





## Improving Radar QPE with CMLs

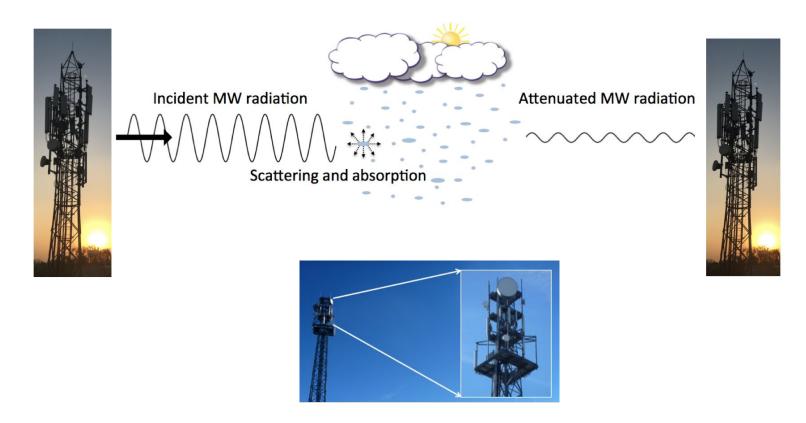
#### Julius Polz<sup>1</sup>, Maximilian Graf<sup>2</sup> and Christian Chwala<sup>1</sup>

<sup>1</sup> Institute of Meteorology and Climate Research, Karlsruhe Institute of Technology, Campus Alpin, Garmisch-Partenkirchen, Germany <sup>2</sup> Institute of Geography, University of Augsburg, Augsburg, Germany



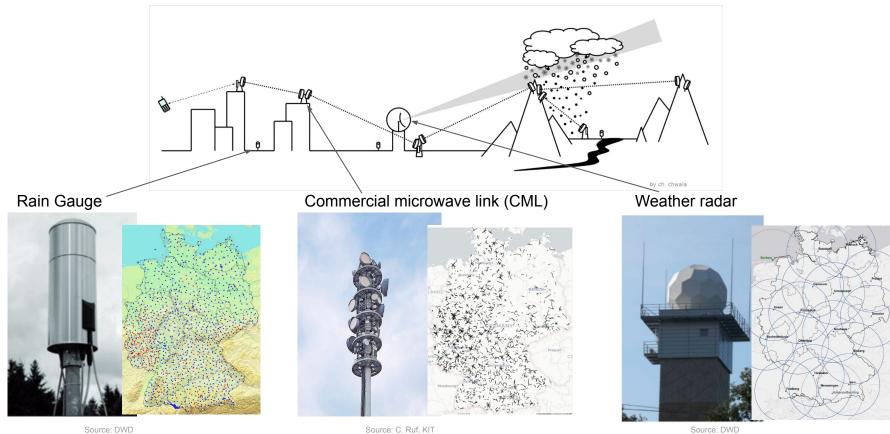
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## **Commercial Microwave Links**





## **Rainfall estimation in Germany**



Source: DWD

Source: C. Ruf, KIT

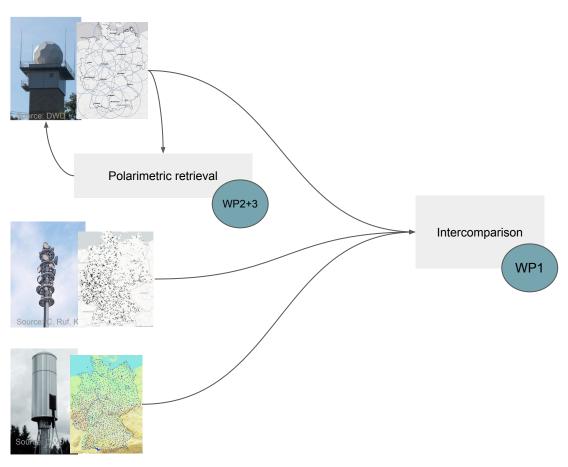


## Topics

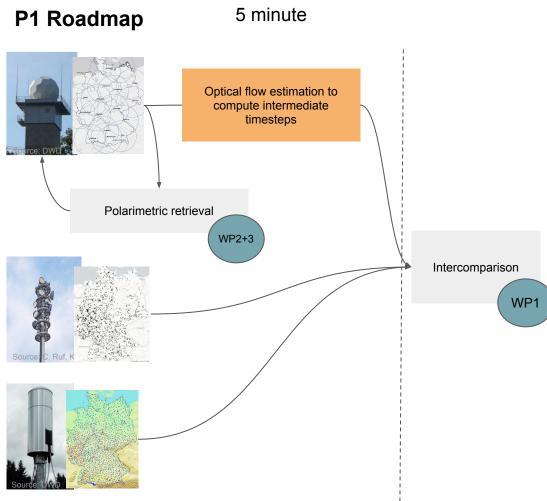
- RealPEP P1 Roadmap
- Updates from the CML data acquisition at DWD
- Collection of rainfall data for upcoming studies
- Deep learning based correction of radar QPE
- High resolution rainfall maps for West Africa



