Towards hydrological validation of radar-based precipitation estimates and nowcasts

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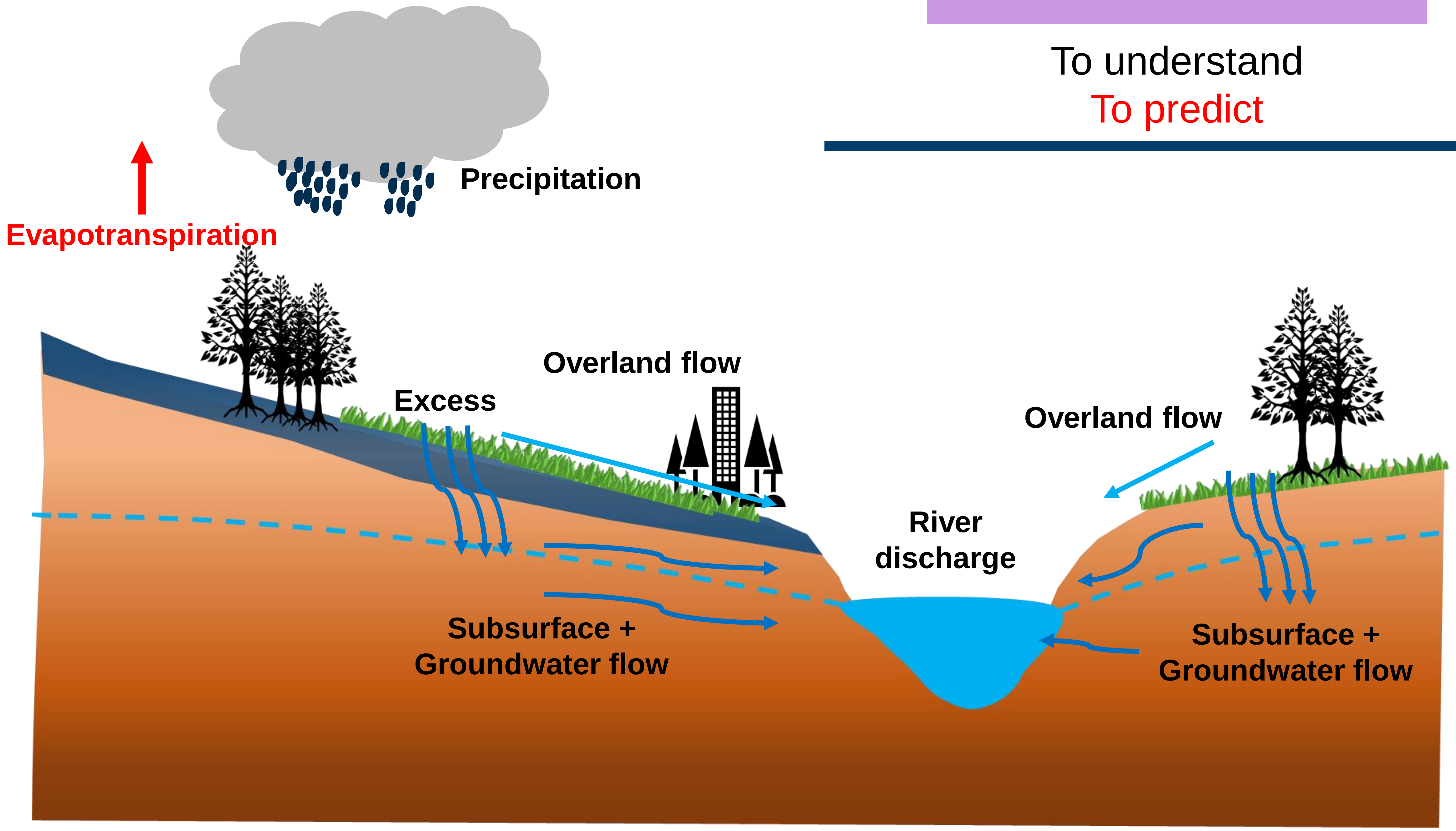
2022-04-28 | RealPEP meeting

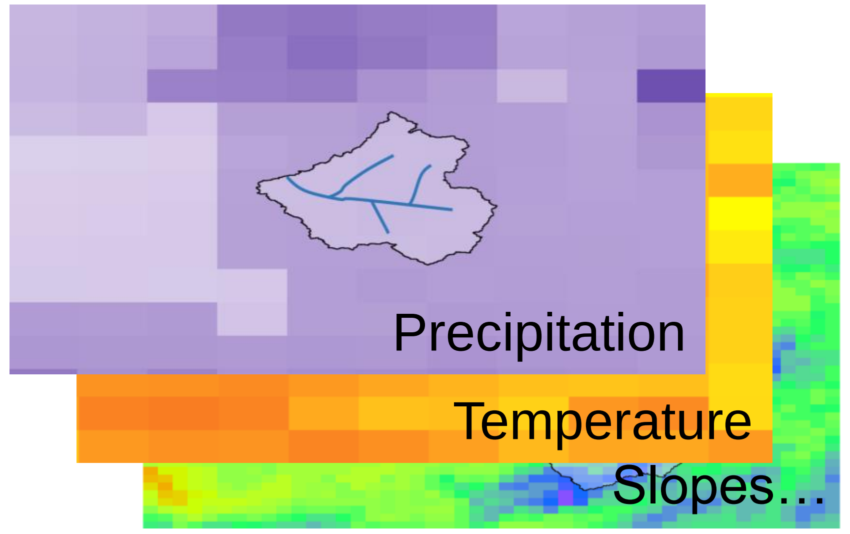
1| Context and objectives



Conceptualization

To understand
To predict

Climate+ Landscape properties



Hydrological model

River discharge

Soil moisture

Water table depth

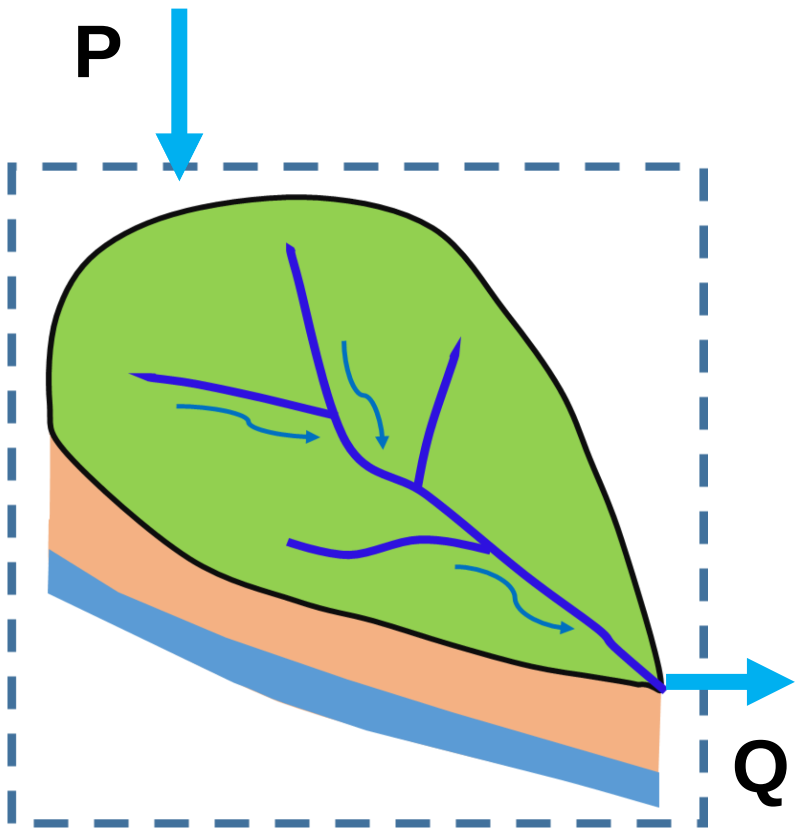
…

Precipitation is one of the main controls on continental hydrological processes, especially at the event-scale

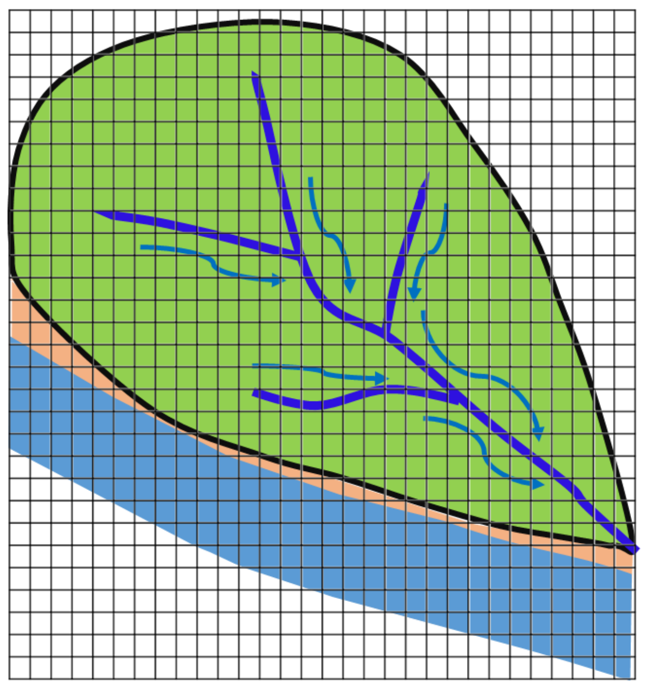
It impacts model outputs

1| Context and objectives

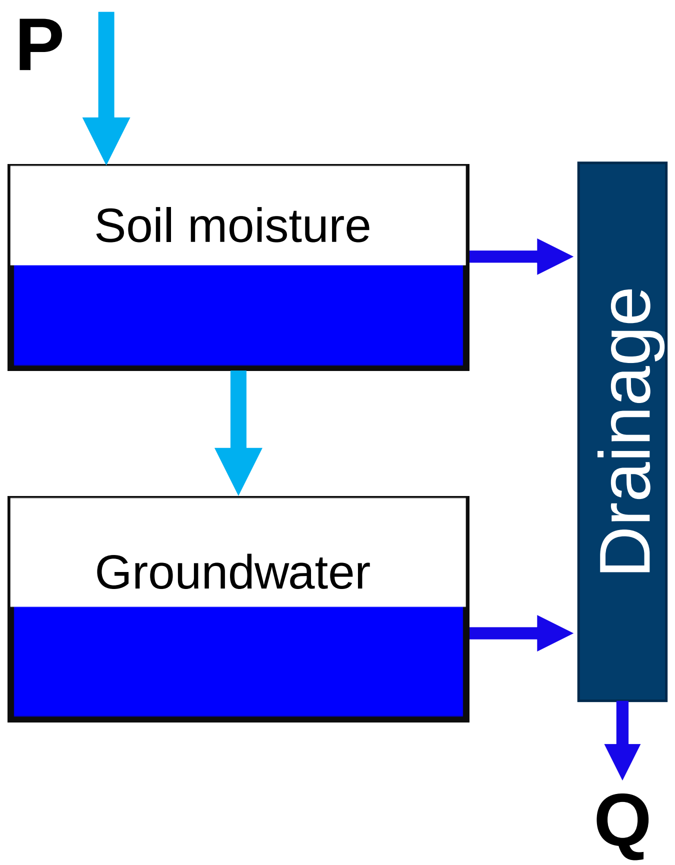
A hydrological model can be:



