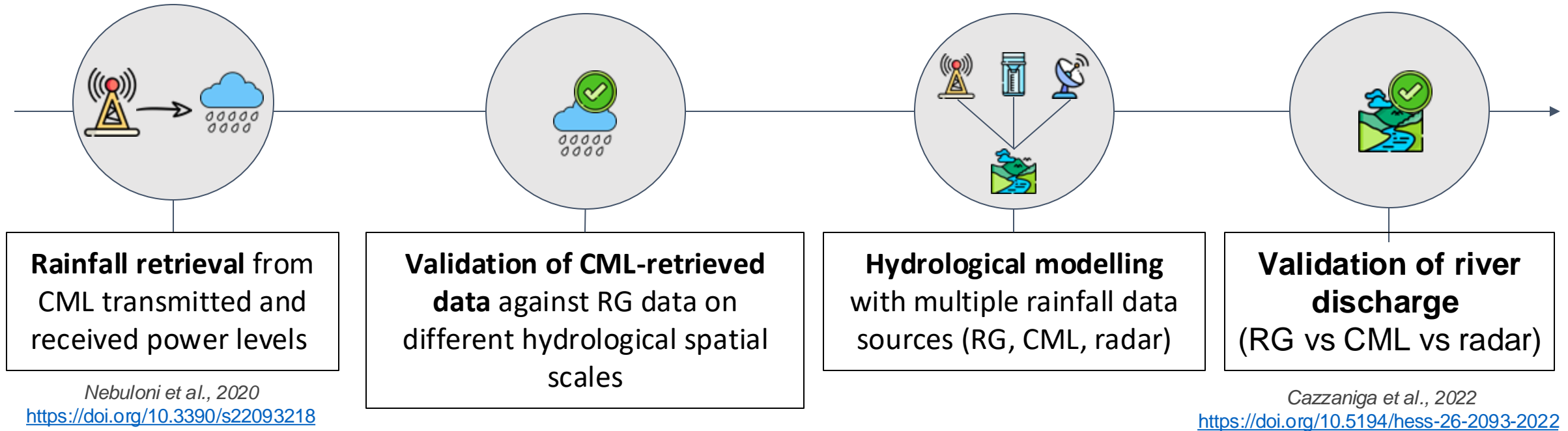
Why using OS data in hydrological modelling?

- Obtaining rainfall data remains costly, and these data remain accompanied by uncertainties
- A promising avenue for future development: opportunistic sensing
 - Potential to extend the monitoring network and get rainfall data (almost) at no additional costs
 - ... and to advance hydrological modelling
- Some of the opportunistic sensing (OS) techniques: personal weather stations, satellite microwave links, *commercial microwave links (CML)*



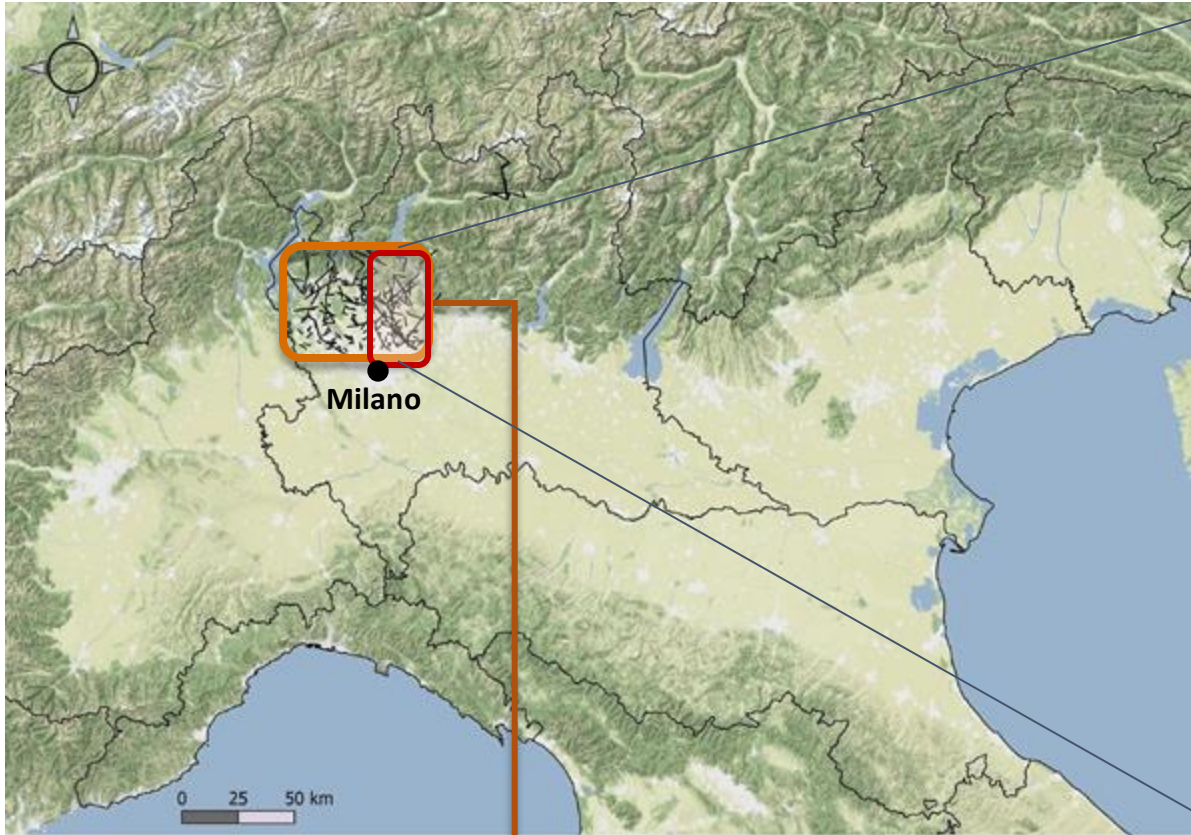
Our project

Investigating the potential of CML-retrieved rainfall data for hydrological modelling

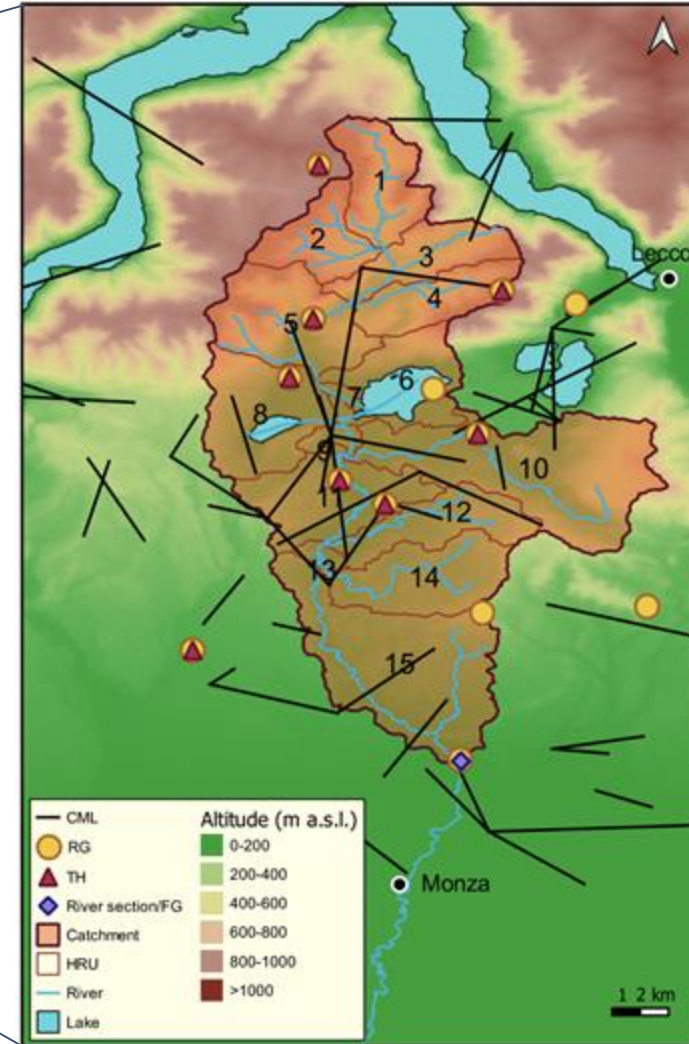


Nebuloni et al., 2022
<https://www.ursi.org/Publications/RadioScienceLetters/Volume2/RSL20-0062-final.pdf>

The Lambro catchment






Peri-urban region
(Lambro-Seveso-Olona)



