

RealPEP P1

Merging Radar and CML QPE

Julius Polz, Maximilian Graf, **Christian Chwala**



RealPEP project meeting, 16.05.23, online

P1 KIT overview

Roadmap by Julius

Roadmap

5 minute

1 minute



Source: DWD

Optical flow estimation to compute intermediate timesteps



Source: C. Ruf, KIT



Source: DWD

Intercomparison



Roadmap

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Intercomparison

Probabilistic QPE
Bayesian inference approach

Random error

Systematic bias

Ensemble QPE

Roadmap

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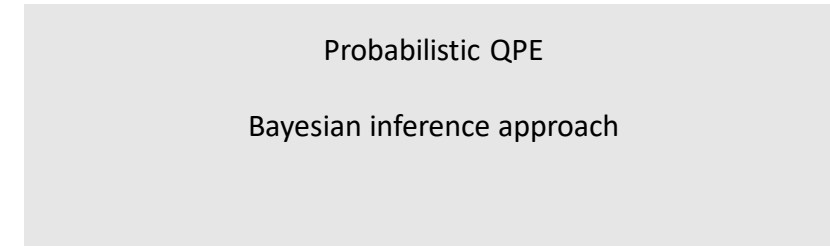


Source: C. Ruf, KIT

Intercomparison



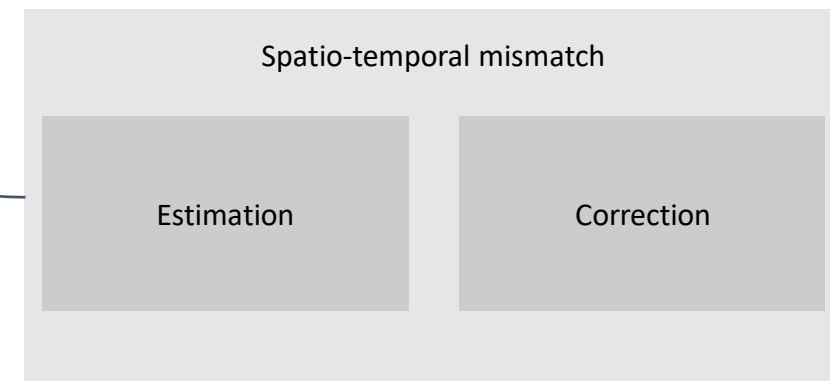
Source: DWD



Random error

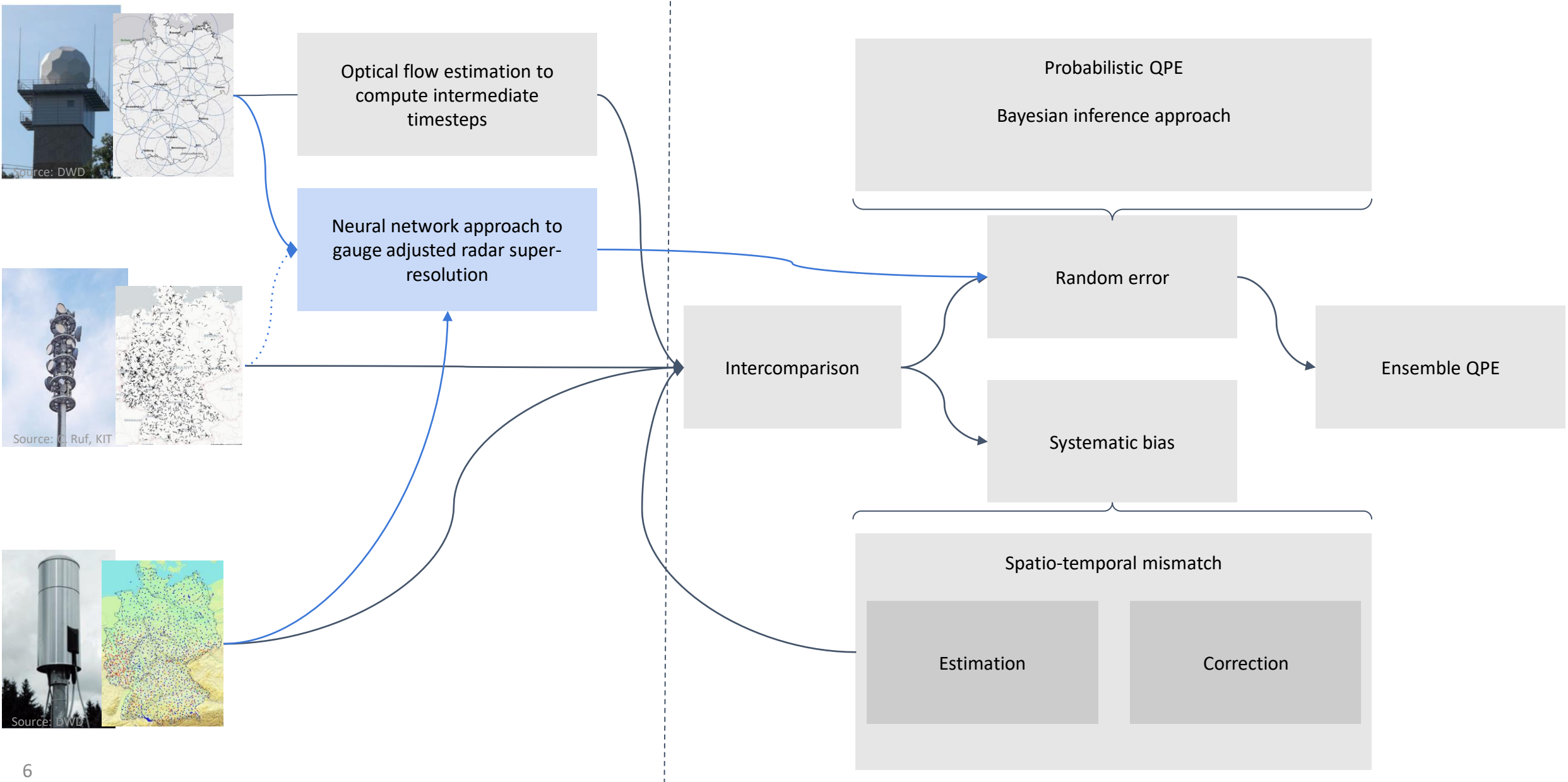
Systematic bias

Ensemble QPE



5 minute

1 minute



5 minute

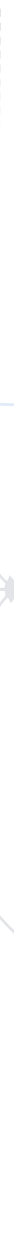
1 minute



Optical flow estimation to compute intermediate timesteps



Neural network approach to gauge adjusted radar super-resolution



Probabilistic QPE
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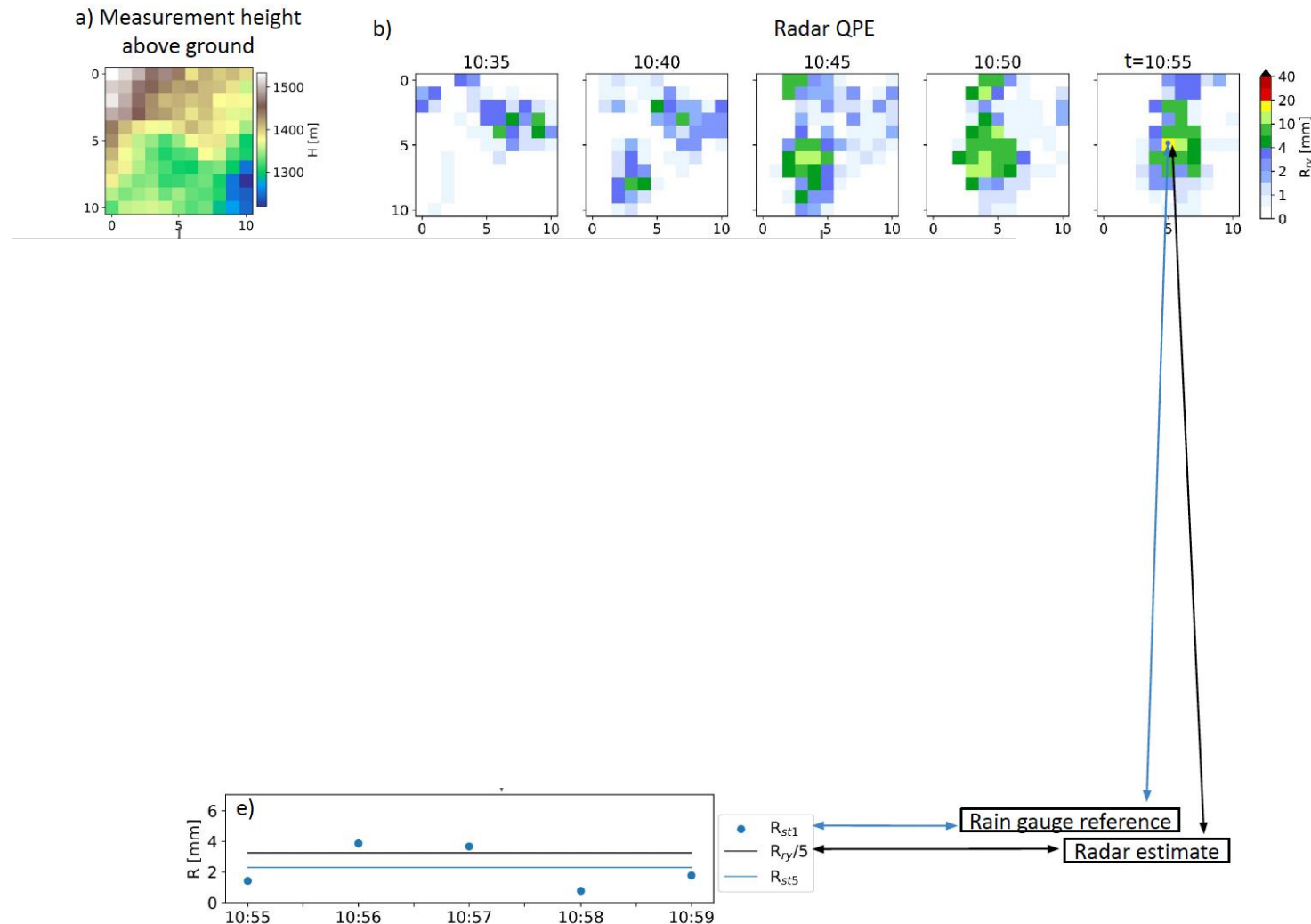
Ensemble QPE