Systemic/lumped



Reductionist/distributed



Conceptual

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

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

Mechanistic

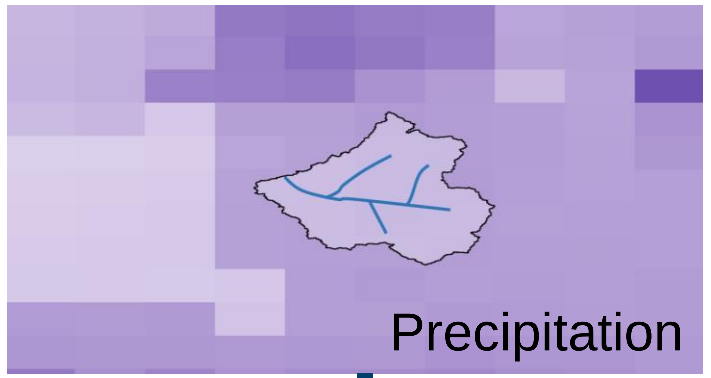
Loss of model interpretability
Less time-consuming, low data demand

Better process representation
Time-consuming and data-demanding

Hrachowitz & Clark (2017)

1| Context and objectives

Hydrological models can be used to check the accuracy of precipitation estimates



Hydrological model

Simulated discharge

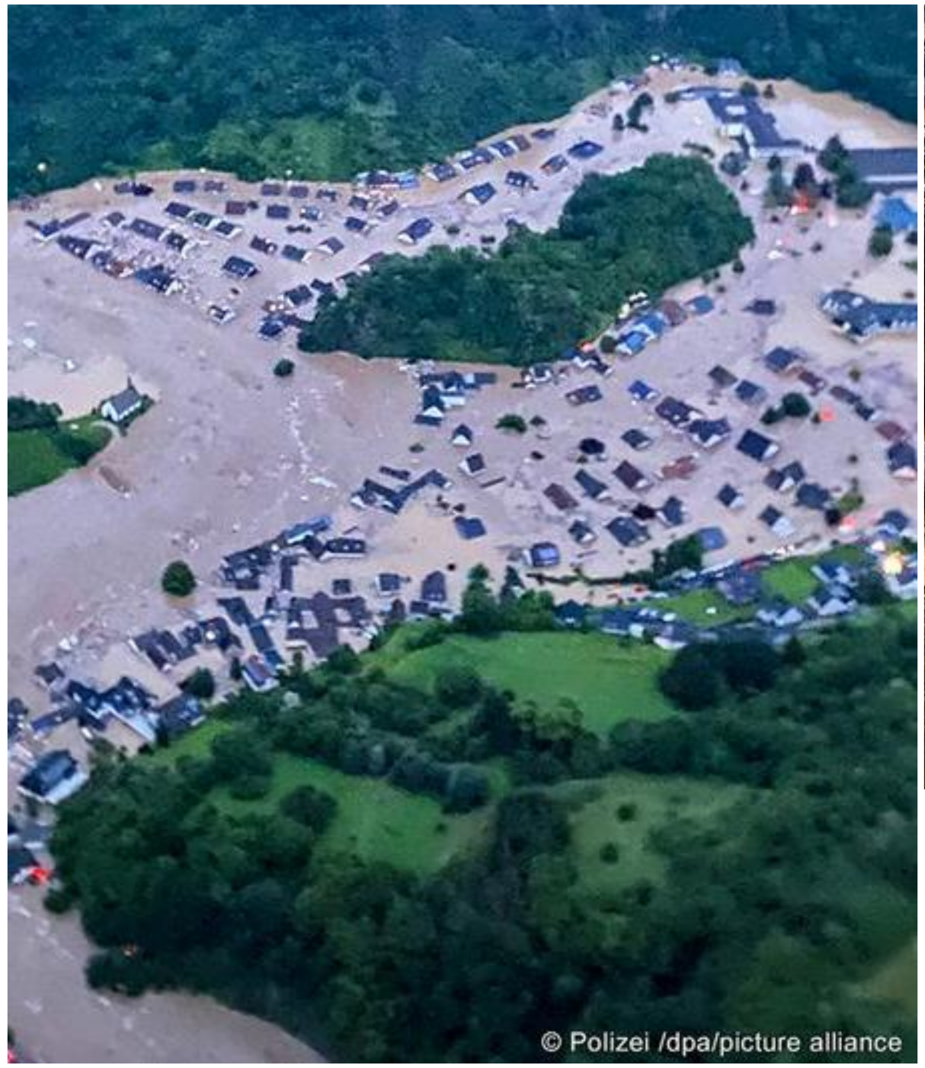
Observed discharge

Precipitation estimates are biased

Errors in model outputs

For extreme floods, accurate precipitation estimates are crucial

But event hydrographs are generally unavailable!



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

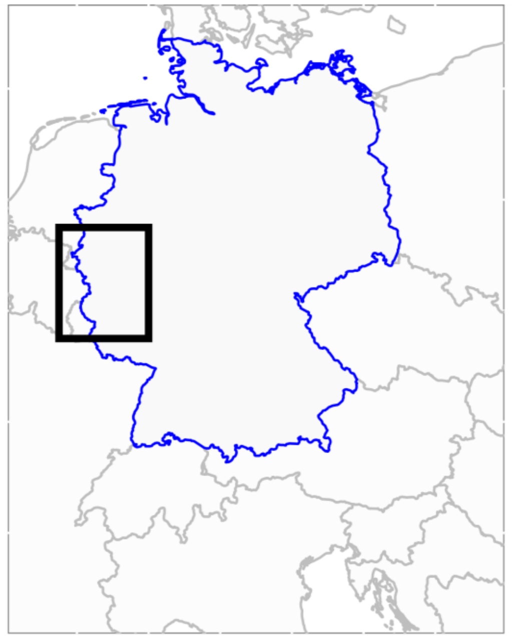
>200 fatalities, up to € 5.5 Billion in insured losses

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

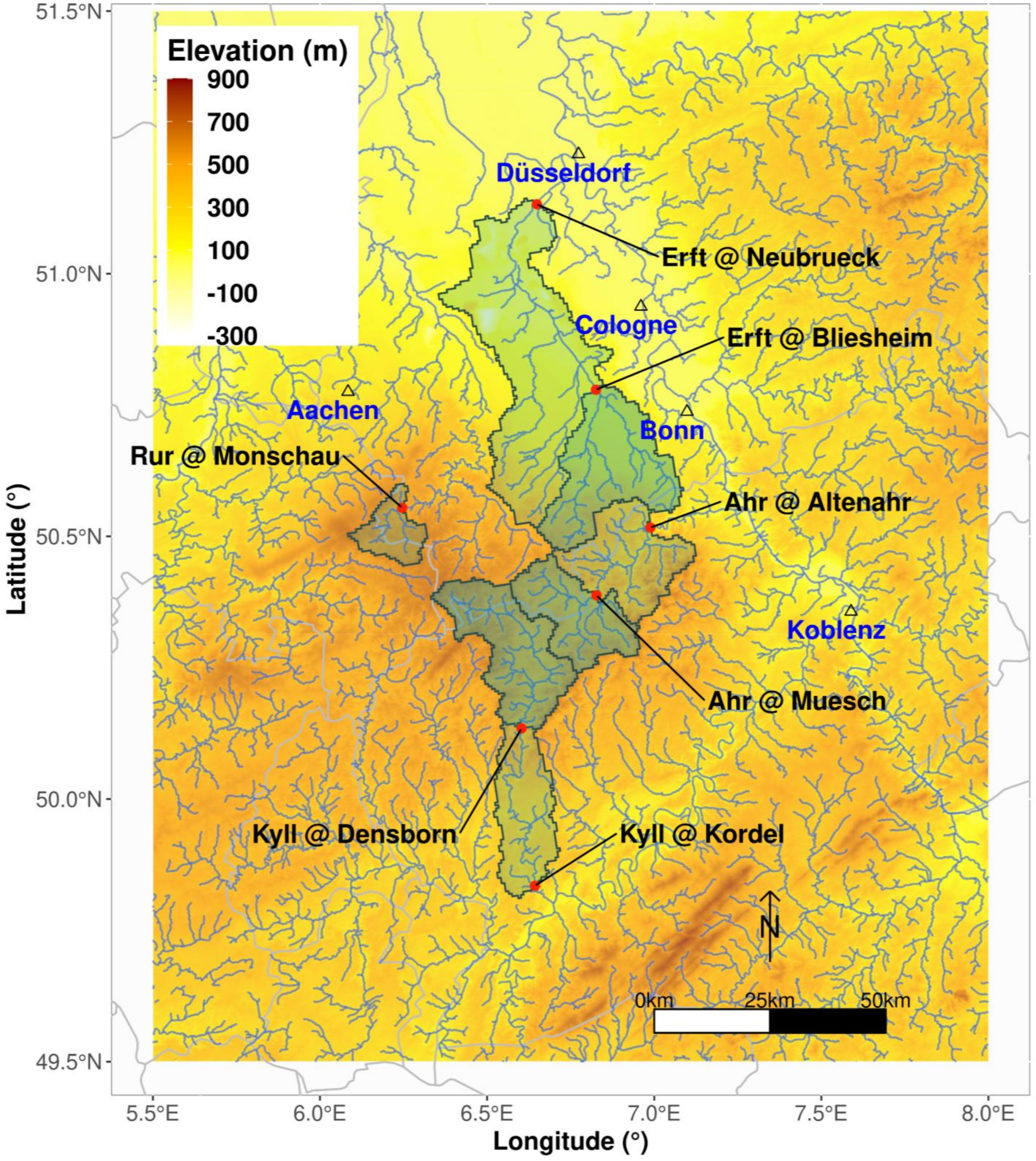
Q2. How do compare different methods of precipitation nowcasting with each other in improving the forecast lead time?

