Towards hydrological validation of radar-based precipitation estimates and nowcasts

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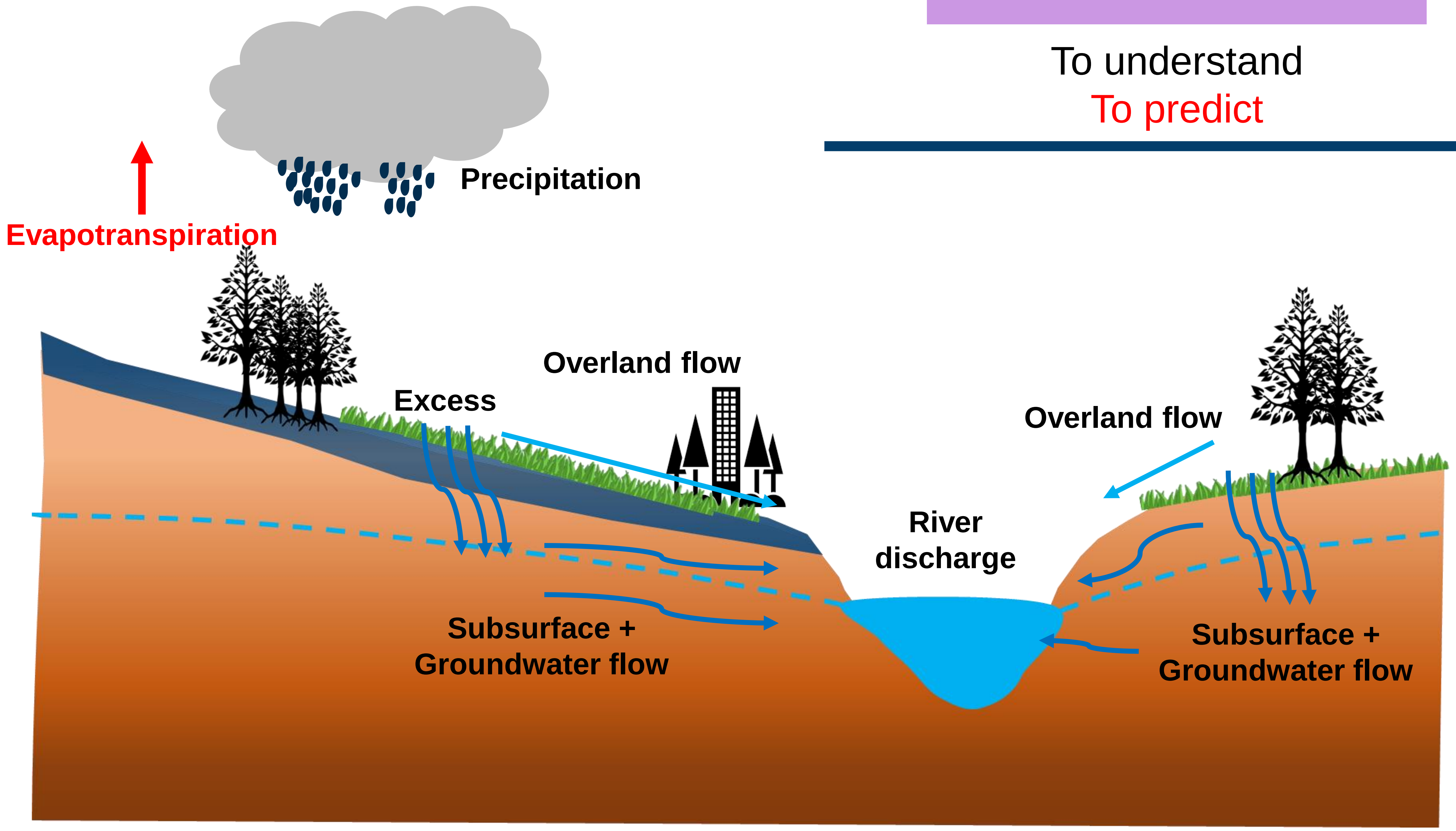
2022-02-01 | RealPEP meeting

1| Context and objectives

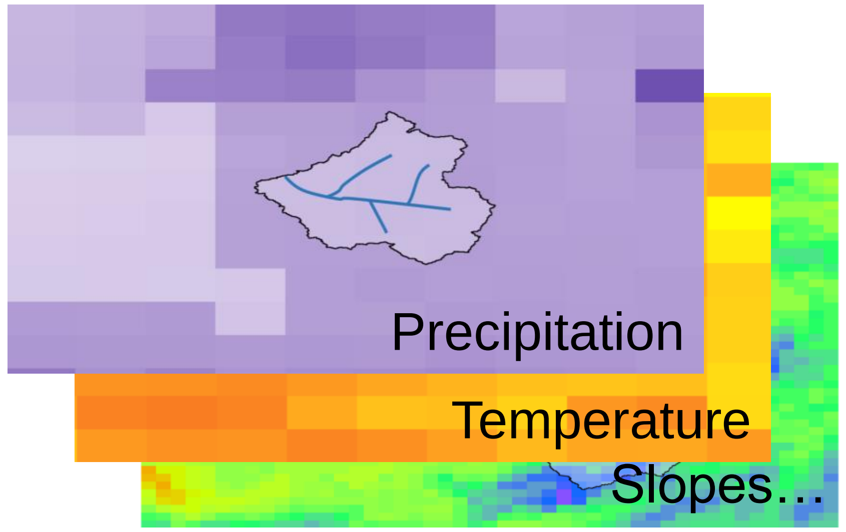


Conceptualization

To understand
To predict

Precipitation is one of the main controls on continental hydrological processes, especially at the event-scale → It impacts model outputs

Climate+ Landscape properties



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Hydrological model

↓

River discharge

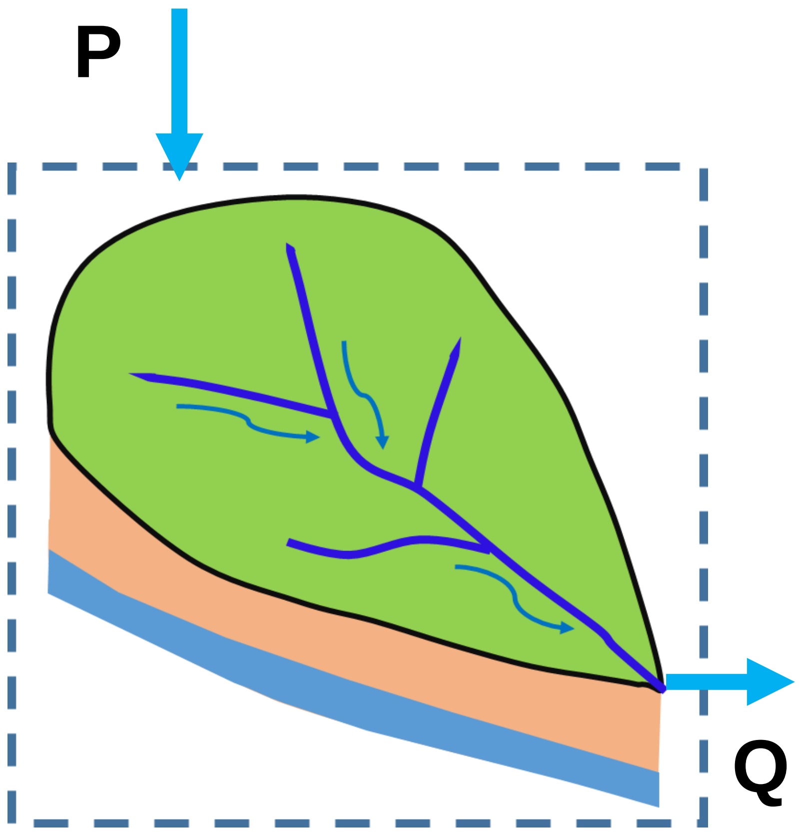
Soil moisture

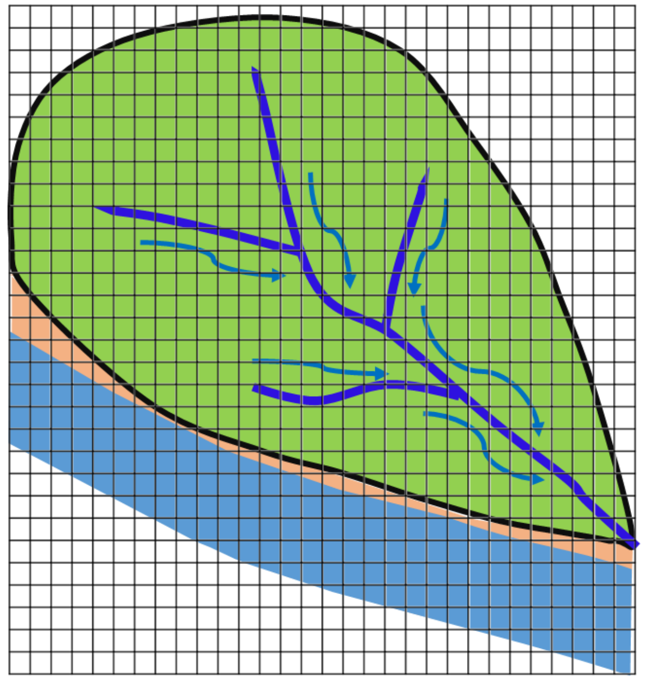
Water table depth

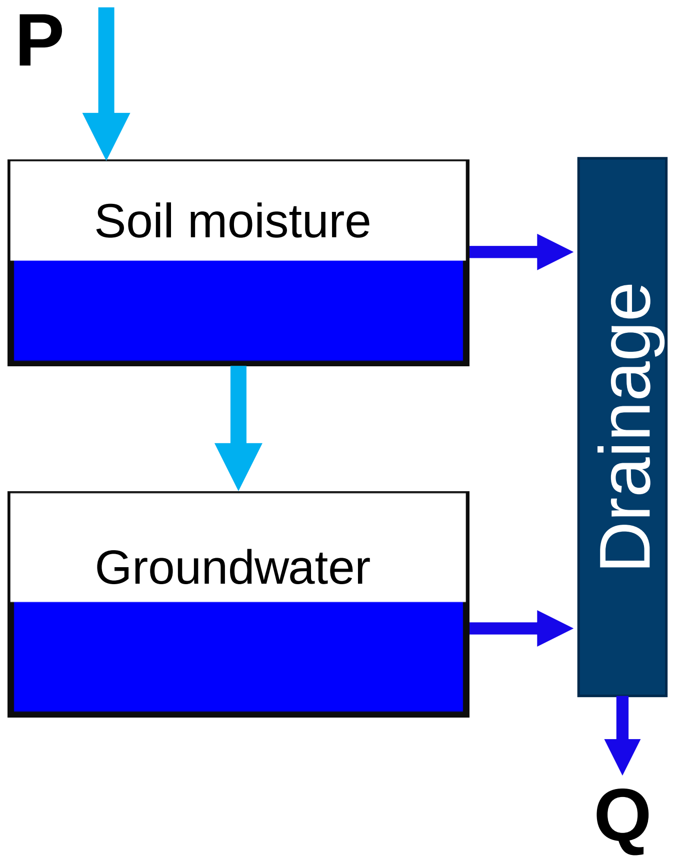
…

1| Context and objectives

A hydrological model can be:







3-D Richards equation

$$\begin{cases} S_s S_w(p)\dfrac{\partial p}{\partial t} + \varphi \dfrac{\partial S_w(p)}{\partial t} = \nabla q + q_s \\ q = -k_s k_r(p) \nabla (p - z) \end{cases}$$

1-D St Venant equation

$$\begin{cases} \dfrac{\partial A}{\partial t} + \dfrac{\partial Q}{\partial x} = q_{lateral} \\ g\dfrac{\partial y}{\partial x} + V\dfrac{\partial V}{\partial x} + \dfrac{\partial V}{\partial t} = g(S_0 - S_f) \end{cases}$$

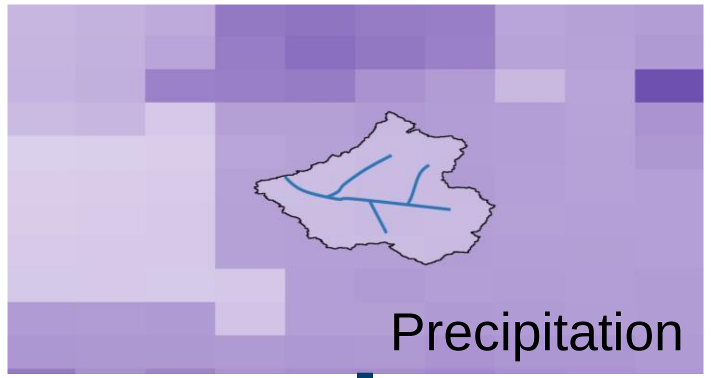
Systemic/lumped | Reductionist/distributed | Conceptual | Mechanistic

