

A probabilistic AI-based merging of Commercial Microwave Link and Radar QPE

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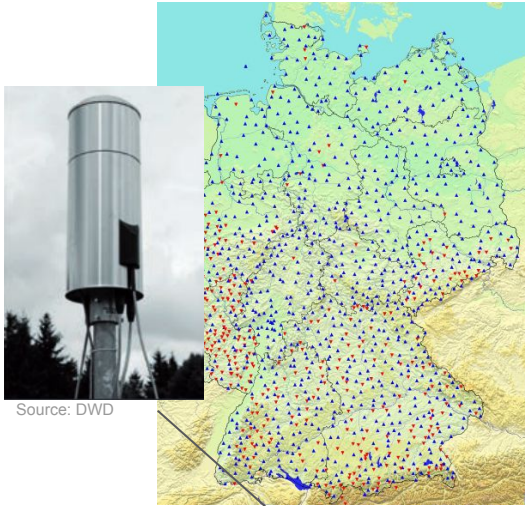
⁴ University of Bonn, Institute for Geosciences - Section Meteorology



Source: Flickr

Rainfall sensors in Germany

Rain Gauge

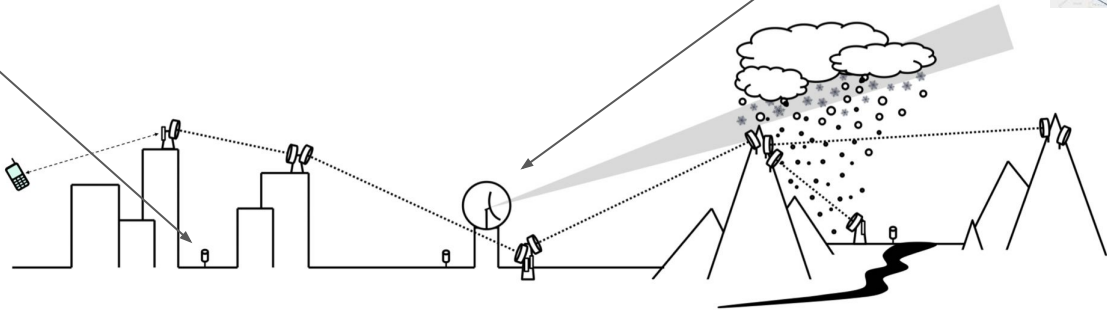


Source: DWD

Weather radar (C-band)

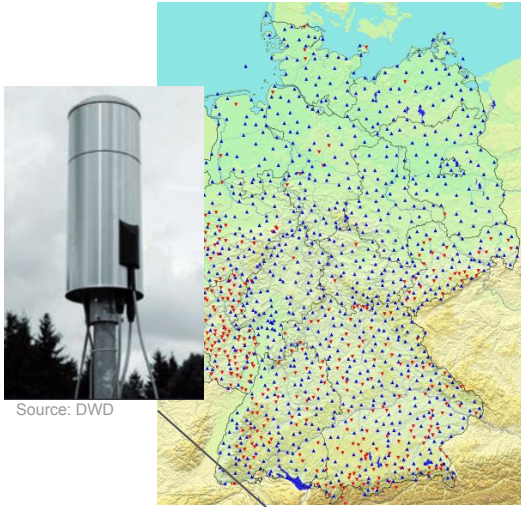


Source: DWD



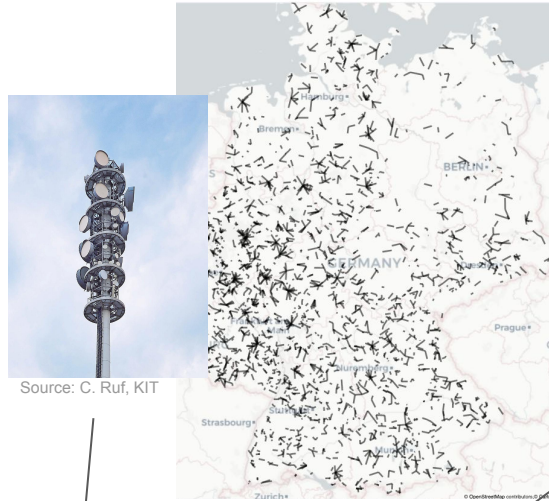
Rainfall sensors in Germany

Rain Gauge



Source: DWD

Commercial microwave link (CML)

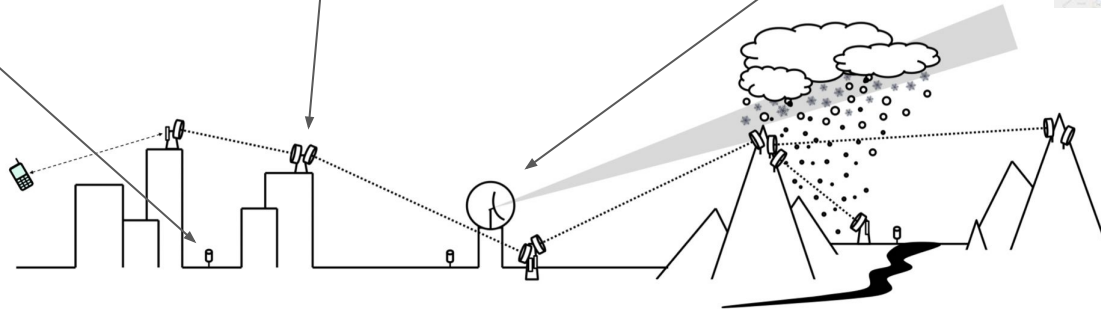


Source: C. Ruf, KIT

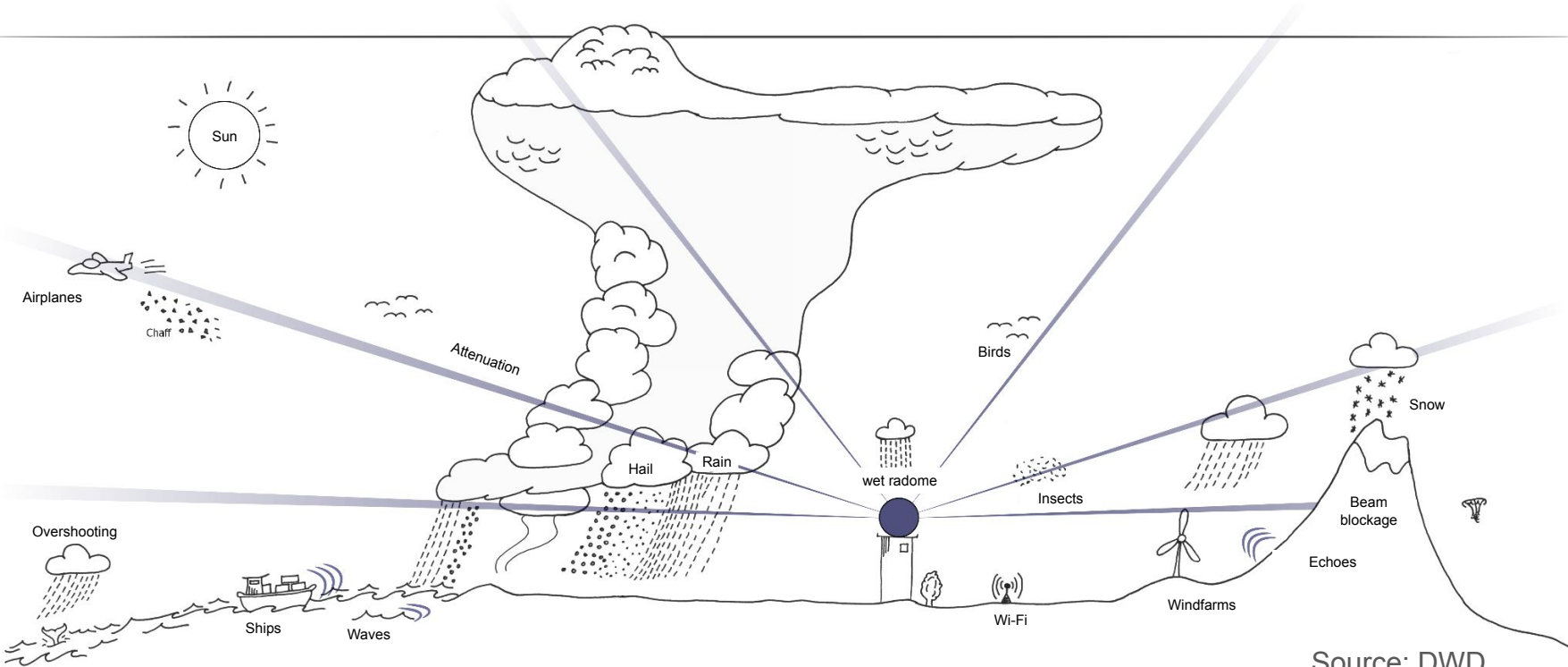
Weather radar (C-band)



Source: DWD



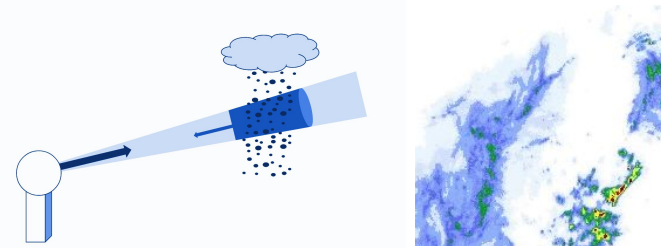
Systematic measurement errors



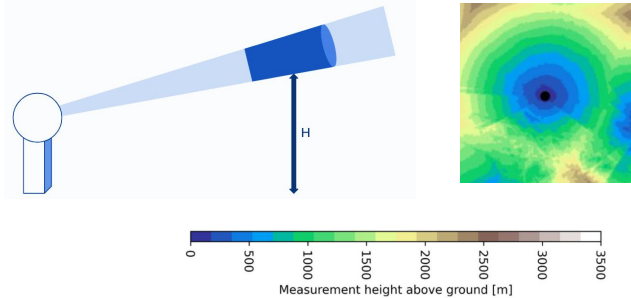
Source: DWD

Problem formulation

Input:
Radar QPE (RADOLAN-RY)
5 min res.

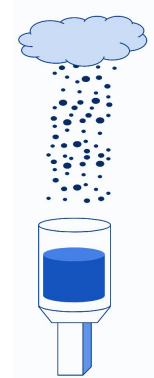


Radar Measurement height



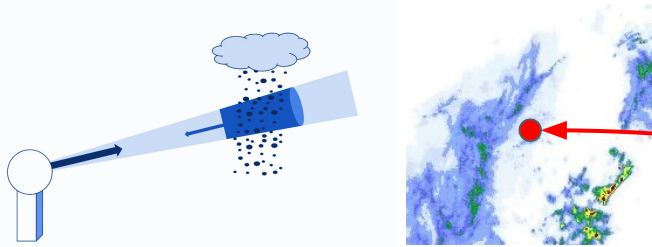
Prediction via deep learning approach

Target:
Rain gauge QPE
1 min res.