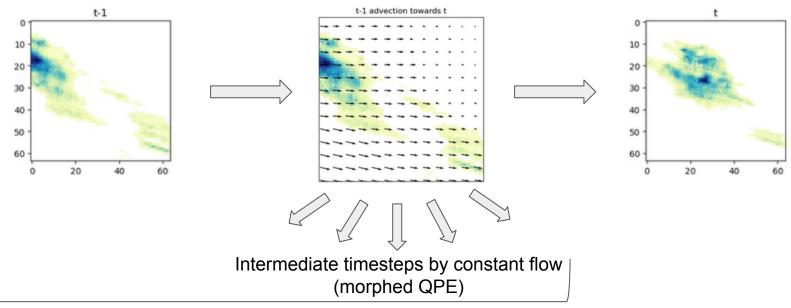
## P1 Roadmap 5 minute









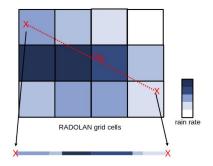


#### Estimated optical flow by Lucas-Kanade method (from PySTEPS)

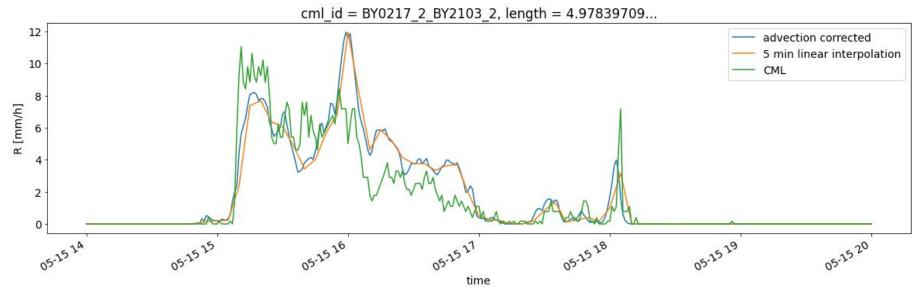
Advection correction by temporal aggregation



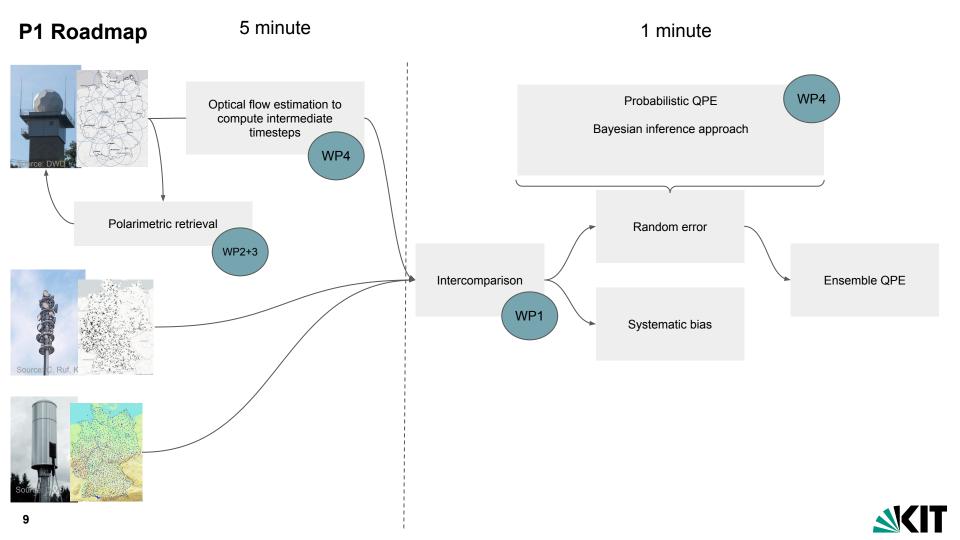
#### Advection correction: 1 minute radar along CML