Loss of model interpretability
Less time-consuming, low data demand

Better process representation
Time-consuming and data-demanding

Hrachowitz & Clark (2017)

1| Context and objectives



Hydrological model

Simulated discharge

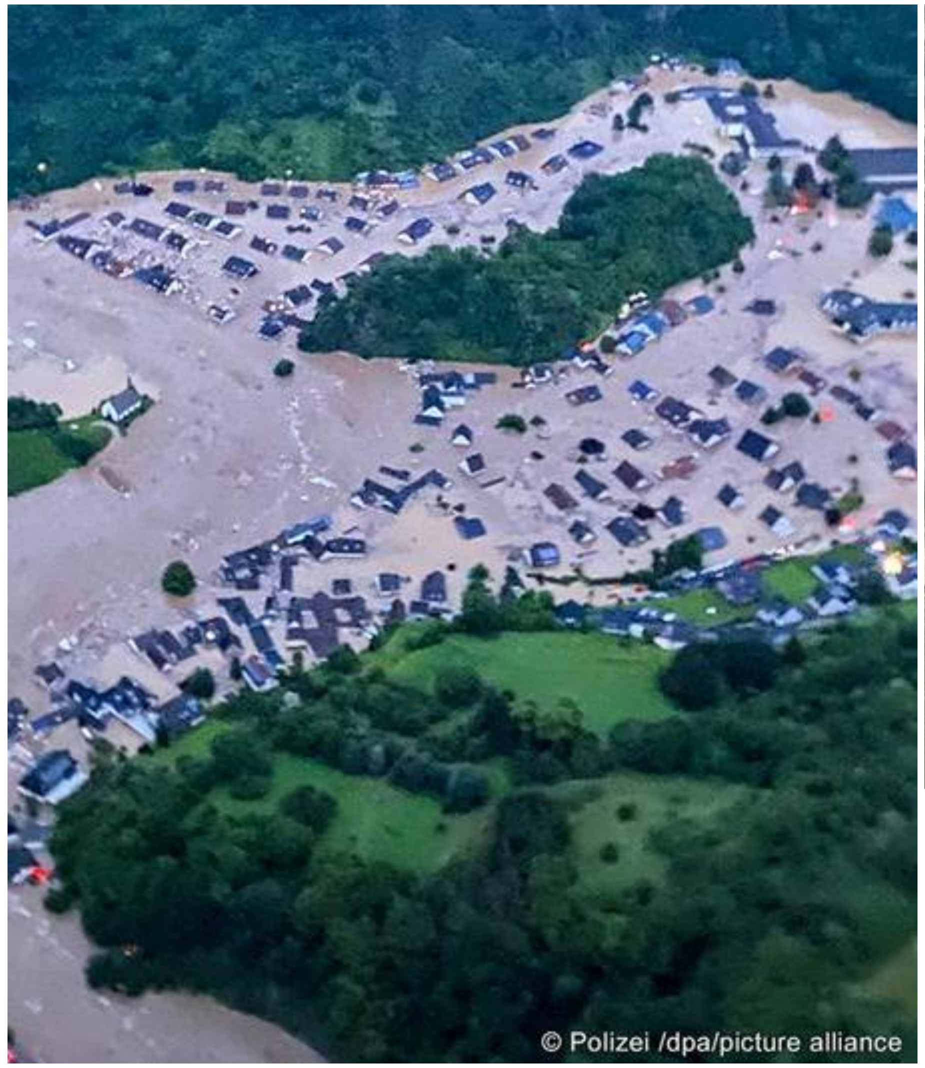
Observed discharge

Precipitation estimates are biased

Errors in model outputs

Hydrological models are valuable tools to validate the precipitation estimates

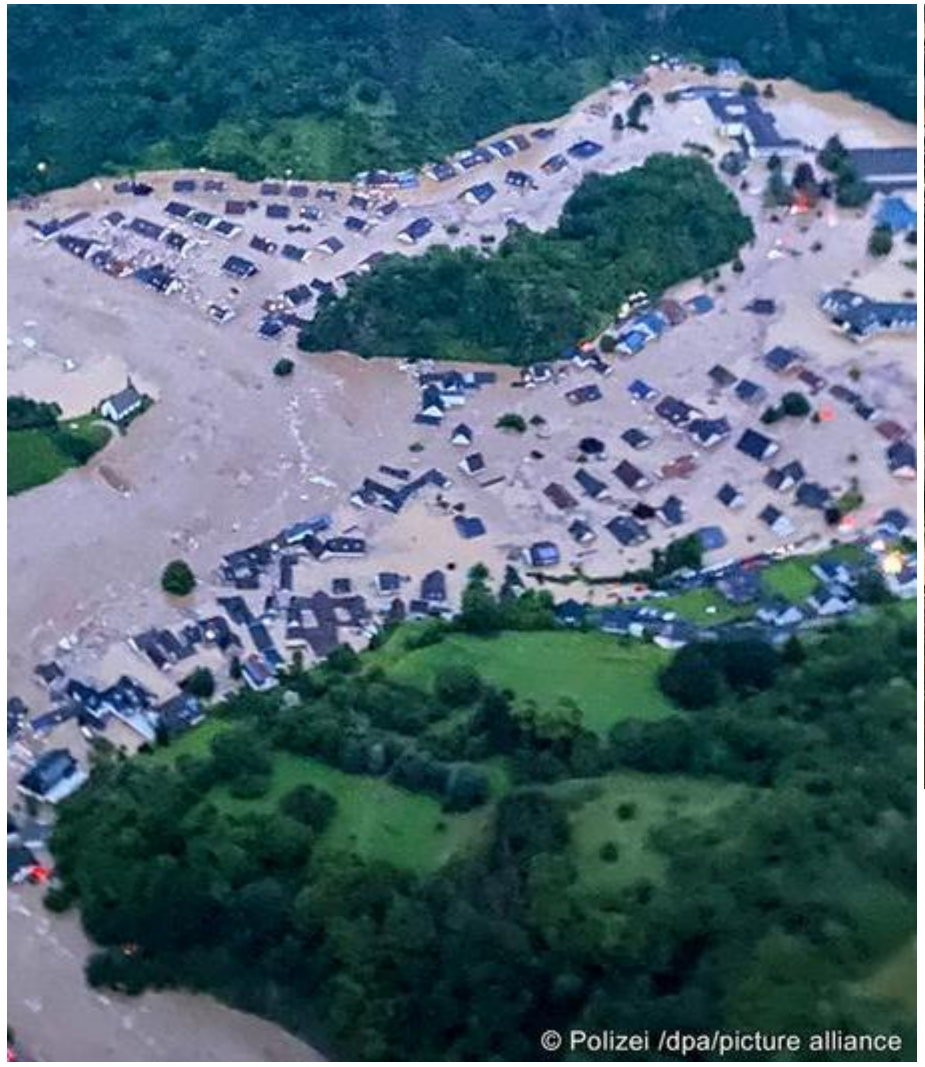
For flash flood cases (convective summer events), reliable precipitation estimates are crucial



July 2021 events at Altenahr and Erftstadt-Blessem (source: DW.com)

Challenge: instruments are generally destroyed, no discharge measurements for validation!

1| Context and objectives



July 2021 events at Altenahr and Erftstadt-Blessem (source: DW.com)

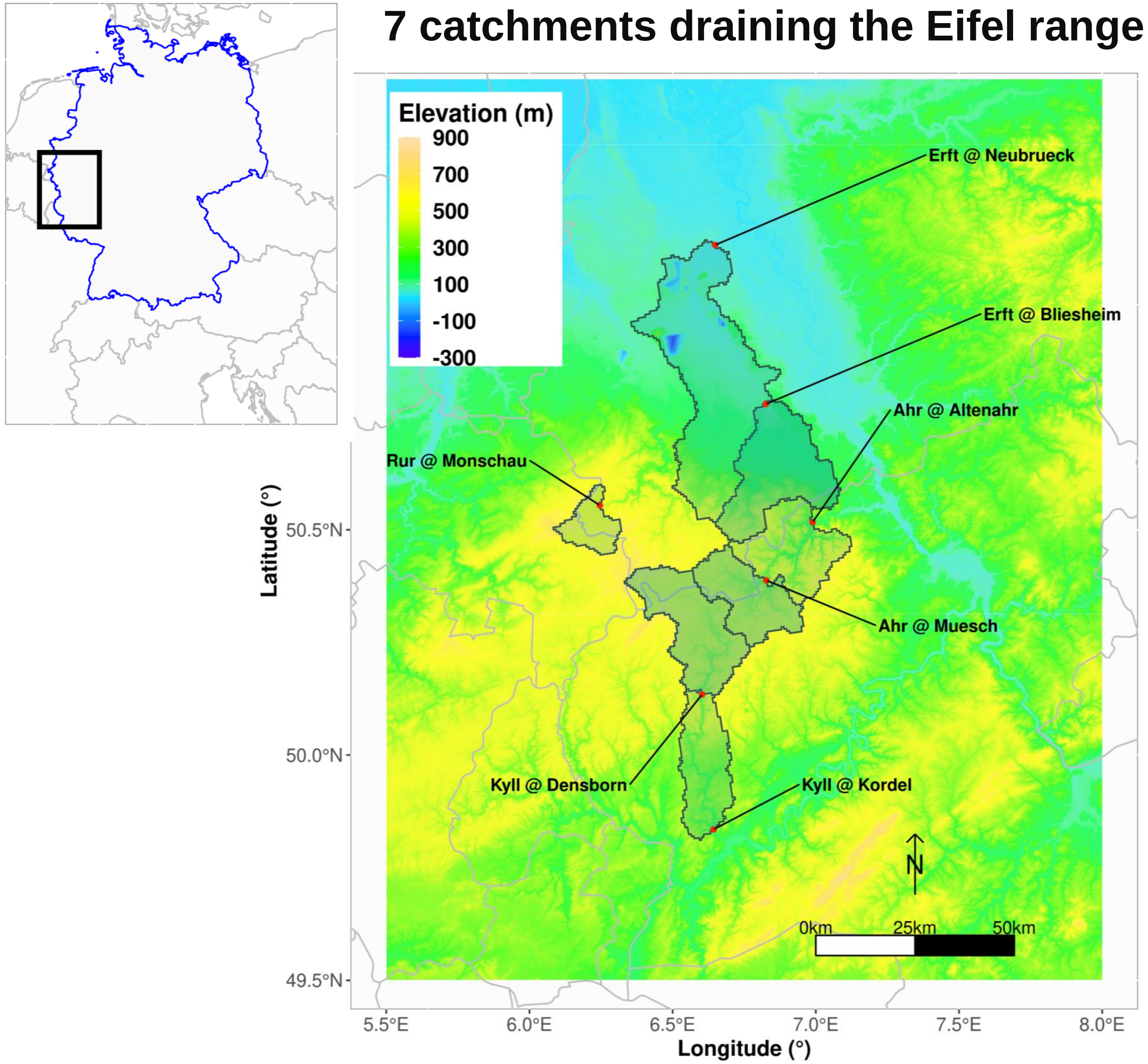
Q1. What were the chances of exceeding the highest measured peakflow, given different precipitation estimates (QPE) and hydrological models?