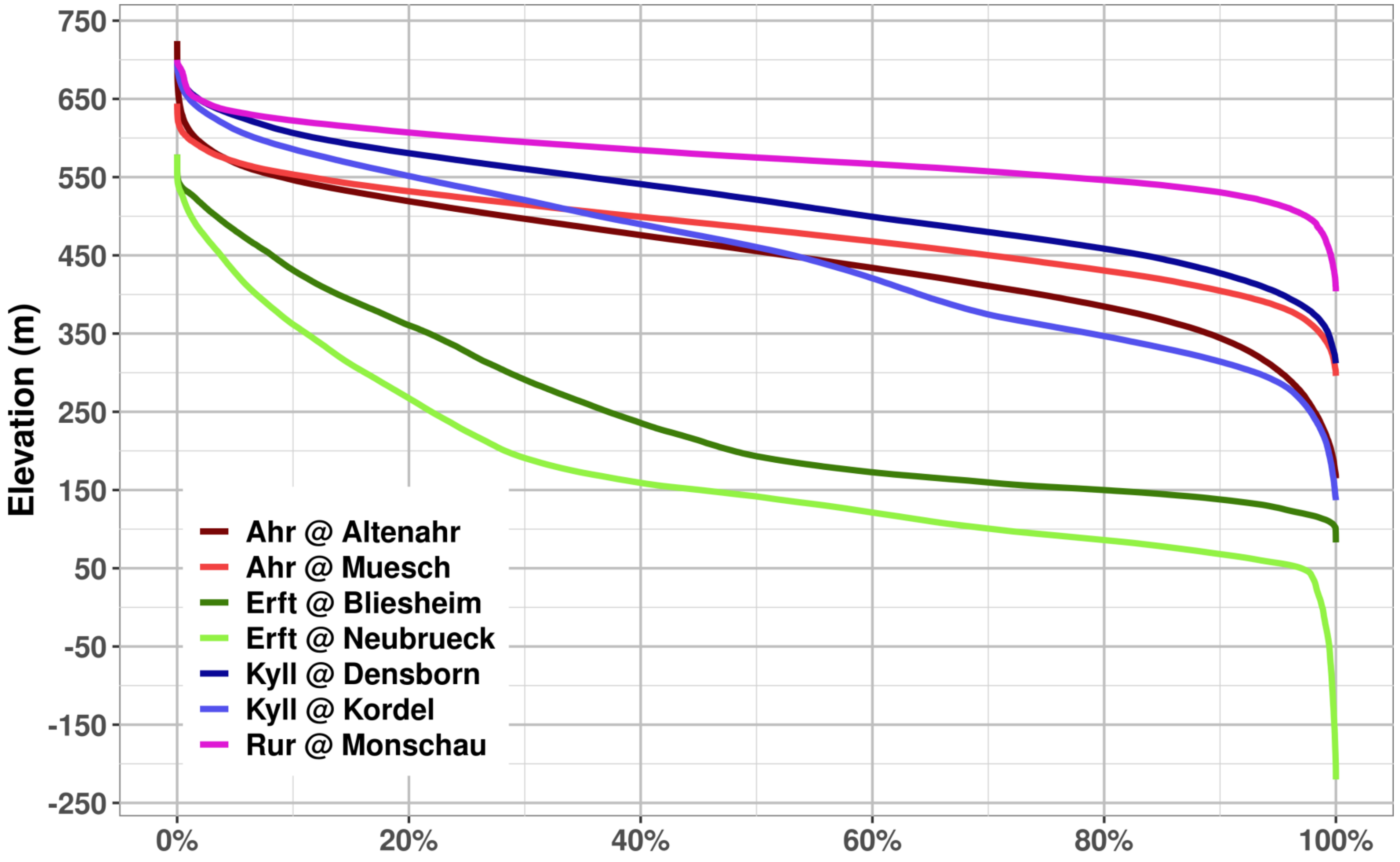
2| Catchments, models and data

2.1 | Catchments



7 catchments draining the Eifel range



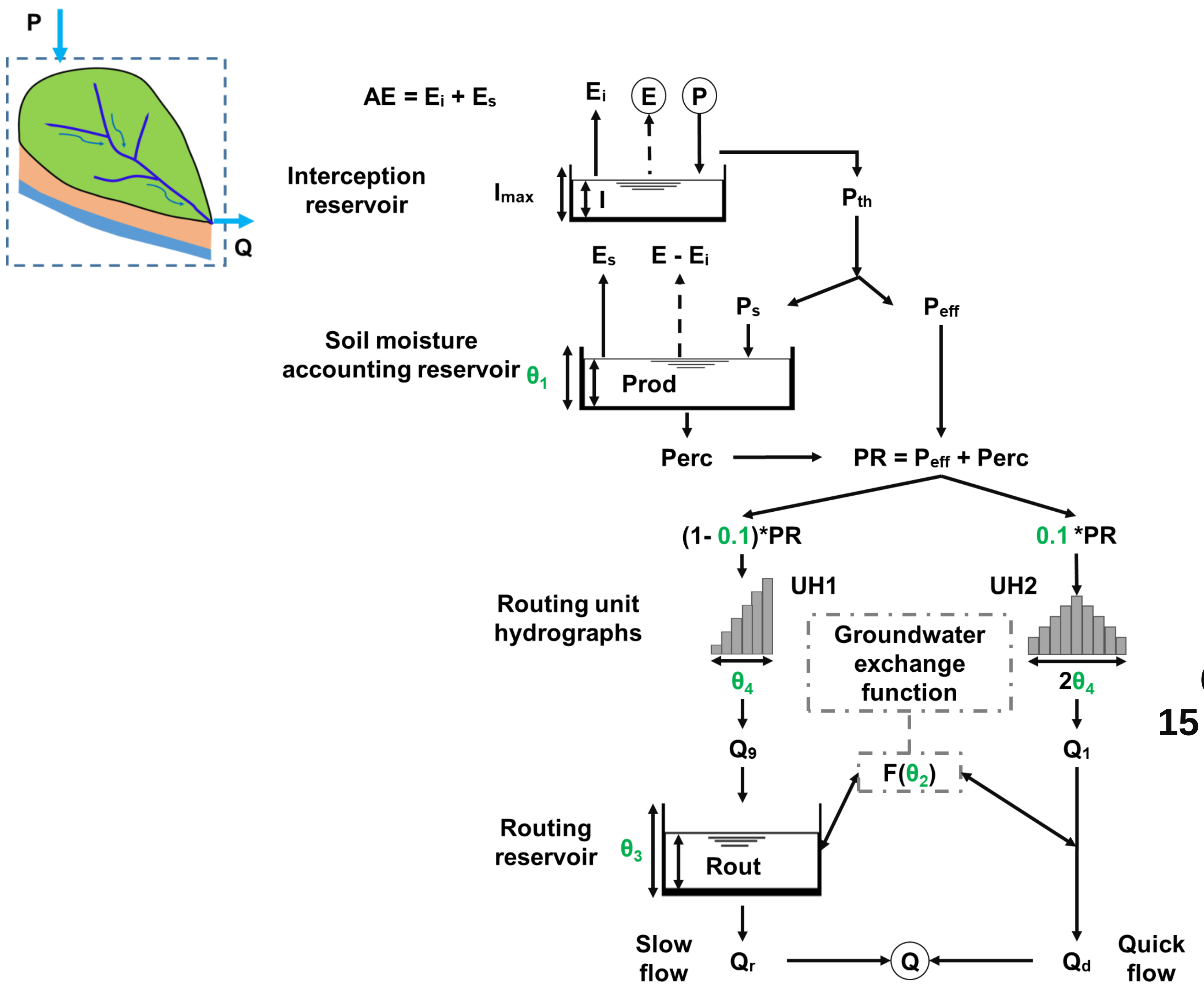


Area (km^2)	140 – 1670
Mean precipitation (mm/yr)	700 – 1070
Aridity index (-)	0.52 – 0.89
Mean discharge (mm/yr)	130 – 760

2| Catchments, models and data

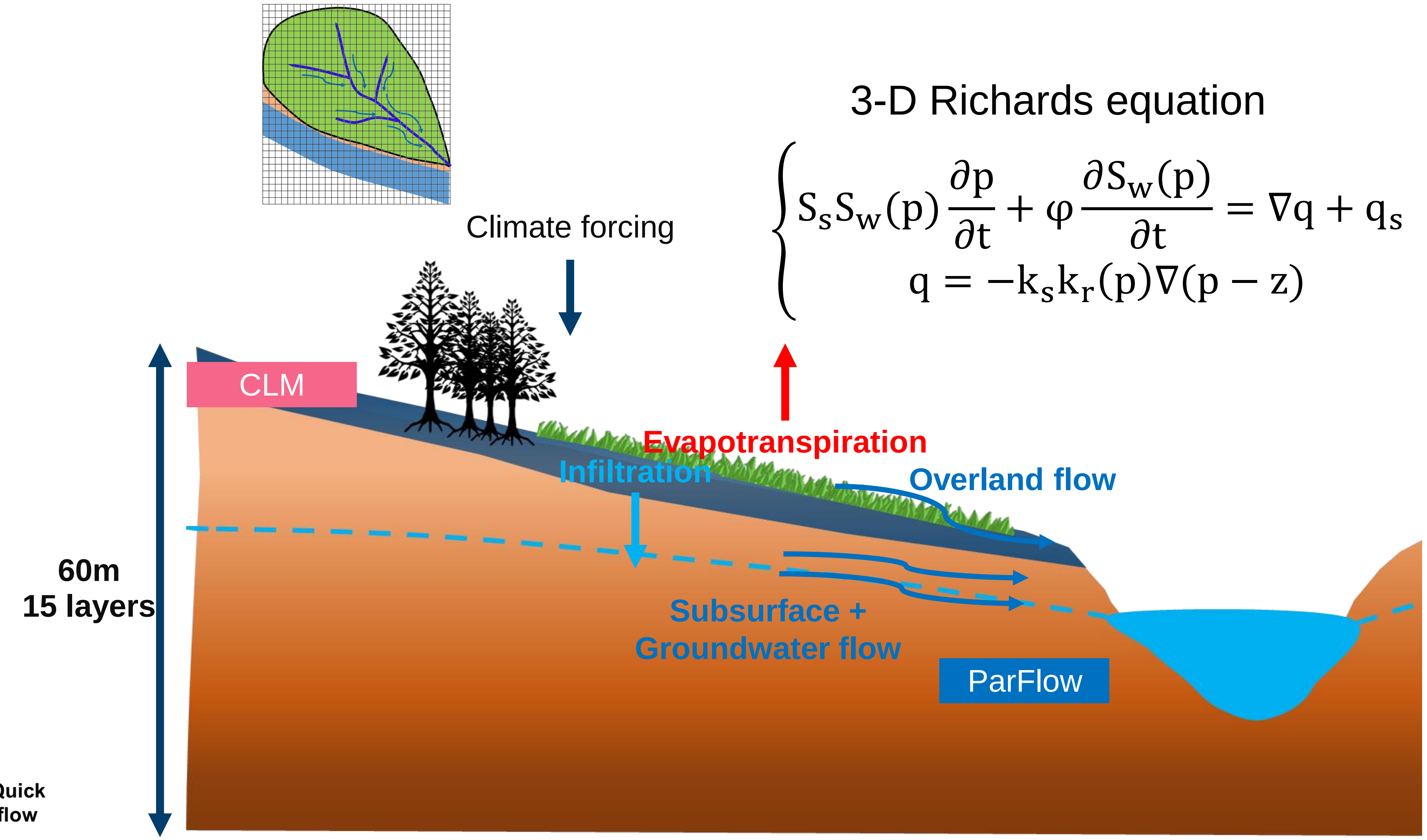
2.2 | Models

GR4H (Ficchì et al. 2019)



Conceptual, lumped, hourly

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



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

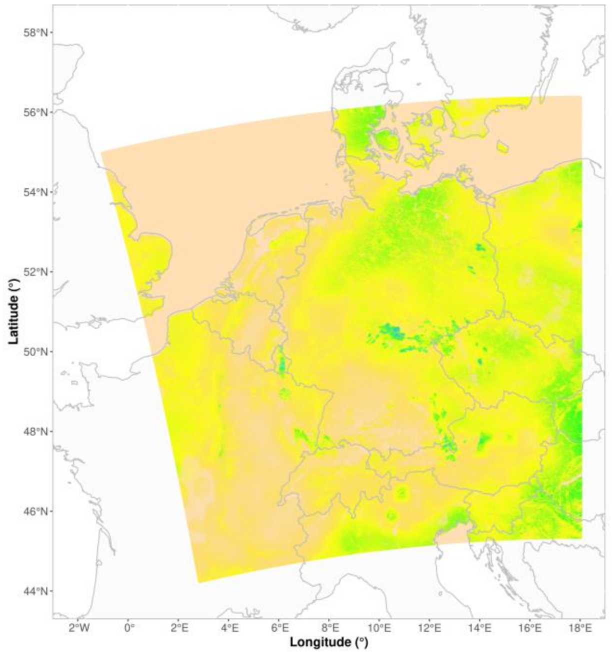
- 4 parameters, calibrated using discharge data (LANUV-NRW, LfU-RLP), 2007-2021
- Calibration needs definition of objective function and period of calibration → **12 optimal parameter sets for each catchment**

Runs on local computer

ParFlow-CLM (Kollet & Maxwell, 2006)