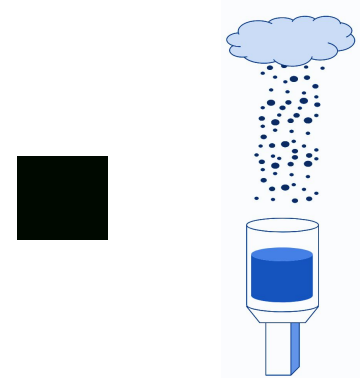


Problem formulation

Input:
Radar QPE (RADOLAN-RY)
5 min res.

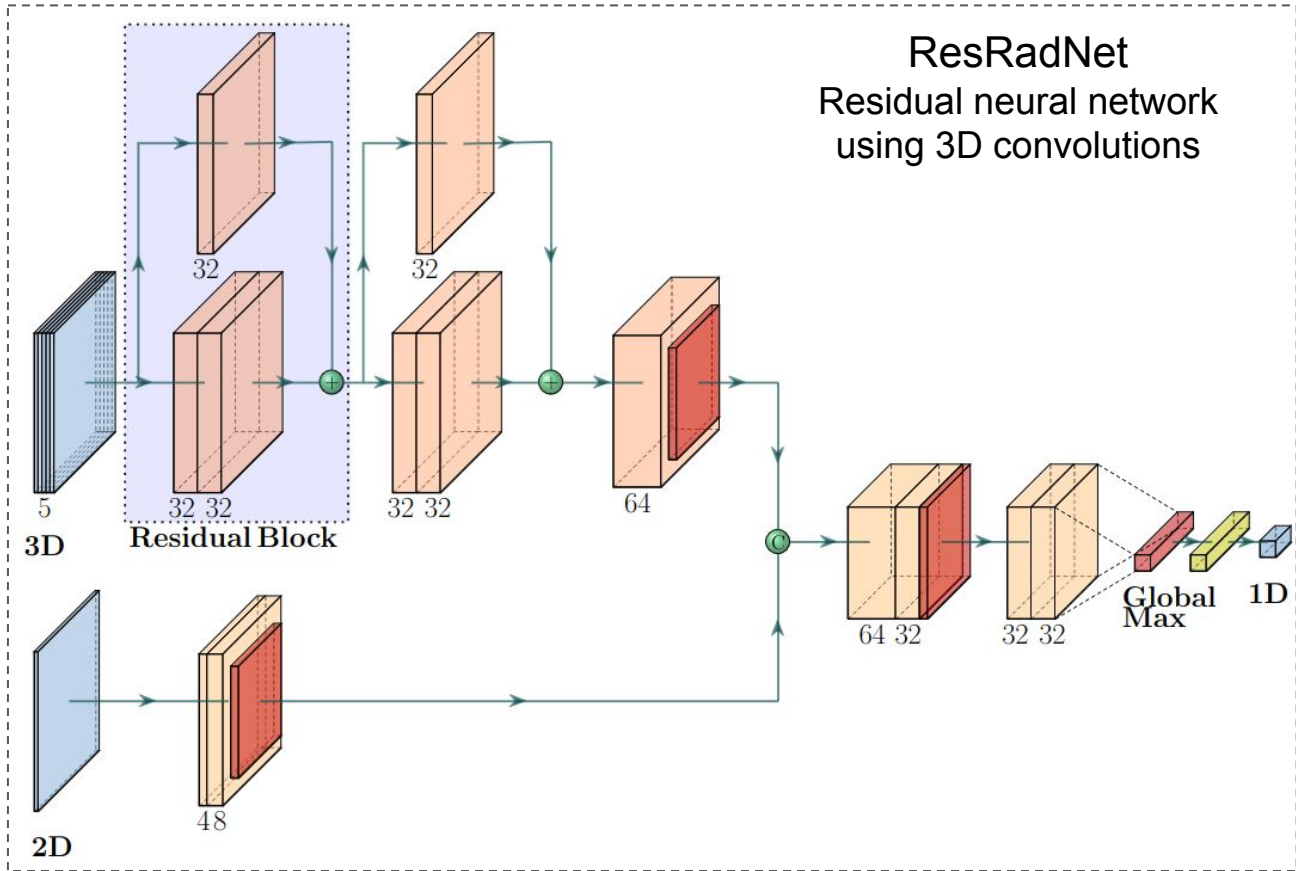
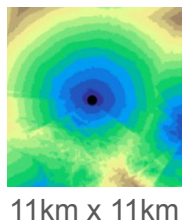
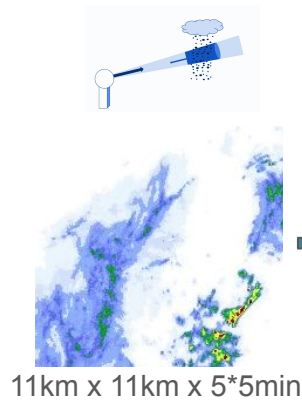


Target:
Rain gauge QPE
1 min res.



Objectives:

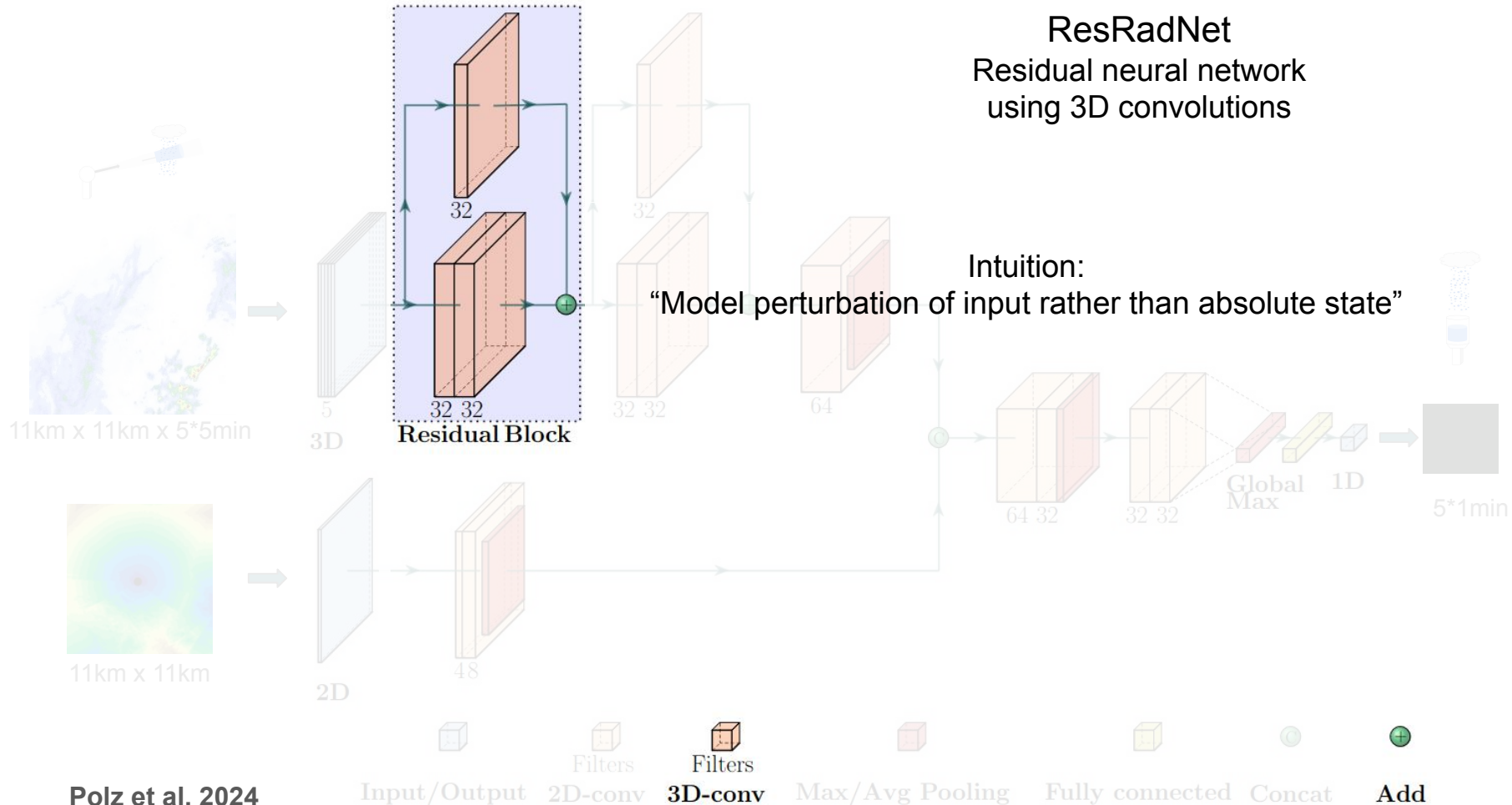
- Short-term prediction of five 1-min time-steps
- Reduce biases compared to rain gauges
- Spatiotemporal consistency of rainfall maps