The Lambro catchment

Rainfall measurements

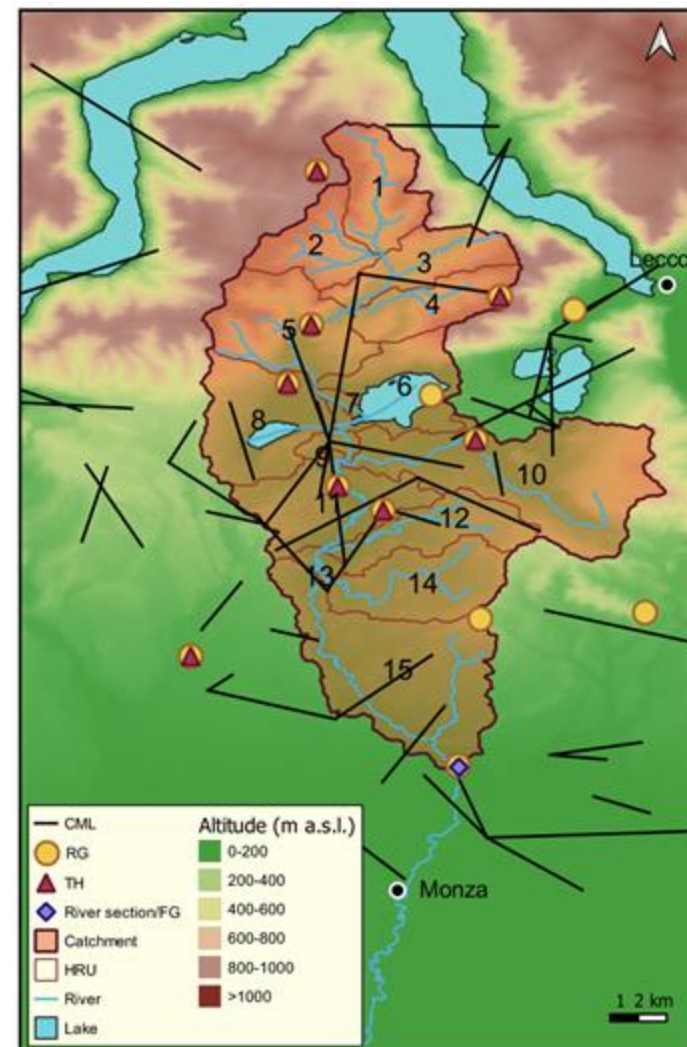
-  50 commercial microwave links (CML)
-  13 rain gauges (RG)
-  radar

Temperature

-  8 thermometers

River discharge

-  hydrometer



Rainfall datasets on the Lambro catchment



Rain gauges



TIME RESOLUTION

10 minutes

ACCURACY

0.2 mm

AVAILABILITY

- Available at <https://www.arpalombardia.it/>
- Data from January 2018 until June 2020



Radar



TIME RESOLUTION

5 minutes

SPATIAL RESOLUTION

1km x 1km

AVAILABILITY

- Available on demand from [MétéoSuisse](#) with a small fee for data extraction
- Data from October 2019 until June 2020



Commercial microwave links



TIME RESOLUTION

15 minutes MIN-MAX power data

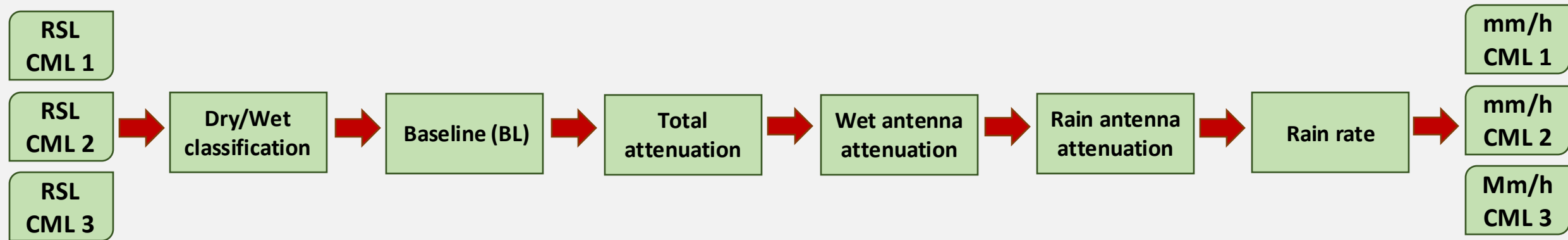
ACCURACY

1 dB

AVAILABILITY

- For a fee and confidential (provided by Vodafone)
- 12 rainy events from June 2019 until June 2020

Rainfall retrieval from CML data



Overeem et al. 2016
<https://doi.org/10.1073/pnas.1217961110>

Some details on the data processing:

→ $A = LkR^\alpha$ Calibration of k and α parameters from the Drop Size Distribution of hydrometeors (from disdrometers)

Nebuloni et al., 2022

$$\rightarrow \bar{R} = \frac{1}{1.14} \cdot \frac{R_{min} + R_{max}}{2}$$

Unbiased estimator for 15 minutes average rain intensities

Nebuloni et al., 2020



Rainfall measurements: CML vs rain gauges

Comparison between CML and rain gauges accumulated rainfall

 High intensity events
(max rain depth ≥ 15 mm per hour)

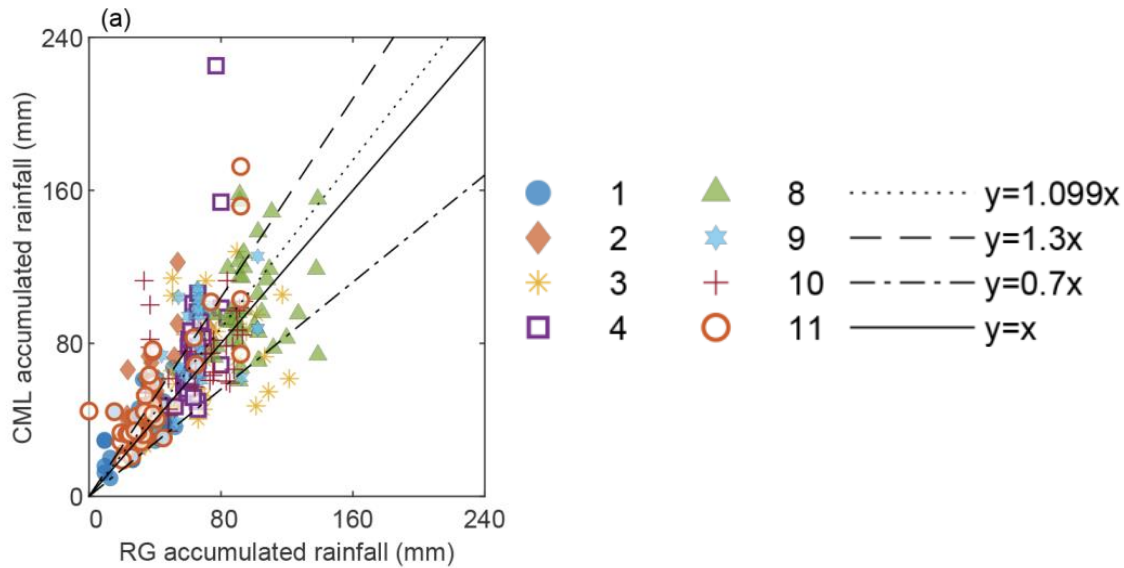
 Low intensity events
(max rain depth < 15 mm per hour)

Rainfall measurements: CML vs rain gauges

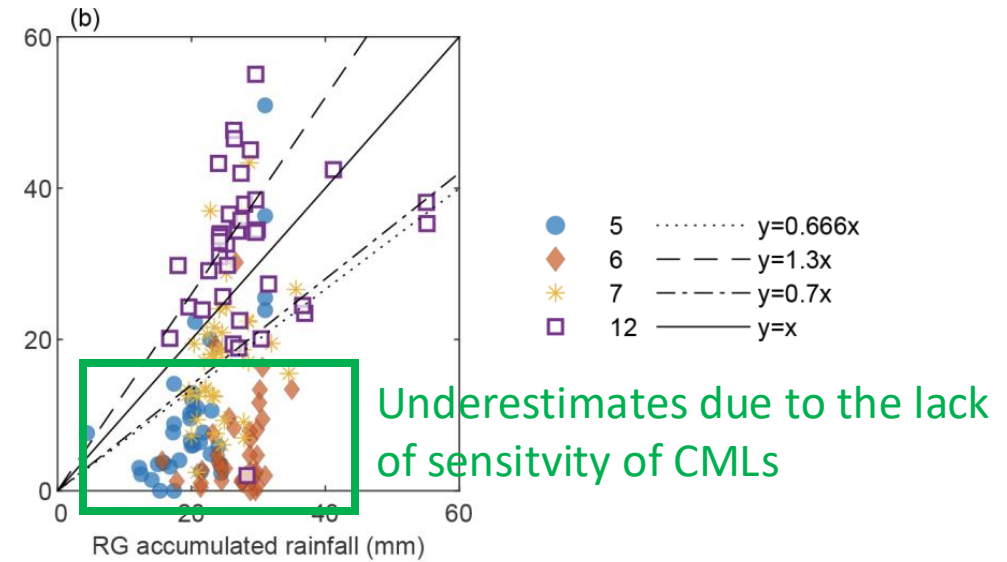
Comparison between CML and rain gauges accumulated rainfall