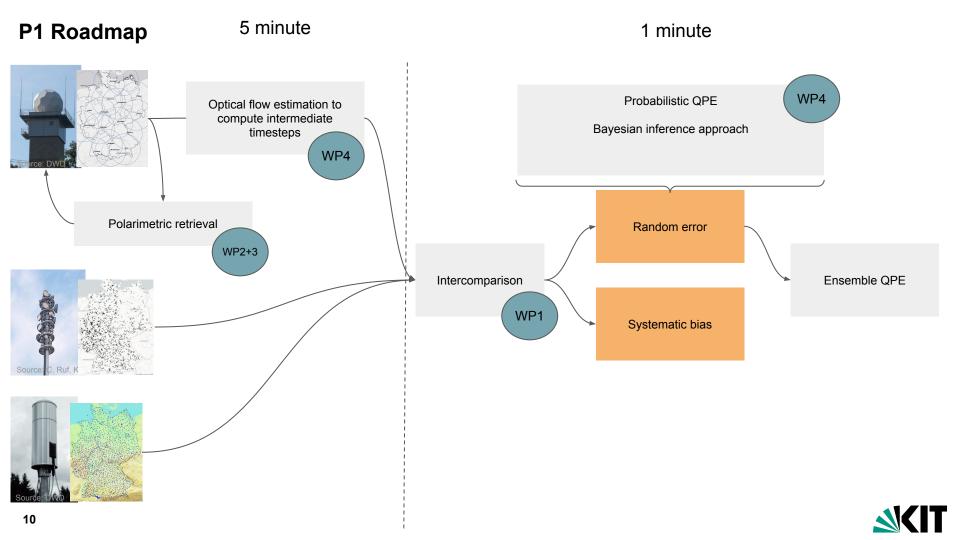


Path averaged rain rate by weighted length of intersects









## Error sources of radar QPE (according to Villarini and Krajewski 2010)



#### Miscalibration

Ground clutter / Anomalous Propagation

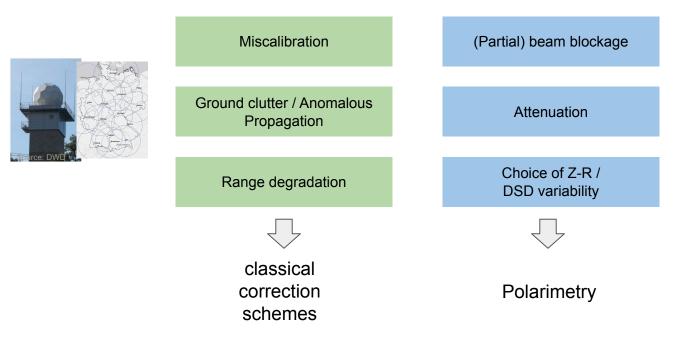
Range degradation