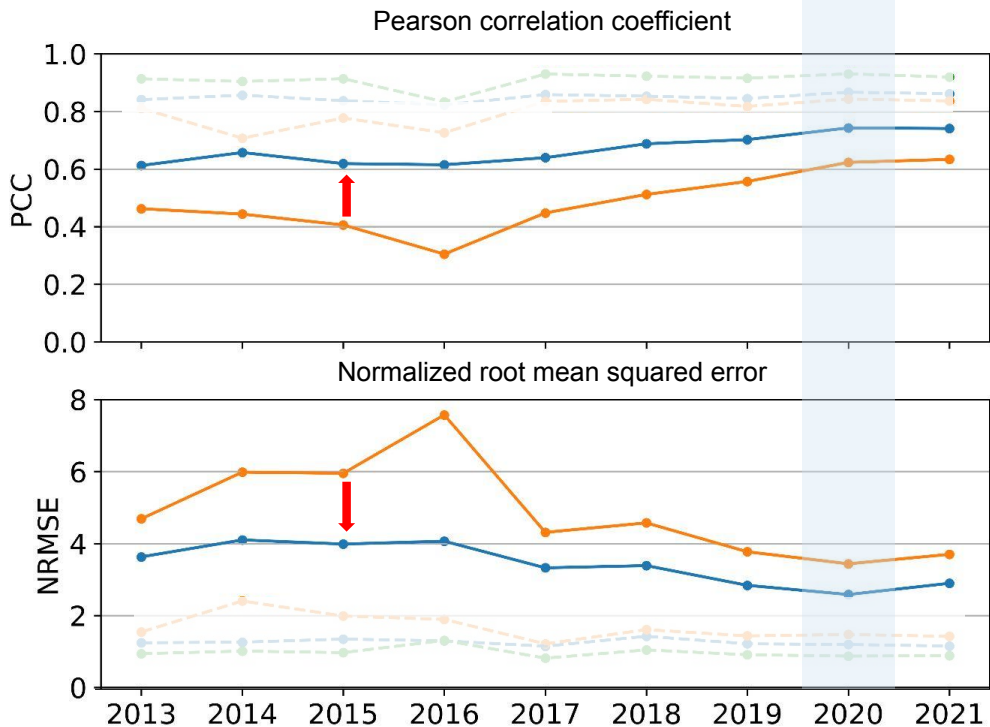


5*1min

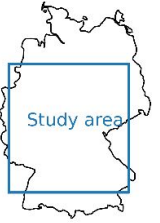


Polz et al. 2024
TGRS





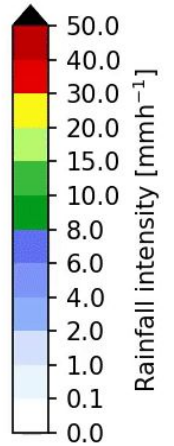
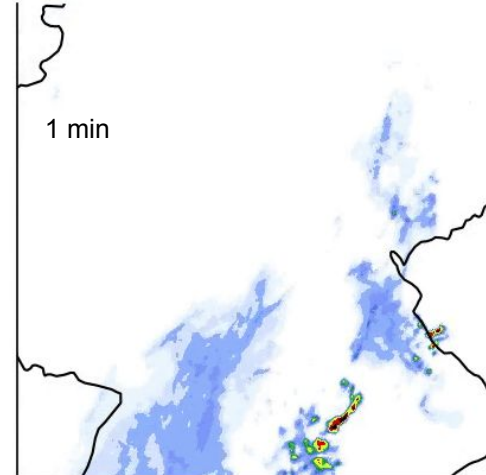
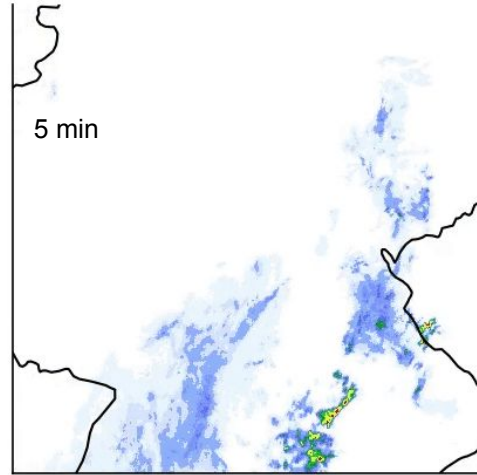
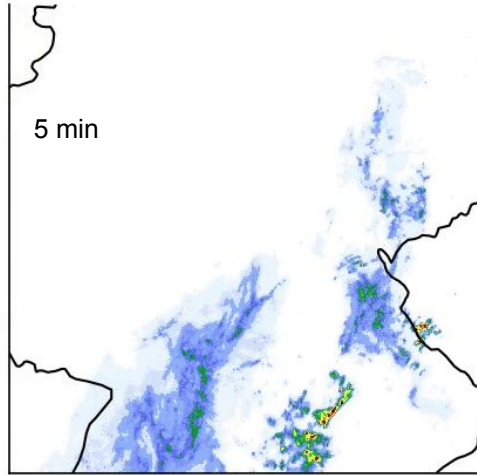
- Neural network vs. daily
- RADOLAN-RY vs. daily
- RADOLAN-RW vs. daily
- Neural network vs. 5 min
- RADOLAN-RY vs. 5 min



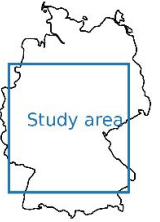
Raw radar

Gauge adjusted radar

ResRadNet



Animation: July 6 2021



Raw radar

Gauge adjusted radar

ResRadNet

5 min

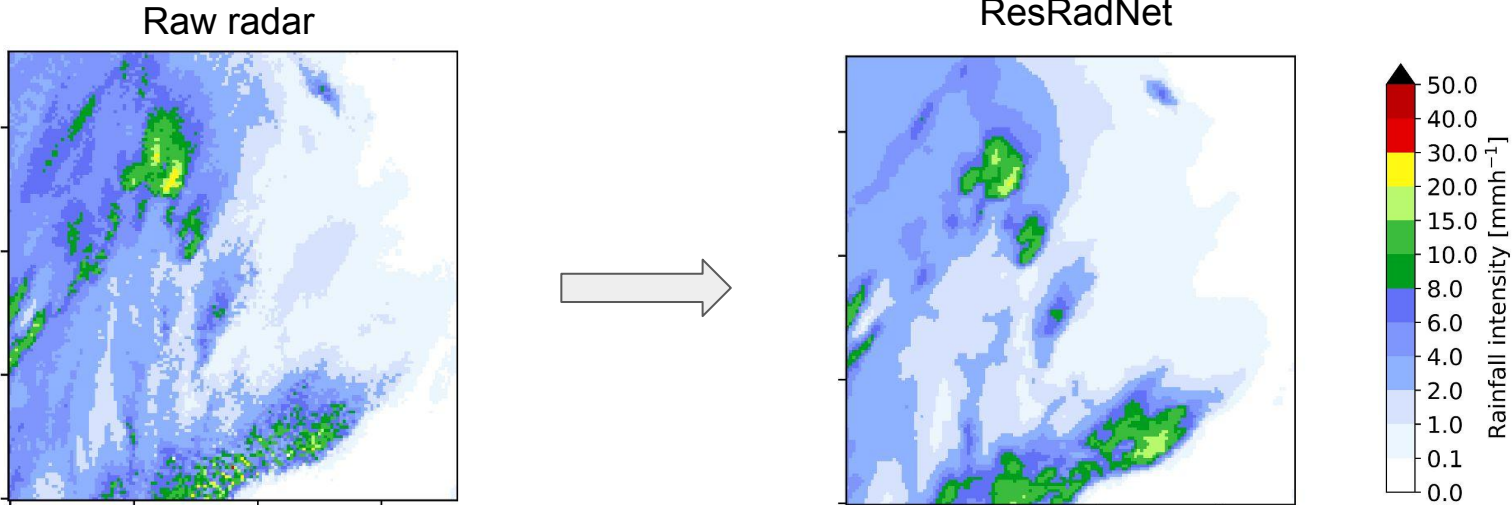
5 min

5 min

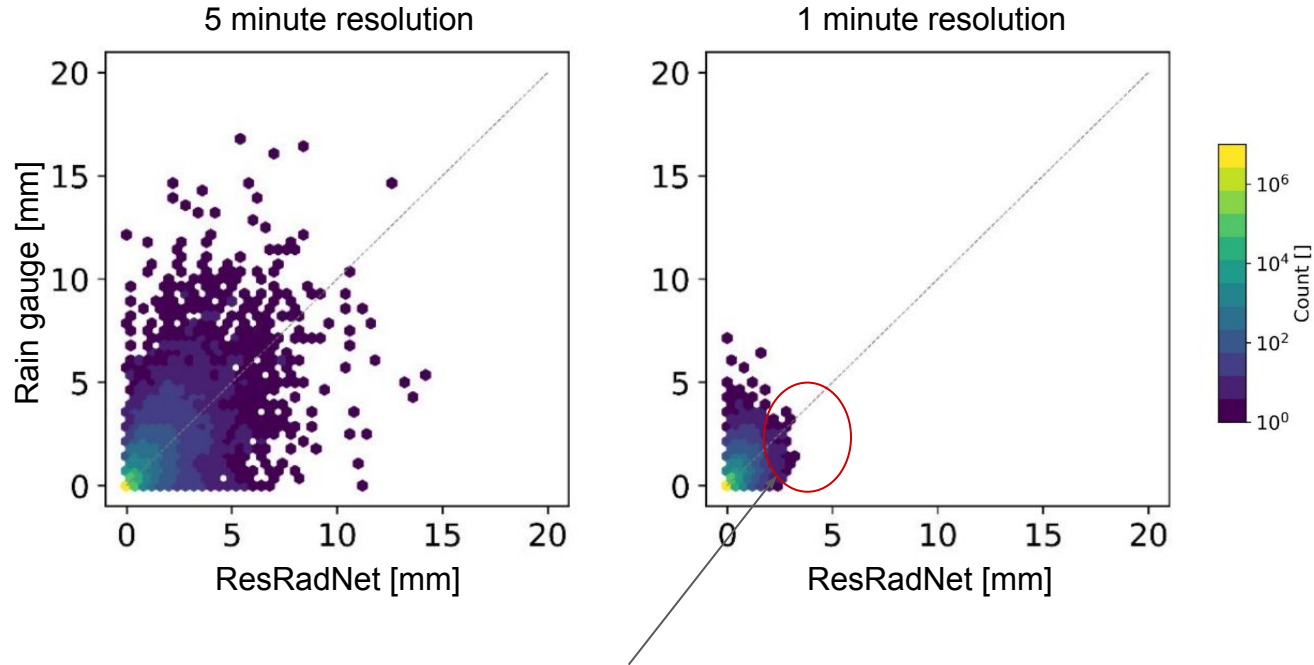
Animation: July 6 2021

→ Less Blue and Red!