High intensity events
(max rain depth ≥ 15 mm per hour)

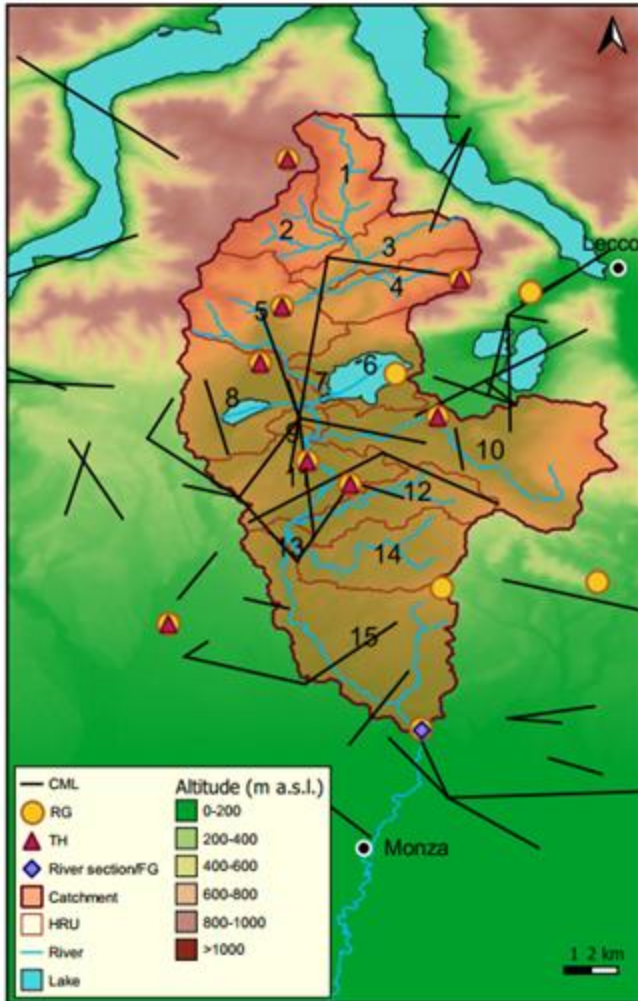


Low intensity events
(max rain depth < 15 mm per hour)

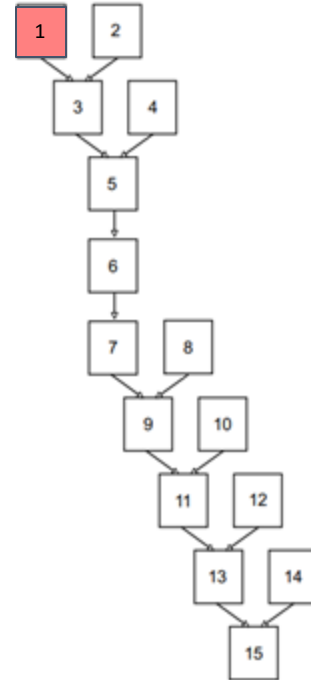


The hydrological model

Semi-distributed model

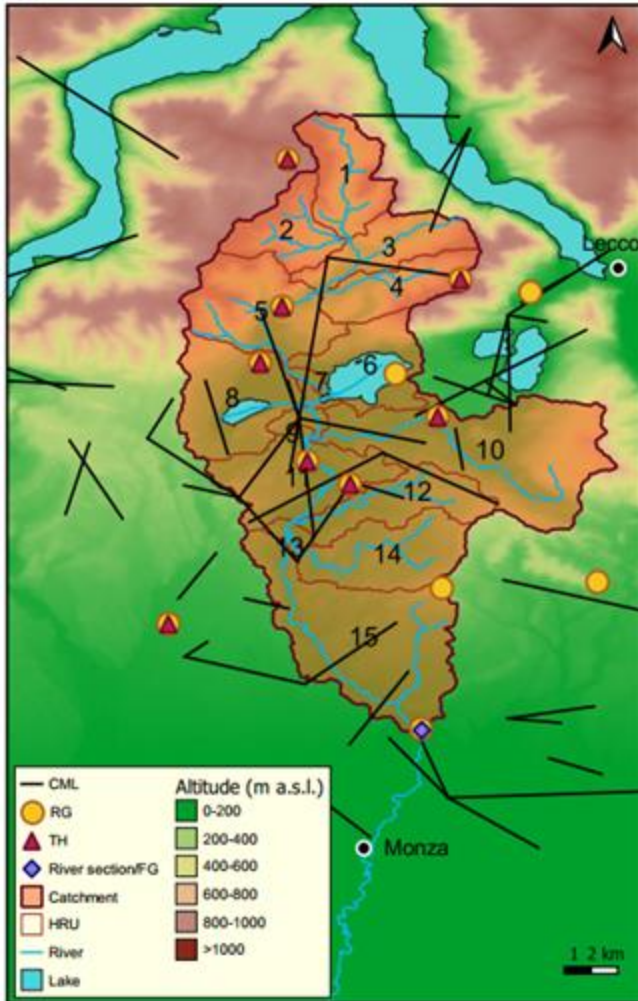


Sub-catchment or hydrological response unit (HRU)

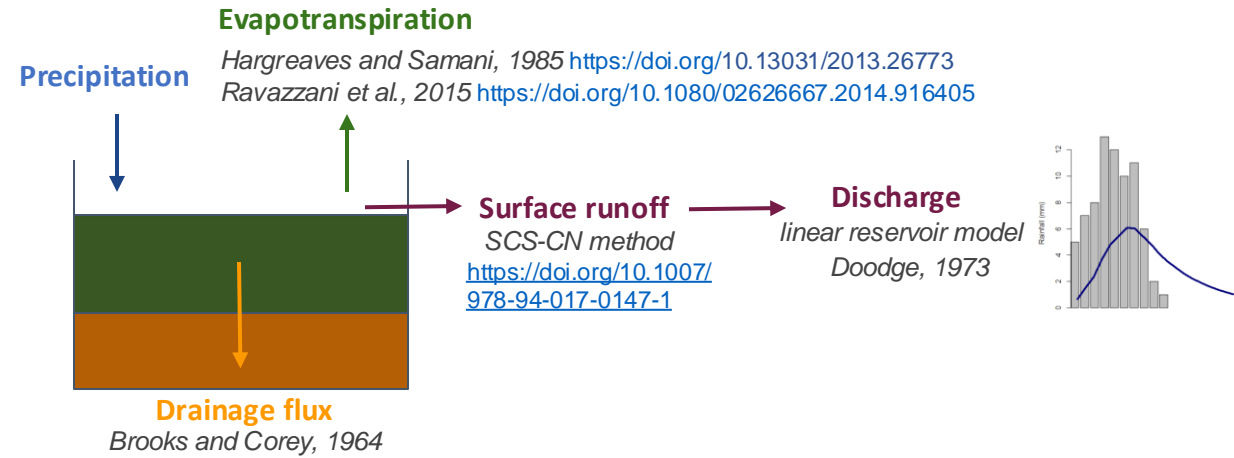
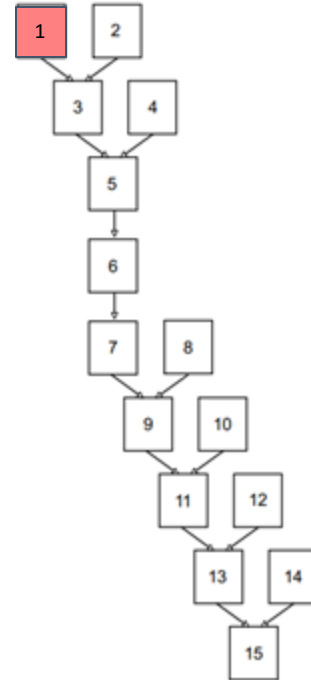