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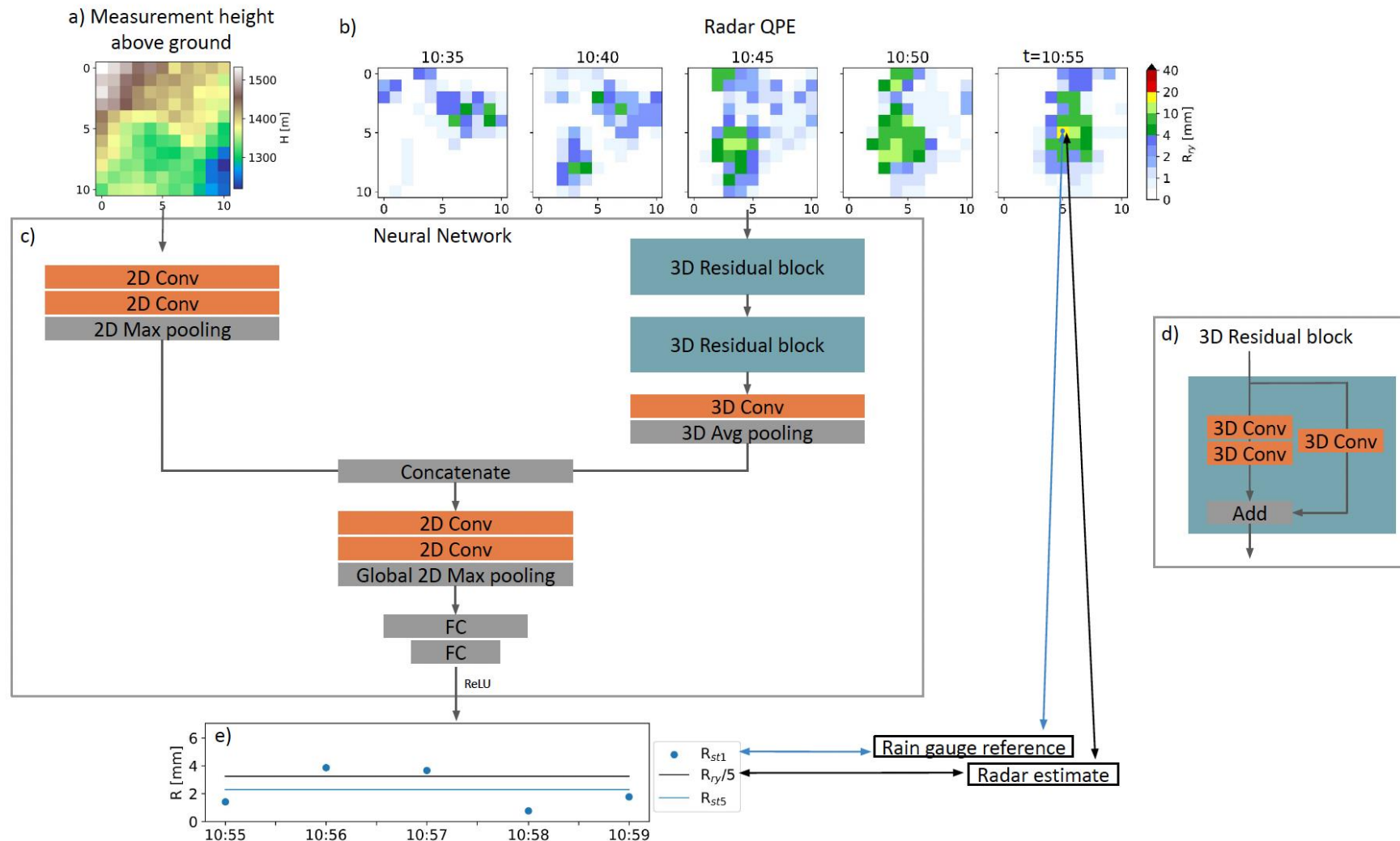
Spatio-temporal mismatch

Estimation Correction

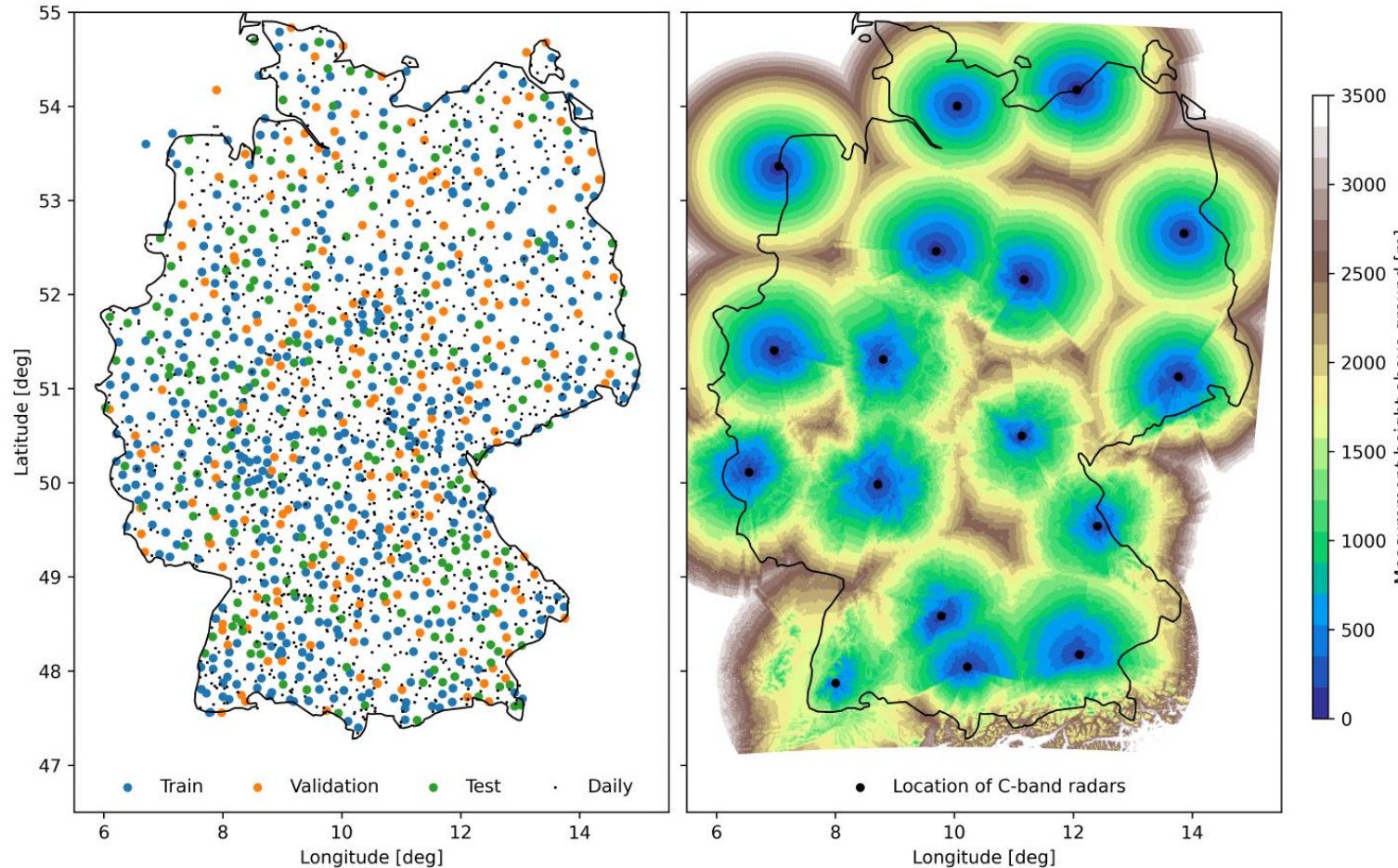
A deep convolutional neural network with residual blocks is trained to fit radar patches to gauge data



A deep convolutional neural network with residual blocks is trained to fit radar patches to gauge data