classical correction schemes

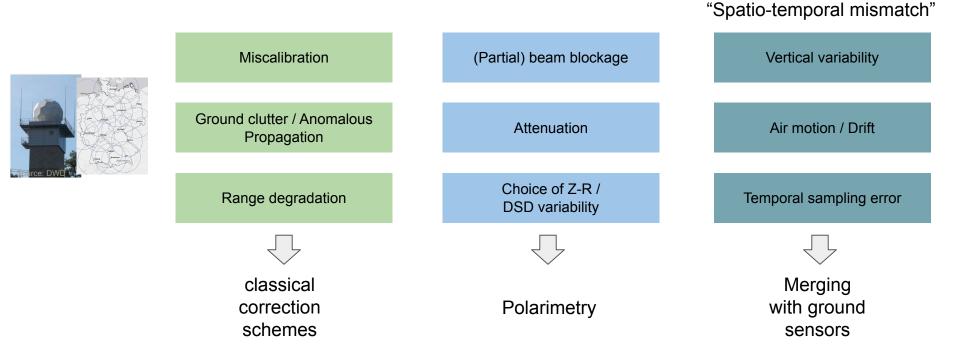


# Error sources of radar QPE (according to Villarini and Krajewski 2010)



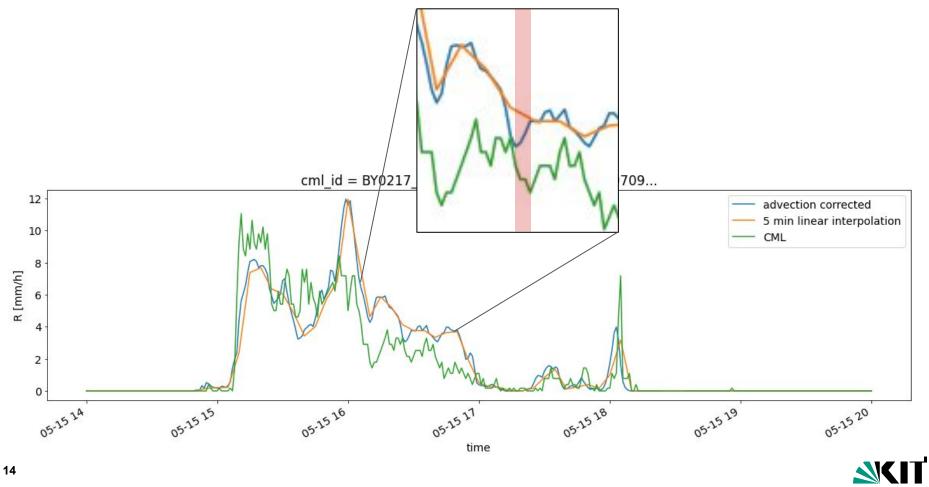


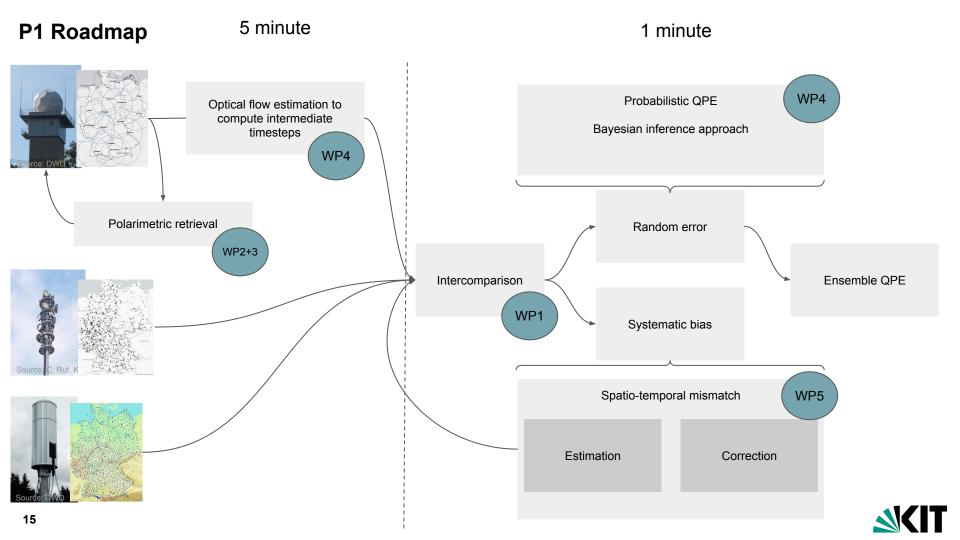
# Error sources of radar QPE (according to Villarini and Krajewski 2010)