The hydrological model

Semi-distributed model

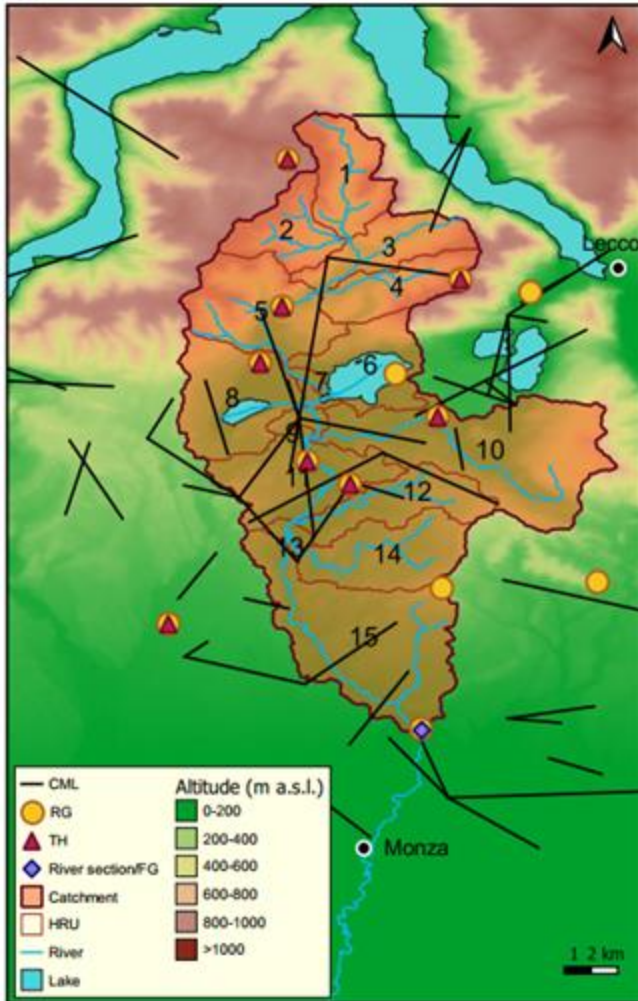


Sub-catchment or hydrological response unit (HRU)

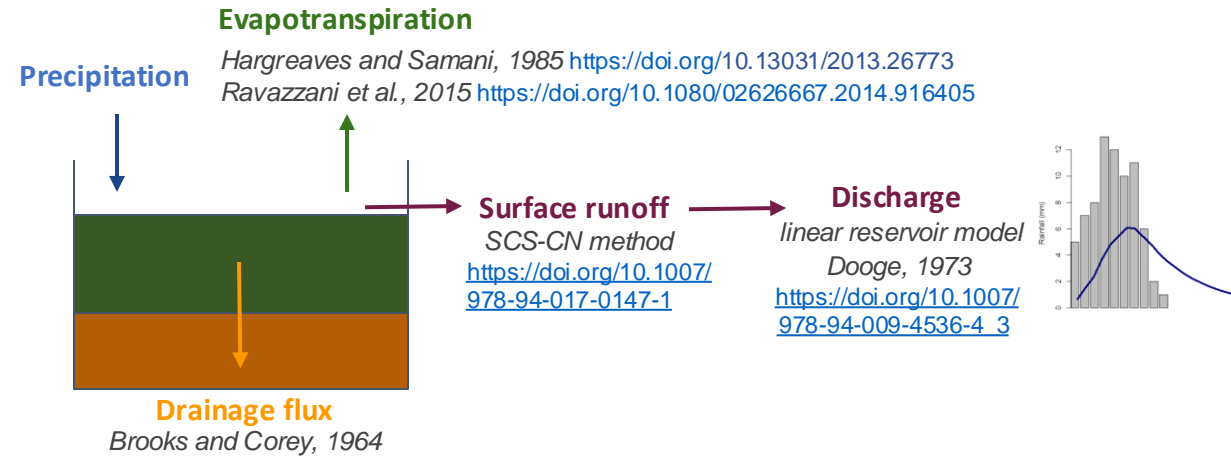
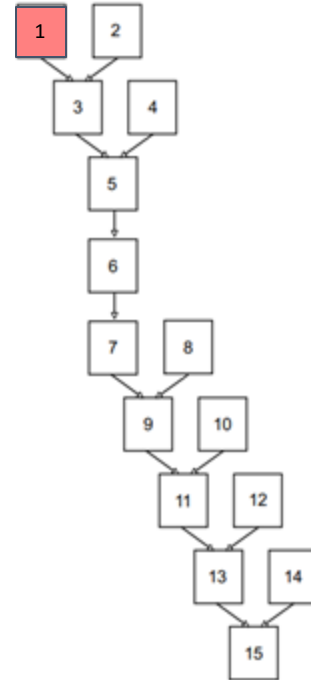


The hydrological model

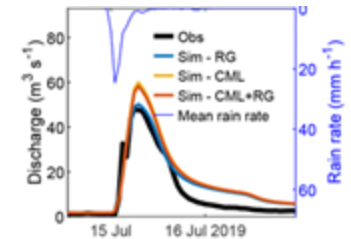
Semi-distributed model



Sub-catchment or hydrological response unit (HRU)

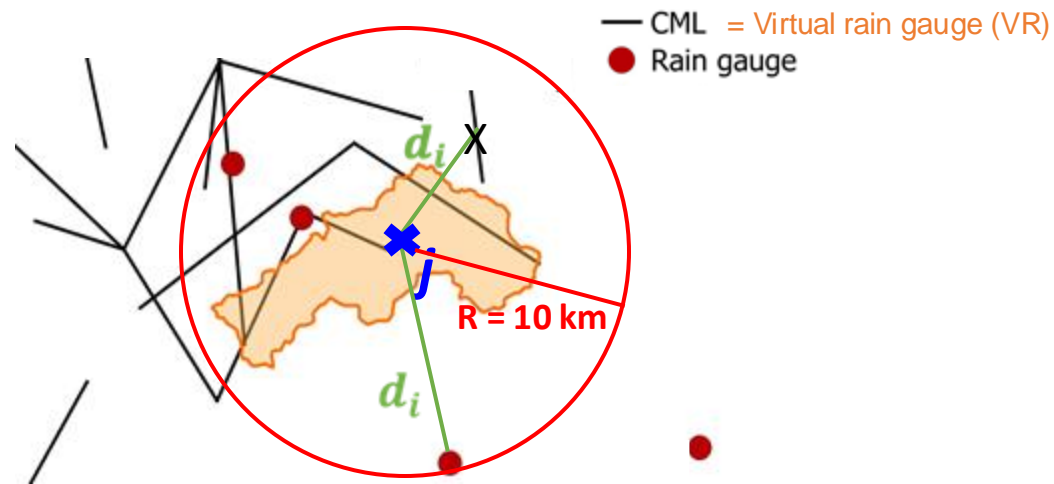


- ❖ Continuous and event-based simulation at hourly time scale
- ❖ Calibration over 1 year of data, maximizing the Nash-Sutcliffe efficiency



Integration of rainfall data into the hydrological model

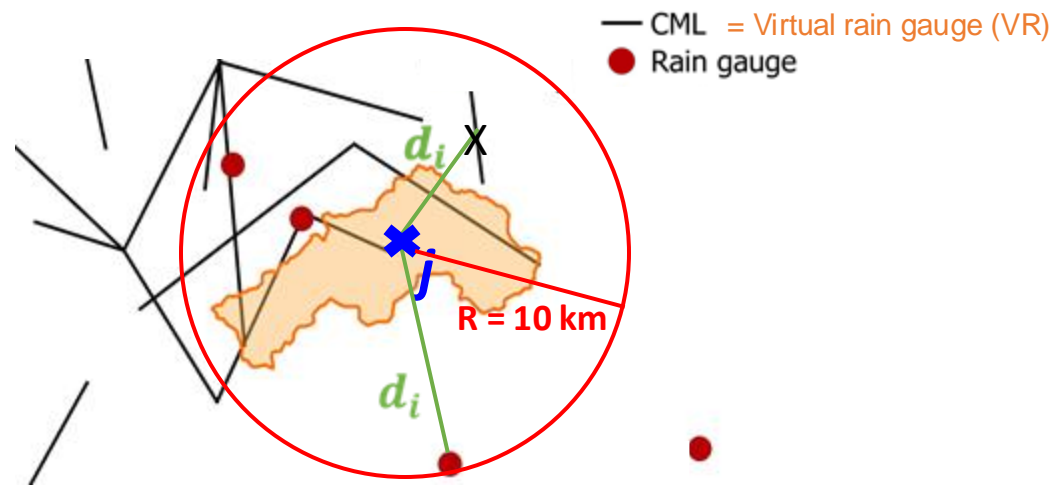
CML- and RG-based data:
Inverse distance weighting method



$$R_j = \frac{\sum_{i=1}^N w_i P_i}{\sum_{i=1}^N w_i} \quad w_i = \frac{1}{d_i^3}$$