Advection correction



Maps of rainfall sum between 16:00 and 19:00 on 6 July 2021

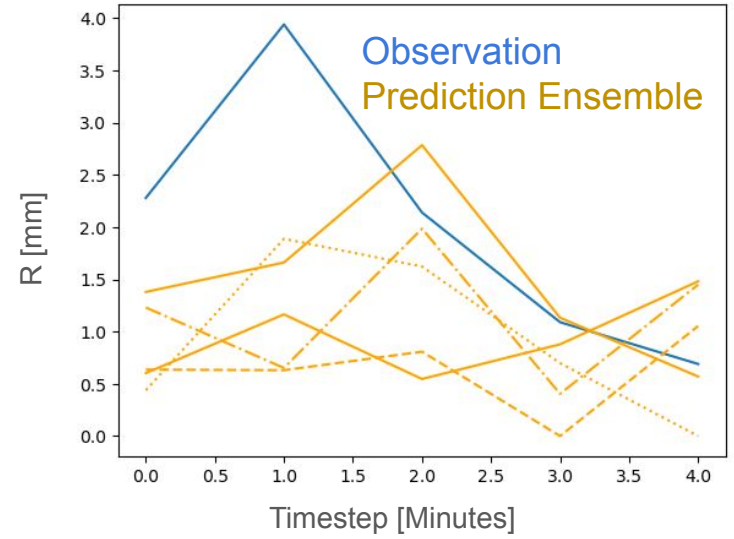
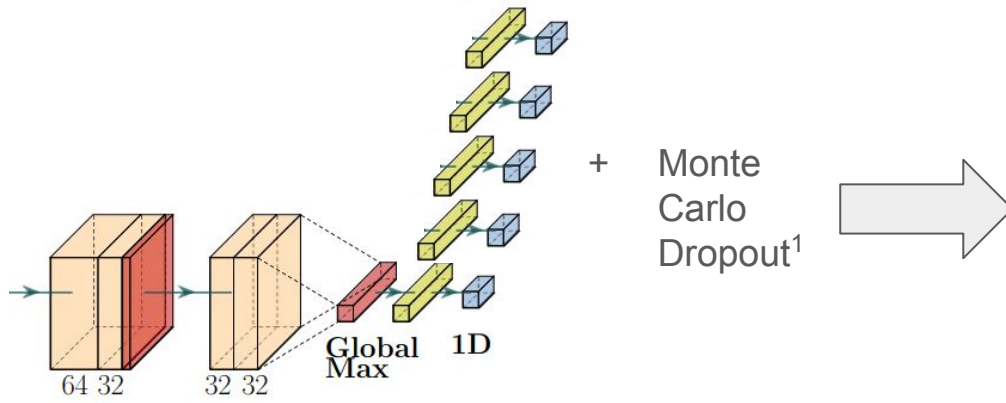


Missing extremes due to uncertainty and double penalty effect
 →behaves like an ensemble mean prediction

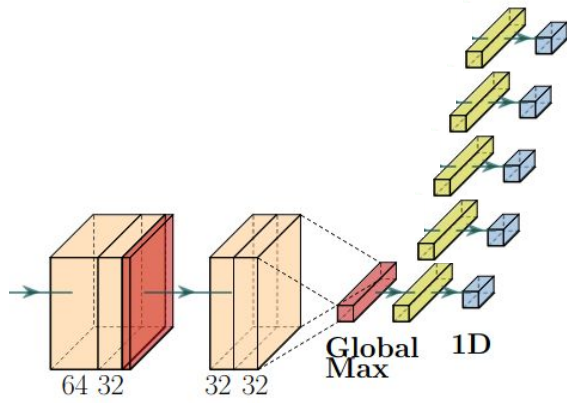
Disclaimer:

The following results are much less validated

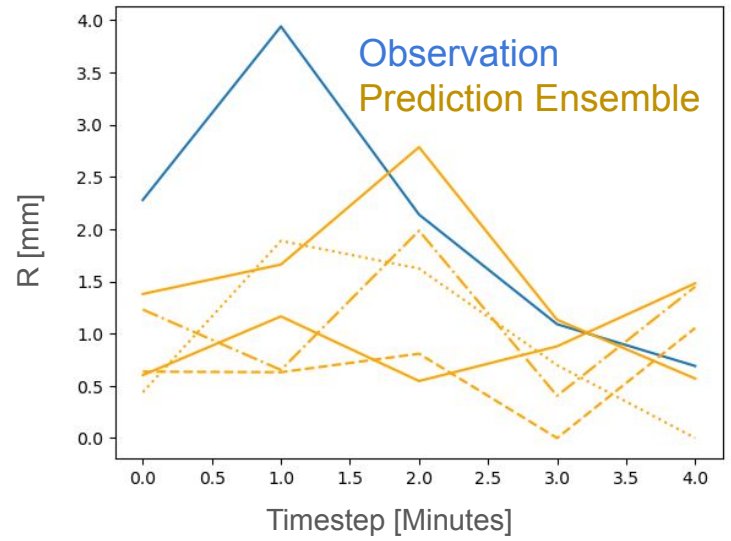
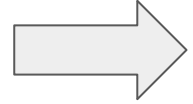
The presented ideas are valid though ;)



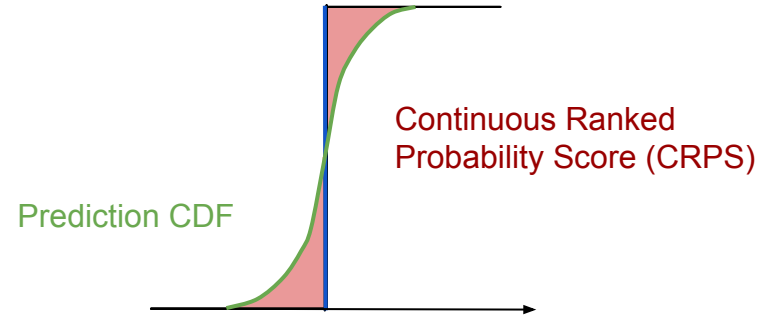
¹Gal & Ghahramani, 2016. Dropout as a bayesian approximation: Representing model uncertainty in deep learning. ICML



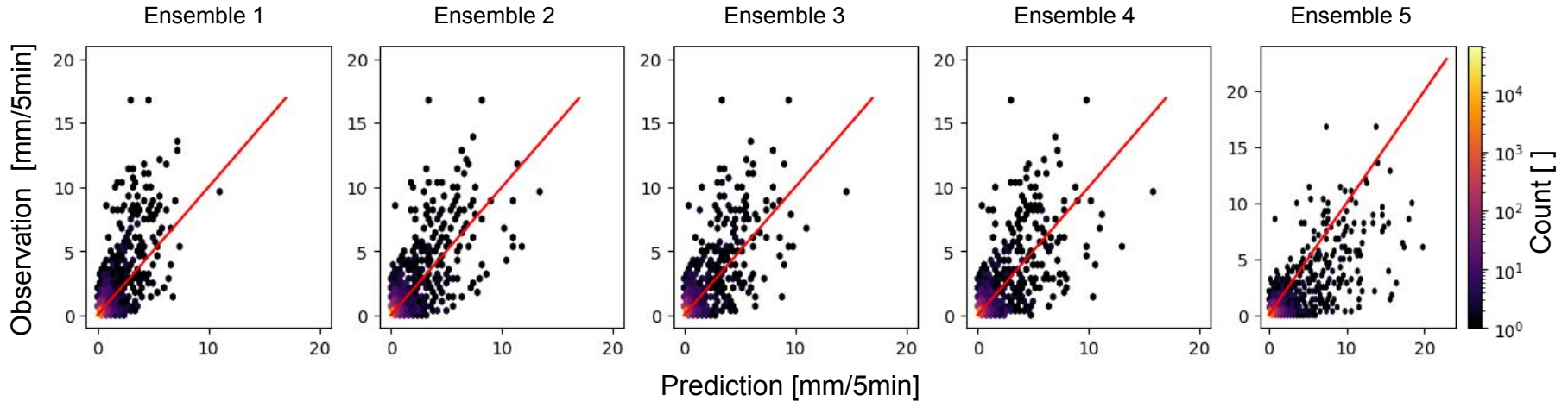
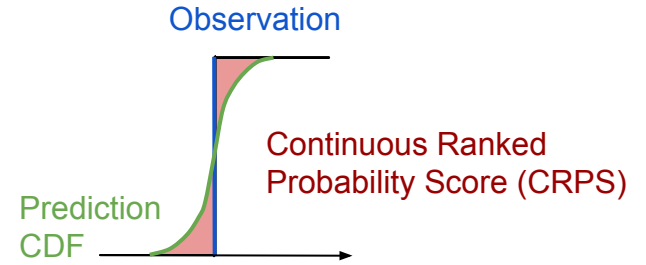
+ Monte Carlo Dropout

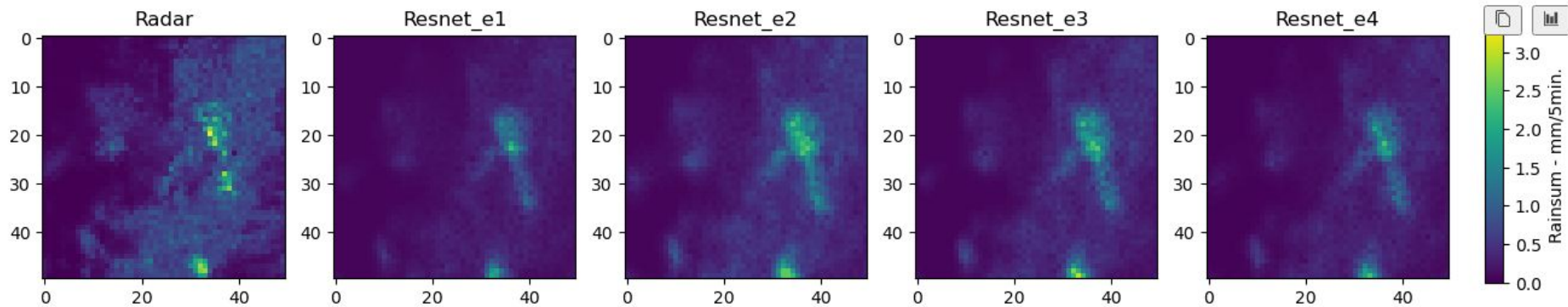


Observation



Train: June 2020
Test: July 2020



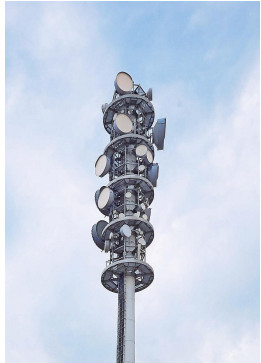
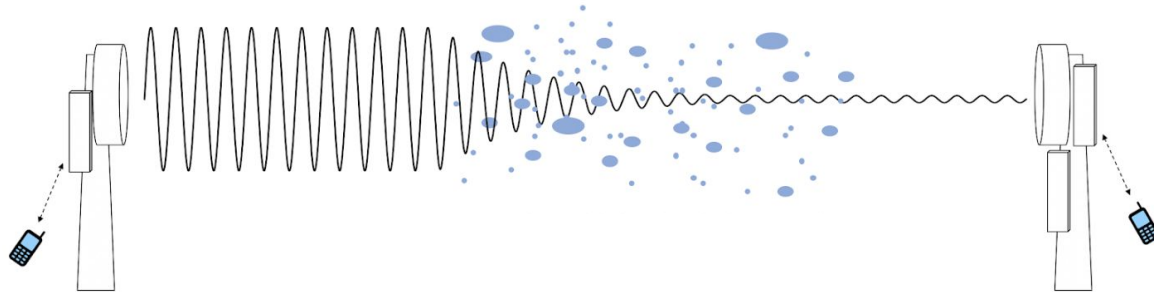