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

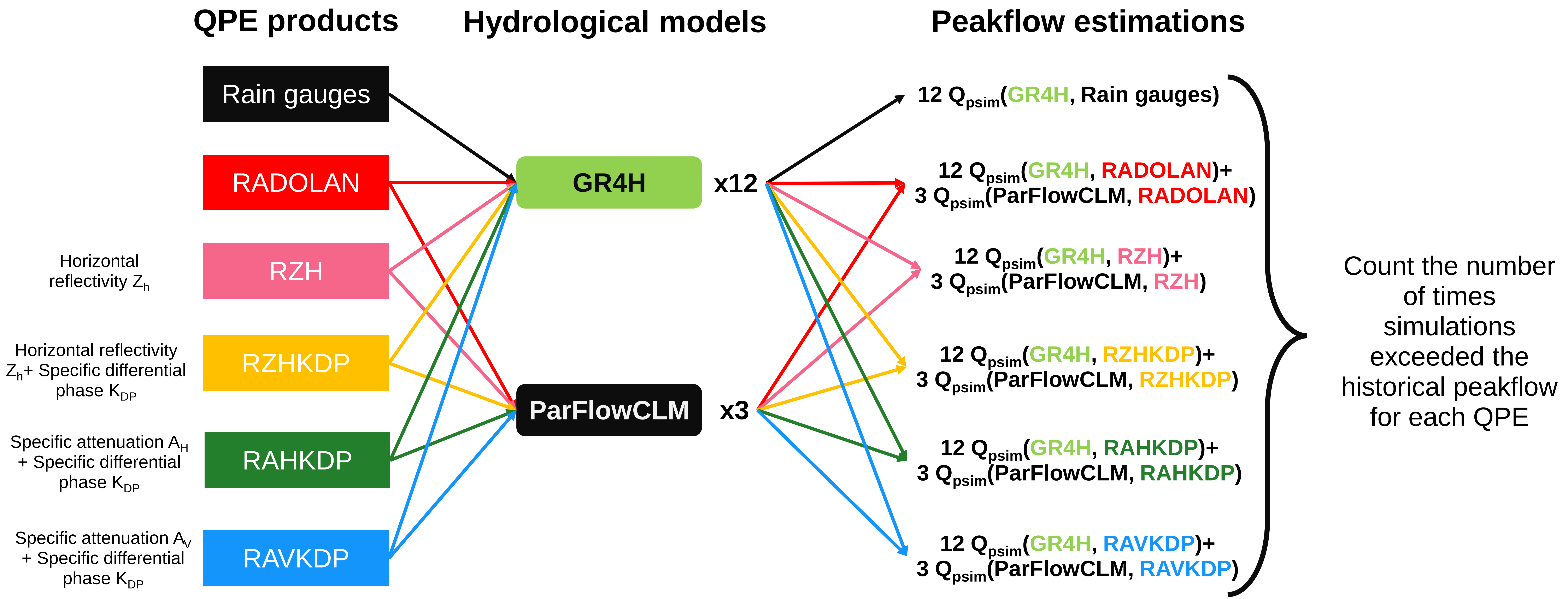
- Topography: ASTER+MERIT DEMs
- Land cover: CLC2018, reclassed in 18 IGBP types
- Soil types: SoilGrids250m, grouped into 12 USDA classes and IHME
- **3 tested Manning's n**

0.2 s/m$^{1/3}$ (HMann) **0.1 s/m$^{1/3}$ (MMann)** **0.02 s/m$^{1/3}$ (LMann)**

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

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

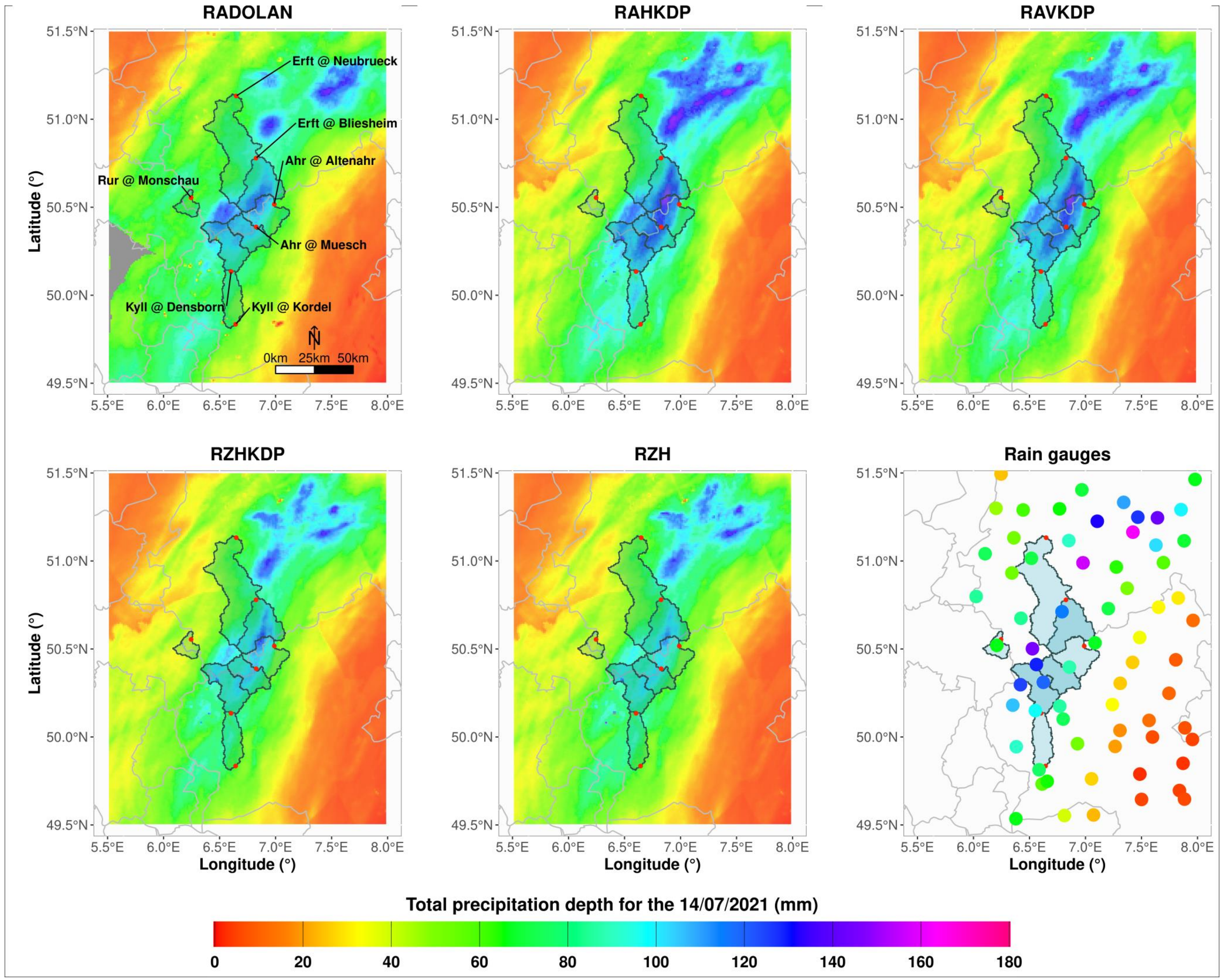
3.1 | QPE products for the 14.07.2021



Chen et al. (2021)

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

3.2 | Result 1: Differences between QPE products



At the pixel scale

Similar spatial pattern

Higher rainfall rates for RAHKDP and RAVKDP

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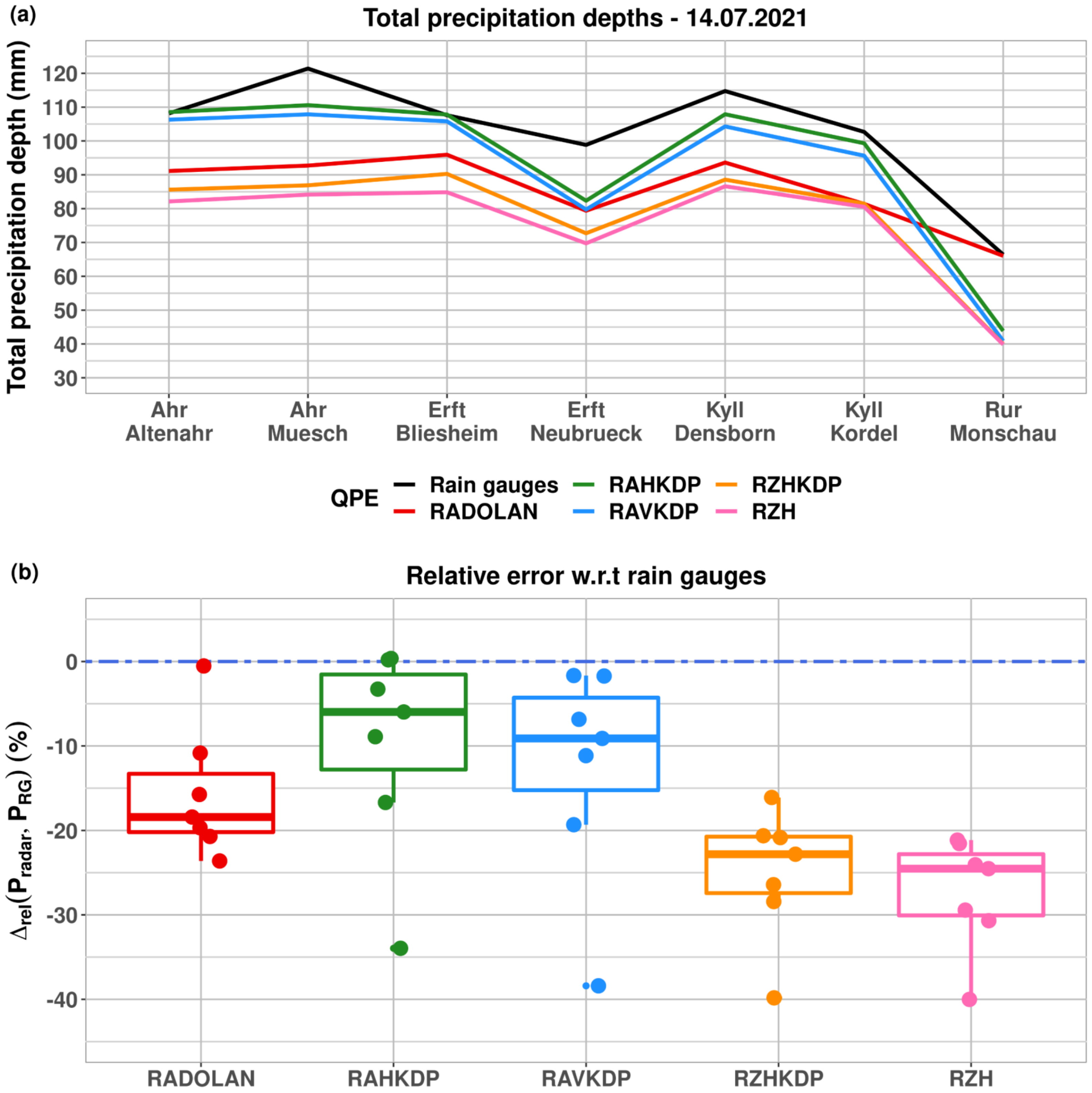