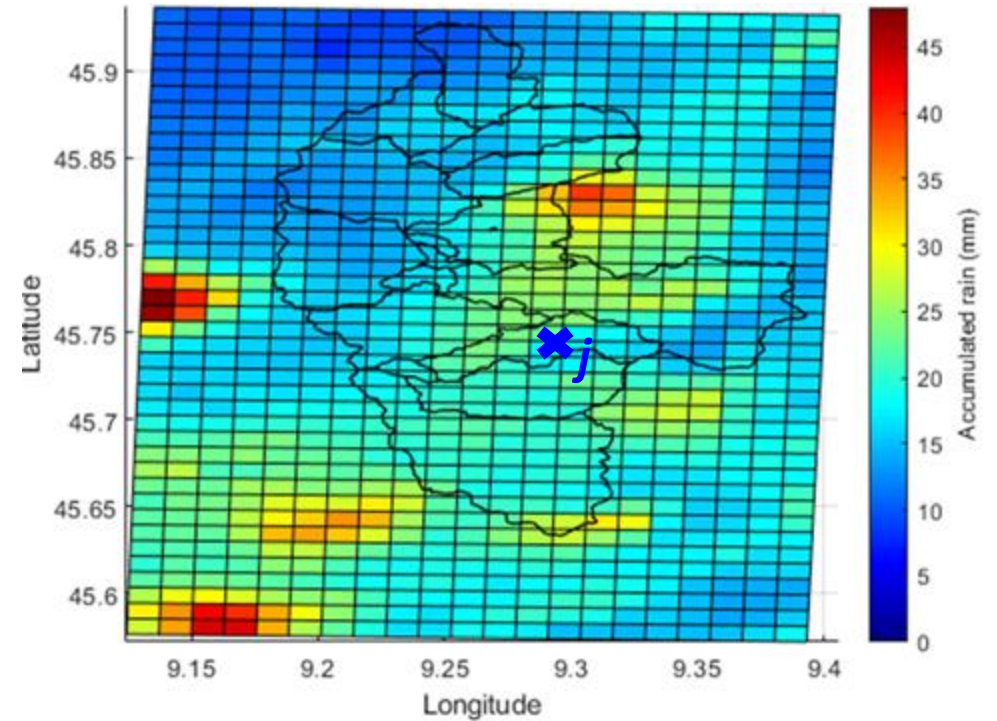
Integration of rainfall data into the hydrological model

CML- and RG-based data:
Inverse distance weighting method



$$R_j = \frac{\sum_{i=1}^N w_i P_i}{\sum_{i=1}^N w_i} \quad w_i = \frac{1}{d_i^3}$$

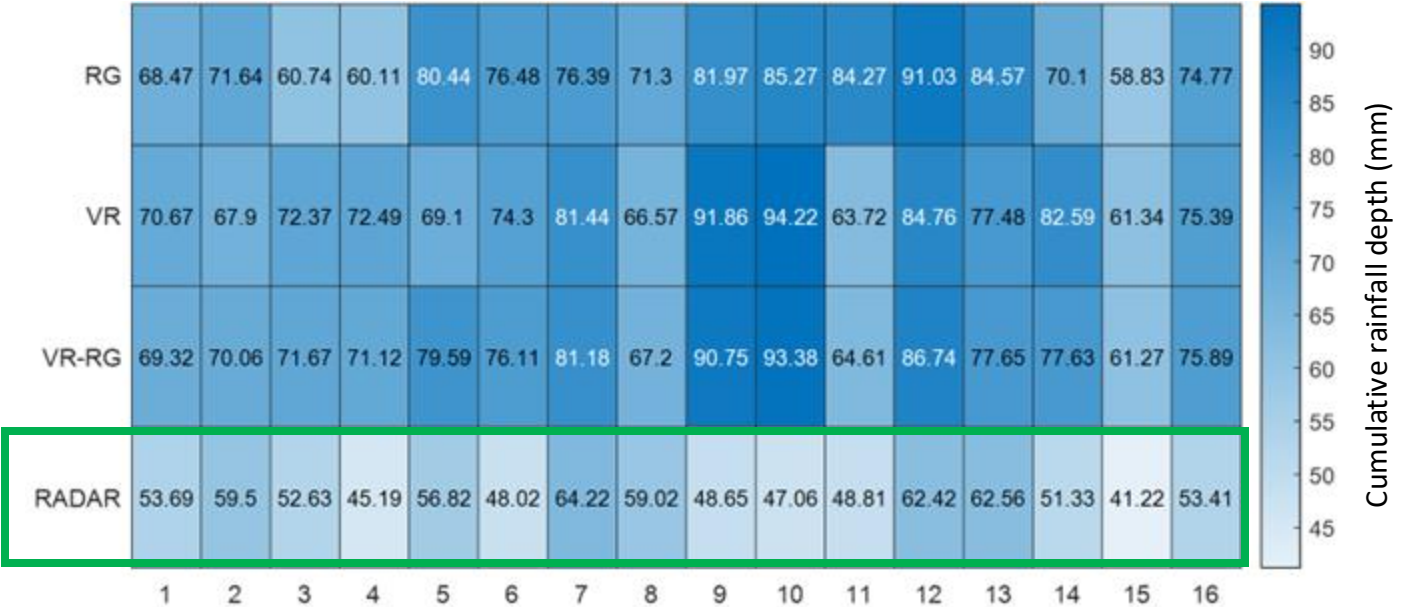
Radar-based data: spatial average



$$R_j = \frac{1}{N} \sum_{i=1}^N R_i \quad i = \text{pixel inside the } j\text{-th HRU}$$

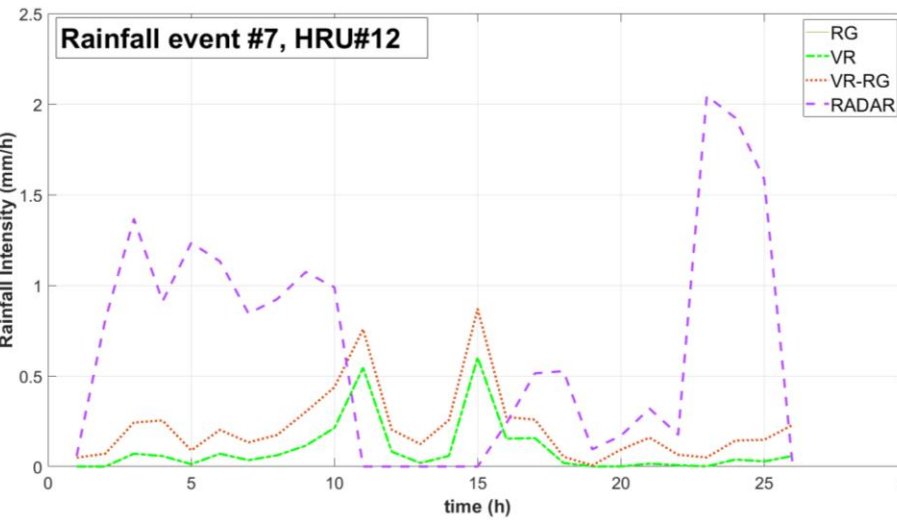
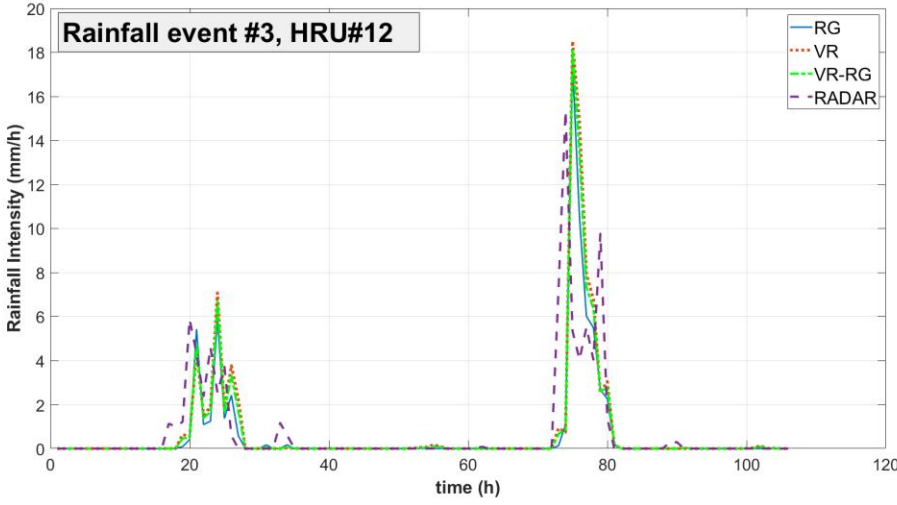
Rainfall measurements: CML vs rain gauges vs radar