Variability? 😊

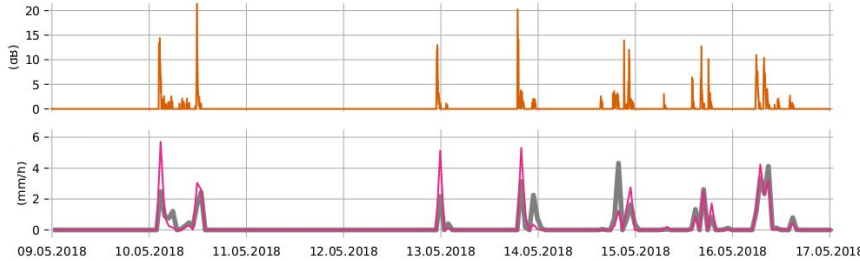
Extremes? 😞

→ explore alternative randomisation

QPE with commercial microwave links



Attenuation (dB)

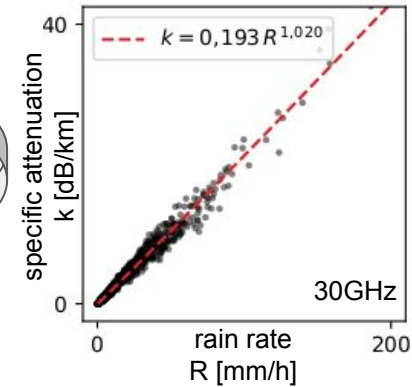


Rainfall (mm/h)

Graf, Polz and Chwala; PiuZ 2021



Power law regression

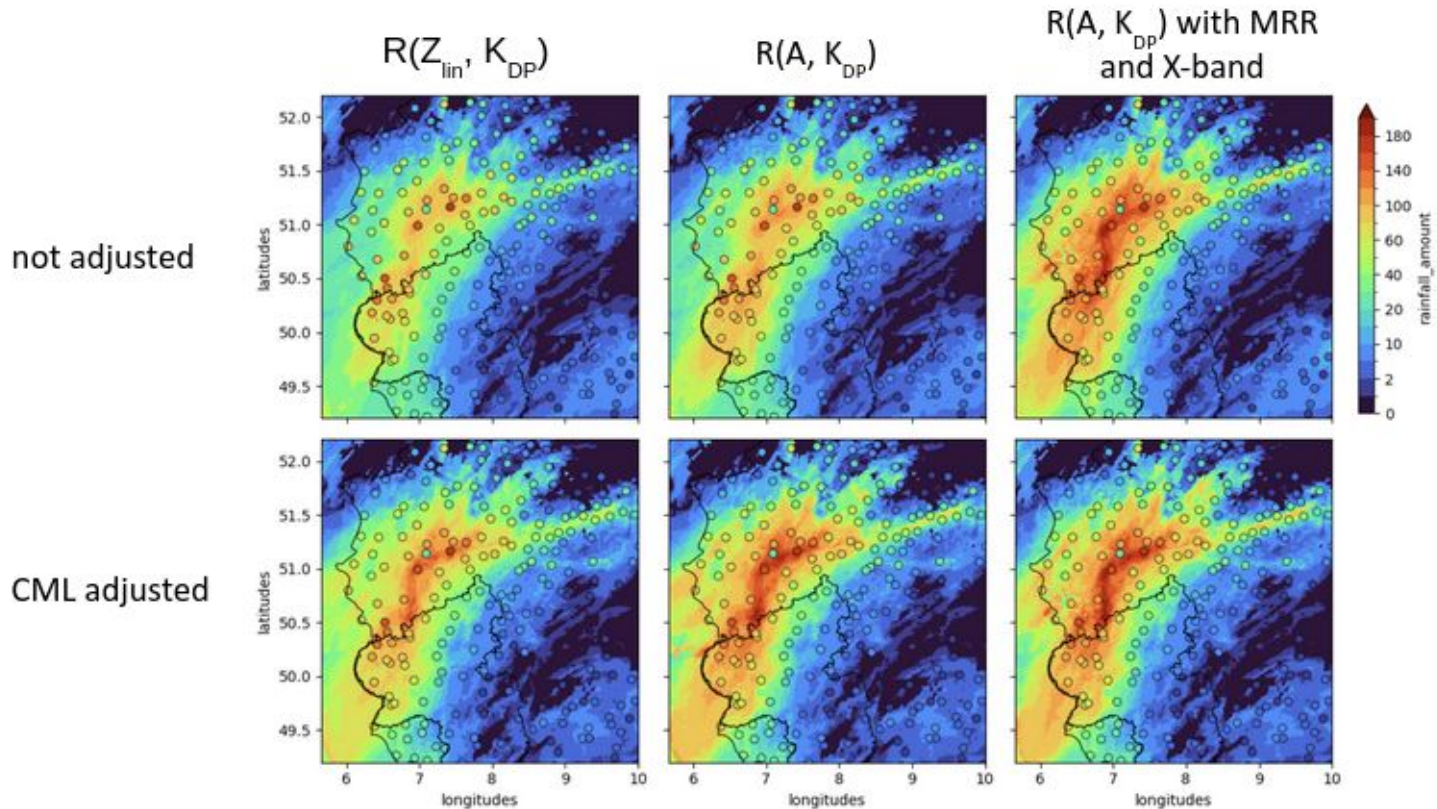


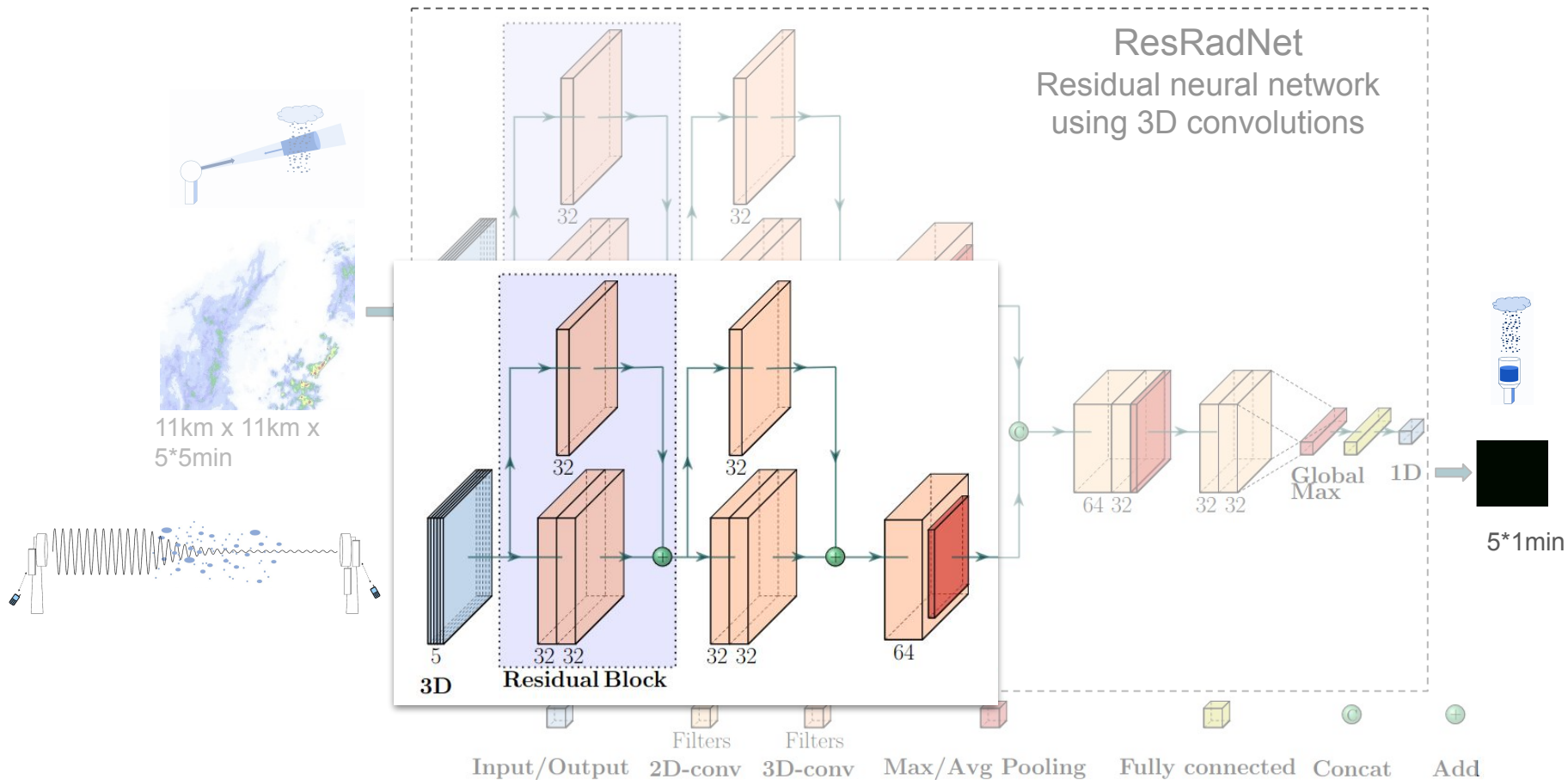
Commercial microwave links (CML)



- 3904 CMLs
- instantaneous measurement of **transmitted and received signal level**
- 1-minute resolution