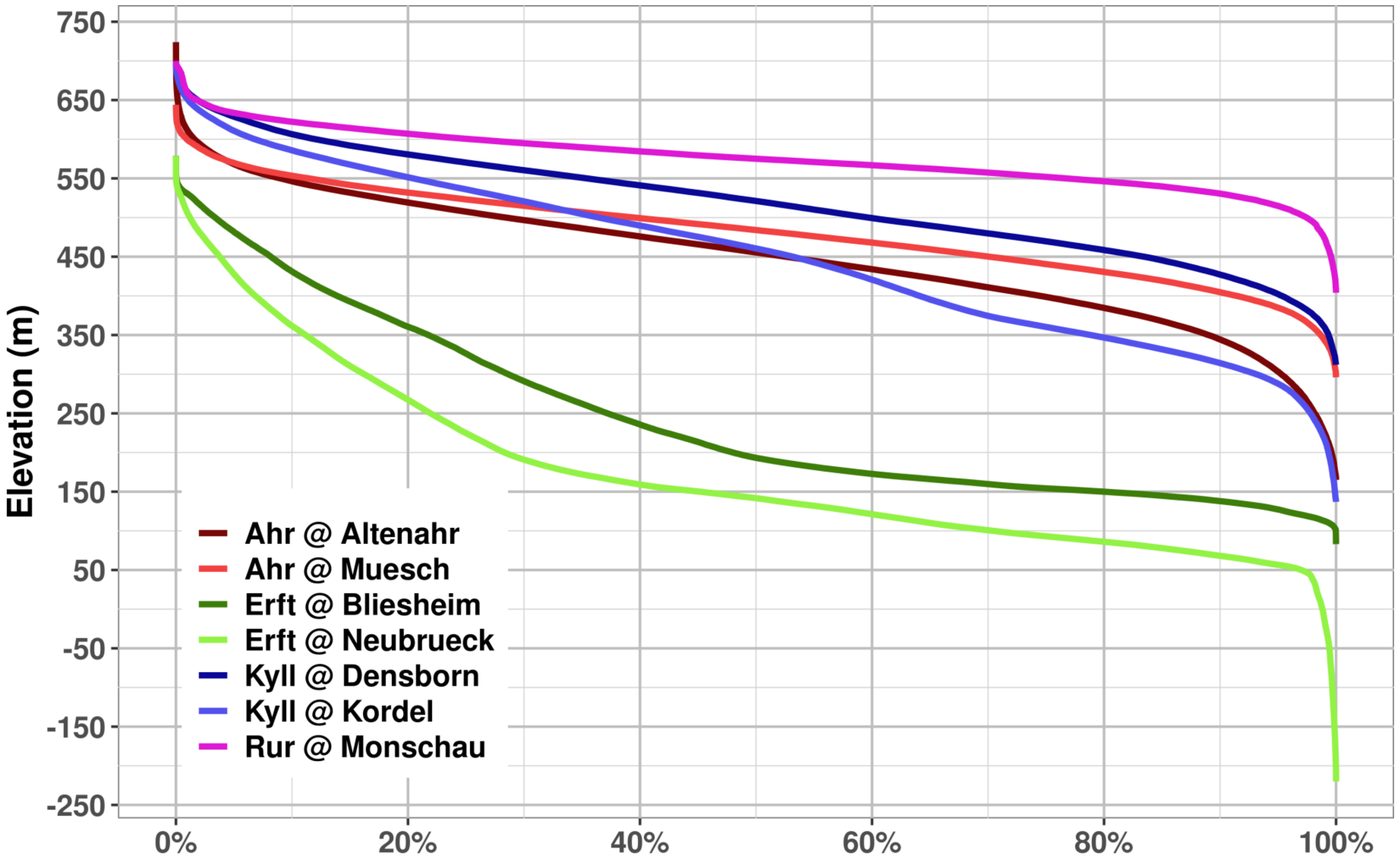
Q2. How do compare different methods of precipitation nowcasting in improving the lead time?

2| Catchments, models and data

2.1 | Catchments

7 catchments draining the Eifel range



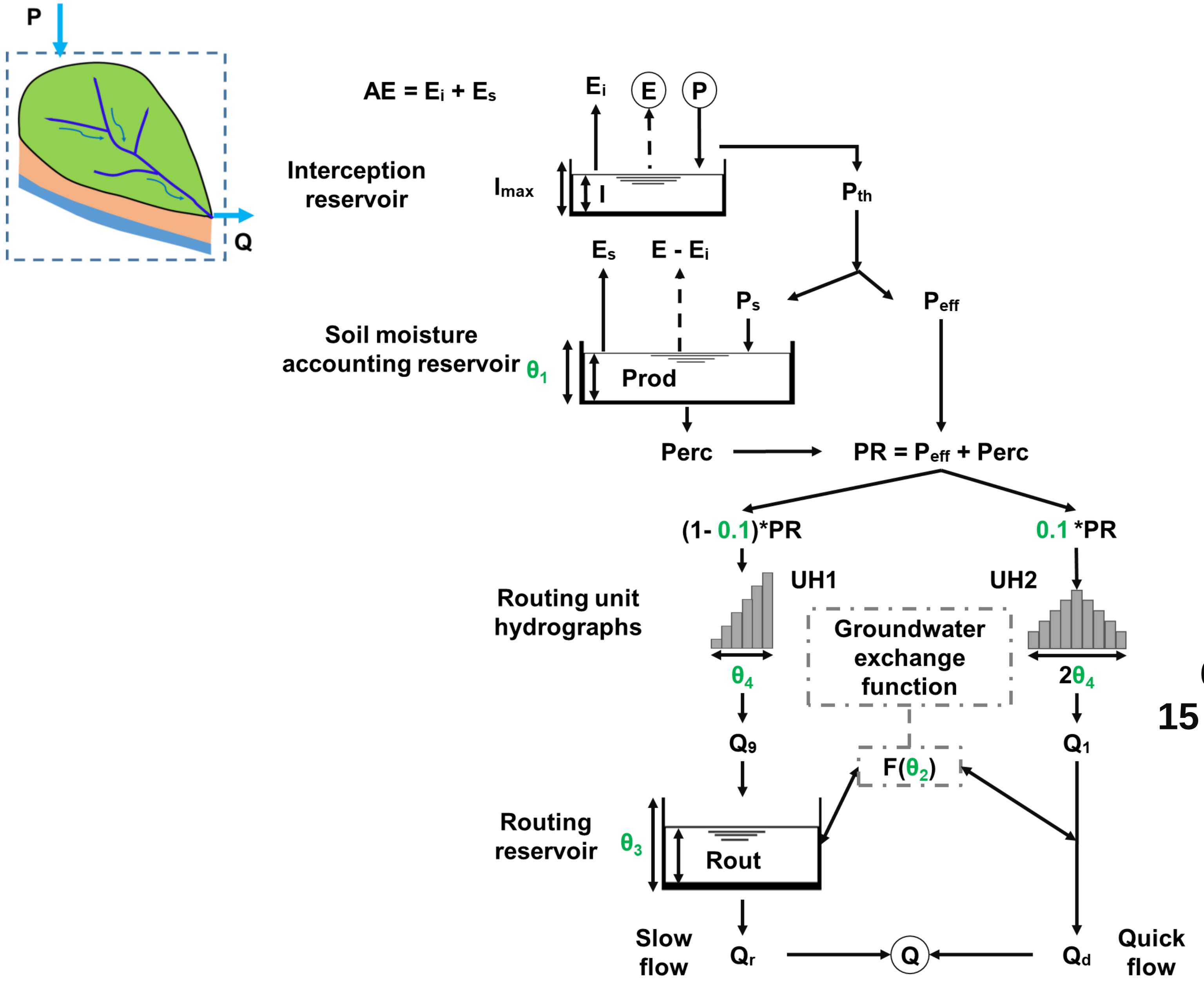


Area (km^2)	140 – 1670
Mean precipitation (mm/yr)	700 – 1070
Aridity index (-)	0.52 – 0.89
Mean discharge (mm/yr)	130 – 760

2| Catchments, models and data

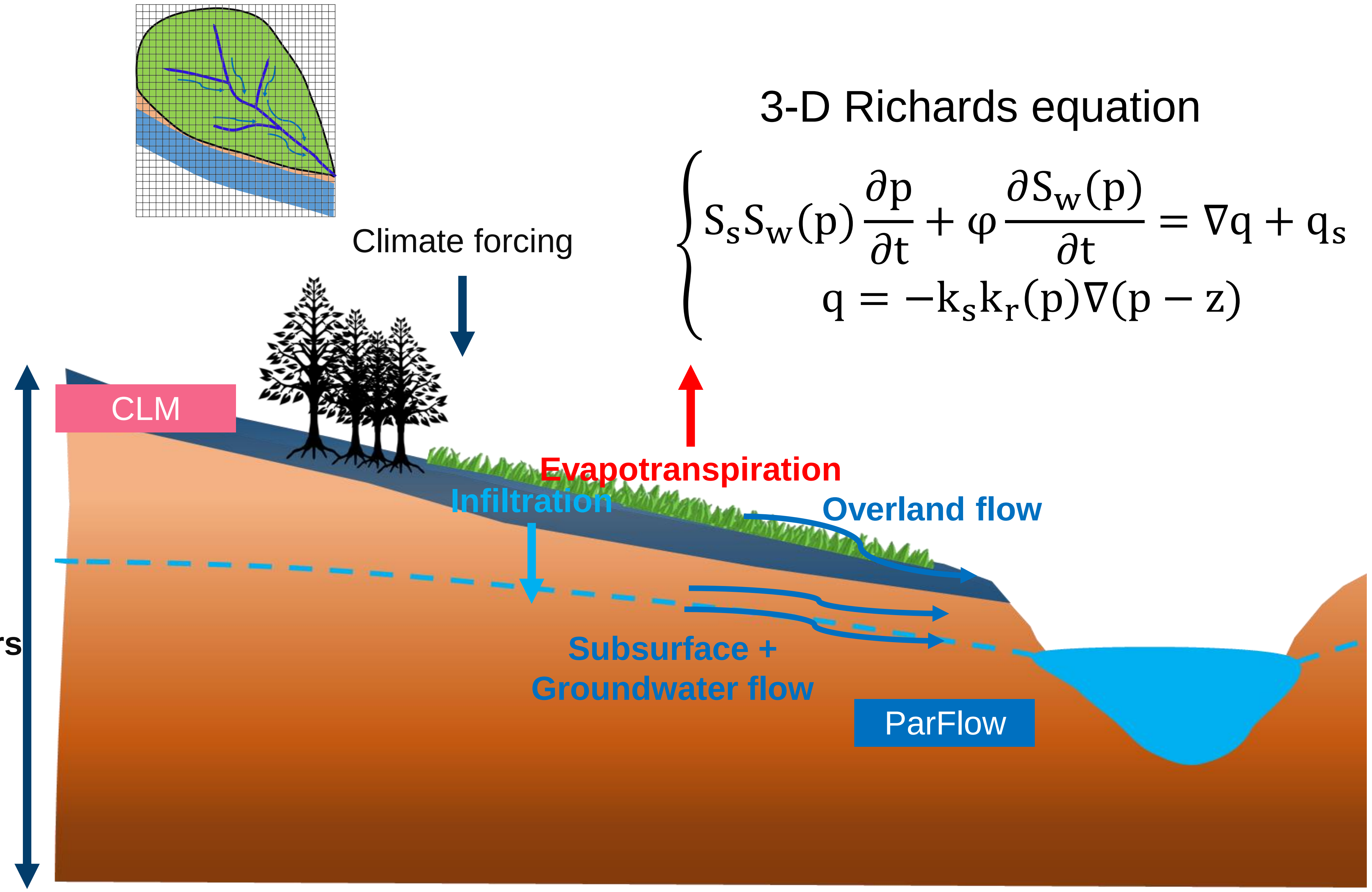
2.2 | Models

GR4H (Ficchì et al. 2019)



Conceptual, lumped, hourly

ParFlow-CLM (Kollet & Maxwell, 2006, 2008)



$$\begin{cases} S_s S_w(p)\dfrac{\partial p}{\partial t} + \varphi\dfrac{\partial S_w(p)}{\partial t} = \nabla q + q_s \\ q = -k_s k_r(p)\nabla(p - z) \end{cases}$$

PDE-based, 3D distributed model, hourly

2| Catchments, models and data

2.3 | Data

GR4H (Ficchì et al. 2019)

Catchment-averaged inputs

- Precipitation (RADOLAN)
- 2-m air temperature (ERA5-LAND)

Catchment-averaged parameters

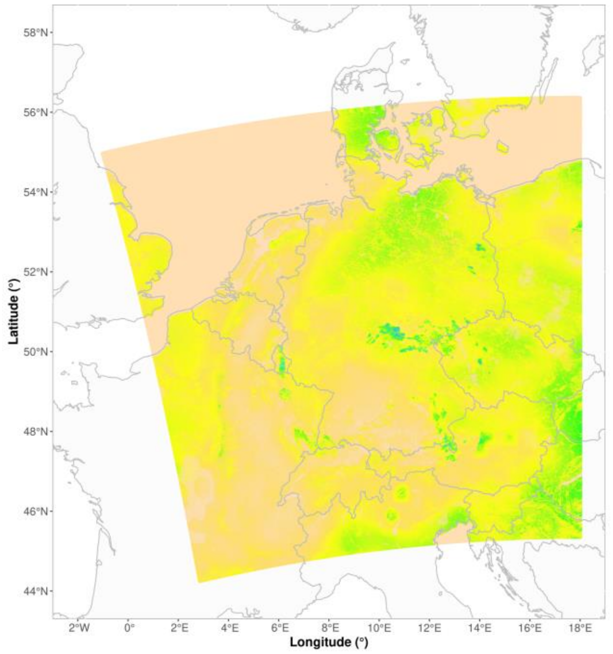
- 4 parameters, calibrated using discharge data (LANUV-NRW, LfU-RLP), 2007-2021
- Calibration needs definition of objective function and period of calibration → **12 optimal parameter sets for each catchment**

Runs on local computer

ParFlow-CLM **(Kollet & Maxwell, 2006, 2008)**

Cell-averaged inputs (for 2000x2000x15 cells over Central Europe, 611m resolution)