Event #3



Underestimates due to the presence of mountains

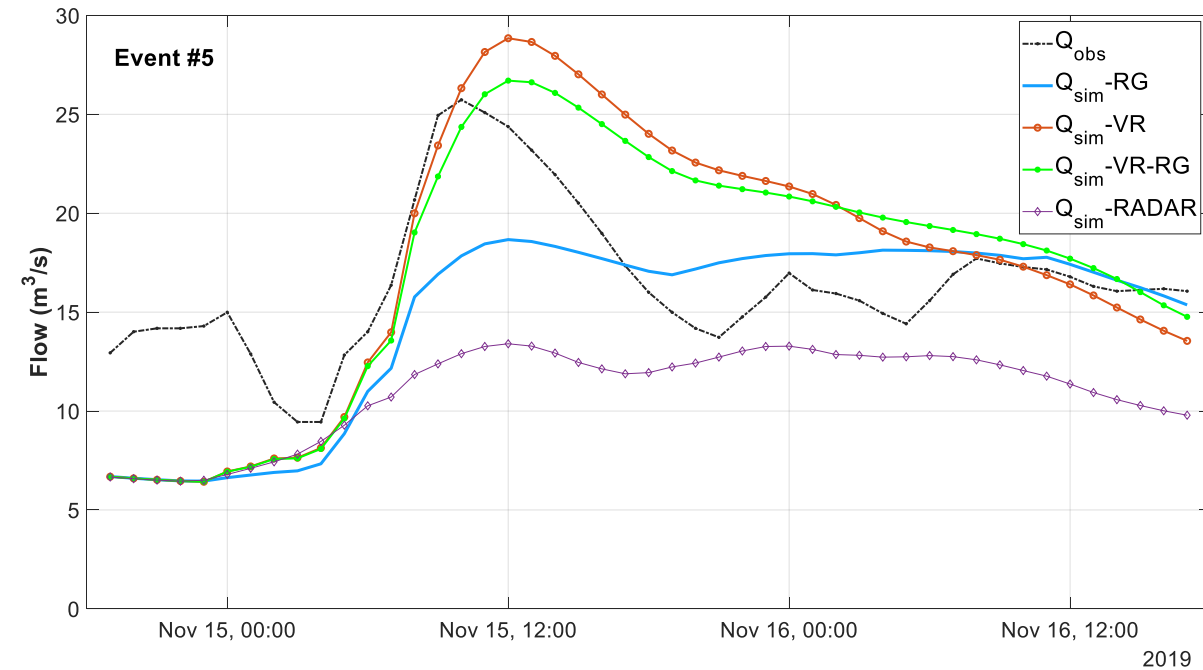
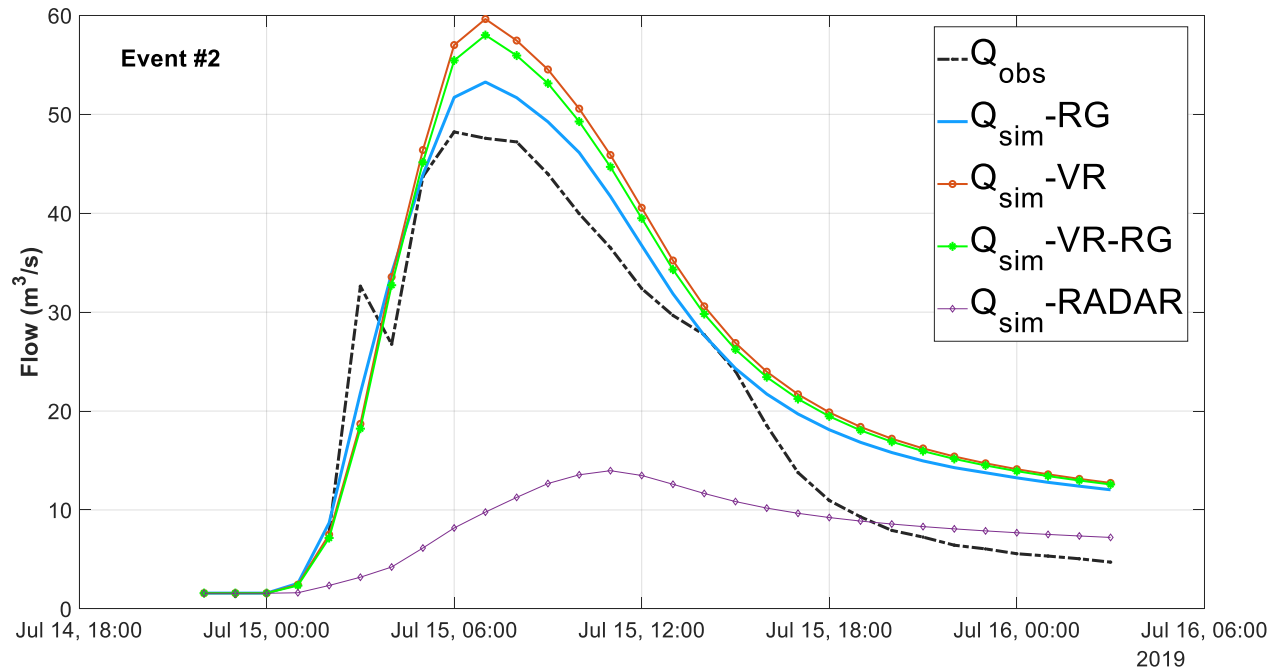
- RG - rain gauge
- VR - virtual rain gauge (CML data)
- VR-RG - rain gauge and CML data combined
- RADAR data



For some events the radar is unable to capture the rainfall dynamics

Results – Sensitivity to the rainfall input

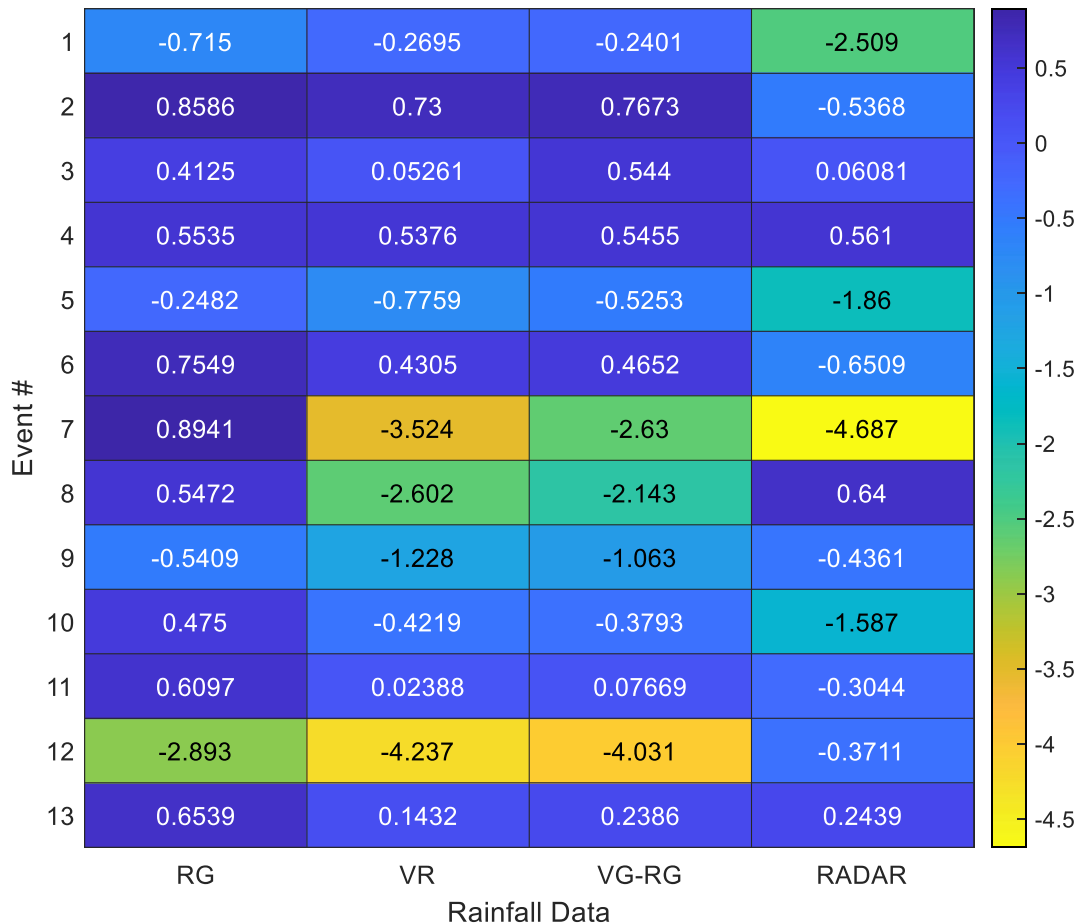
Rainfall input affects simulated hydrographs by the reference model