We use a large database of RADOLAN-RY and 1-minute gauge data

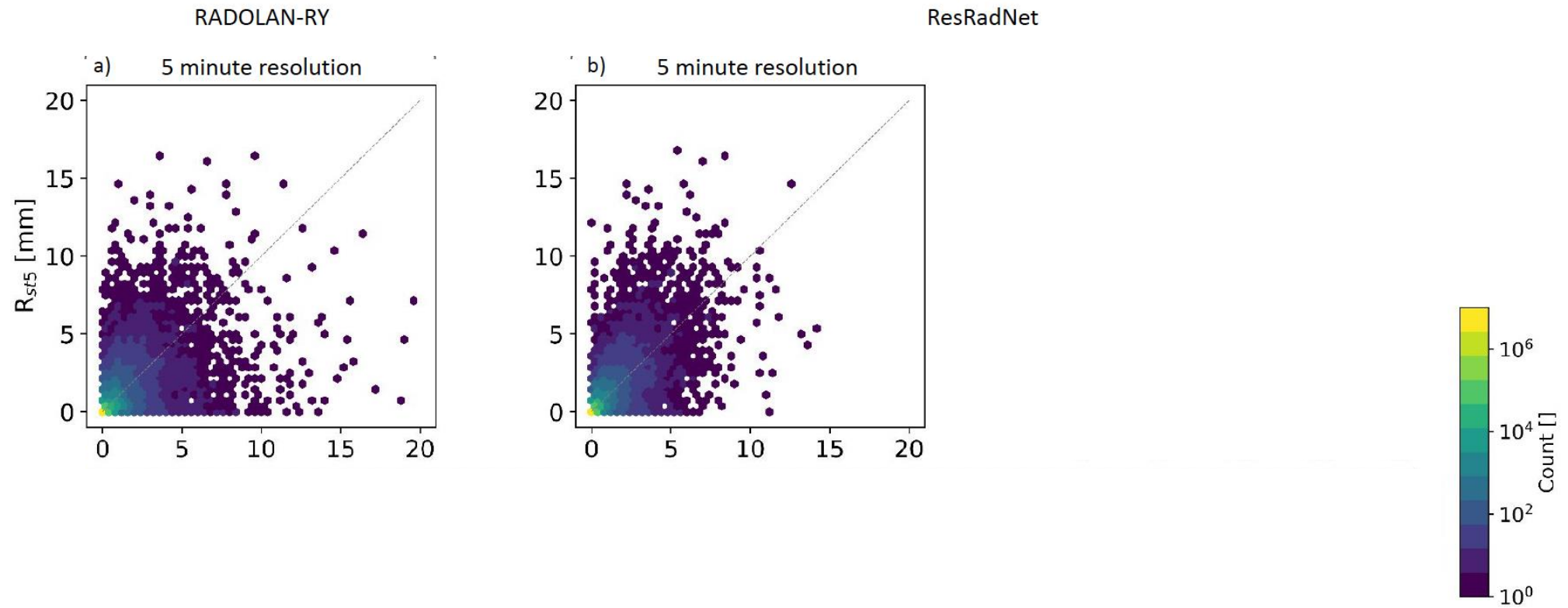


Training data: 2020

Validation data: 2021

Test data: 2013 to 2021

ResRadNet shows clear improvement of RADOLAN-RY

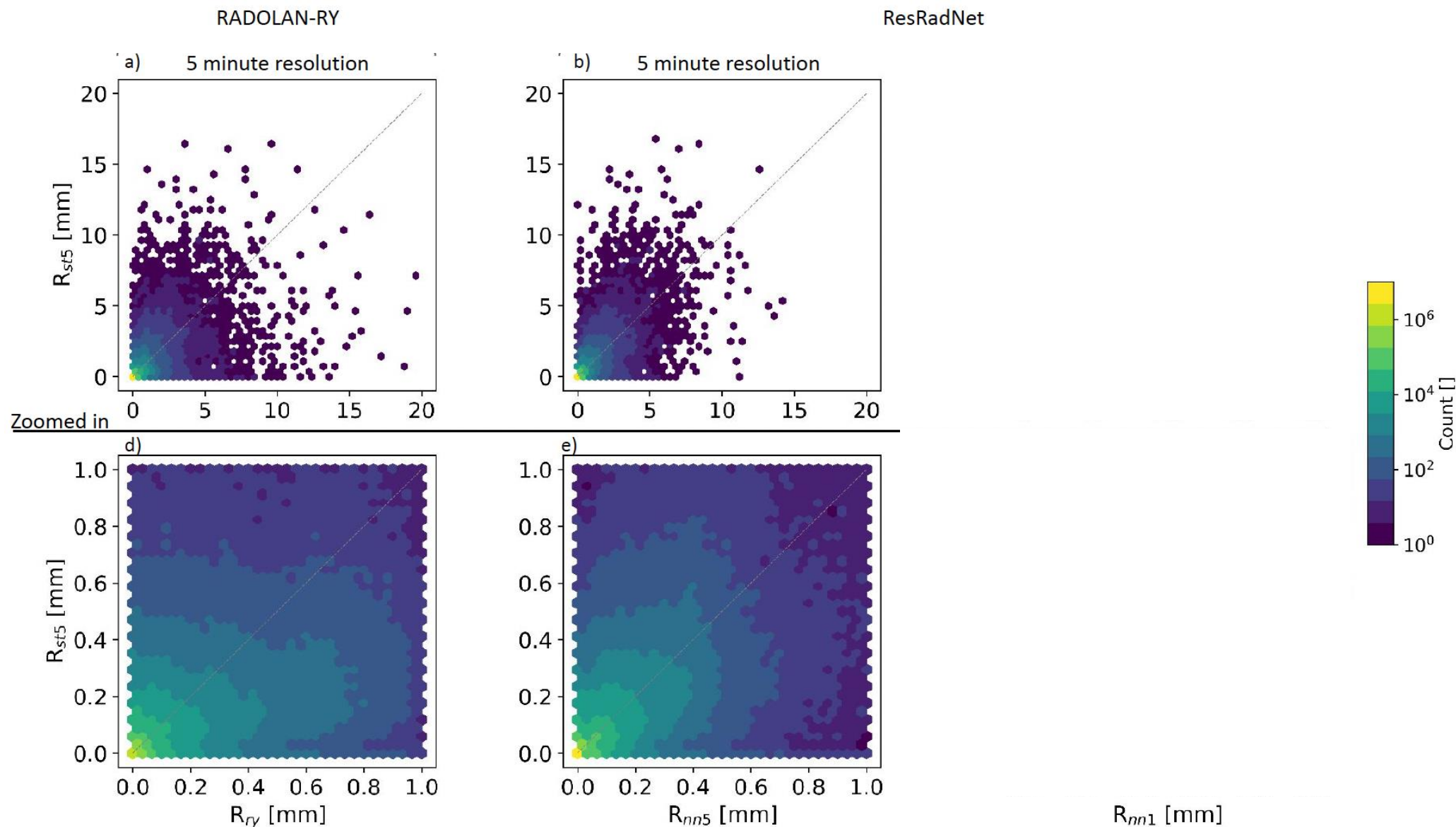


R_{ry} [mm]

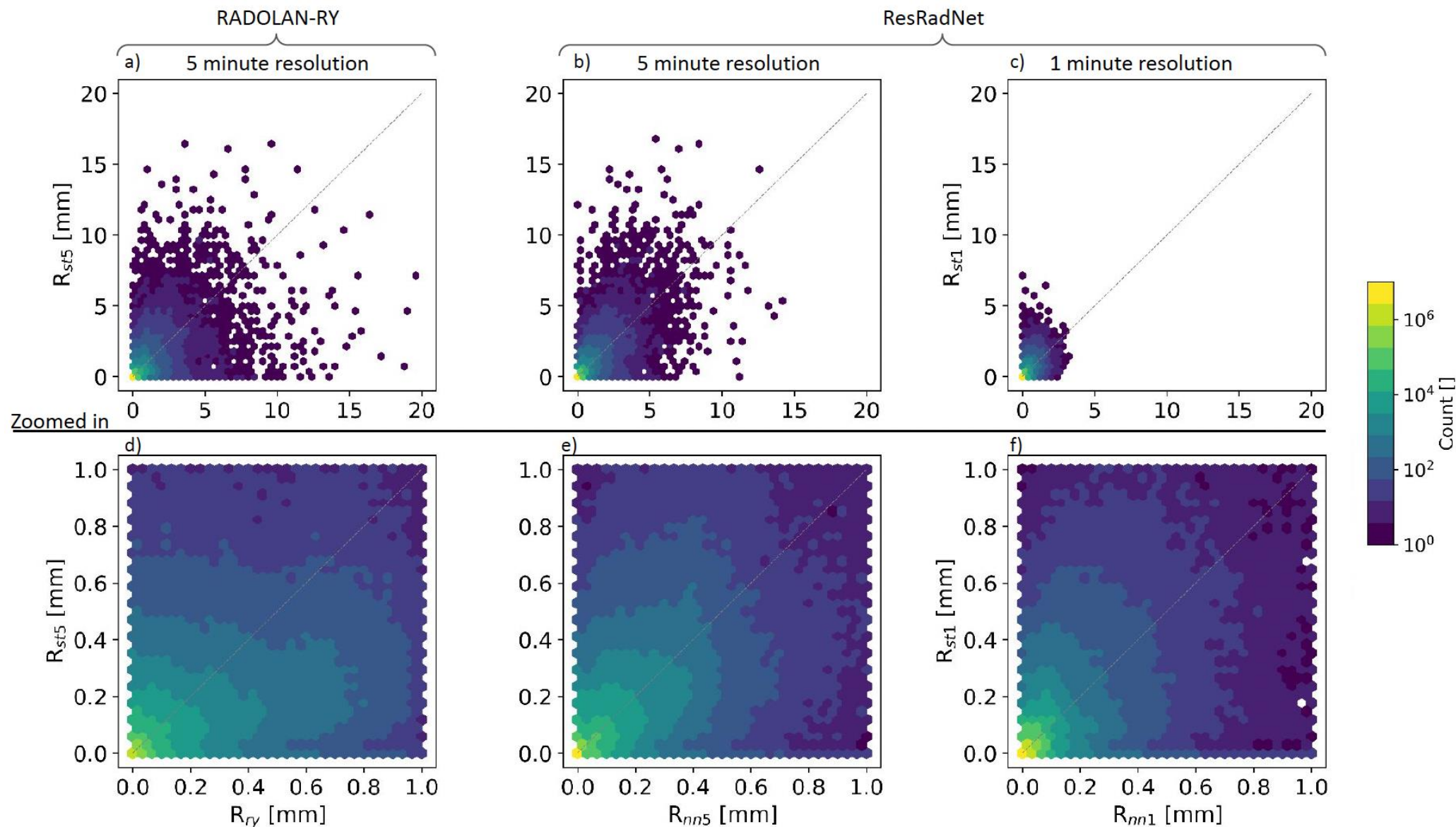
R_{nn5} [mm]