At the pixel scale

Similar spatial pattern

Higher rainfall rates for RAHKDP and RAVKDP

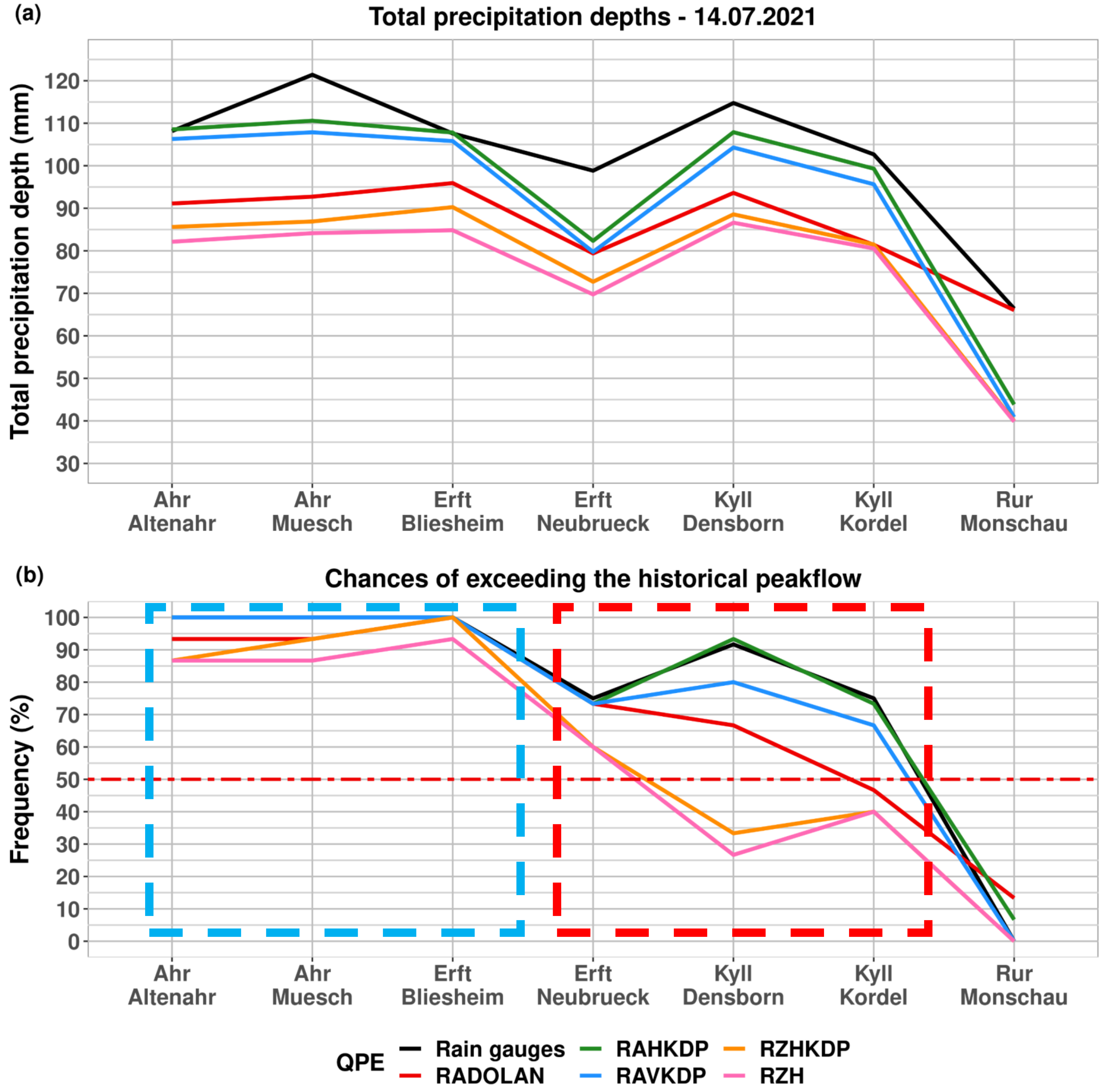
At the catchment scale

All radar-based QPE underestimated the total precipitation from rain gauges

For most catchments, RAHKDP and RAVKDP are the ones that agreed most with estimations from rain gauges

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

3.2 | Result 2: Chances of breaking the historical records of peakflow



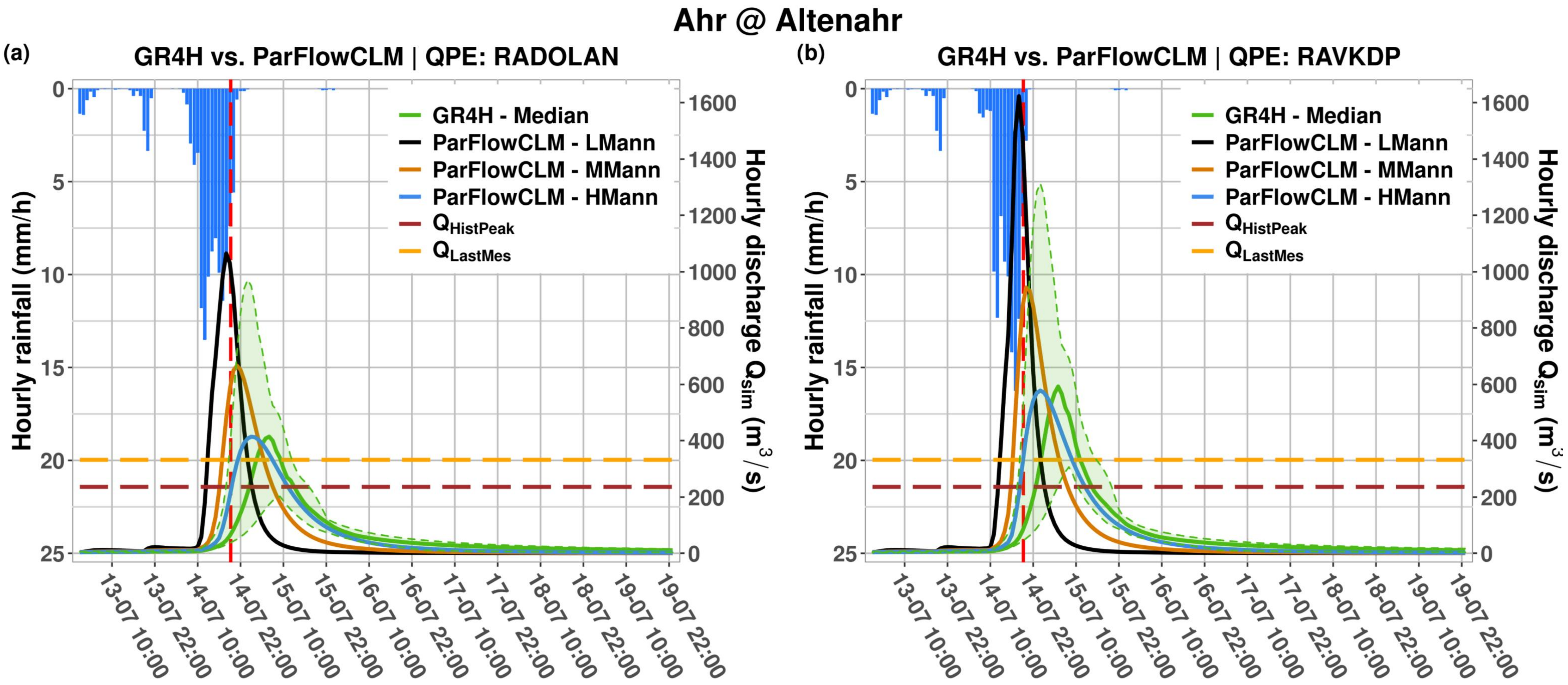
Catchment	Historical peakflow (m^3/s)
Ahr @ Altenahr	236
Ahr @ Muesch	132
Erft @ Bliesheim	55.8
Erft @ Neubrueck	46.64
Kyll @ Densborn	180
Kyll @ Kordel	218
Rur @ Monschau	109.63

The effect of the QPE on the (simulated) severity of the event varied among catchments

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| Q1. Impact of QPE & modeling choices on peakflow

3.2 | Result 3: Uncertainties from model parameters vs. from QPE products

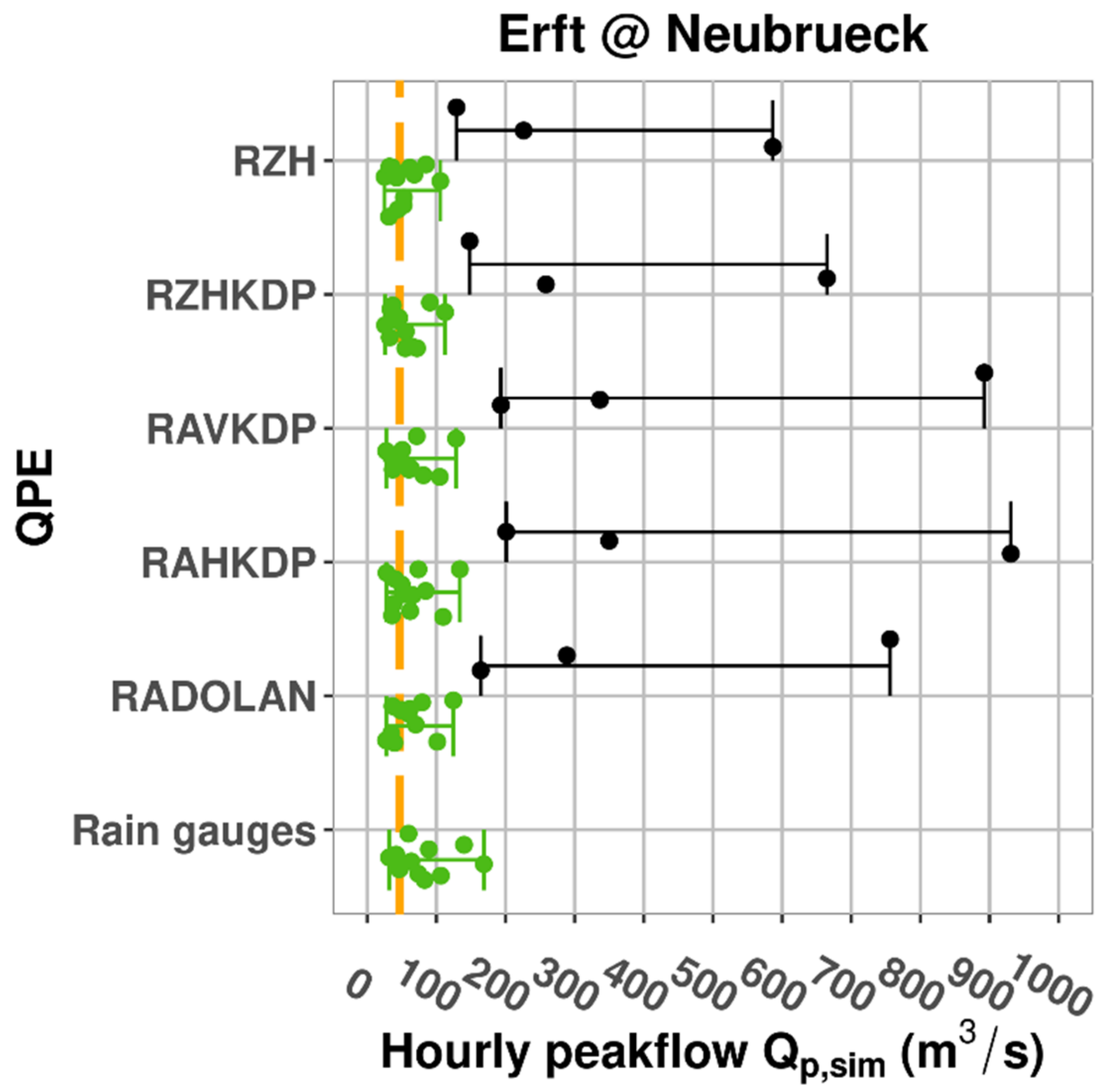


Additional uncertainty from model parameter estimation
GR4H simulations bracketed only HMann and MMann