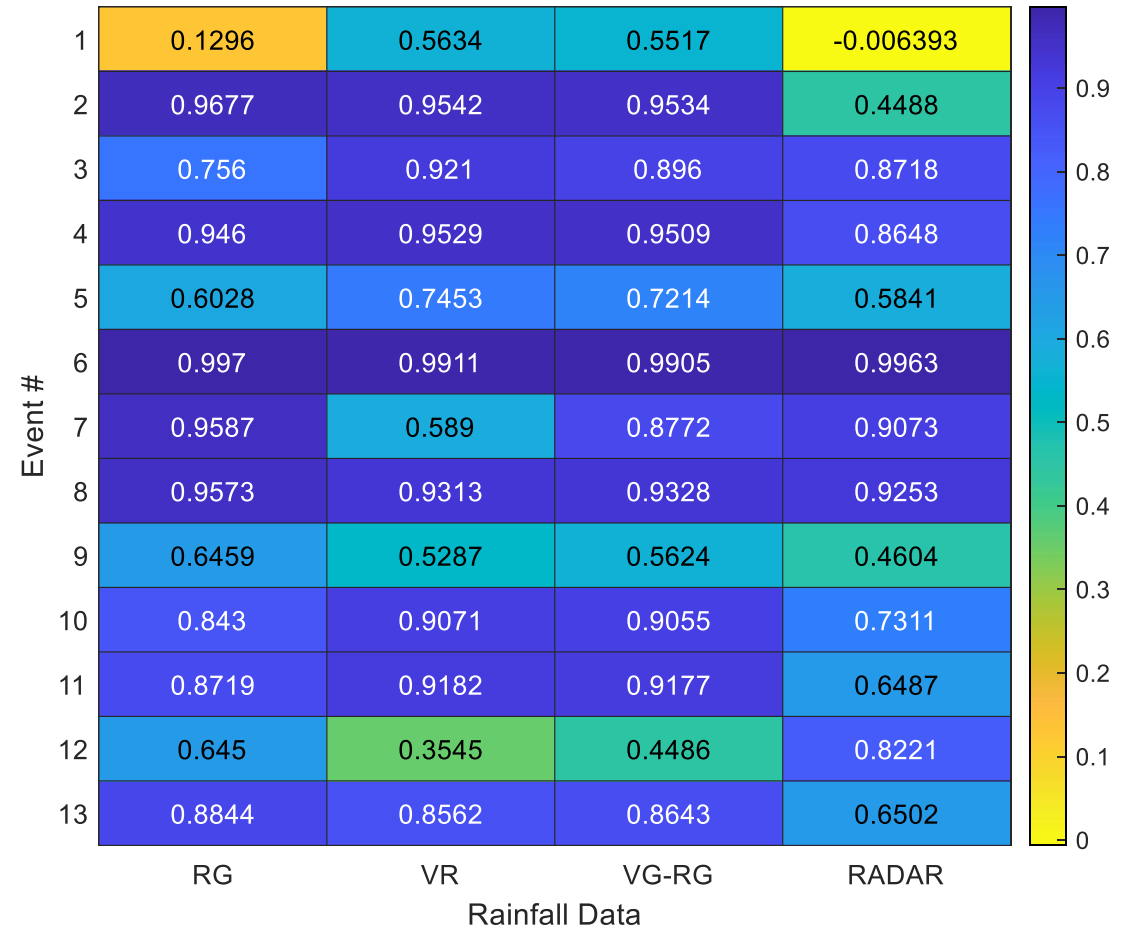
Results – Sensitivity to the rainfall input

Observed vs simulated streamflows by the reference model

NSE

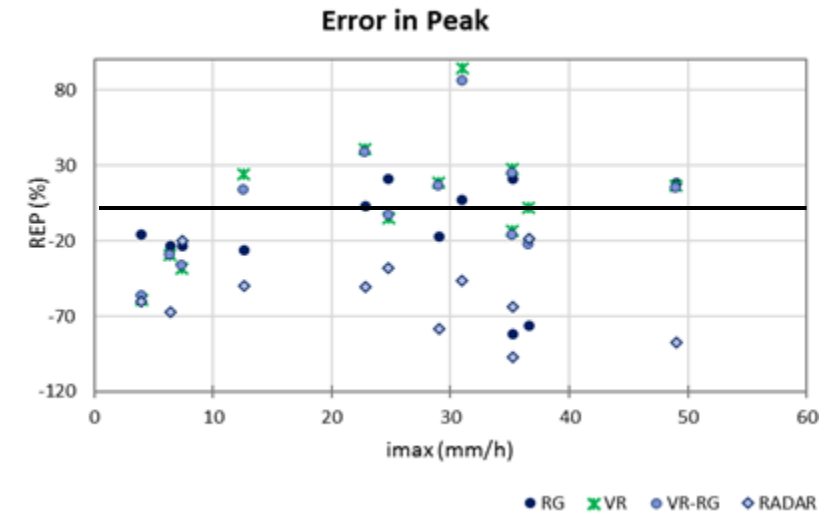
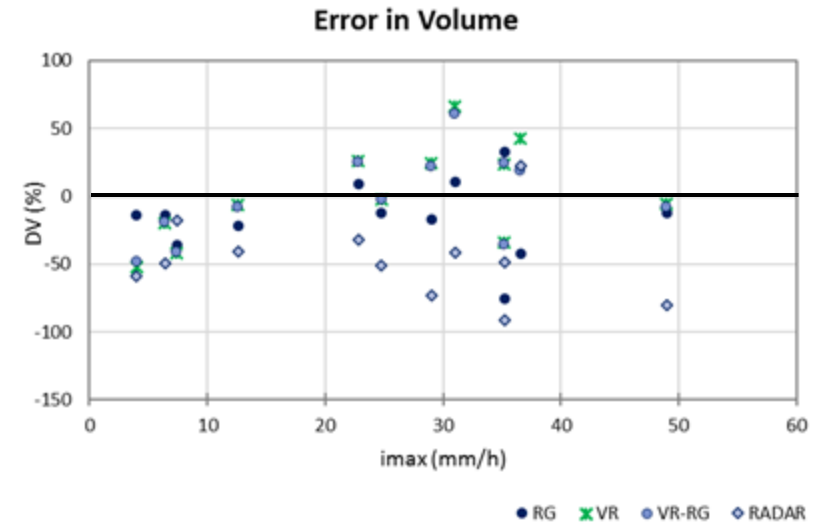
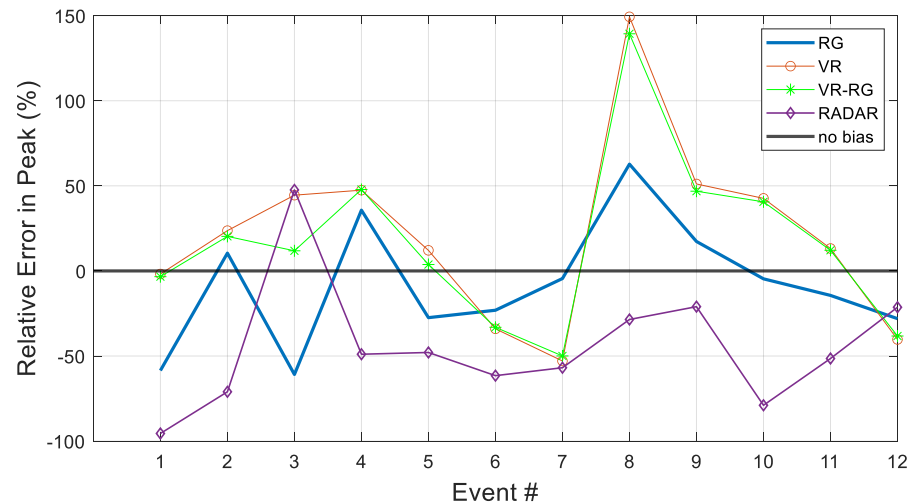
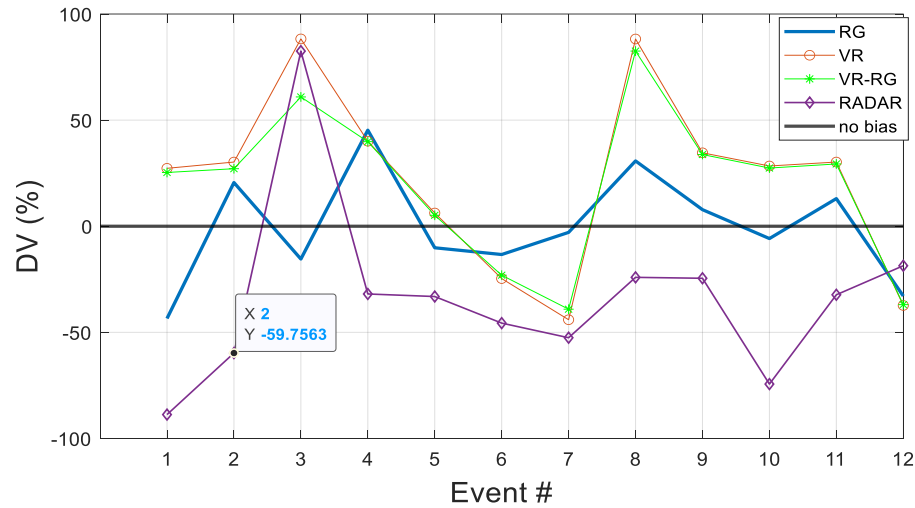