R_{nn1} [mm]

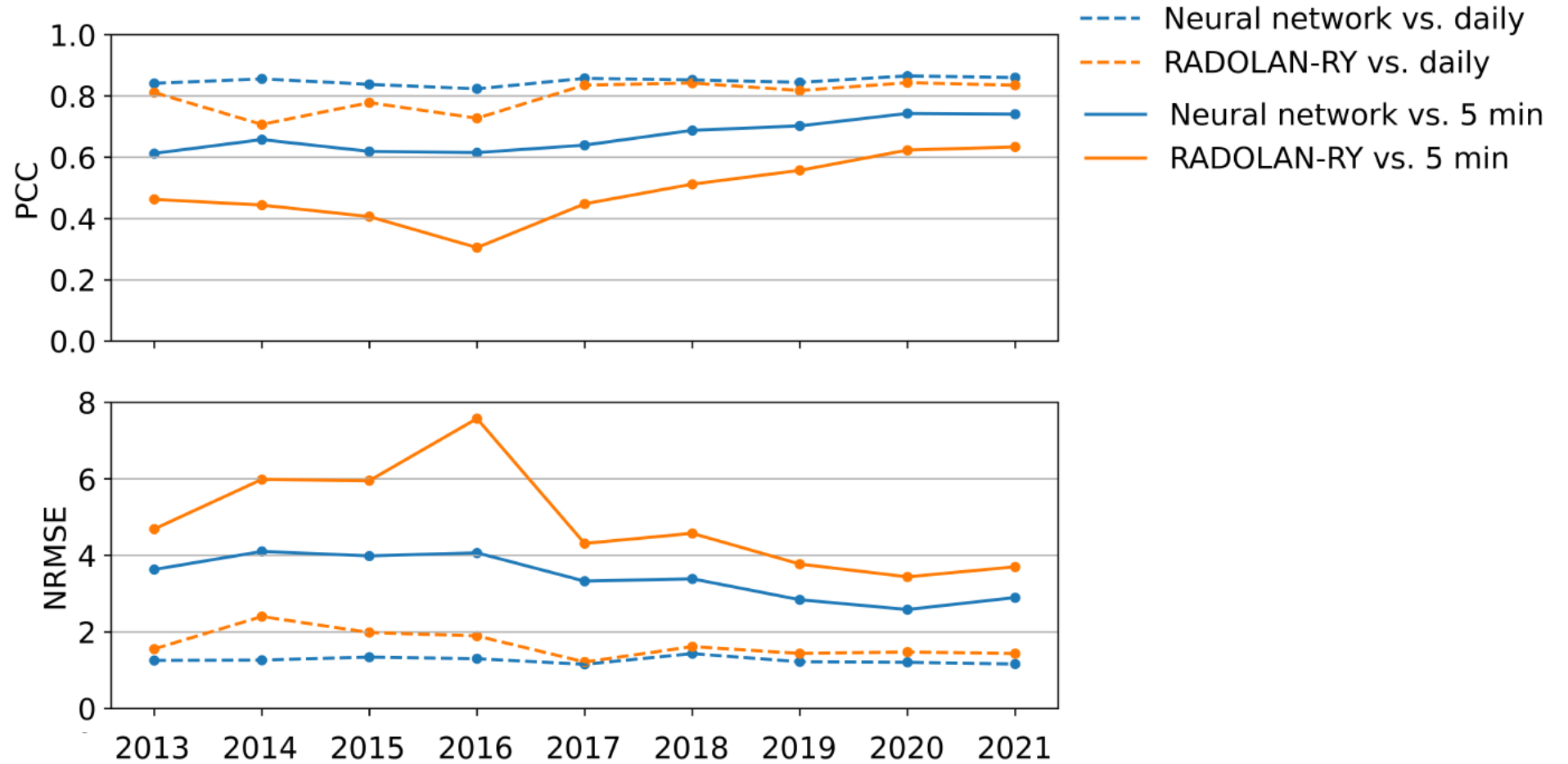
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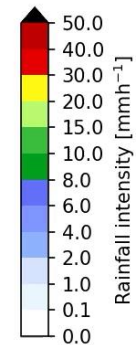
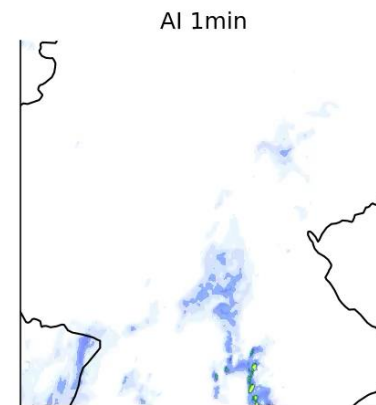
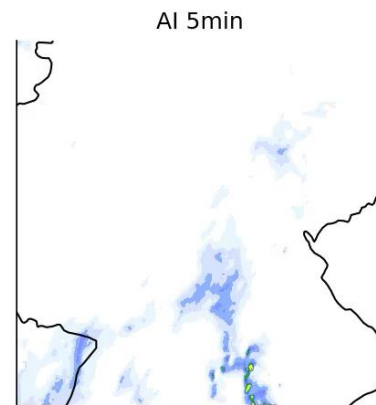
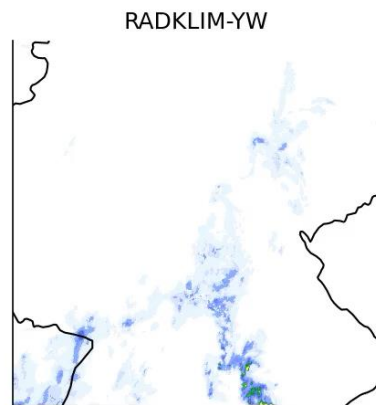
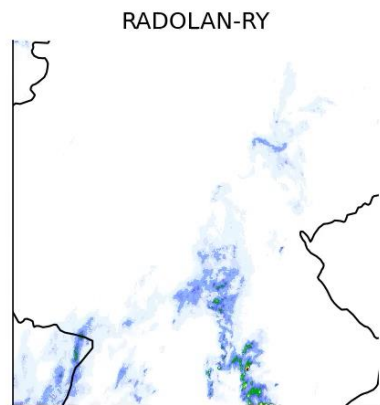
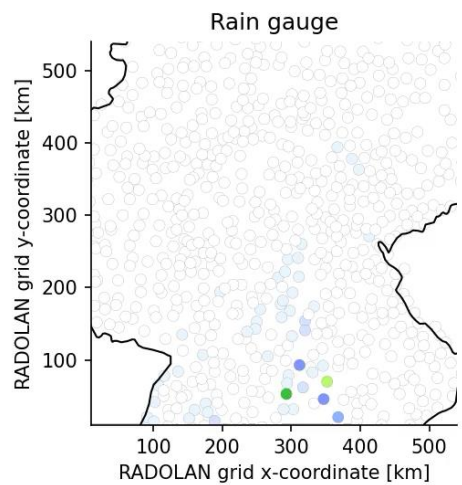
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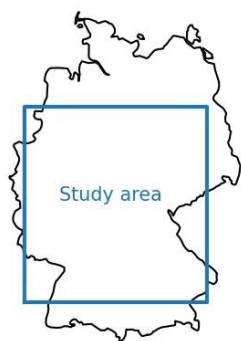
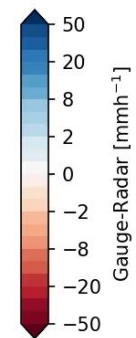
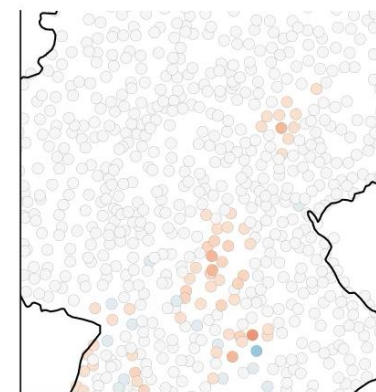
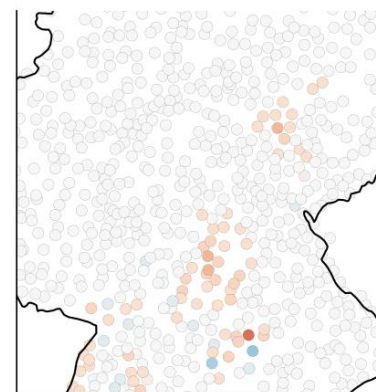
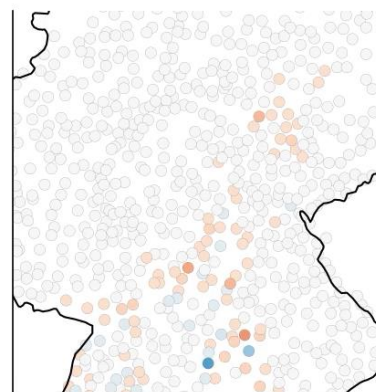
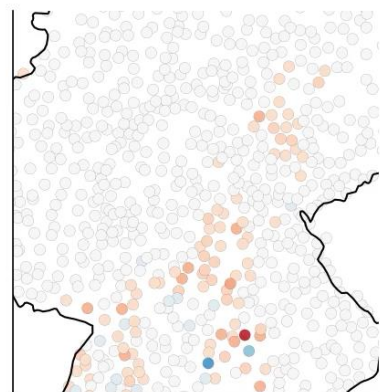
Improvement is also consistent over time