- Precipitation (RADOLAN & ERA5-LAND)
- 2-m air temperature (ERA5-LAND)
- Surface pressure (ERA5-LAND)
- 10-m u and v wind components(ERA5-LAND)
- Surface solar/thermal radiation downwards (ERA5-LAND)



Cell-averaged parameters

- Topography: ASTER+MERIT DEMs
- Land cover: CLC2018, reclassed in 18 IGBP types
- Soil types: SoilGrids250m, grouped into 12 USDA classes and IHME
- Manning's n = $5.5\cdot10^{-5}$ h·m$^{-1/3}$
- **Only 1 parametrization for the whole domain**

Runs on GPUs of the JUWELS HPC system
(4 nodes x 512 GiB)

3| Q1. Impact of QPE & modeling choices on peakflow

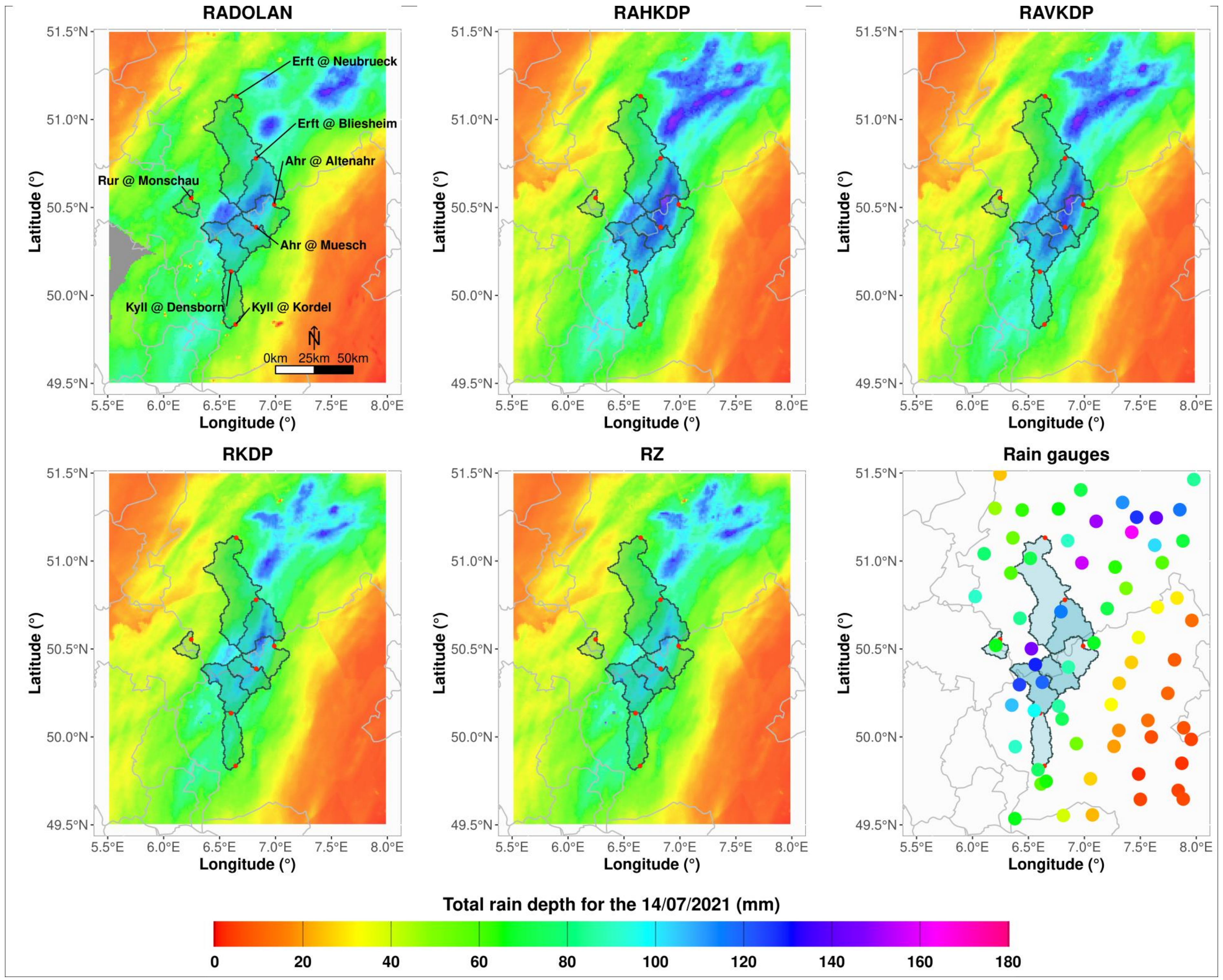
3.1 | QPE products for the 14.07.2021

Name	Parameters	Source	Run with
Rain Gauges	-	DWD	Only GR4H
RADOLAN	Reflectivity, gauge-adjusted	DWD	GR4H and ParFlowCLM
RZ	Horizontal reflectivity $R(Z_h)$	Chen et al. (2021)	
RKDP	Horizontal reflectivity + specific differential phase $R(Z_h)/R(K_{DP})$		
RAHKDP	Specific attenuation of horizontally polarized radar waves + specific differential phase $R(A_h)/R(K_{DP})$		
RAVKDP	Specific attenuation of vertically polarized radar waves + specific differential phase $R(A_V)/R(K_{DP})$		

Chen et al. (2021)

3| Q1. Impact of QPE & modeling choices on peakflow

3.2 | Result 1: Differences between QPE products



Similar spatial pattern

Higher rainfall rates for RAHKDP and RAVKDP

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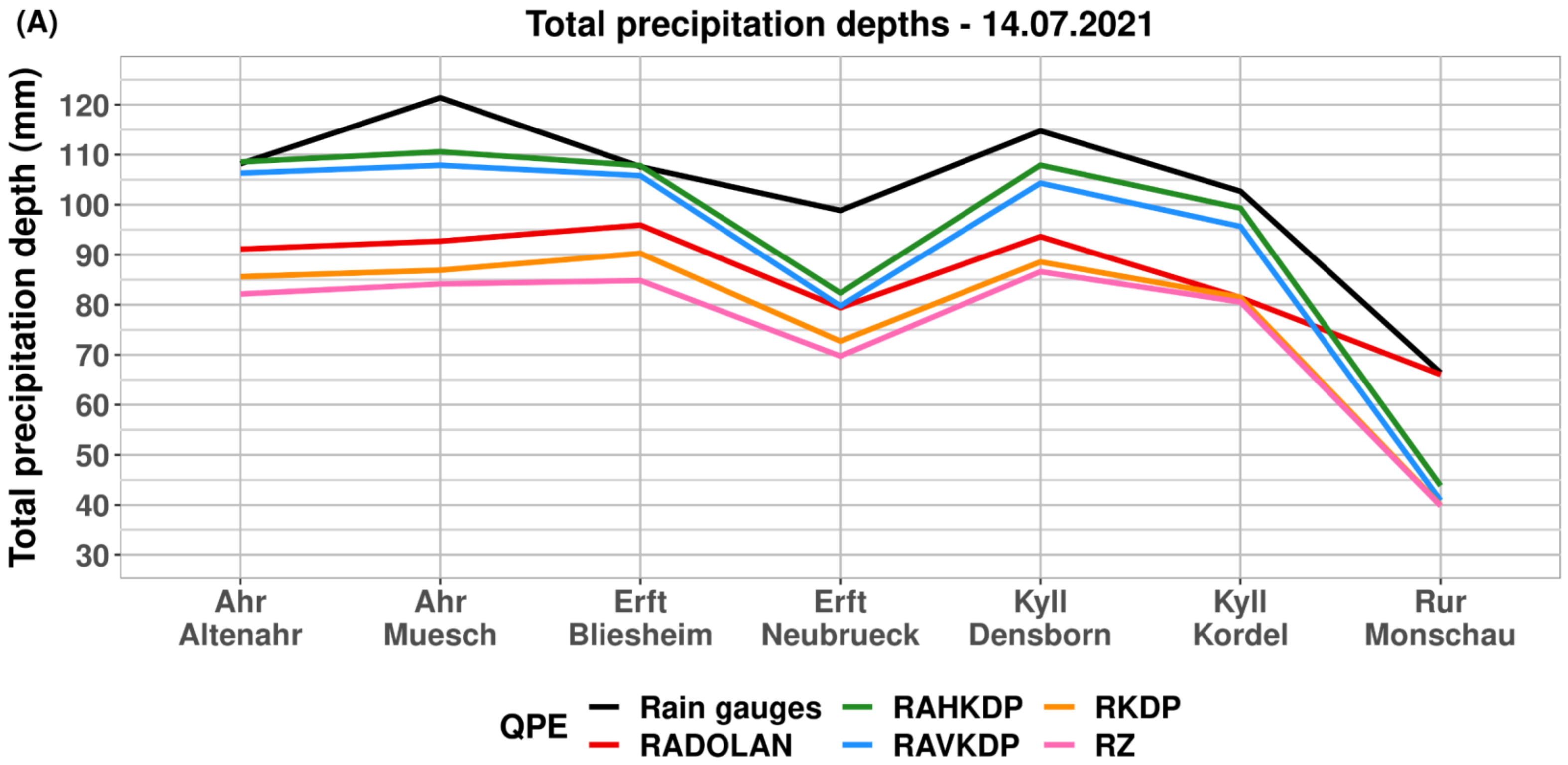
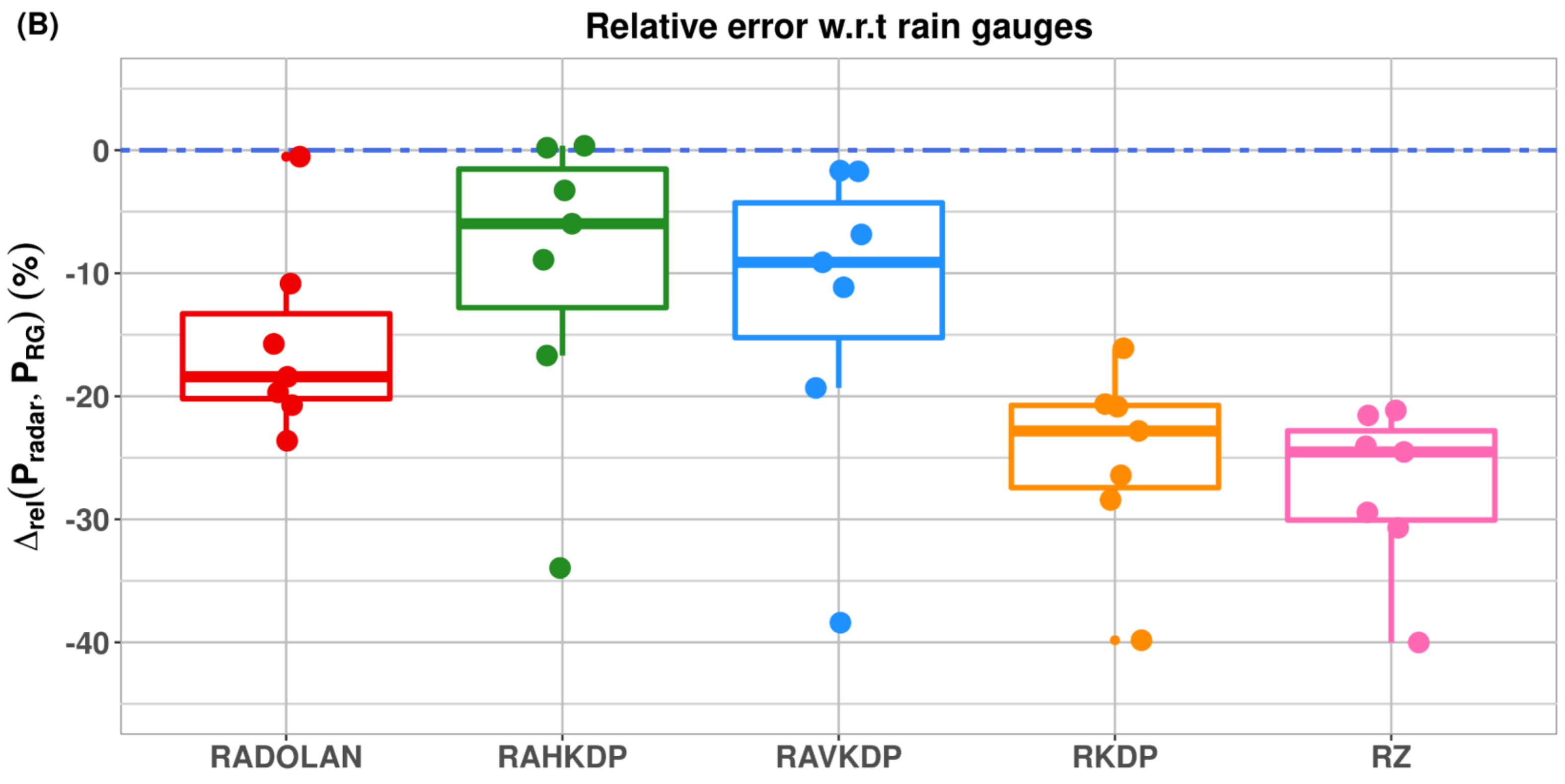
3.2 | Result 1: Differences between QPE products