Merging Radar and CML

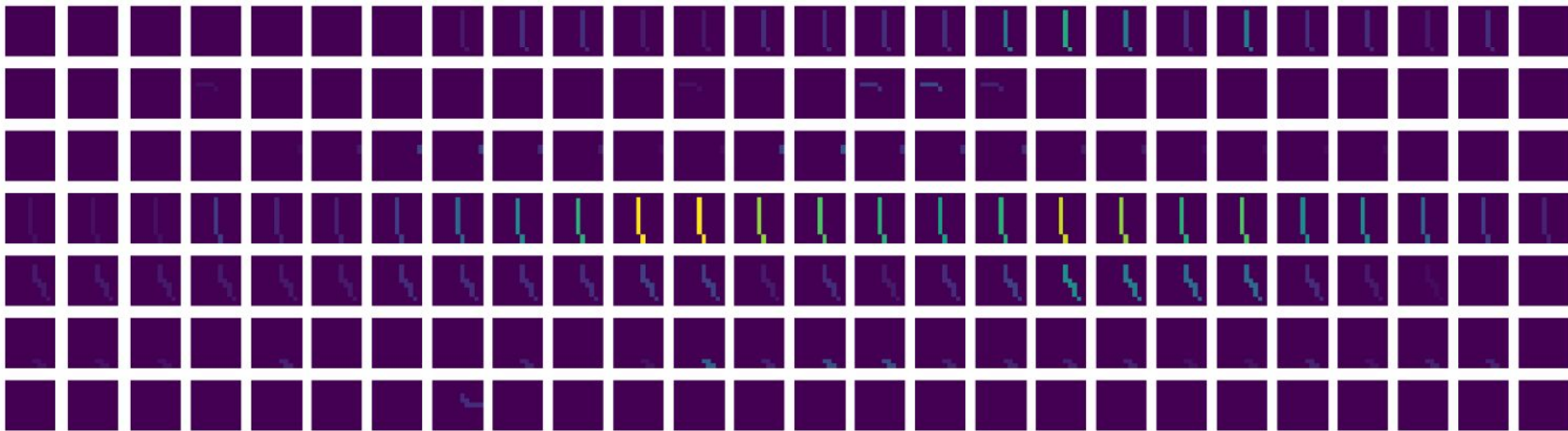




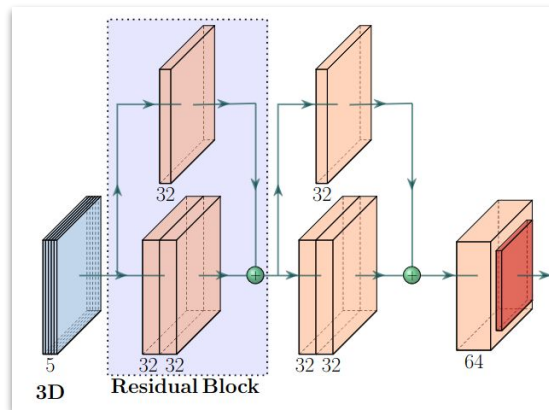
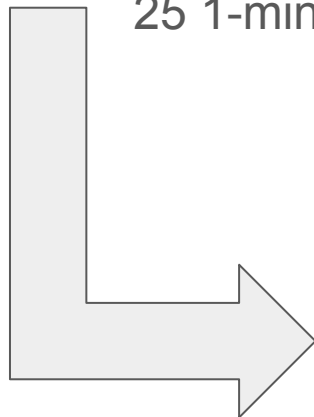
up to 25 CMLs