2021-07-06T16:50



Difference to rain gauge



Conclusion for Radar-DeepLearning-adjustment

- Neural network approach improves common metrics significantly (PCC, NRMSE etc.)
- Result not satisfying for extreme values

Julius' interpretation:

- Probabilistic approach necessary to predict range of possible values.
- Neural network likely to learn the mean (maximum likelihood).
- Bias stemming from large amount of small rain rate values during training

Also try in the future:

- ~~Predict the five 1-minute values of the station → similar to advection correction (done)~~
- Add CML information as additional input

Paper under review (Polz et al., 2023, TGRS)

5 minute

1 minute



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Neural network approach to gauge adjusted radar super-resolution

Intercomparison

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Bayesian inference approach

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Ensemble QPE

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Roadmap

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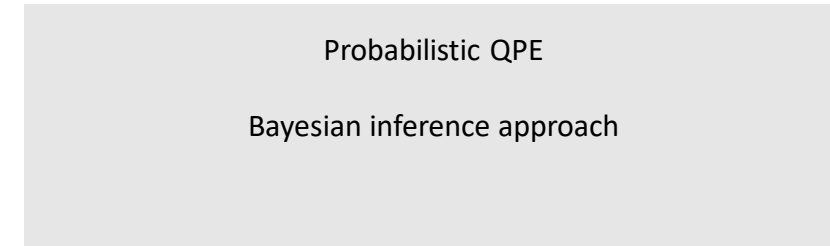


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“simple” merging

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Bayesian inference approach

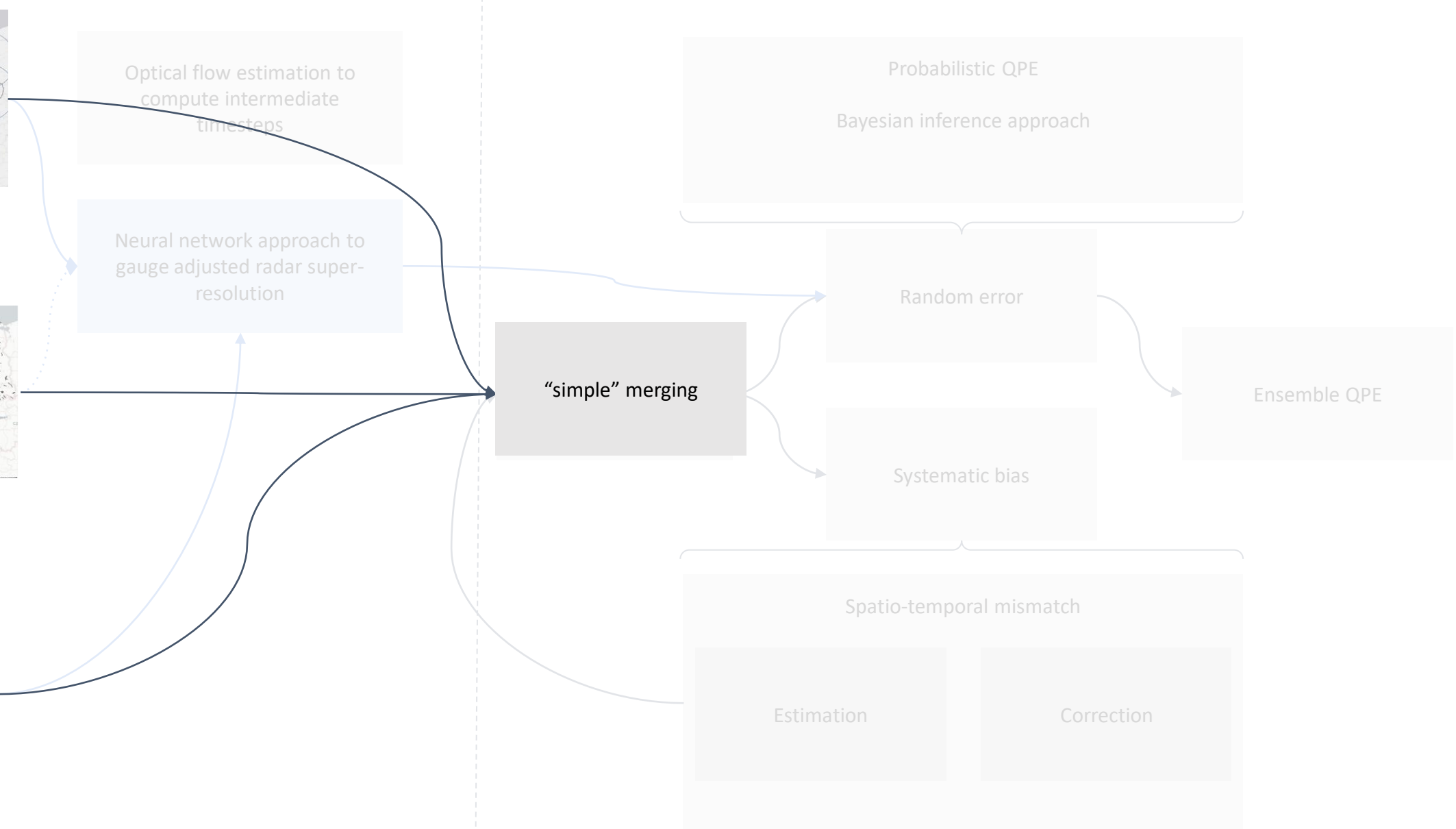
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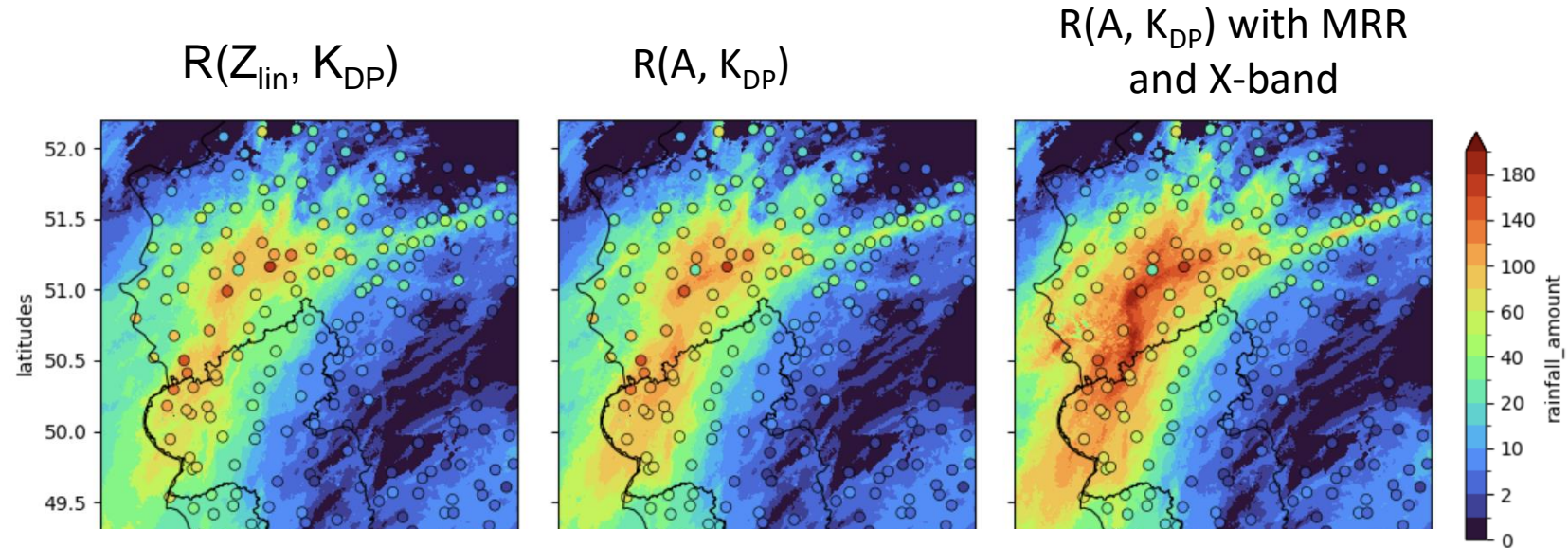
Preliminary results for Dual-Pol QPE CML adjustment