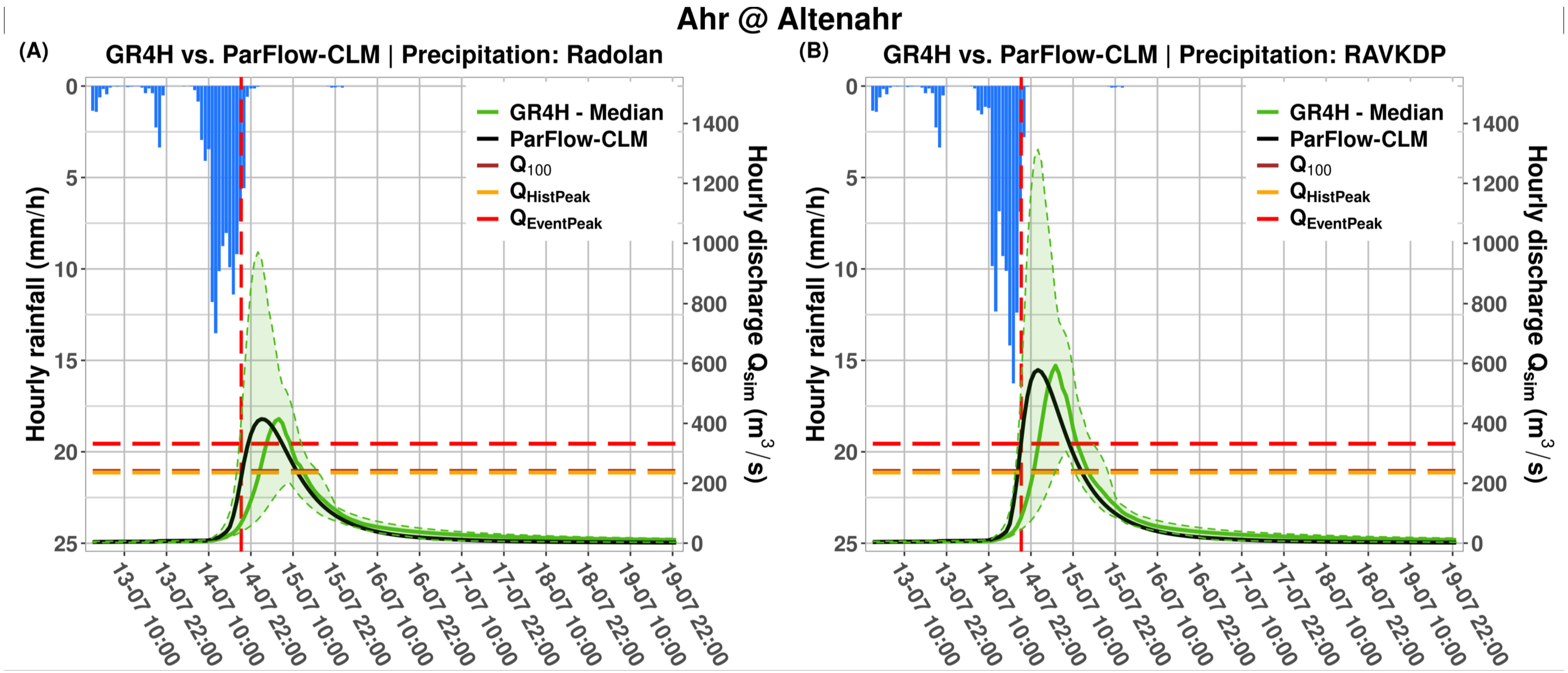
Similar spatial pattern

Higher rainfall rates for RAHKDP and RAVKDP

For most catchments, RAHKDP and RAVKDP gave similar results to rain gauges, compared to the other QPEs

3| Q1. Impact of QPE & modeling choices on peakflow

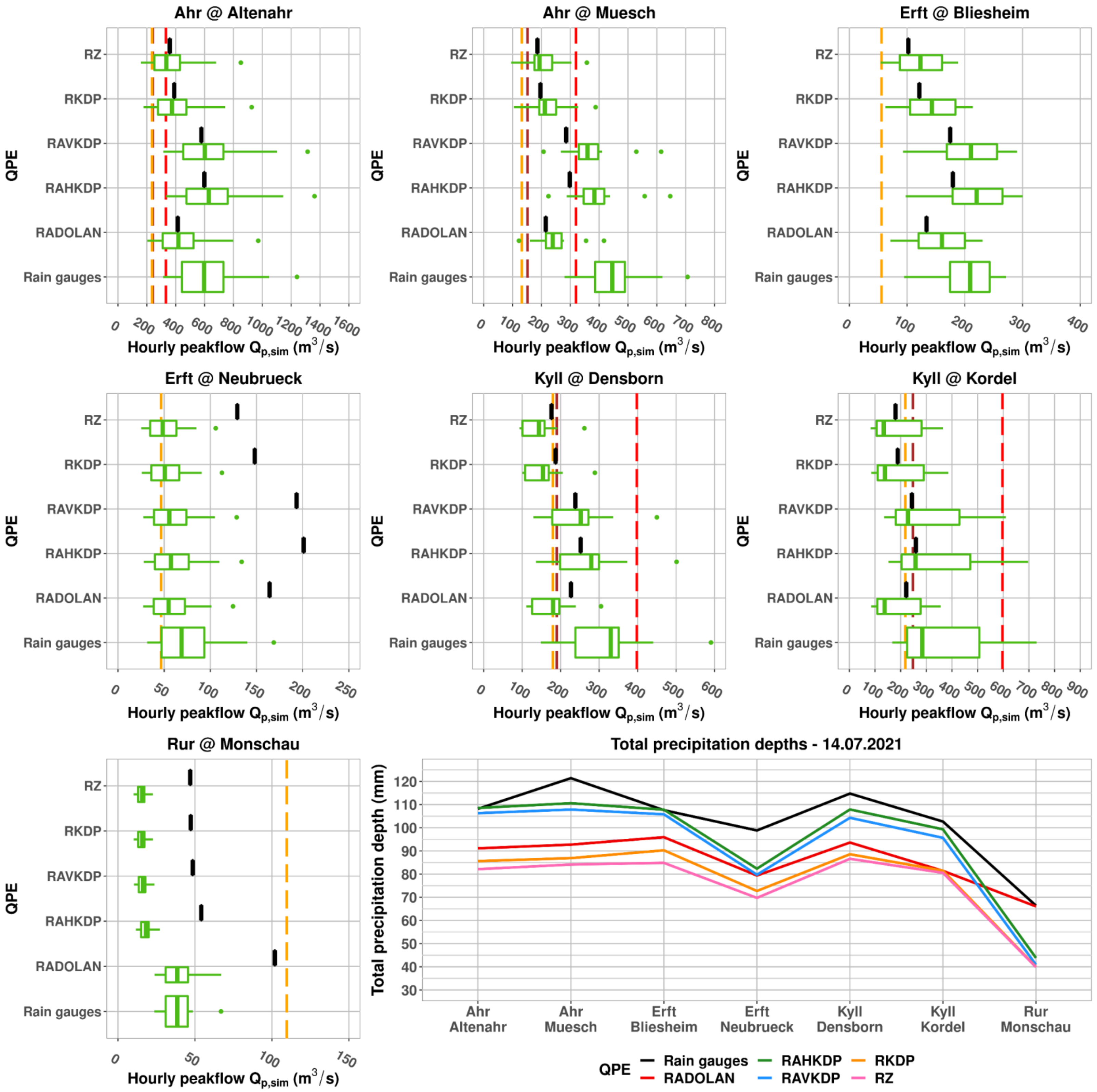
3.2 | Result 2: Differences between hydrological models

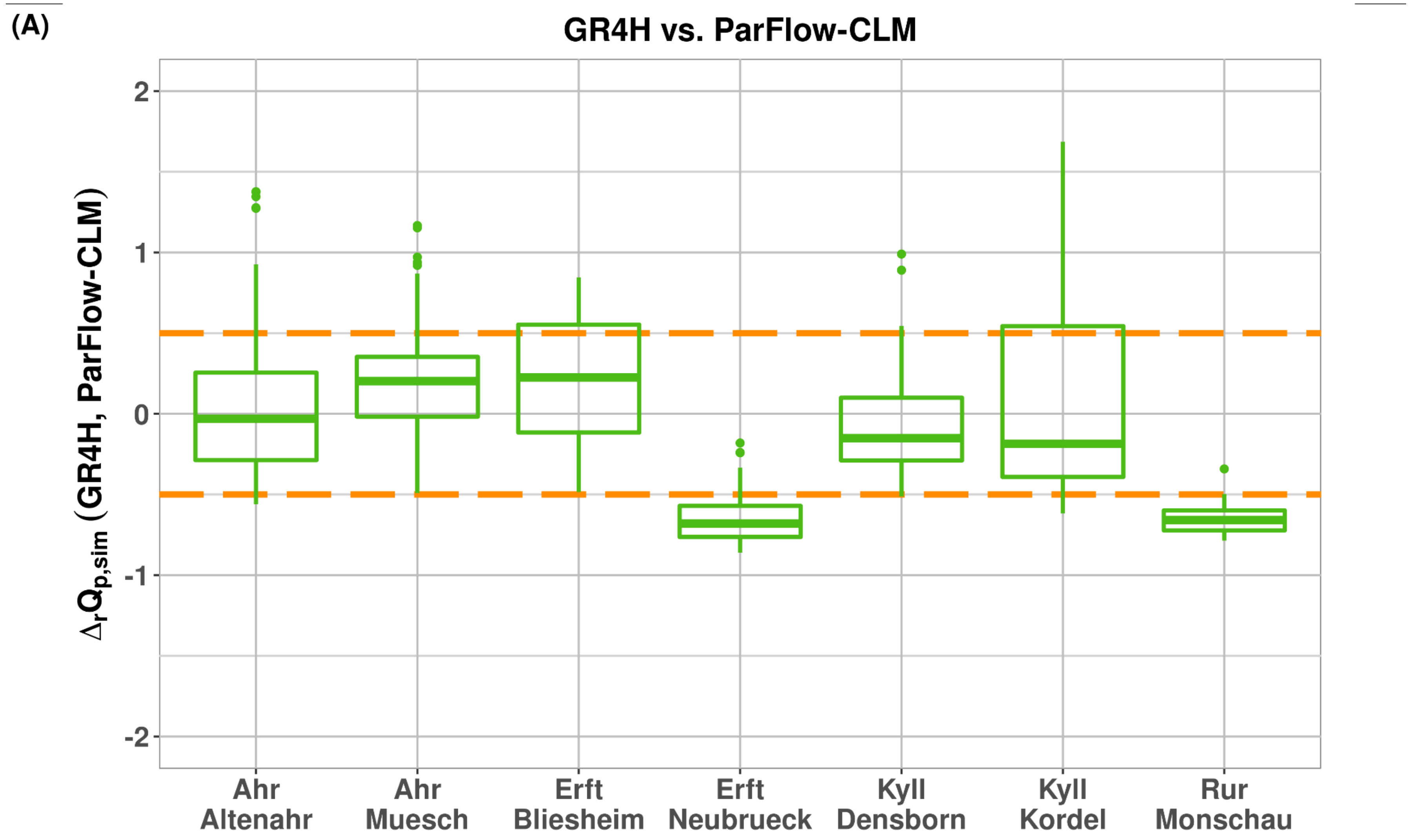


Similar model simulations for 4/7 catchments
Effect of QPE is more pronounced on peakflows

3| Q1. Impact of QPE & modeling choices on peakflow

3.2 | Result 2: Differences between hydrological models





If we change from ParFlow-CLM to GR4H, the median relative errors are limited (except for Erft @ Neubrueck and Rur @ Monschau)