11

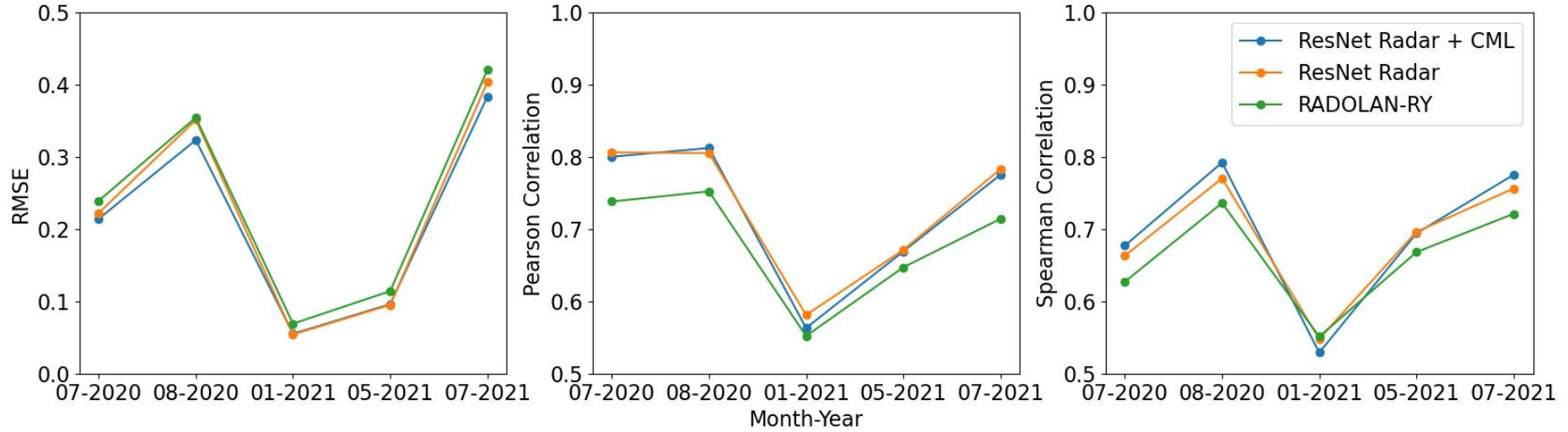
11



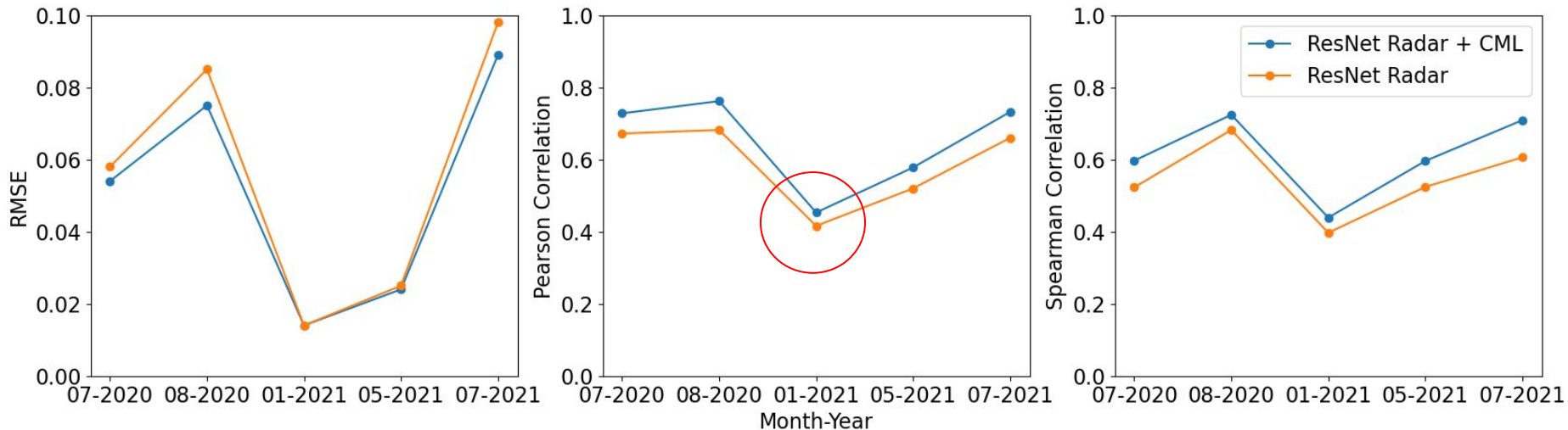
25 1-minute time steps



Performance of different models at 5-minute resolution

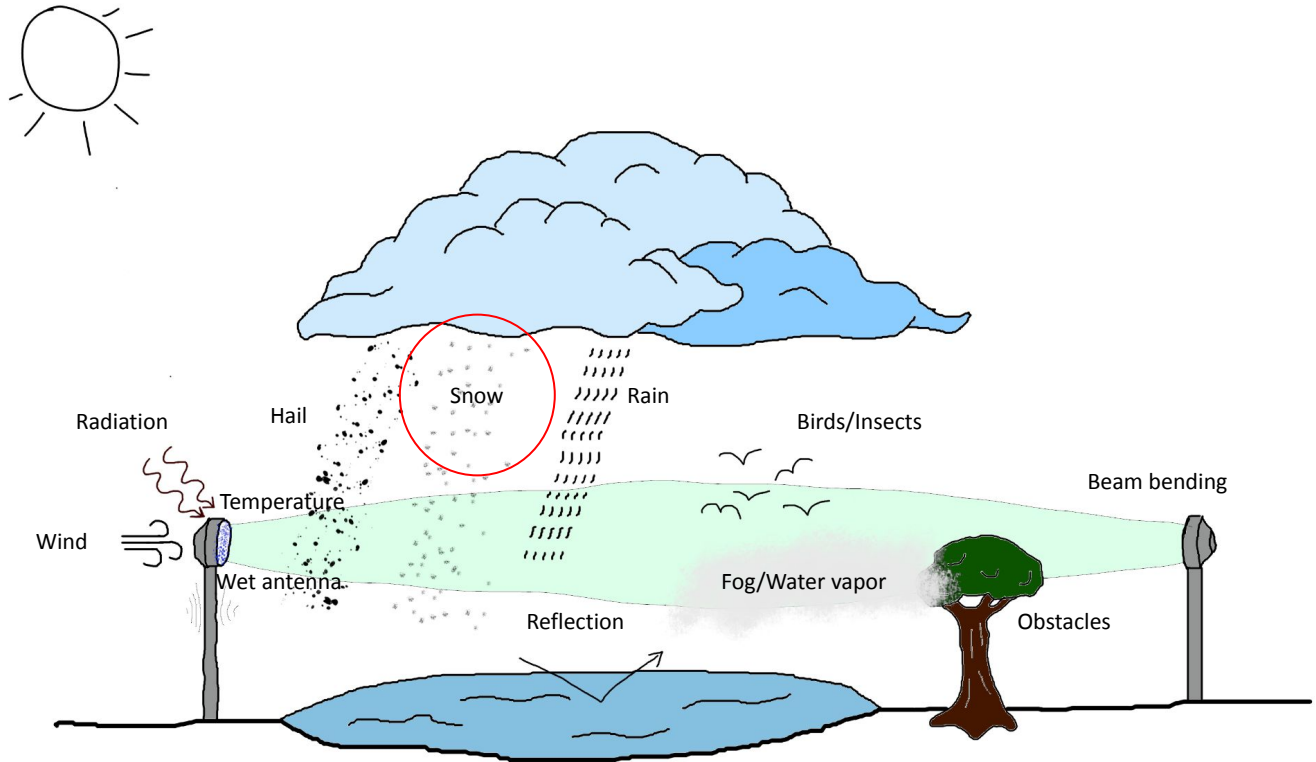


Performance of different models at 1-minute resolution



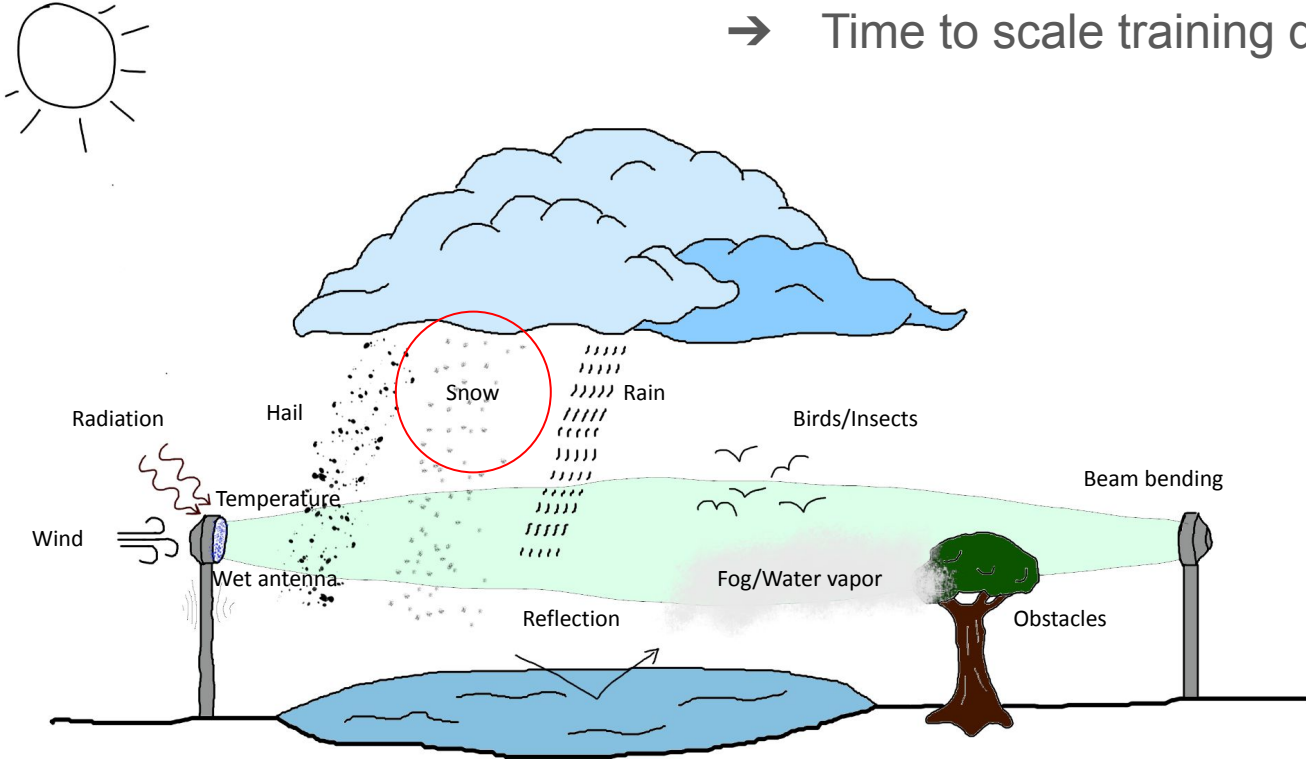
Model not trained on winter data

Systematic measurement errors - CML



Systematic measurement errors - CML

→ Time to scale training data

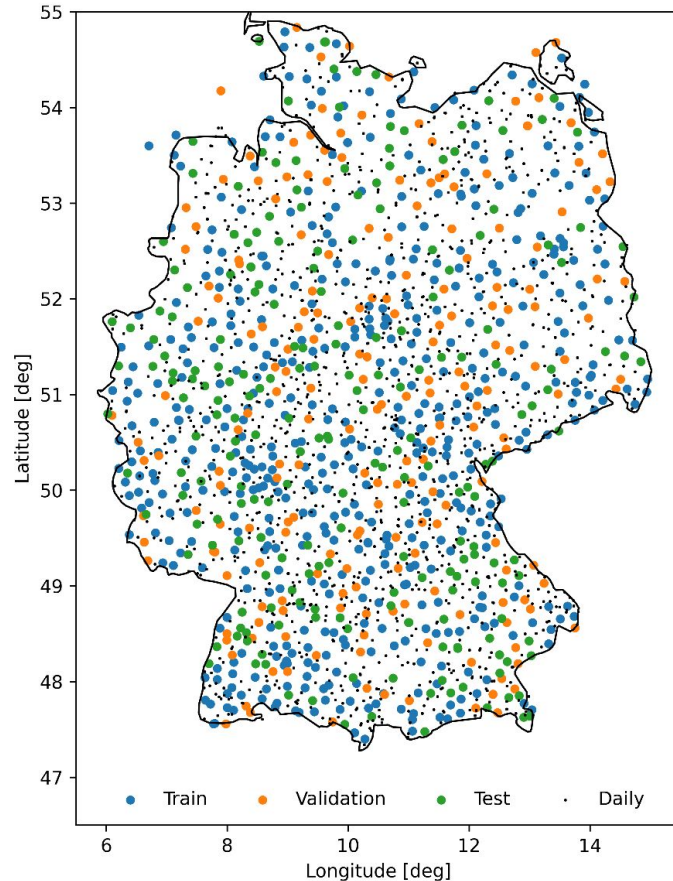


Conclusion:

- ResNet approach for radar adjustment works
- CRPS loss + dropout
 - creates reasonable variability
 - does not solve missing extremes
- CMLs provide valuable information, especially at 1-minute resolution

Thank you!

Data splitting



Train

→ 60% of stations, 2020



Test

→ 20% of stations, 2021



Validation

→ 20% of stations, 2013-2021

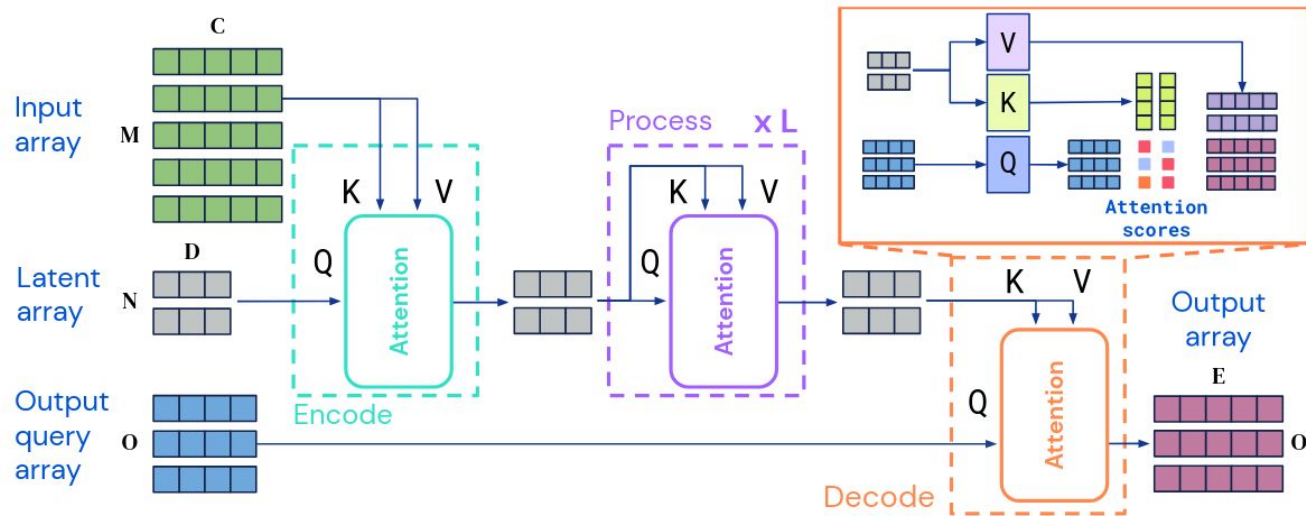


Daily validation

→ >1000 independent stations, 2013-2021

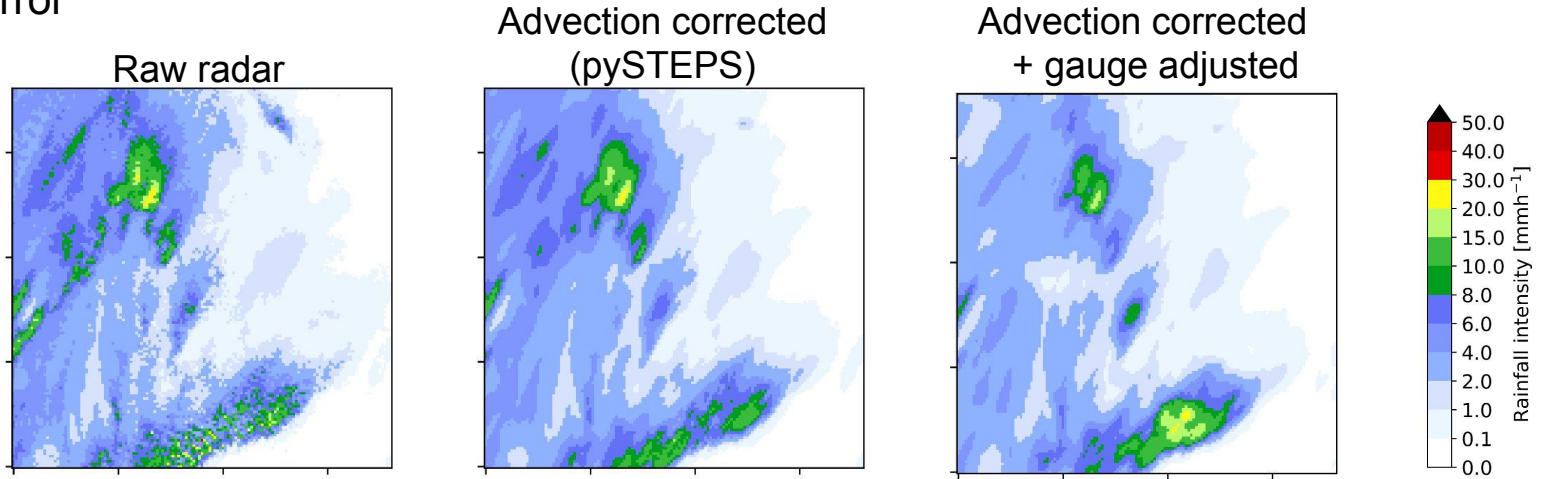
Important: spatio-temporally independent validation!