$R(Z_{lin}, K_{DP}) = R(Z_{lin})$ combined with $R(K_{DP})$ for $Z > 40$ dBZ

Chen et al. (2023), JHM

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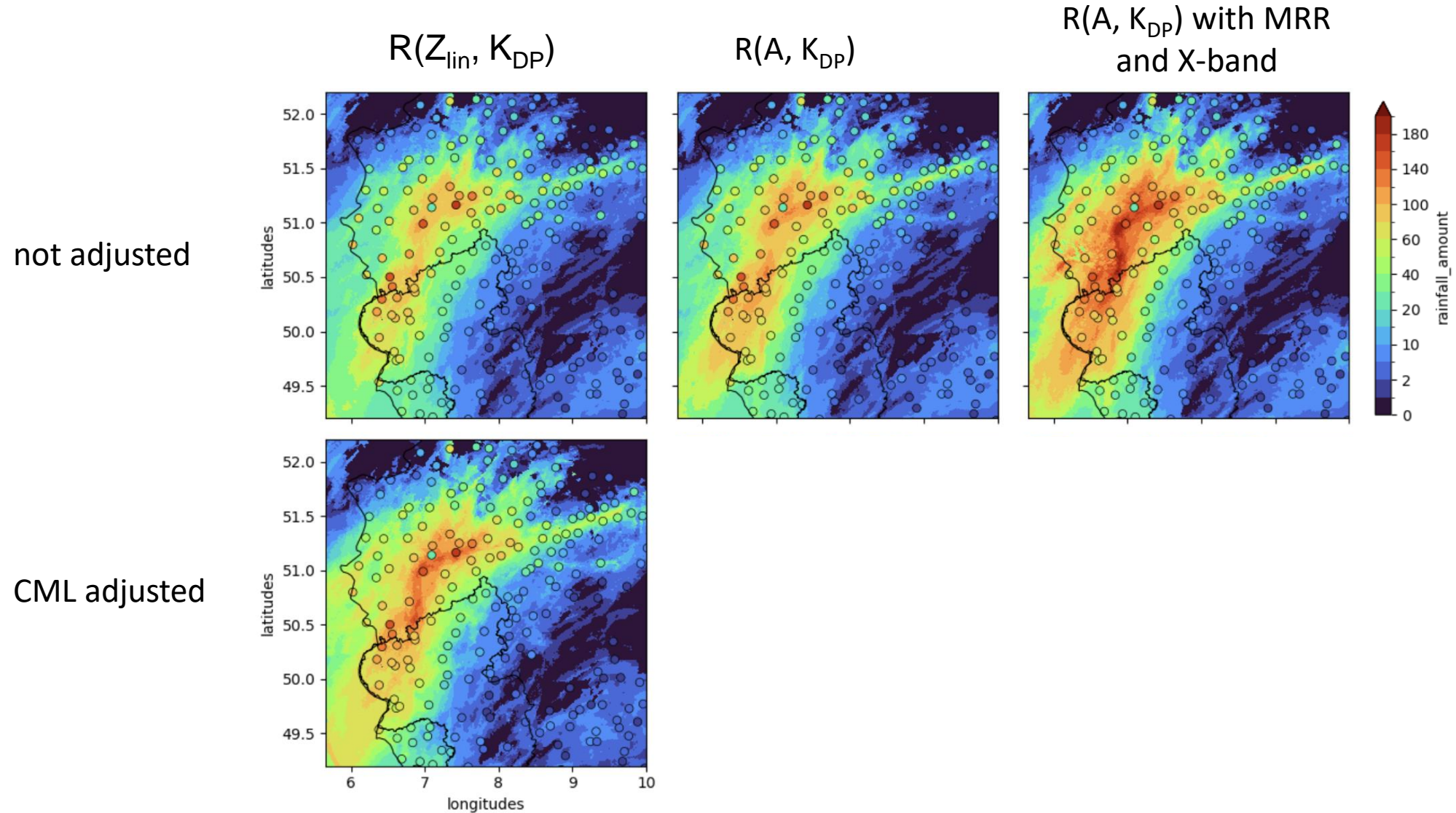
$R(A, K_{DP}) = R(A)$ combined with $R(K_{DP})$ for $Z > 40$ dBZ

$R(A, K_{DP})$ with

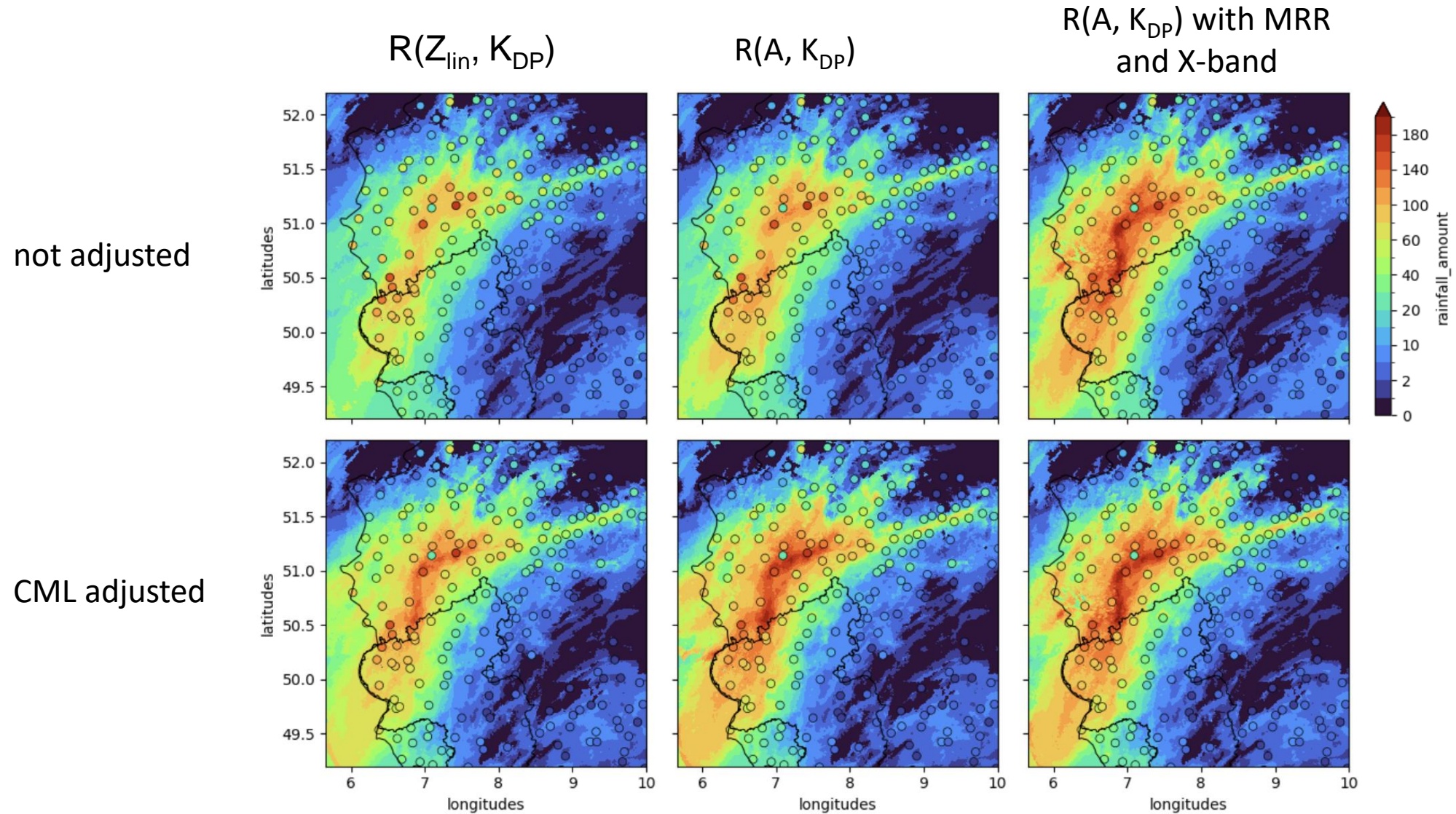
- MRR (vertical profile correction of Z and K_{DP})
- gap filling with X-band radar observations

Chen et al. (2023), JHM

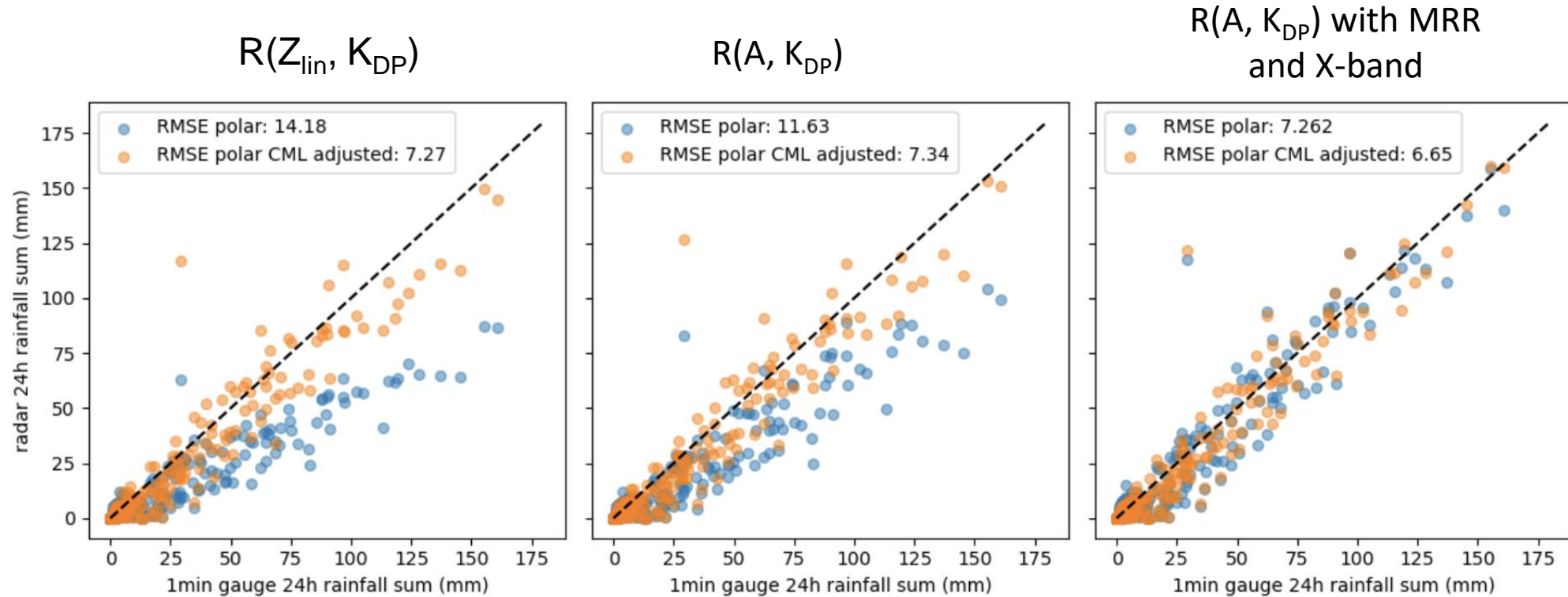
Preliminary results for Dual-Pol QPE CML adjustment