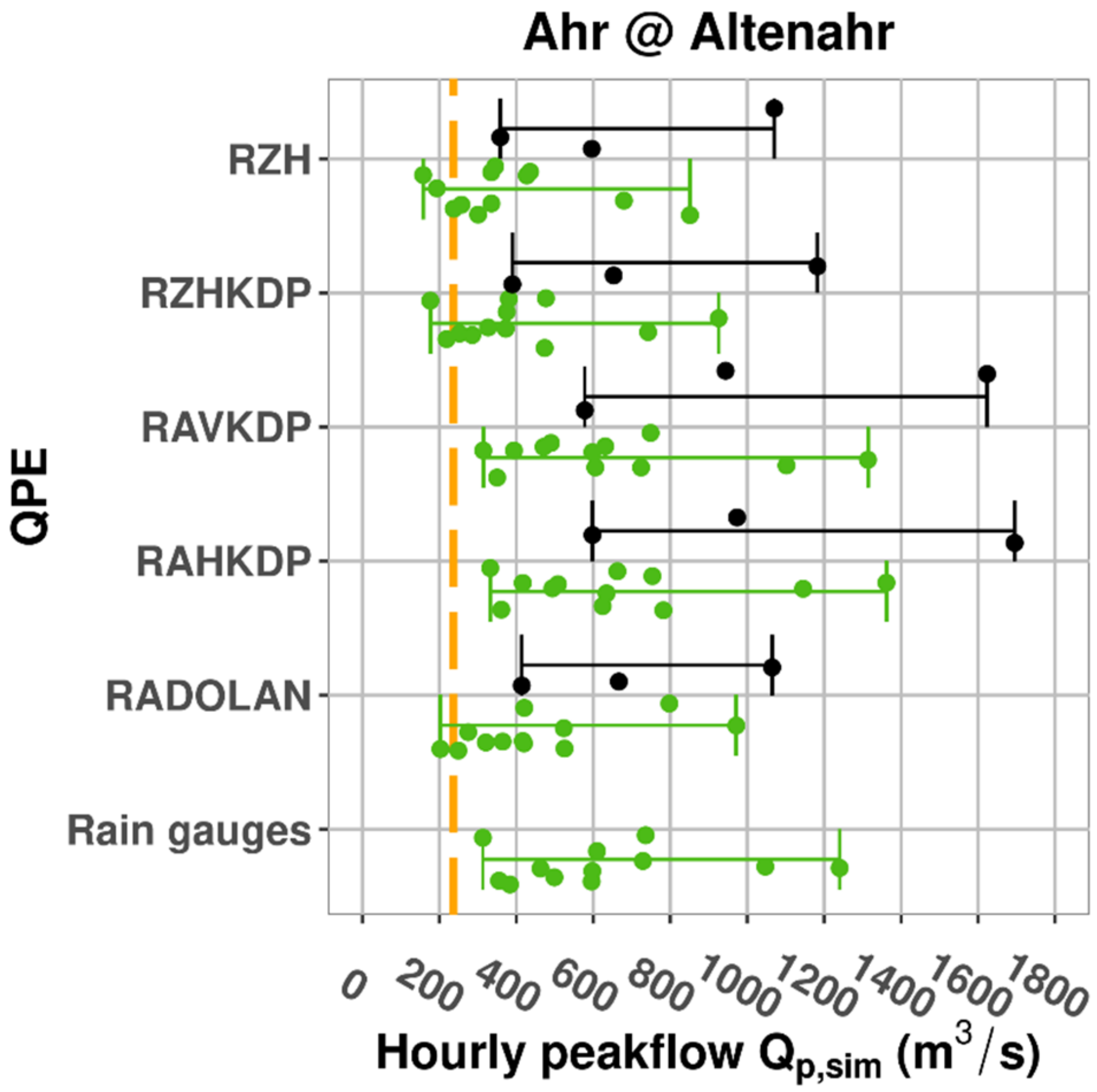
3| Q1. Impact of QPE & modeling choices on peakflow

3.2 | Result 3: Uncertainties from model parameters vs. from QPE products

Largely influenced catchment



Slightly influenced catchment



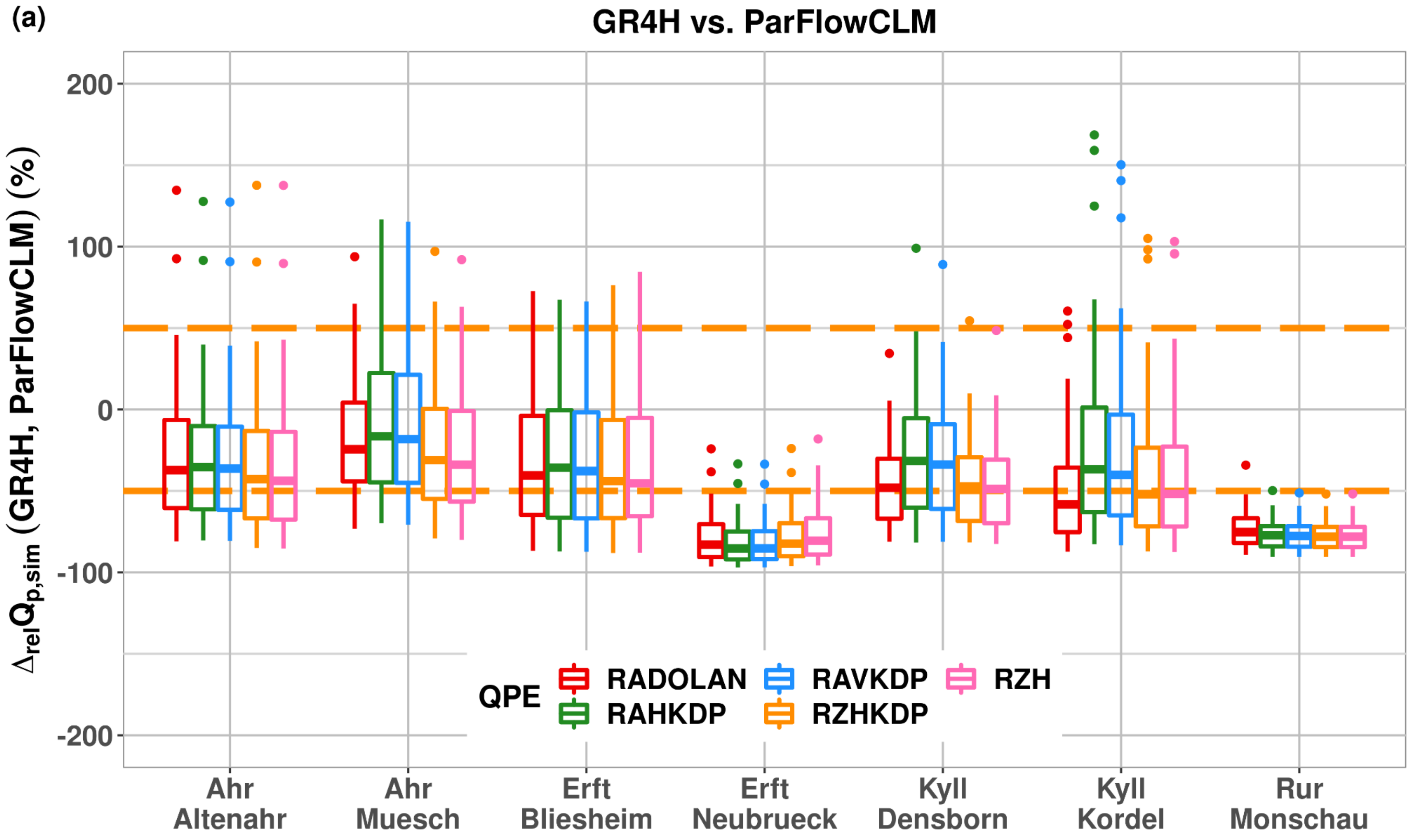
Model disagreement due to anthropogenic influence ?

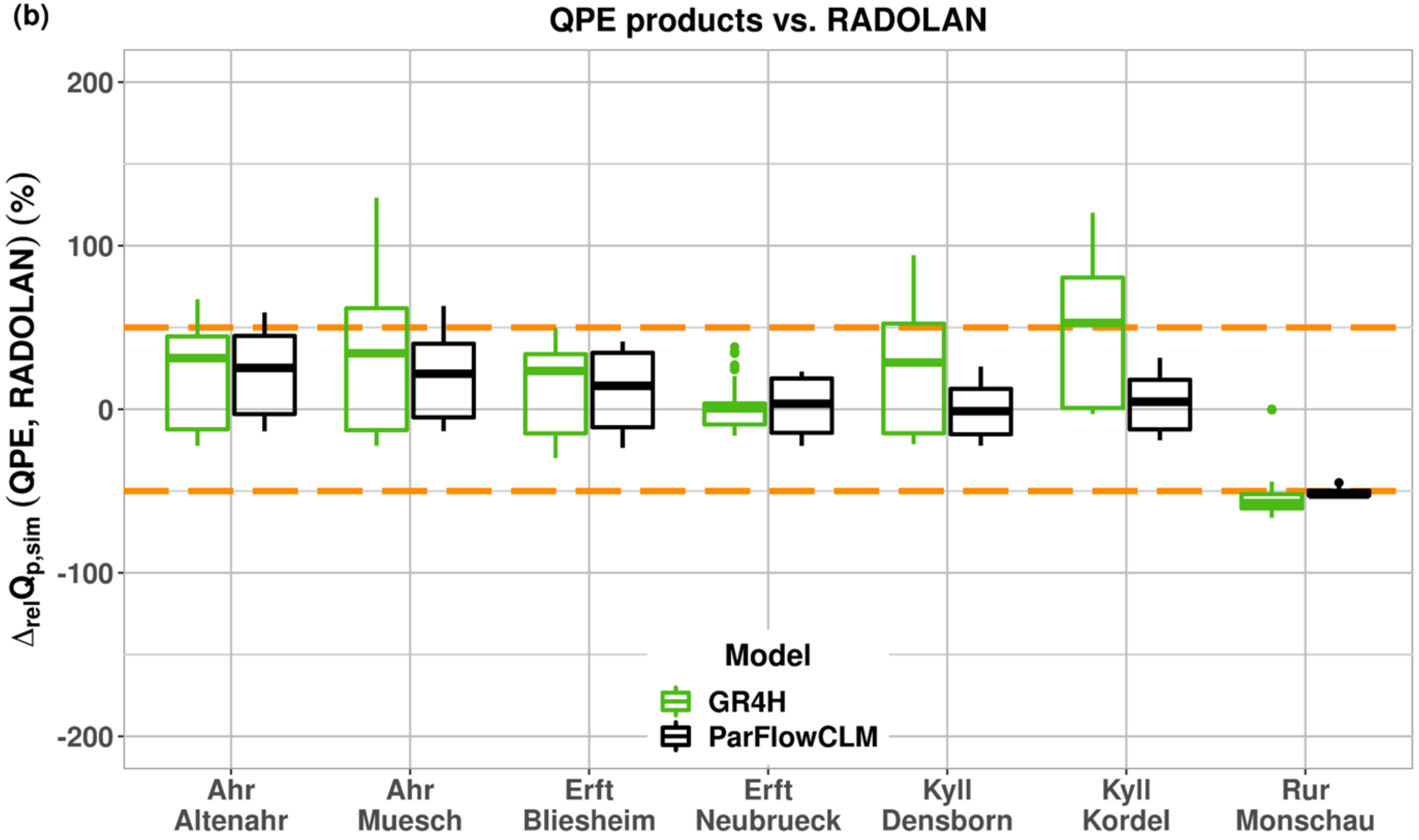
3| Q1. Impact of QPE & modeling choices on peakflow

3.2 | Result 3: Uncertainties from model parameters vs. from QPE products

$$\frac{Q_{psim}(GR4H, QPE) - Q_{psim}(ParFlowCLM, QPE)}{Q_{psim}(ParFlowCLM, QPE)}$$

$$\frac{Q_{psim}(QPE, Modx) - Q_{psim}(RADOLAN, Modx)}{Q_{psim}(RADOLAN, Modx)}$$





If we change from **ParFlowCLM** to **GR4H**, we tend to have lower peakflow estimates