Apart from the obvious scaling and calibration that needs to be done,
we require a more flexible approach to digest the CML data



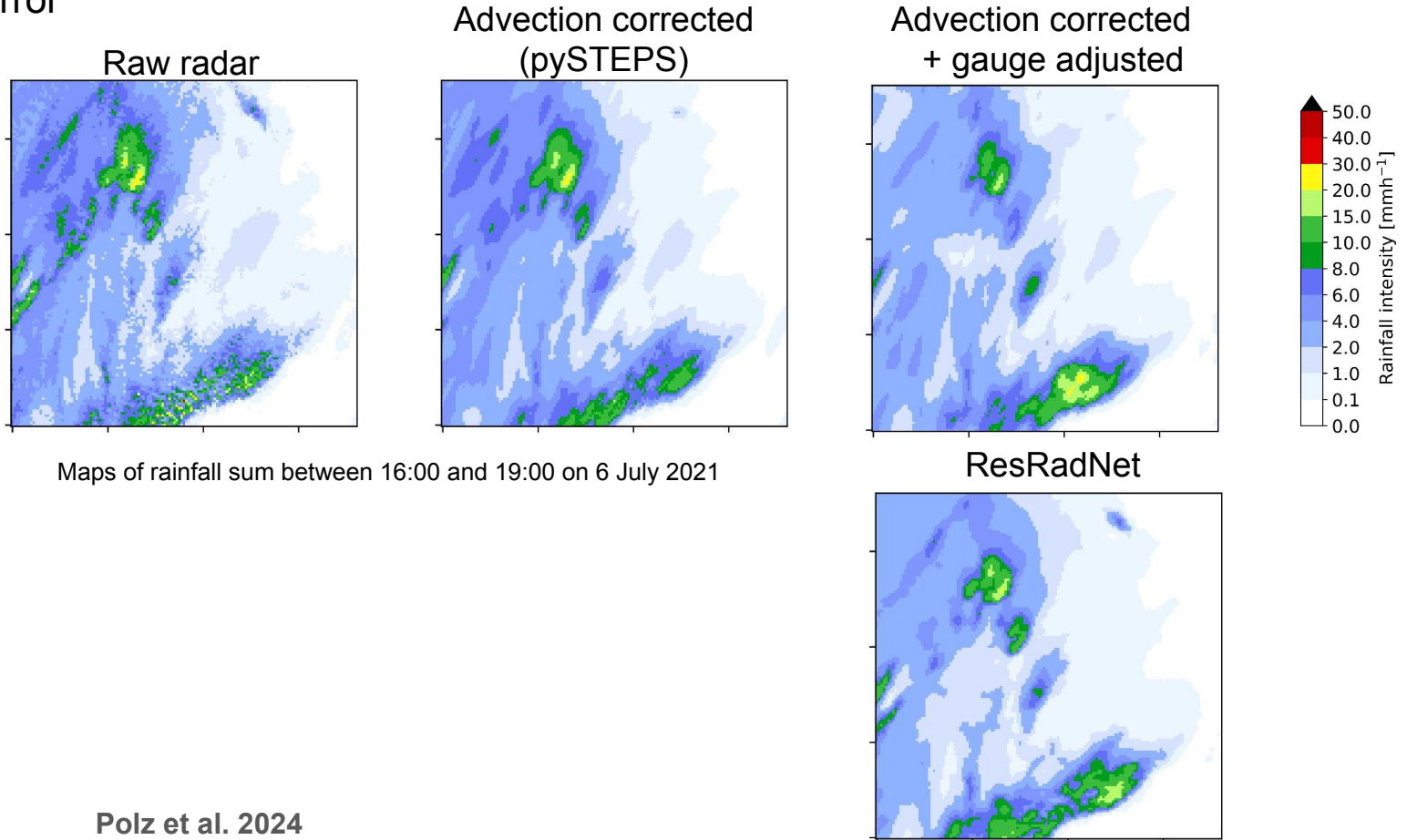
Jaegle, A., Borgeaud, S., Alayrac, J. B., Doersch, C., Ionescu, C., Ding, D., ... & Carreira, J. (2021). Perceiver io: A general architecture for structured inputs & outputs. *arXiv preprint arXiv:2107.14795*.

Sampling error



Maps of rainfall sum between 16:00 and 19:00 on 6 July 2021

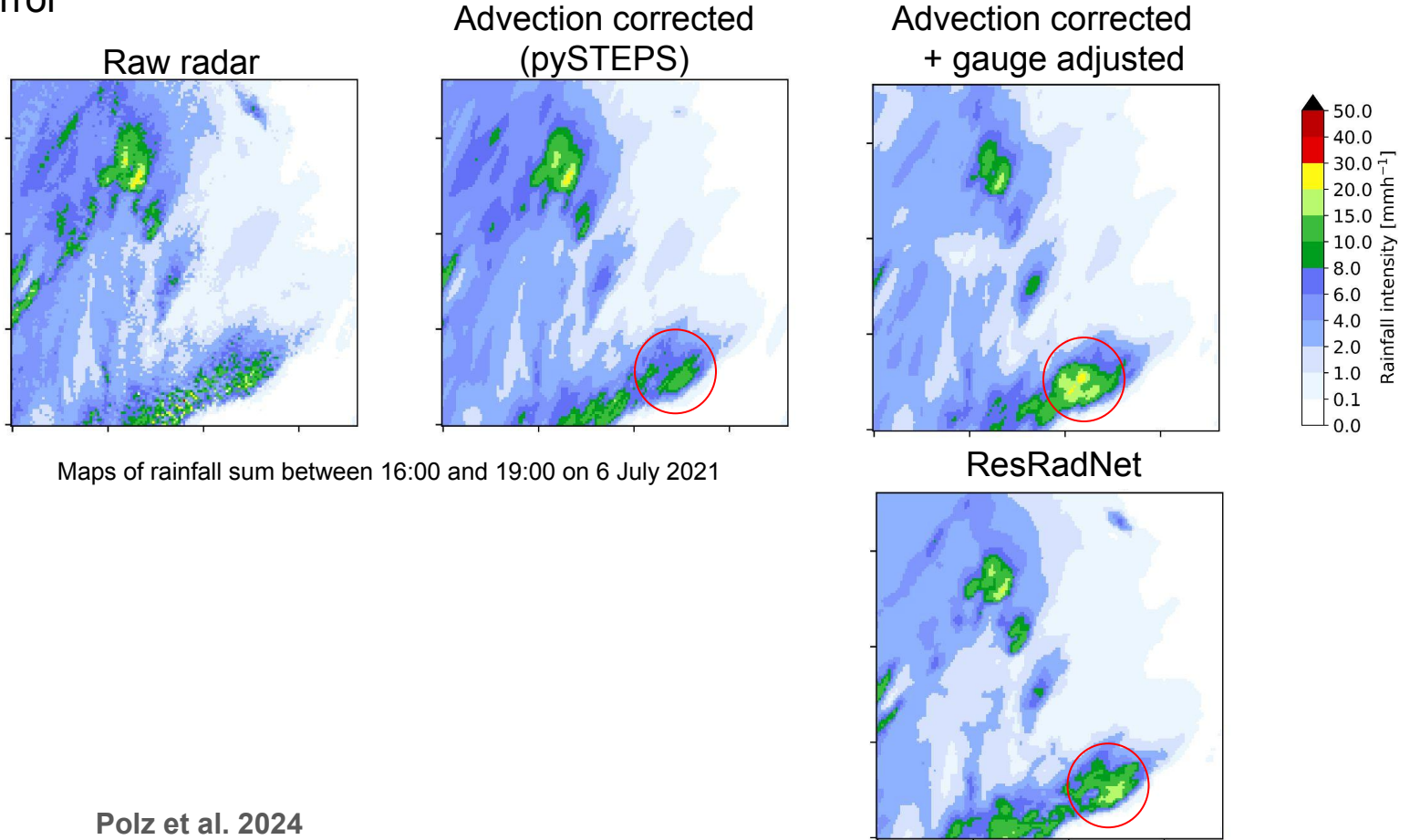
Sampling error



Maps of rainfall sum between 16:00 and 19:00 on 6 July 2021

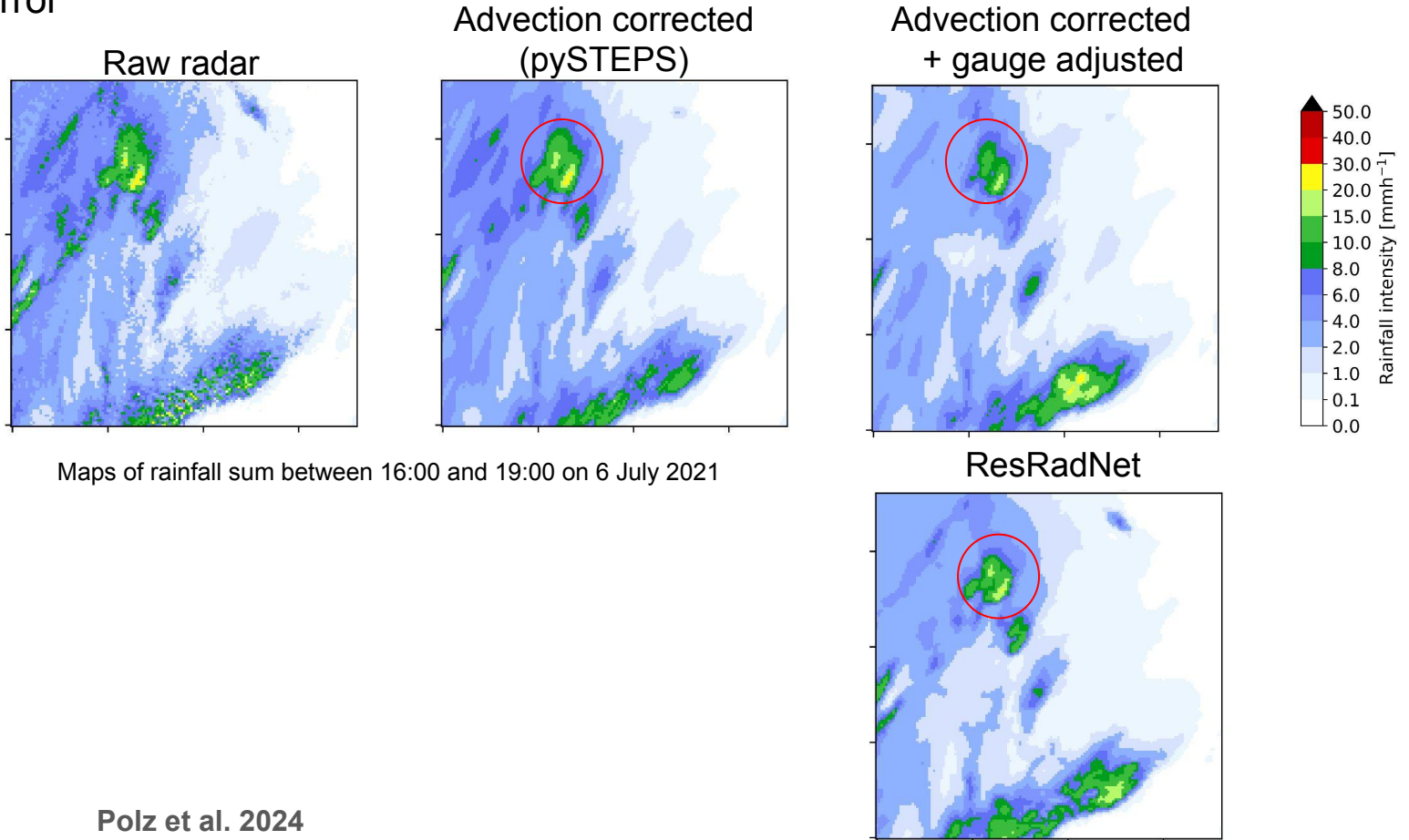
Polz et al. 2024
TGRS

Sampling error



Polz et al. 2024
TGRS

Sampling error



Maps of rainfall sum between 16:00 and 19:00 on 6 July 2021

Polz et al. 2024
TGRS