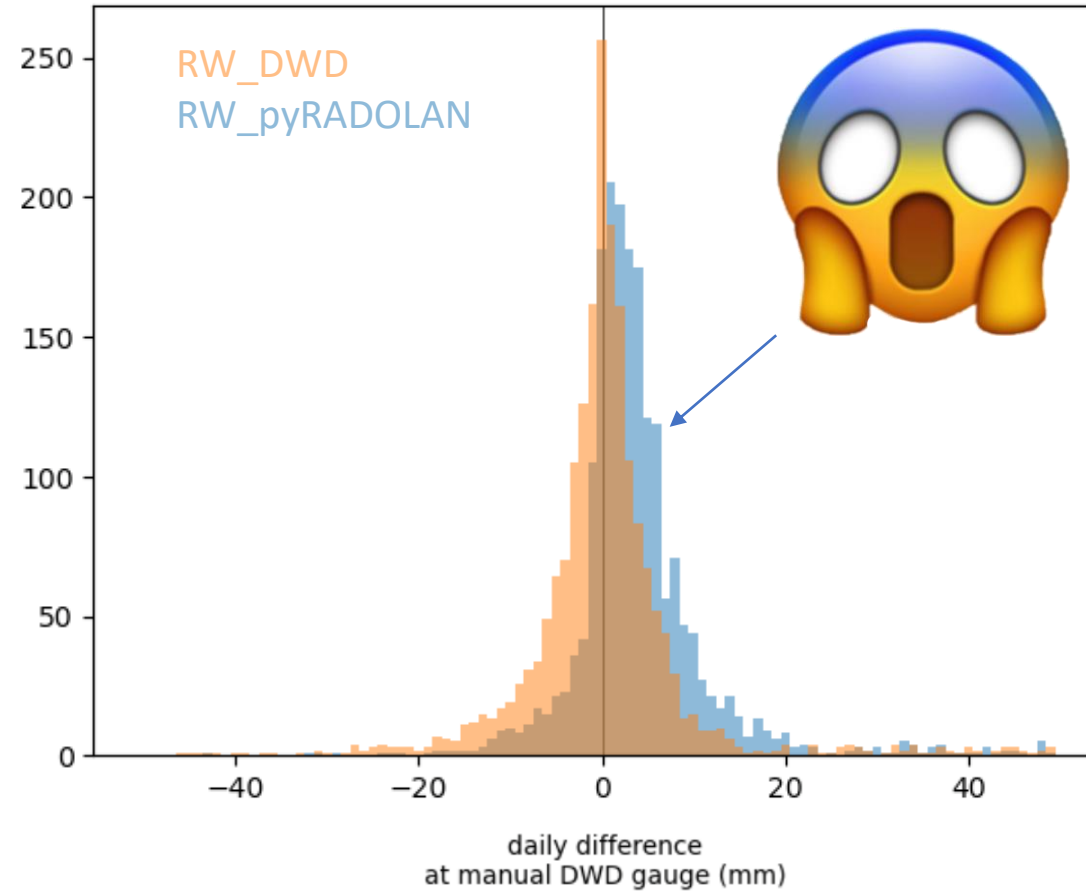
Preliminary results for Dual-Pol QPE CML adjustment



CML adjustment shows clear improvement, except for the case of Radar QPE with X-Band and MRRR data

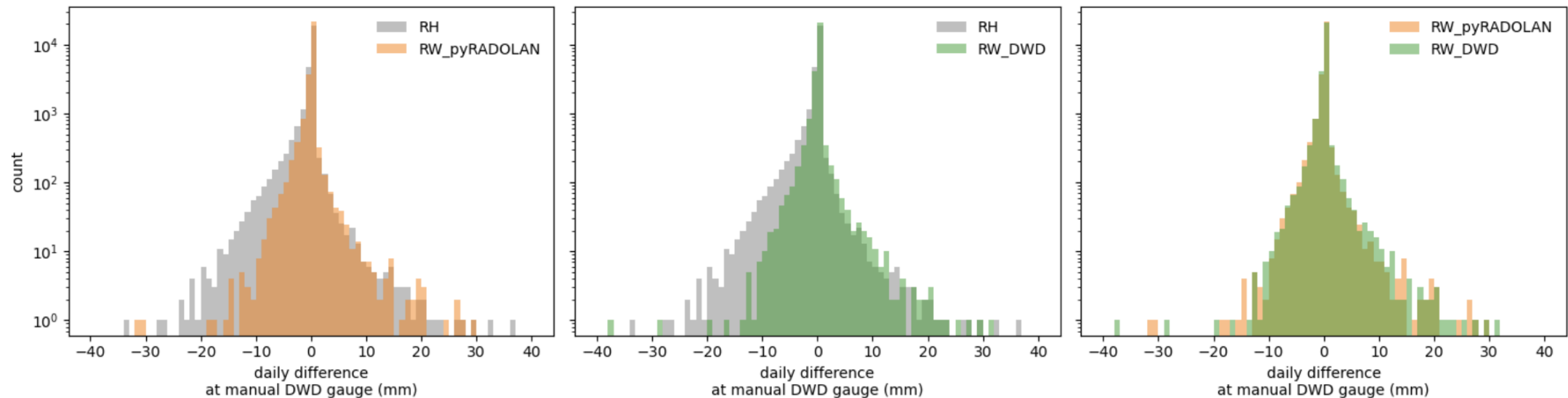


Had to fix bug in pyRADOLAN adjustment code...

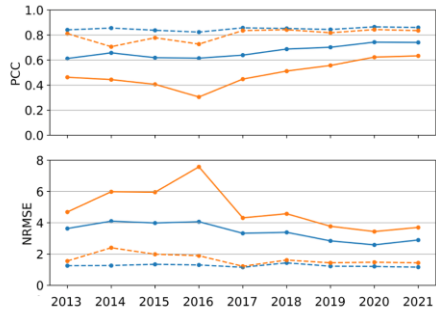


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New long-term comparison of own RW (produced with *pyRADOLAN*) and DWD's RADOLAN-RW shows good agreement



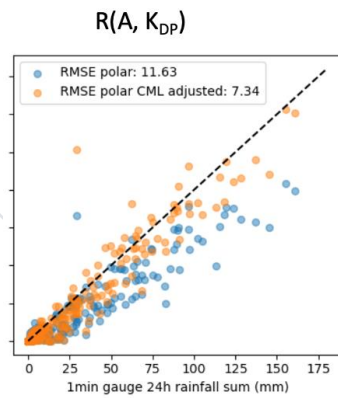
Summary



Neural network approach to gauge adjusted radar super-resolution



“simple” merging



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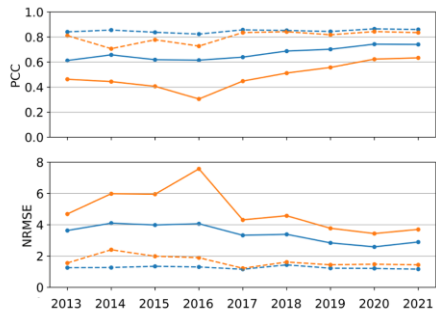
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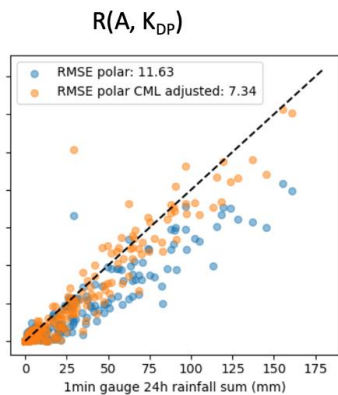
Correction