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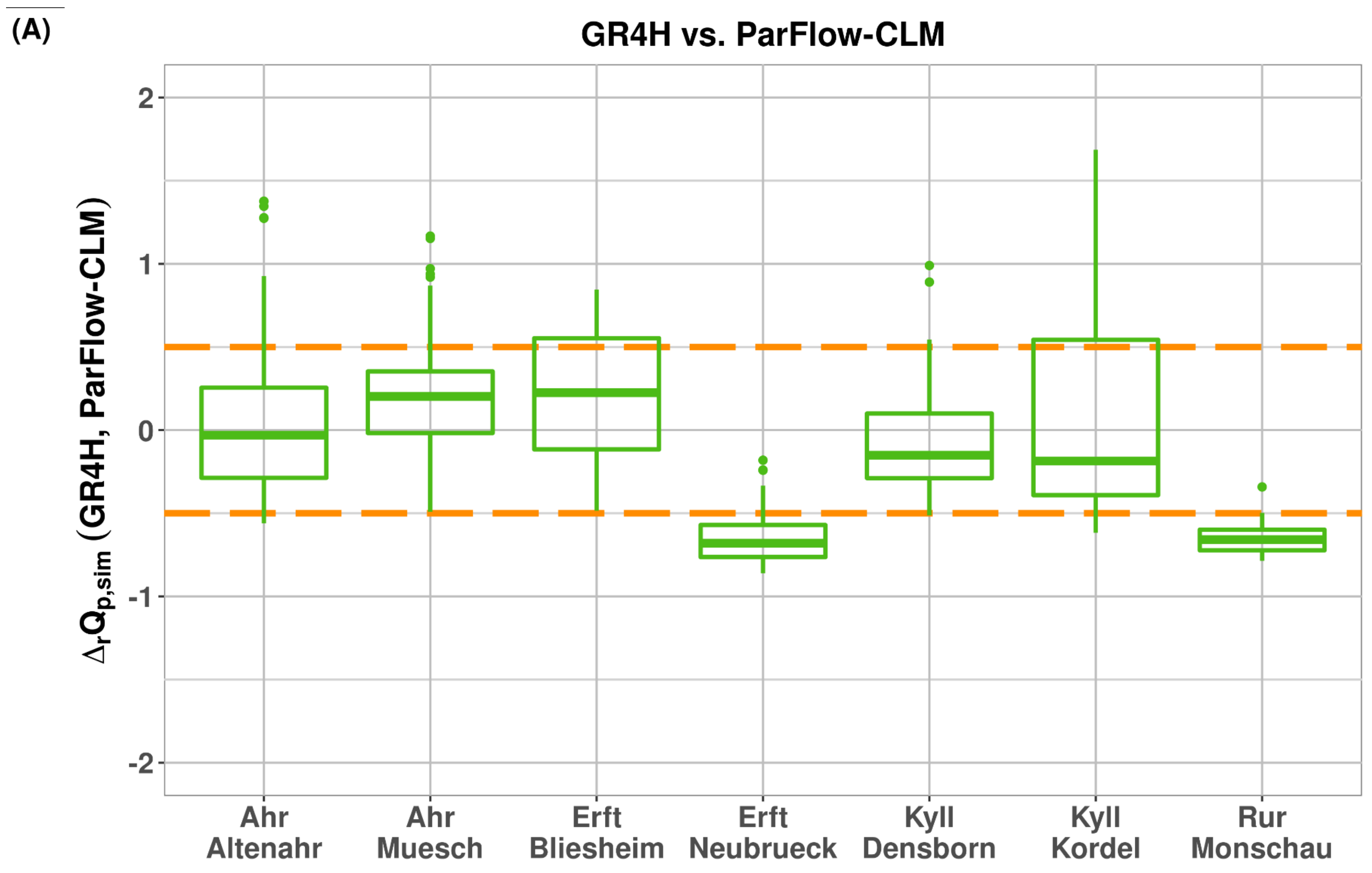
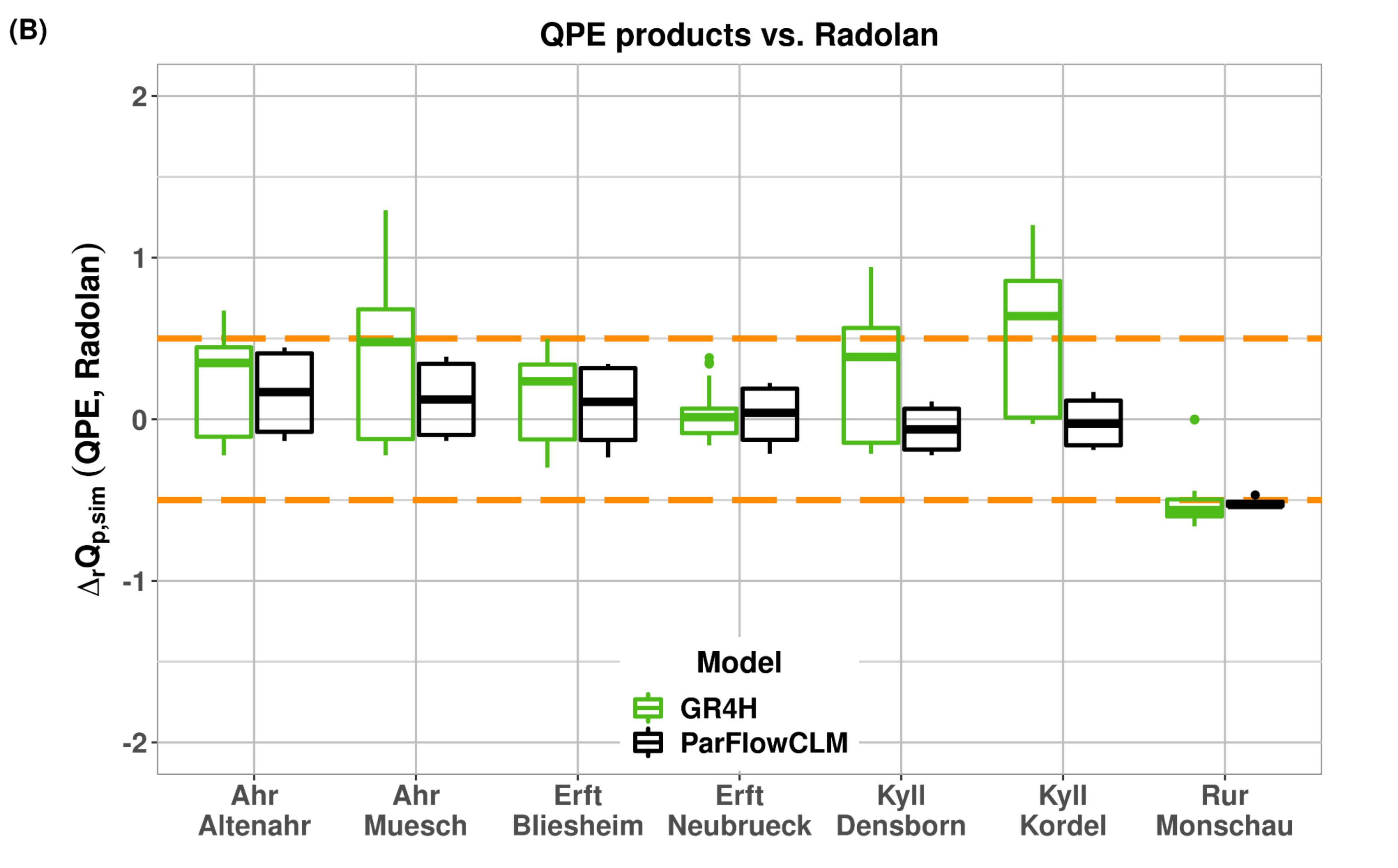
3.2 | Result 2: Differences between hydrological models



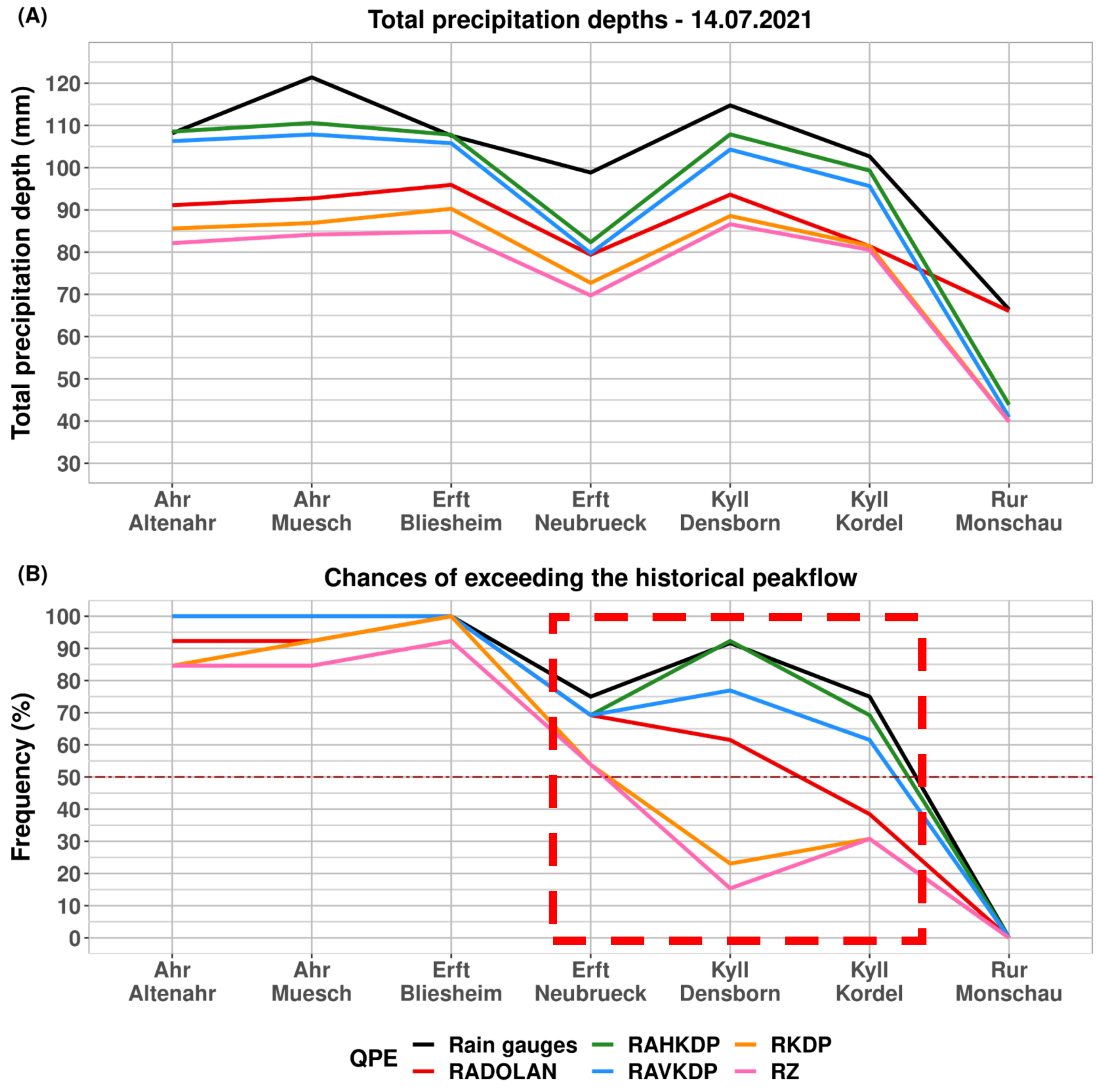


If we change from ParFlow-CLM to GR4H, the median relative errors are limited (except for Erft @ Neubrueck and Rur @ Monschau)

If we change from Radolan to another QPE, the relative errors are more important, especially for GR4H

3| Q1. Impact of QPE & modeling choices on peakflow

3.2 | Result 3: Chances of breaking the historical records of peakflow



Catchment	Historical peakflow (m^3/s)
Ahr @ Altenahr	236
Ahr @ Muesch	132
Erft @ Bliesheim	55.8
Erft @ Neubrueck	46.64
Kyll @ Densborn	180
Kyll @ Kordel	218
Rur @ Monschau	109.63

The effect depends on the catchment:

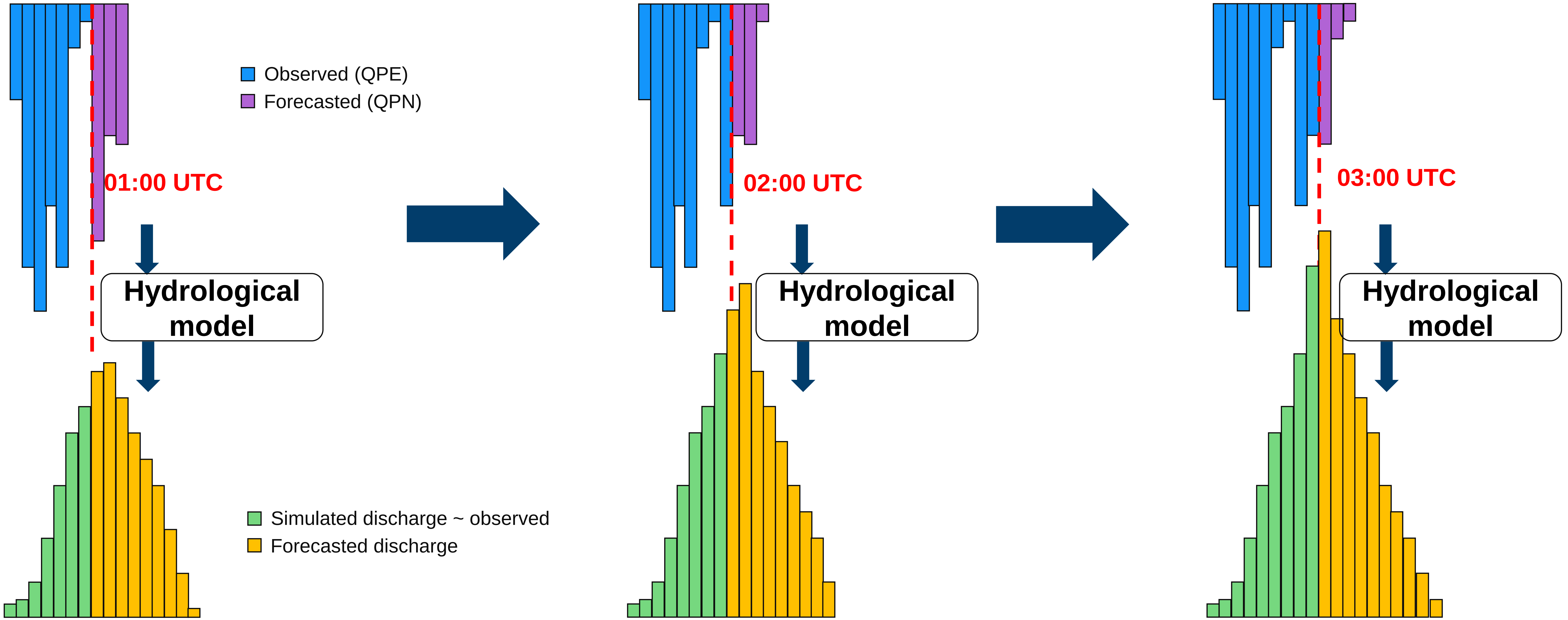
1. Very high chances no matter what QPE product is used
2. Very low chances for the Rur @ Monschau
3. High dependency on QPE for the remaining catchments

3| Q2. Improving the forecasting lead time

3.1 | QPN methods

Based on the QPE product RAVKDP

2 deterministic: Advection and Sprog (Seed, 2003) + **1 stochastic**, with 20 members : STEPS (Bowler et al., 2006)



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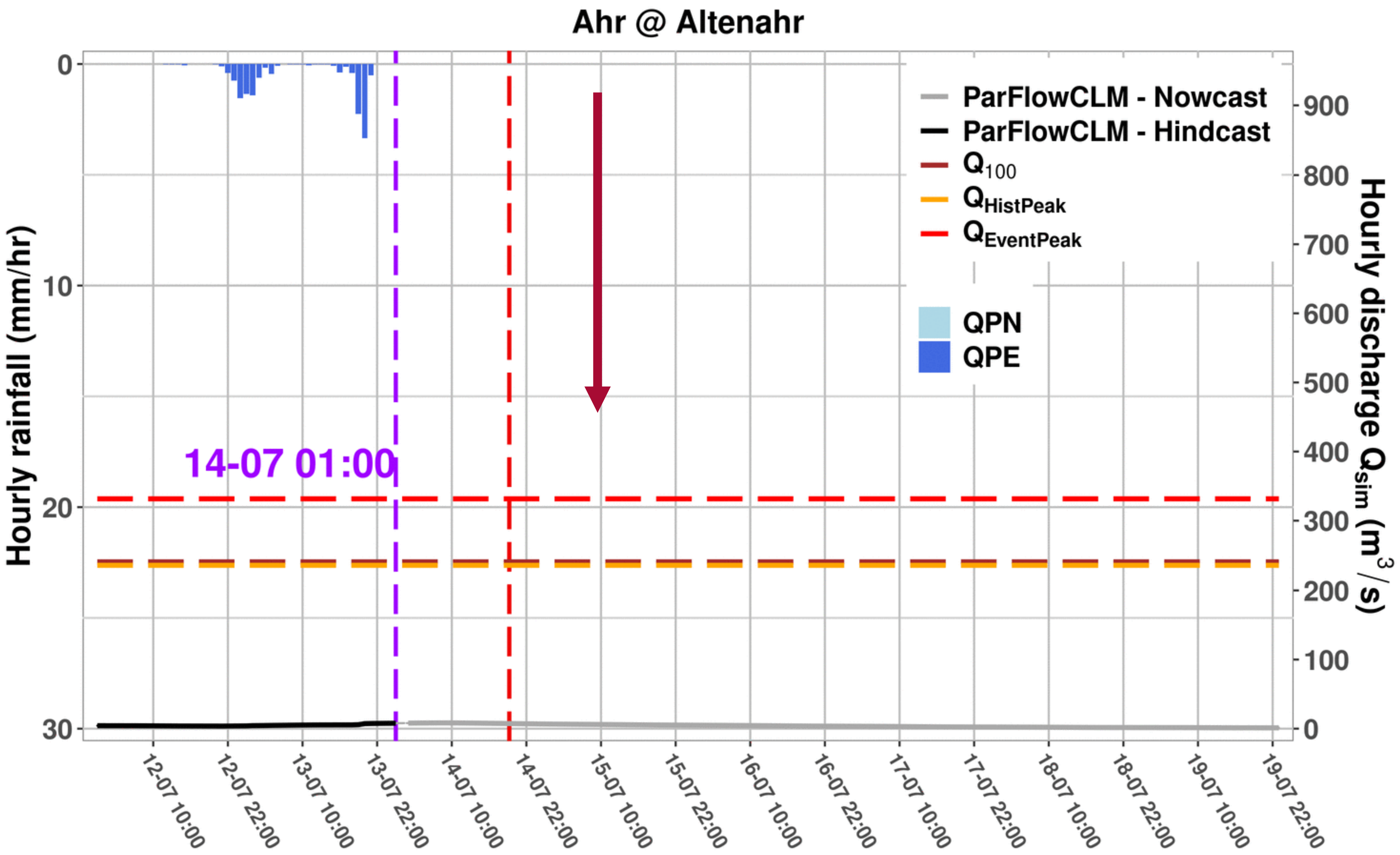

Spawned each hour between 01h00 and 18h00 of 14.07.2021

3| Q2. Improving the forecasting lead time

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Evaluation: construct a virtual forecasted hydrograph for each lead time

Time	Q, LT = 1h	Q, LT = 2h	Q, LT = 4h
01h00	Q(1h00) spawned at 00h00	Q(1h00) spawned at 23h00 j-1	Q(1h00) spawned at 21h00 j-1
02h00	Q(2h00) spawned at 01h00	Q(2h00) spawned at 00h00	Q(2h00) spawned at 22h00 j-1
03h00	Q(3h00) spawned at 02h00	Q(3h00) spawned at 01h00	Q(3h00) spawned at 23h00 j-1
04h00	Q(4h00) spawned at 03h00	Q(4h00) spawned at 02h00	Q(4h00) spawned at 00h00
05h00	Q(5h00) spawned at 04h00	Q(5h00) spawned at 03h00	Q(5h00) spawned at 01h00
06h00	Q(6h00) spawned at 05h00	Q(6h00) spawned at 04h00	Q(6h00) spawned at 02h00

Virtual because assembled out of different hydrographs

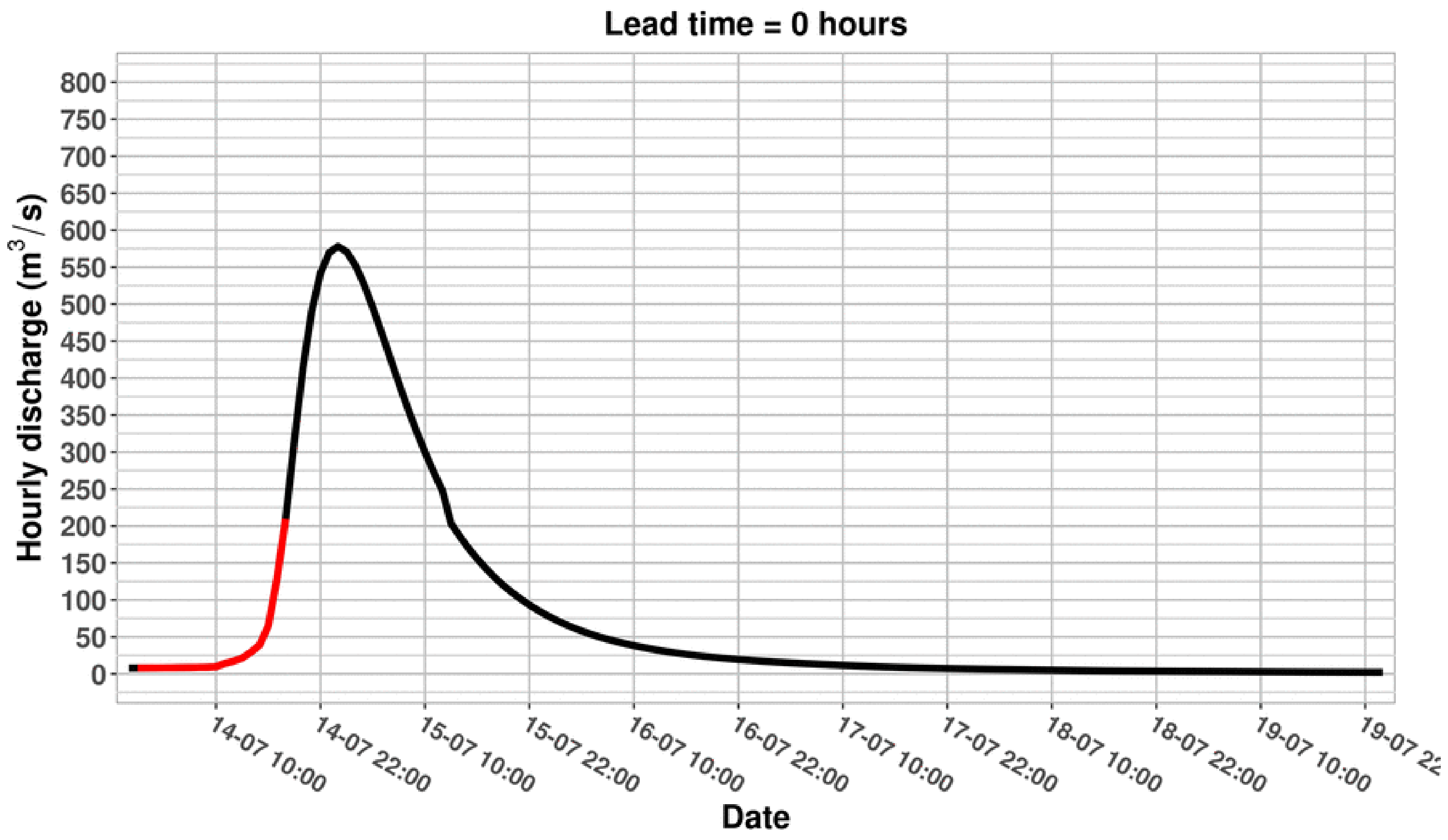
4| Q2. Improving the forecasting lead time

4.1 | QPN methods

Based on the QPE product RAVKDP

2 deterministic: Advection and Sprog (Seed, 2003) + **1 stochastic**, with 20 members : STEPS (Bowler et al., 2006)

Evaluation: construct a virtual forecasted hydrograph for each lead time



Simulated hydrograph with QPE to be compared with **forecasted hydrograph**

Evaluation metrics

$$\mathrm{NSE(LT)} = 1 - \frac{\sum_h \left(Q_{QPE} - Q_{QPN,LT}\right)^2}{\sum_h \left(Q_{QPE} - \overline{Q_{QPE}}\right)^2}$$

Perfect score = 1 **Acceptable: ≥ 0.9**

$$\mathrm{KGE(LT)} = 1 - \sqrt{(1-r)^2 + \left(1 - \frac{\overline{Q_{QPN,LT}}}{\overline{Q_{QPE}}}\right)^2 + \left(1 - \frac{\sigma_{QPN,LT}}{\sigma_{QPE}}\right)^2}$$