Pearson correlation coefficient



Results – Sensitivity to the rainfall input

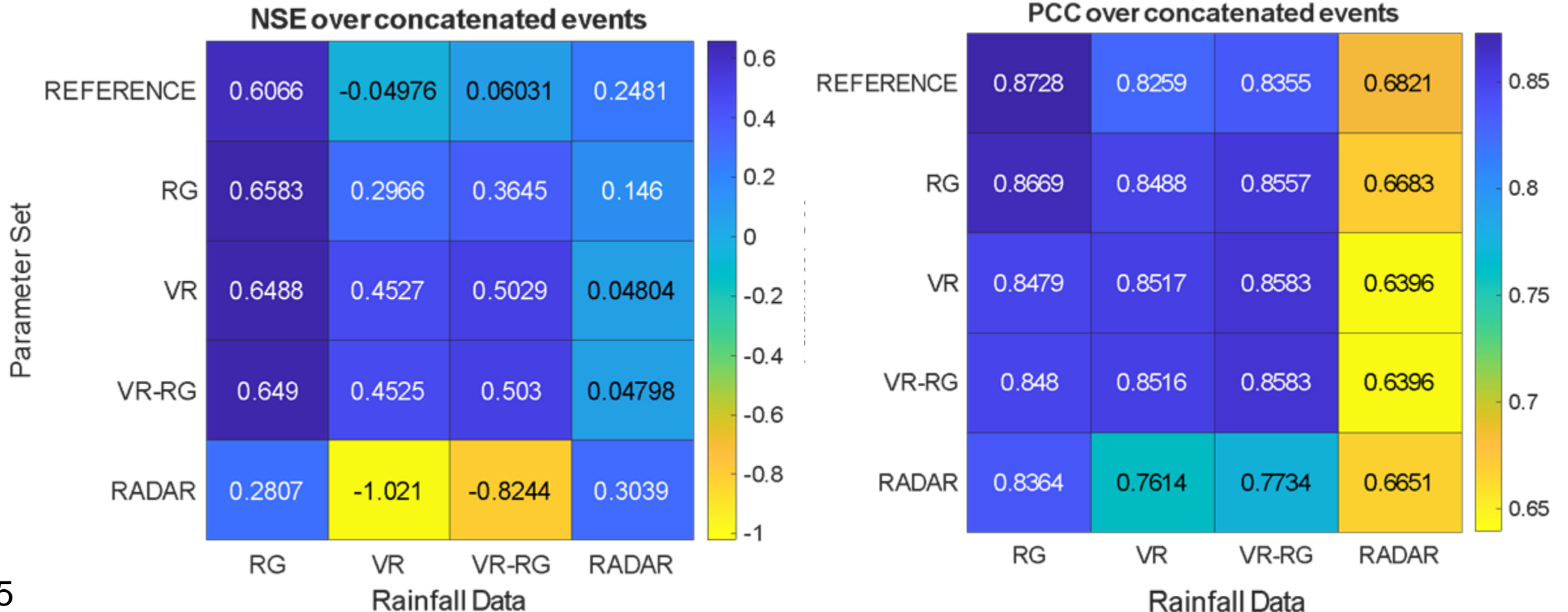
Errors in the simulated streamflows by the reference model



Results – Transferability across rainfall data

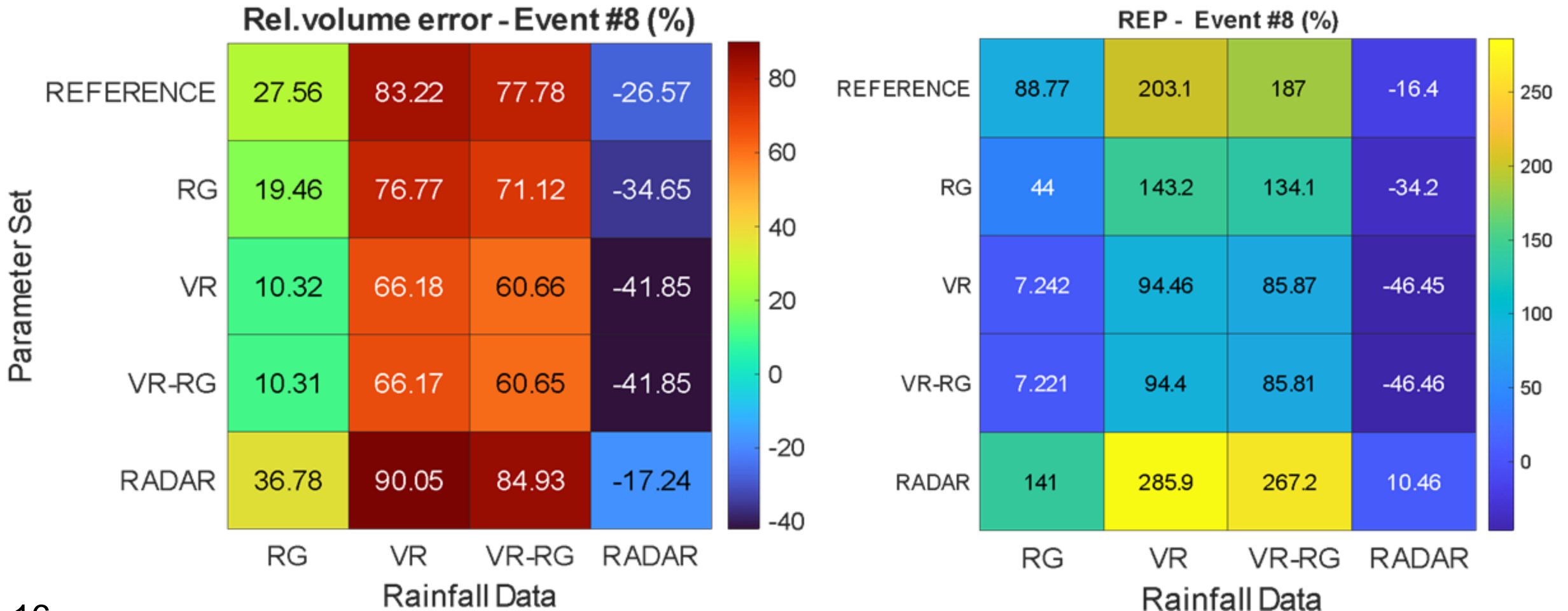
Parameter optimisation cannot compensate for the adequacy of rainfall data

- Additional model calibrations were performed for different rainfall data



Results – Transferability across rainfall data

Performance during a single rain event





Conclusions



Validation of rainfall measurements

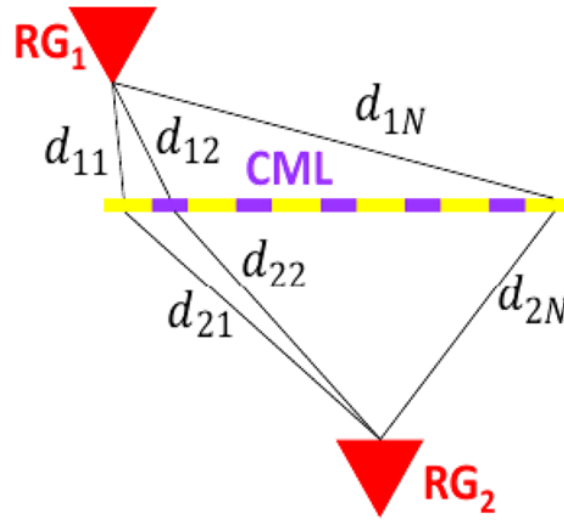
- ❖ **high-intensity events** detected by CML are **in a good accordance** with RG measurements;
- ❖ **inability of CMLs** to detect **low rain rates**, due to the coarse 1dB quantization step of raw data
- ❖ **radar-based** rainfall measurements tend to **underestimate** with respect to RG and CML data, due to the presence of mountains in the study region.



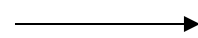
Validation of CML-derived streamflows

- ❖ **high model performance** can be obtained with the CML-derived rainfall data, although performance can vary across the events;
- ❖ **limited transferability** of models with the respect to the different **rainfall data**.

CML - nearby RGs comparison



$$\bar{d}_{RG1-CML} = \frac{1}{N} \sum_{i=1}^N d_{1i}$$



$$R = \frac{\sum_{i=1}^{N_{RG}} w_i R_{RG_i}}{\sum_{i=1}^{N_{RG}} w_i}, w_i = \frac{1}{d_{RG_i-CML}^3}$$