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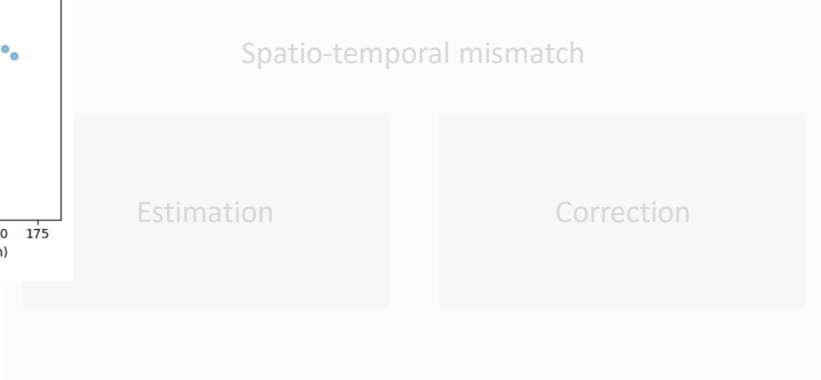
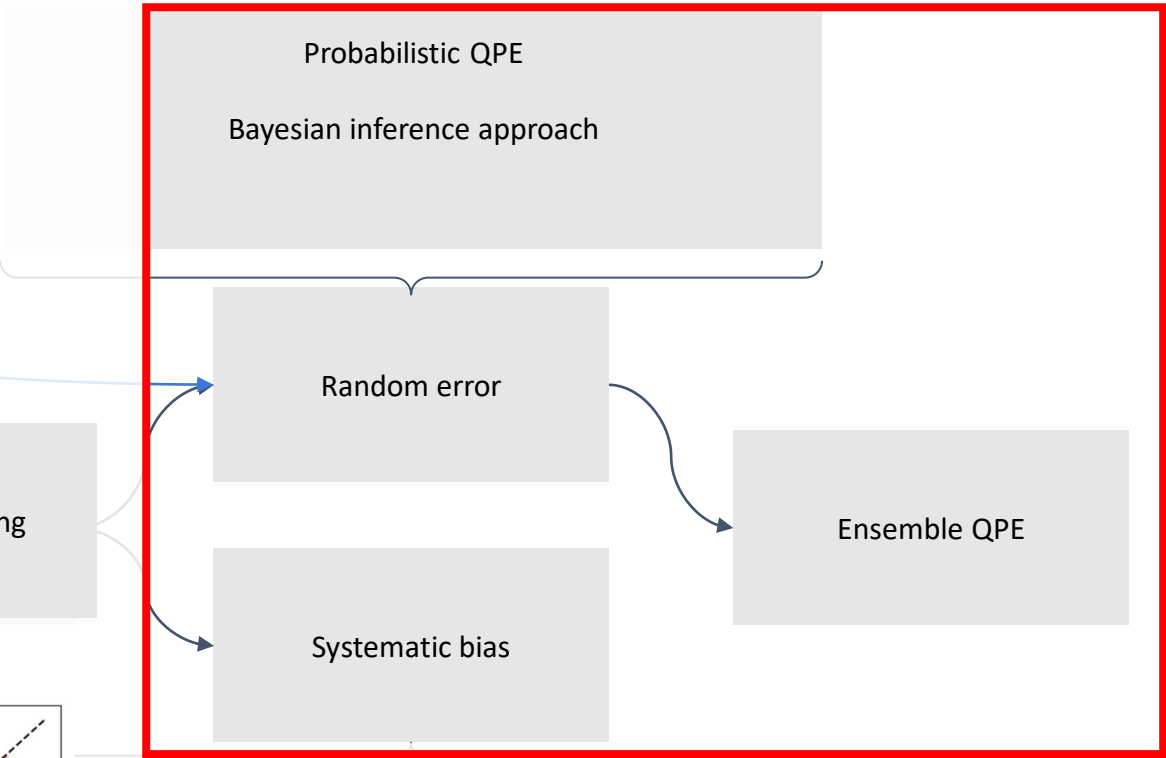


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“simple” merging



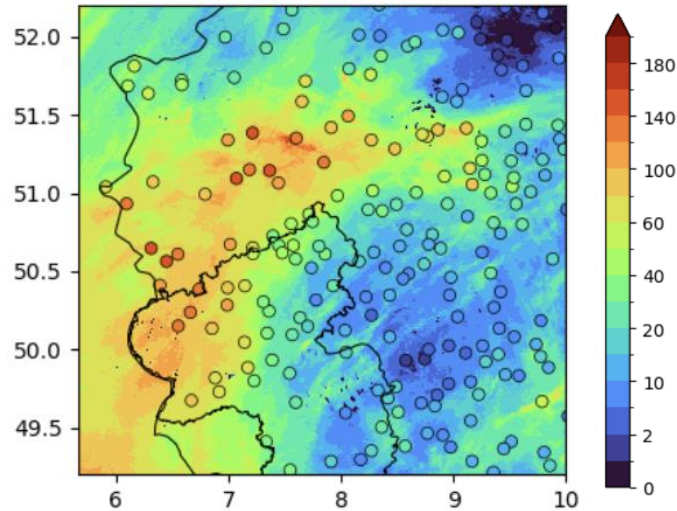
Still a lot to do here...



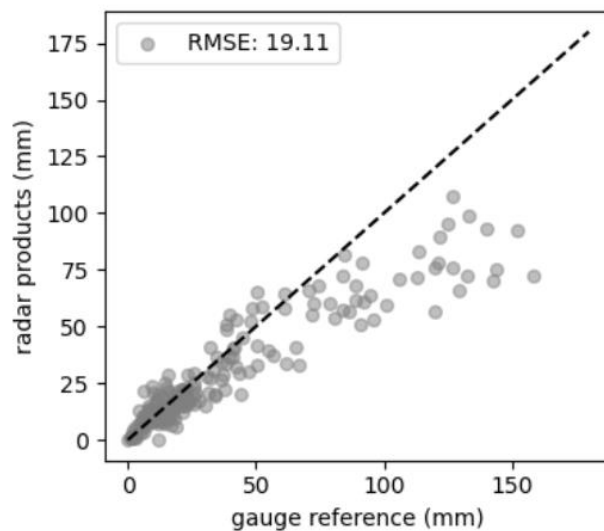
Backup slides

Ahr-Hochwasser: Unangeeichtes Radar unterschätzt stark

Radar unangeeicht



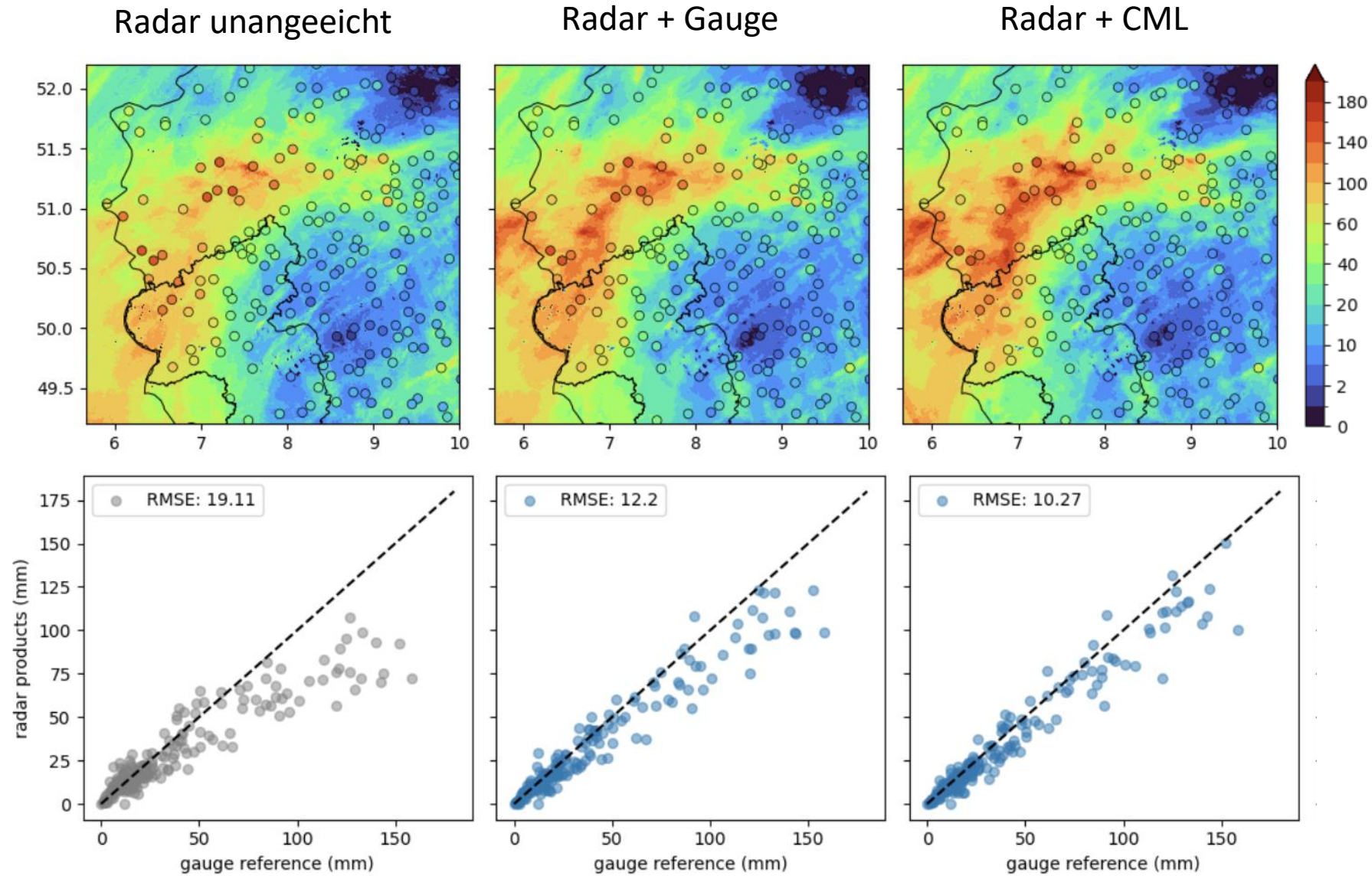
Niederschlagssumme
13.-15. Juli 2021



Aktuelle Ergebnisse
aus dem Projekt HoWa-PRO



Korrektur durch CML-Aneichung ist ähnlich zu Stationsaneichung



Beste RMSE für Aneichung mit CML + Stationen