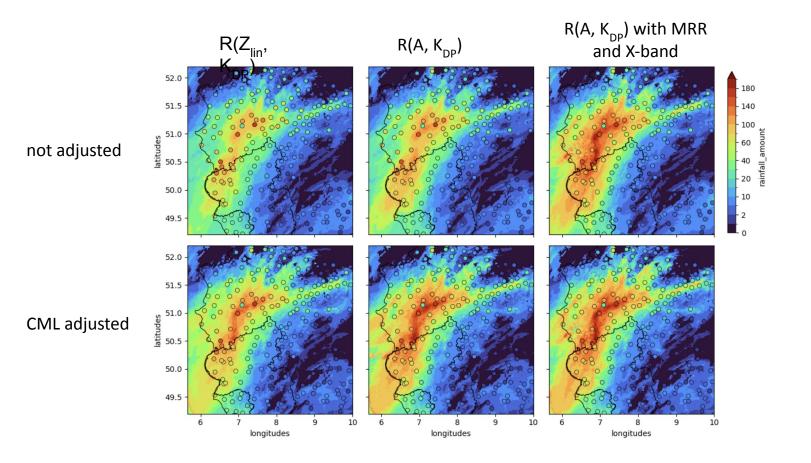


Advection correction: 1 minute radar along CML



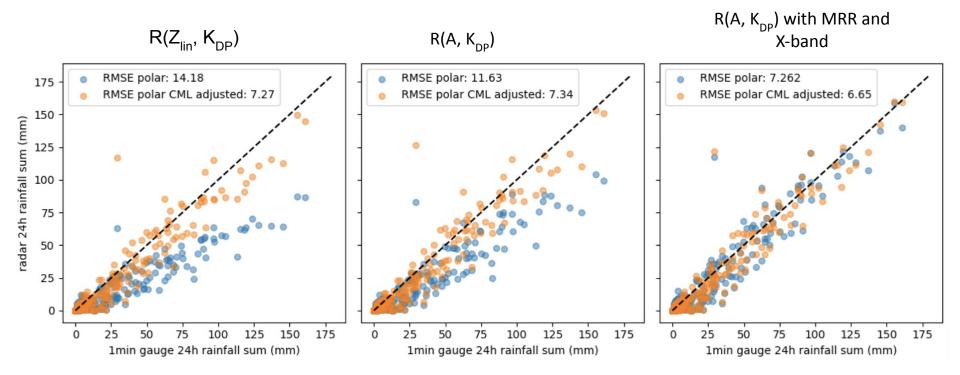


## Merging Radar and CML





## Merging Radar and CML





Simple merging of pol. Radar and CML

Correction of sampling error for 5 min radar data



Current	+1 Step	+2 Step
Simple merging of pol. Radar and CML	Probabilistic Radar QPE using error with respect to CML and Gauge	
Correction of sampling error for 5 min radar data	Large scale comparison of 1 min data →years for R(Z) →months for R(A, K <sub>DP</sub> )	



Current	+1 Step	+2 Step
Simple merging of pol. Radar and CML	Probabilistic Radar QPE using error with respect to CML and Gauge	Probabilistic merging of pol. Radar, CML and Gauges
Correction of sampling error for 5 min radar data	Large scale comparison of 1 min data $\rightarrow$ years for R(Z) $\rightarrow$ months for R(A, K <sub>DP</sub> )	Quantification and correction of spatio temporal mismatch



Current	+1 Step	+2 Step
Simple merging of pol. Radar and CML	Probabilistic Radar QPE using error with respect to CML and Gauge	Probabilistic merging of pol. Radar, CML and Gauges
Correction of sampling error for 5 min radar data	Large scale comparison of 1 min data →years for R(Z) →months for R(A, K <sub>DP</sub> )	Quantification and correction of spatio temporal mismatch
Now, real	ly and if necessary using R(Z) produc	ts first



## CML DAQ @ DWD



### CML DAQ @ DWD

Fact:

- "operational" real-time data acquisition with a 2 min latency
- >5000 unique paths
- 10s temporal resolution  $\rightarrow$  reduction of uncertainty due to instantaneous sampling
- Hourly R(CML) and R(Z)+R(CML) product using RADOLAN adjustment at 5 min latency

Fiction:

• Potential water vapor estimation at E-band (maybe no E-band, maybe incorrect metadata)



**Current data collection at KIT** 



#### Current data collection at KIT



- RADOLAN-RY
  - 2001 until today
  - R(Z)
  - 5 min resolution
- RADOLAN-RW
  - 2001 until today
  - R(Z) gauge adjusted
  - 1H resolution
- RADKLIM-YW
  - o 2006 until today
  - R(Z) gauge and clim adjusted
  - 5 min resolution



- CML 2017 until today
  - 3900 sensors
  - 1 min resolution
- CML 2023 until today
  - >5000 sensors
  - 10 s resolution



- Automatic
  - o from 2007
  - ~1000 rain gauges
  - 1 min resolution
- Manual
  - from 1900 to today
  - ~1000 (year >2010)
  - daily resolution