Perfect score = 1

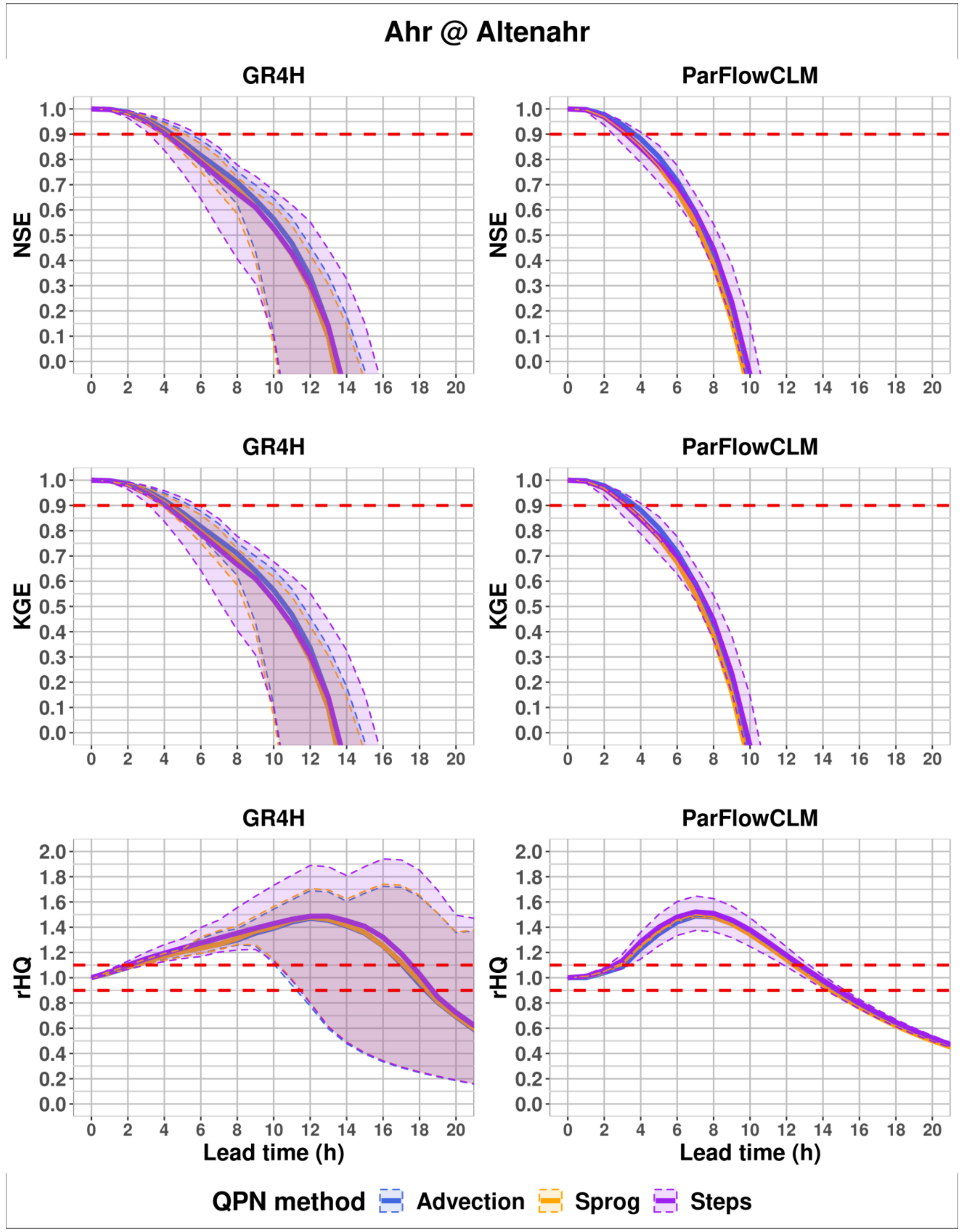
$$\mathrm{rHQ(LT)} = \frac{\max(Q_{QPN,LT})}{\max(Q_{QPE})}$$

Perfect score = 1 **Acceptable: between 0.9 and 1.1**

Nash & Sutcliffe (1970); Gupta et al. (2009)

4| Q2. Improving the forecasting lead time

4.2 | Results



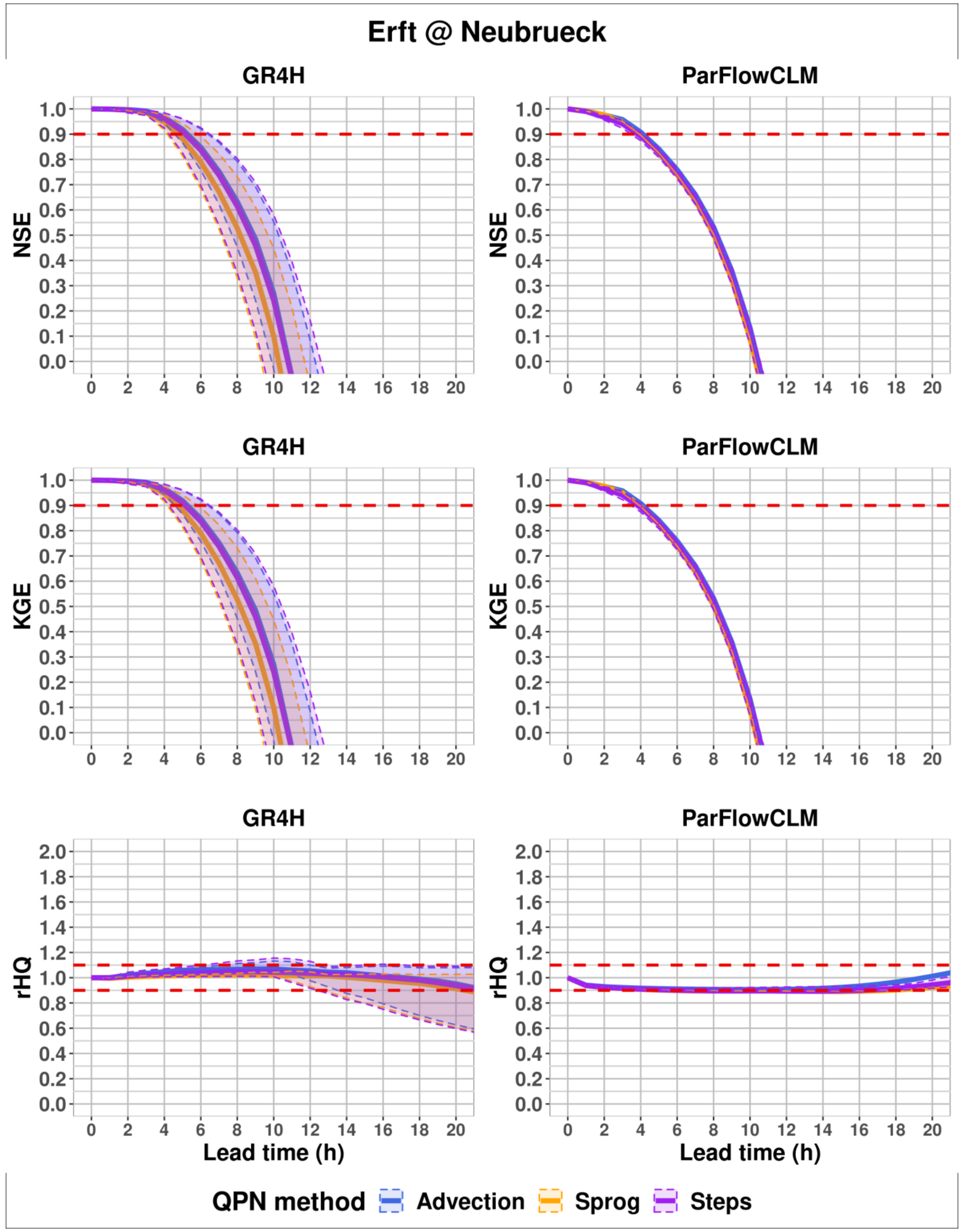
Ahr @ Altenahr (760 km²)

Forecasting skill drops nonlinearly with increasing lead time

GR4H vs. ParFlowCLM: Having an ensemble of parameters can help improve the lead time, but **it is costly**

4| Q2. Improving the forecasting lead time

4.2 | Results



Erft @ Neubrueck (1670 km²)

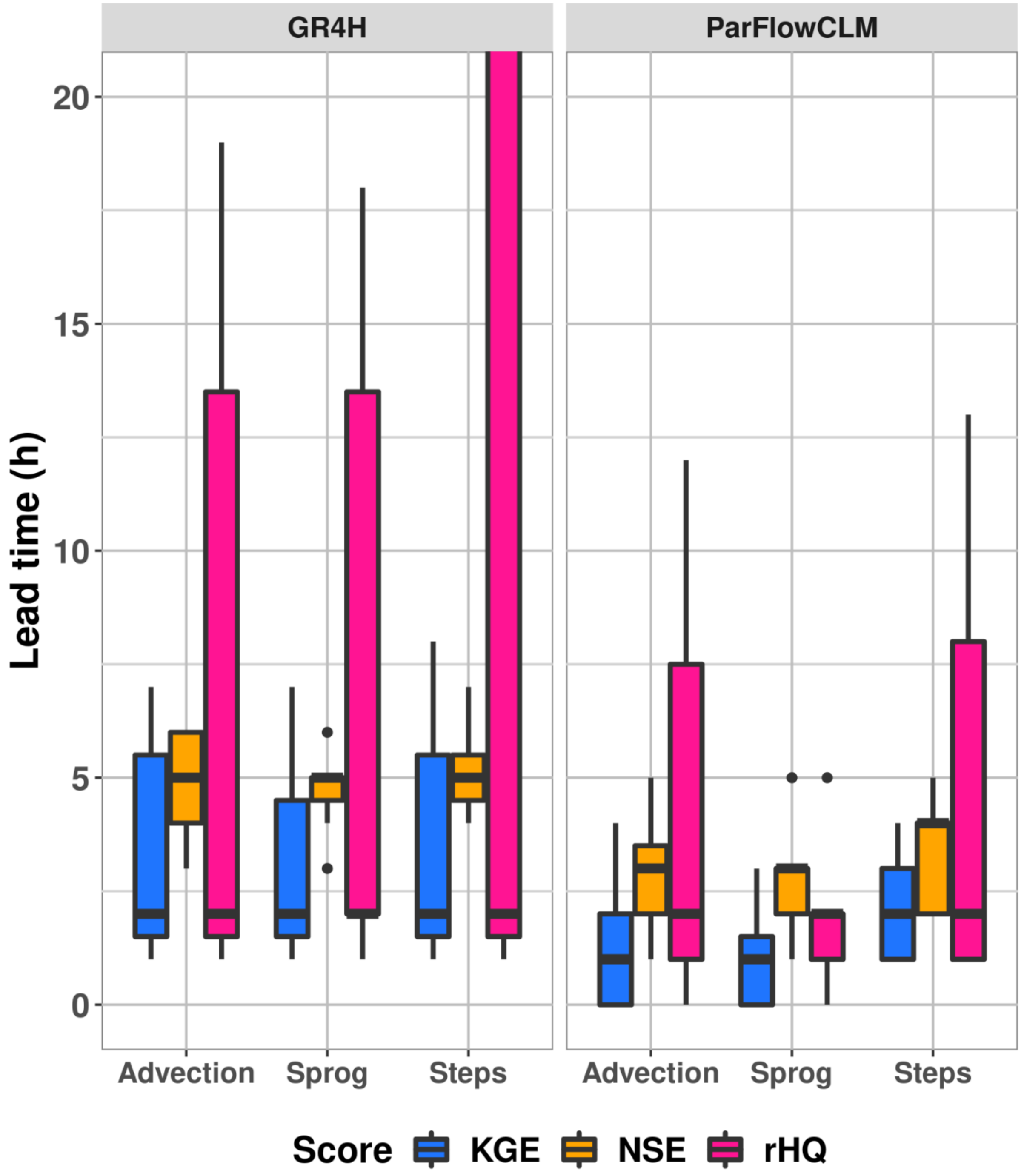
Forecasting skill drops nonlinearly with increasing lead time

GR4H vs. ParFlowCLM: Having an ensemble of parameters can help improve the lead time, but **it is costly**

Better lead times are obtained for larger catchments

4| Q2. Improving the forecasting lead time

4.2 | Results



$\mathbf{KGE} \geq 0.9$ $\mathbf{NSE} \geq 0.9$ $0.9 \leq \mathbf{rHQ} \leq 1.1$

Heuvelink et al .(2020)

Forecasting skill drops nonlinearly with increasing lead time

GR4H vs. ParFlowCLM: Having an ensemble of parameters can help improve the lead time, but **it is costly**

Better lead times are obtained for larger catchments

No significant differences between the QPN methods, but an ensemble of members helps improve the lead time

5| Conclusions

Comparison of modeling philosophies

There is general agreement between GR4H and ParFlowCLM, except for catchments highly influenced or for which ParFlowCLM paramterization should be verified

At this stage, running a conceptual model seems more advantageous, but inundation mapping will need a spatially-distributed approach

Evaluation of QPE products

Including specific attenuation helped improve the radar-based QPE products

The choice of QPE products impacted the ability of models to anticipate a record-breaking flood

Added value of QPN methods

On average, the different QPN methods behaved similarly

Increasing the number of members increases (statistically) the chance of having better lead times

Thank you for your attention!
Questions?

References

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