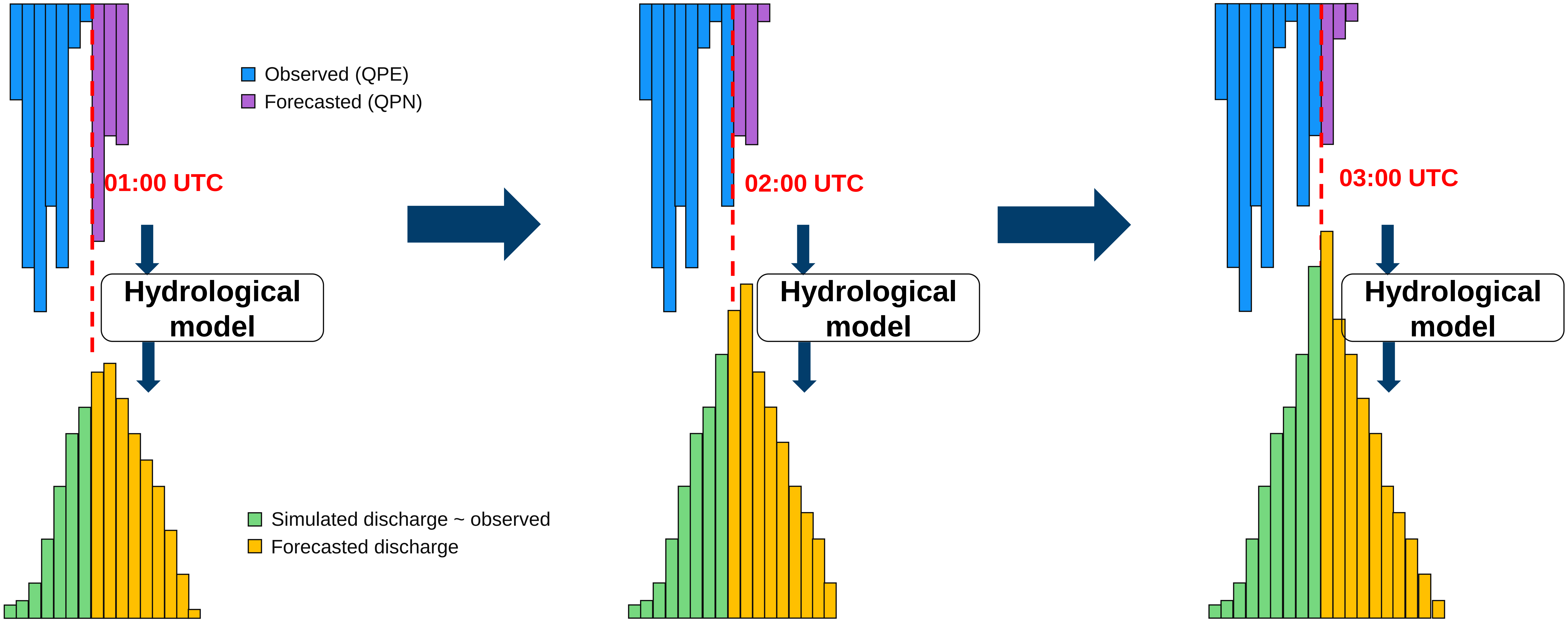
If we change from **RADOLAN** to **any other QPE**, we tend to have higher peakflow estimates

4| Q2. Improving the forecast lead time

4.1 | QPN methods and framework for hydrological evaluation

Based on the QPE product RAVKDP

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



4| Q2. Improving the forecasting lead time

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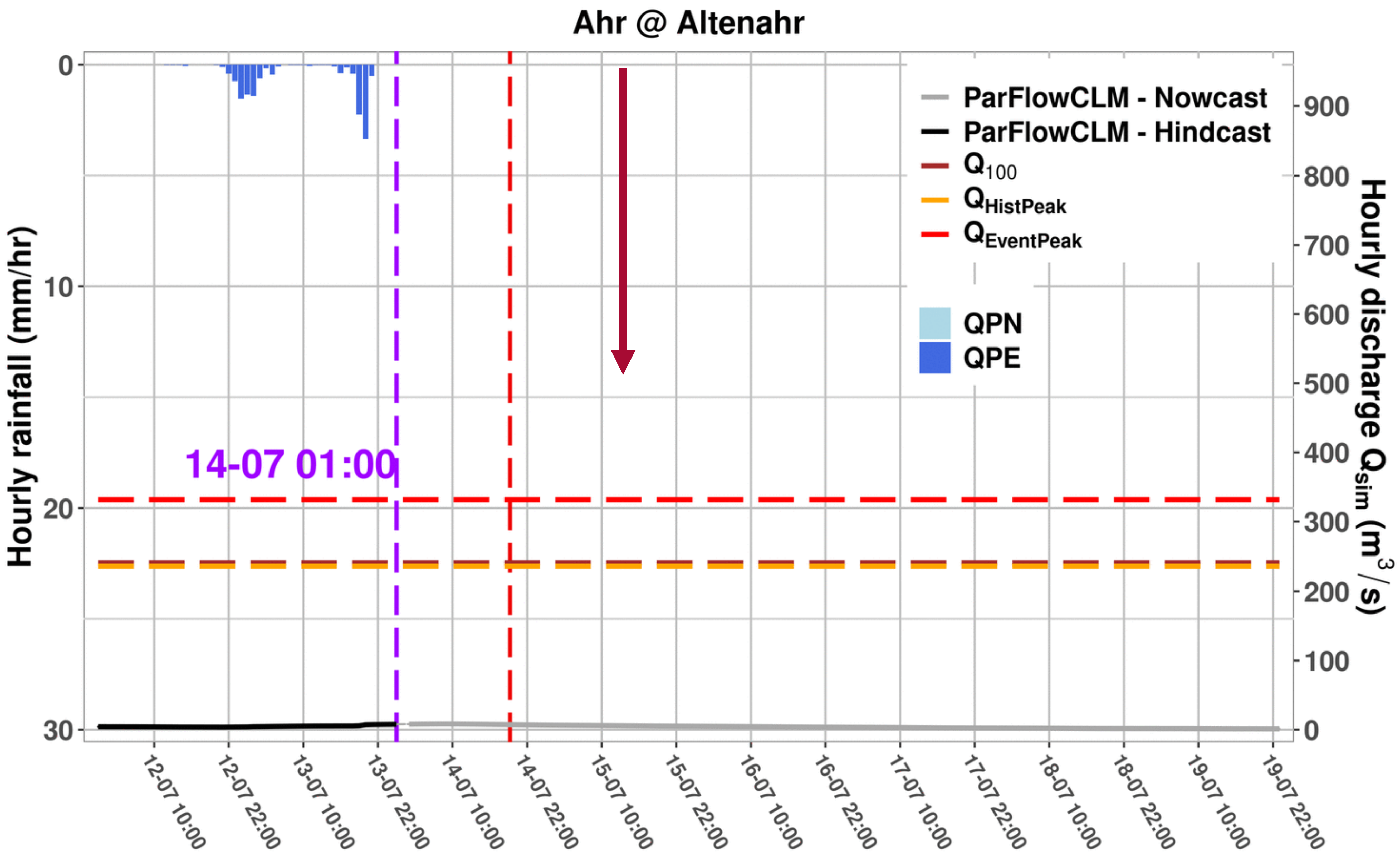

Spawned each hour between 01h00 and 18h00 of 14.07.2021

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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

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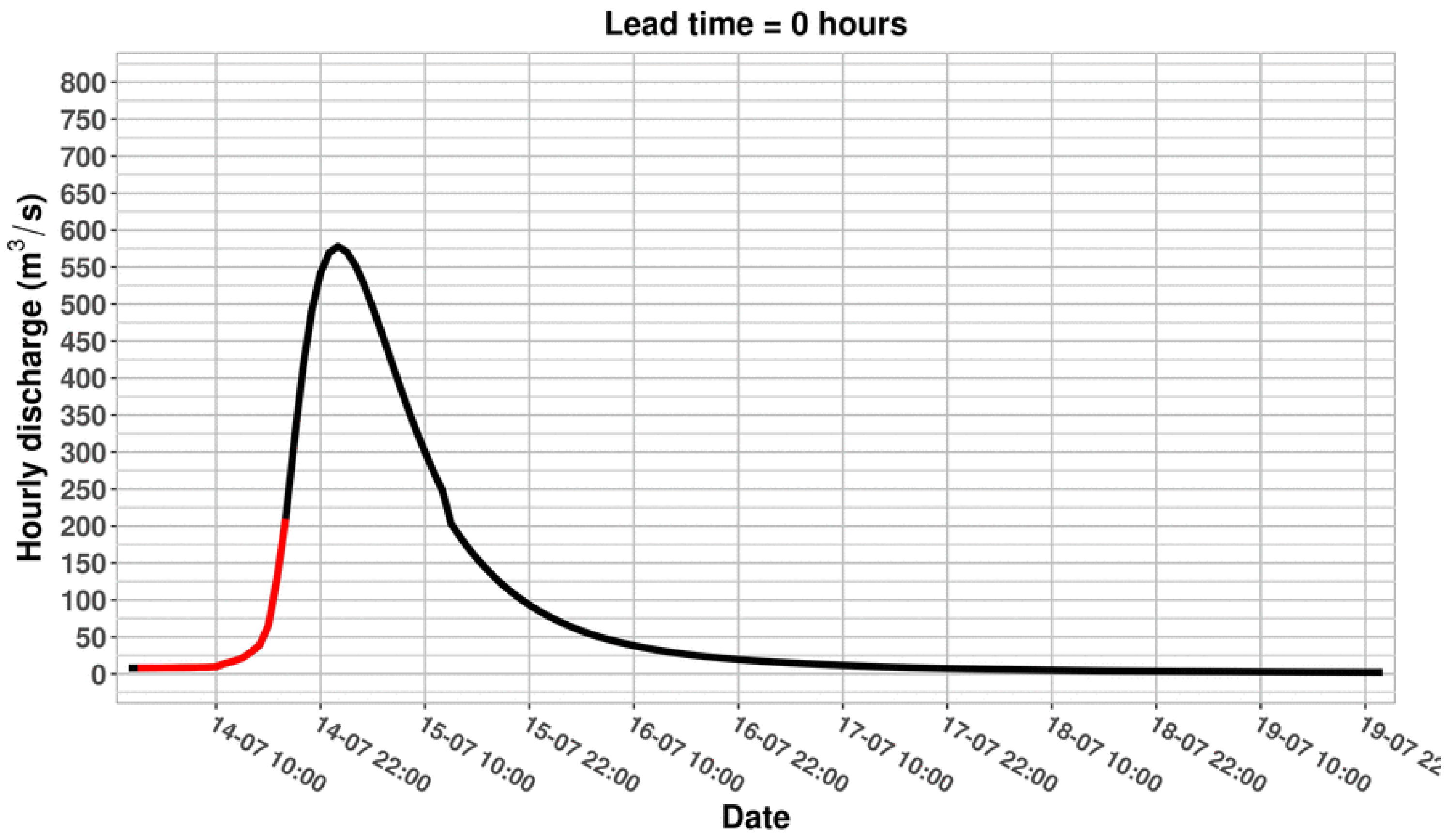


Simulated hydrograph with QPE to be compared with **forecasted hydrograph**

Evaluation metric

$$\text{Skill} = \frac{|\text{error}(\text{Bench})|}{|\text{error}(\text{QPN})| + |\text{error}(\text{Bench})|}$$

$$|\text{error}(\text{QPN})| < |\text{error}(\text{Bench})| \Rightarrow \text{Skill} > 0.5$$

Error estimated using the continuous rank probability score (CRPS)

Chen et al. (2017); Hersbach (2000)

4| Q2. Improving the forecasting lead time

4.2 | Result 1: Hydrological persistence as benchmark

No differences between the three methods

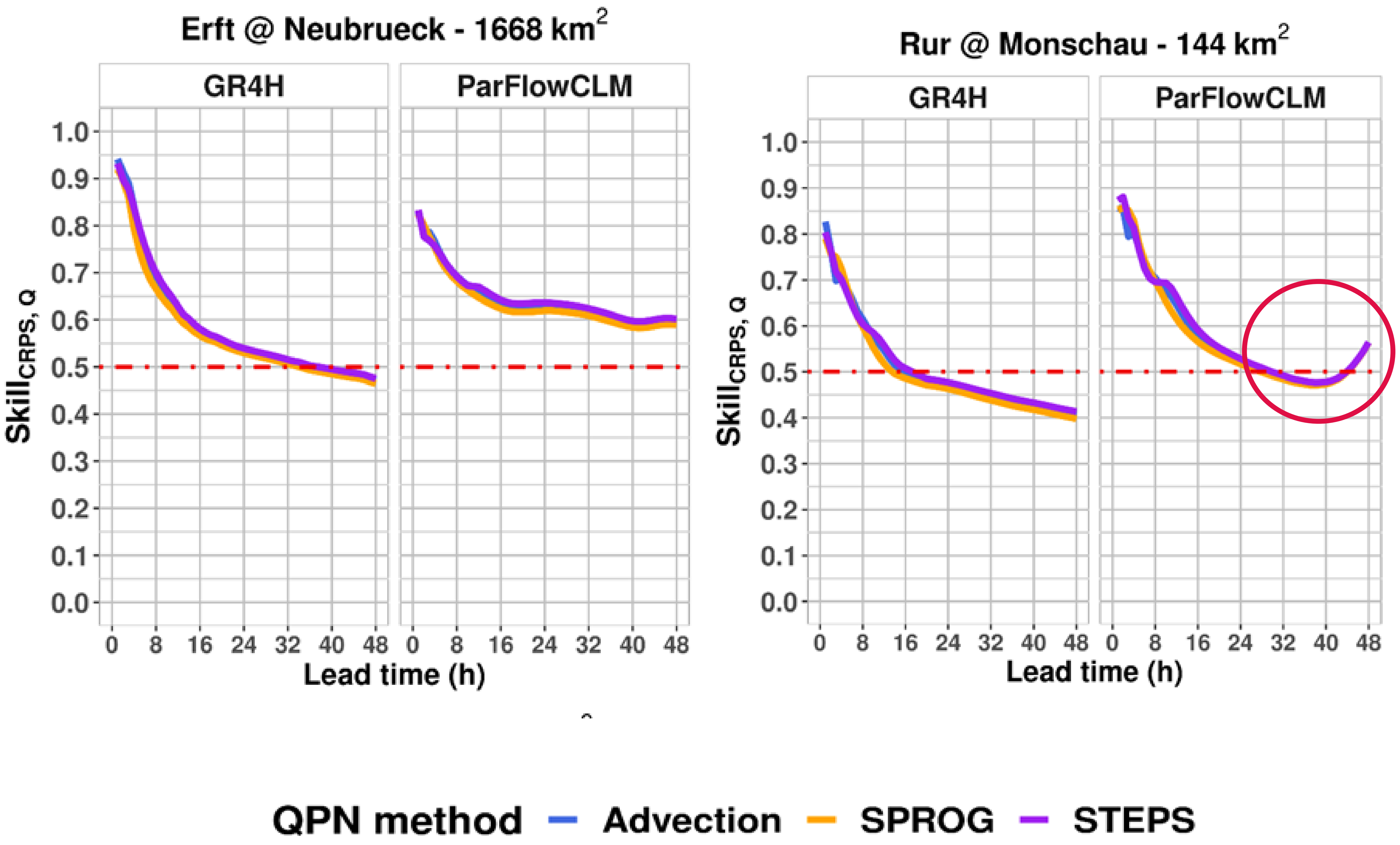
Decreasing skill with increasing lead time

A rebound in the skill curves for the Ahr river, related to rising/falling limbs of the hydrograph

Usefulness that can last as long as 48 h, except for some cases

No significant relation with catchment size

No significant effect of the hydrological model

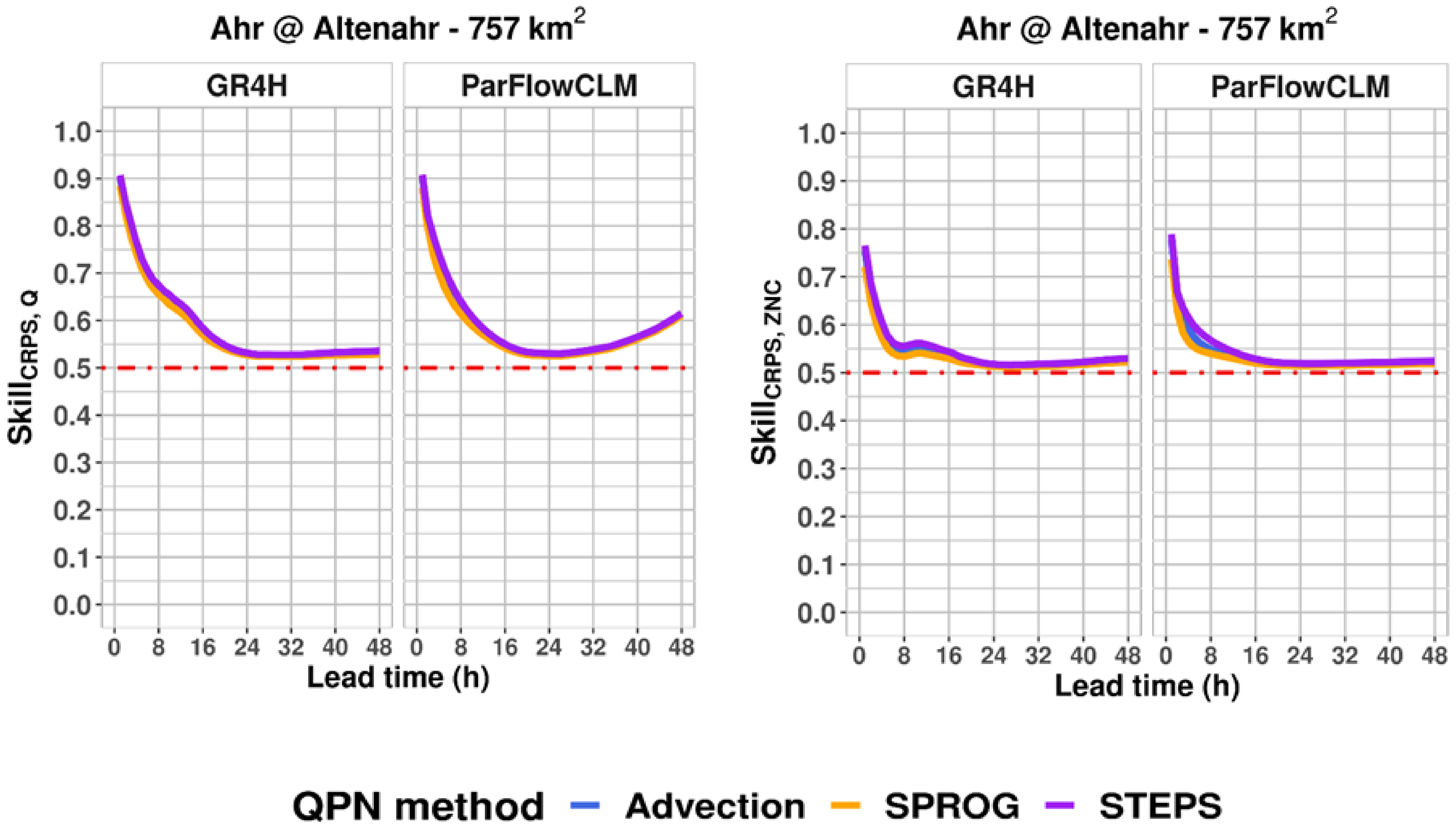


4| Q2. Improving the forecasting lead time

4.2 | Result 2: Zero-precipitation nowcasts as a benchmark

Similar conclusions, but no rebound effect!!

Lower skill compared to hydrological persistence, but more costly with additional model run

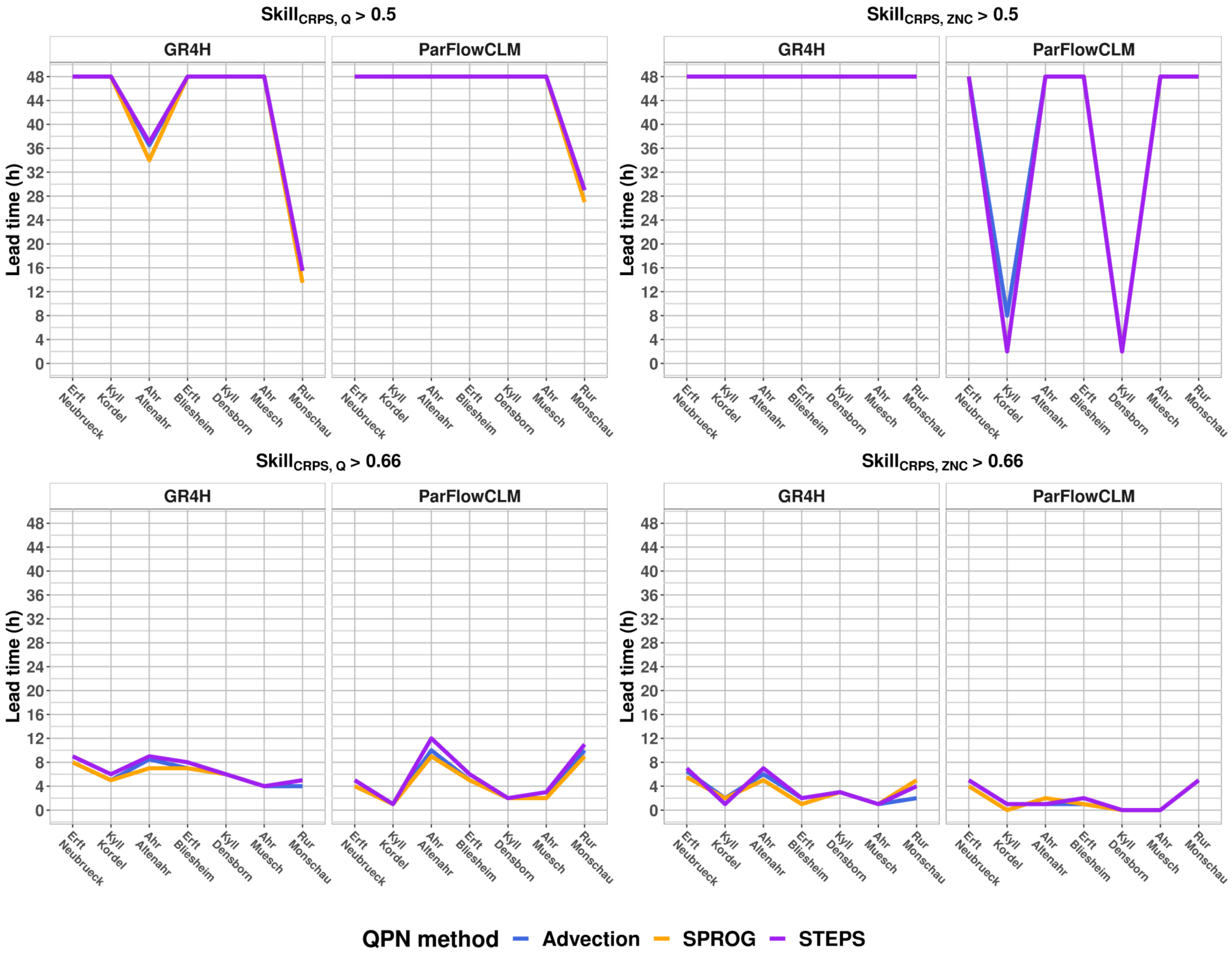


4| Q2. Improving the forecasting lead time

4.2 | Result 3: Effect of skill threshold

$$|\mathrm{error(QPN)}| < |\mathrm{error(Bench)}| \;\Rightarrow\; \mathrm{Skill} > 0.5$$

$$|\mathrm{error(QPN)}| < \frac{1}{2}|\mathrm{error(Bench)}| \Rightarrow \mathrm{Skill} > \frac{2}{3}$$



Changing the skill threshold has a significant impact!

QPN are now useful only up to 12 h at most!

5| Conclusions

Comparison of modeling philosophies

There is general agreement between GR4H and ParFlowCLM, except for highly influenced catchments. Adopting a very low Manning’s explains most of the discrepancies between the models

At this stage, running a conceptual model seems more advantageous, but the distributed model allows for estimations in all points of the domain, regardless of discharge data availability

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

The QPN methods behaved similarly. Possible differences in a less predictable, more spatially variable precipitation event?

The choice of the benchmark model and the skill threshold impacts the evaluation of the QPN

Thank you for your attention!

Questions?

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