Deep learning based correction of radar QPE

IEEE TRANSACTIONS ON GEOSCIENCE AND REMOTE SENSING

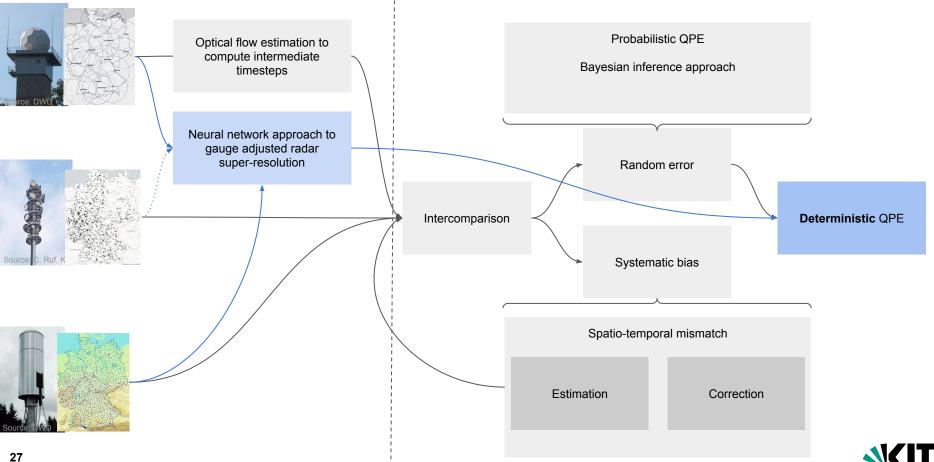
# Temporal Super-Resolution, Ground Adjustment and Advection Correction of Radar Rainfall using 3D-Convolutional Neural Networks

Julius Polz, Luca Glawion, Hiob Gebisso, Lukas Altenstrasser, Maximilian Graf, Harald Kunstmann, Stefanie Vogl, and Christian Chwala

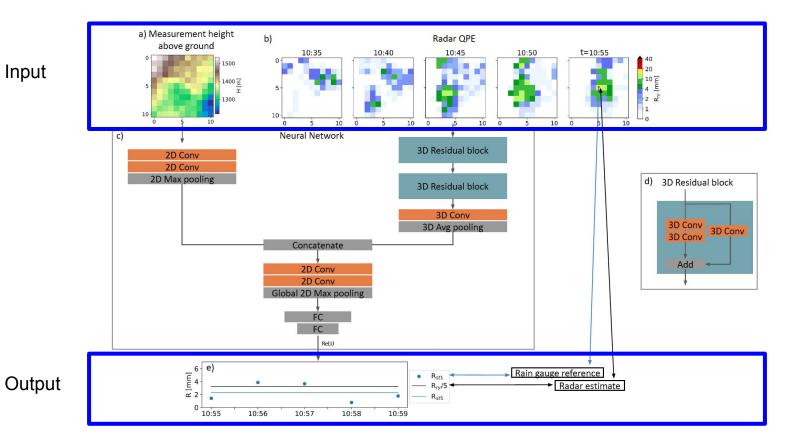




1 minute



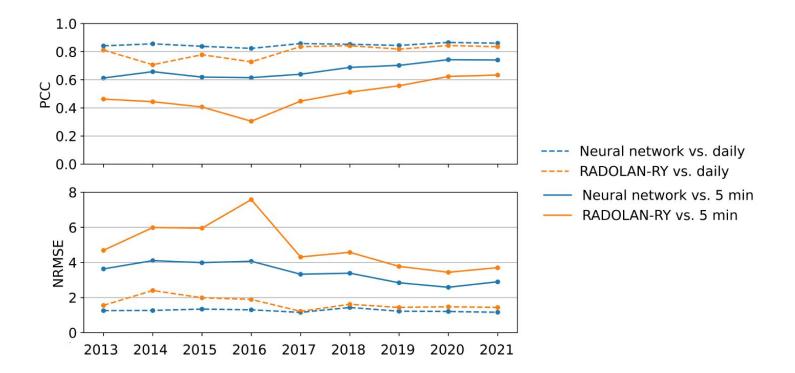
### ResRadNet





28

#### ResRadNet





#### ResRadNet

Study area

Rain gauge RADOLAN-RY RADKLIM-YW AI 5min Al 1min Major 200 Al 5min Al 1min Al 5min Al 1min 1min Al 1min Al 1min Al 1min Al 1min Al 1min Al 1min 1mi

Proof: High potential to reduce overall error including sampling error



-8 -20 -50

50.0 40.0 30.0 20.0 15.0

10.0

- 8.0 - 4.0 - 2.0 - 1.0 - 1.0 - 0.1 - 0.1 - 0.0

2021-07-06T16:50

#### Low hanging fruit: Test deep learning based polarimetric retrieval

1 year of training data enough

- $\rightarrow$  Test with 3 months used in RealPEP
- $\rightarrow$  Repeat using polarimetric QPE (post-processing)
- $\rightarrow$  Repeat using polarimetric observables (full retrieval)

Why?  $\rightarrow$  The full processing pipeline exists and only the input changes. Very low effort! Why not?  $\rightarrow$ 



## High resolution rainfall maps for West Africa



#### Article Type: Research Article

High-resolution rainfall maps from commercial microwave links for a data-scarce region in West Africa

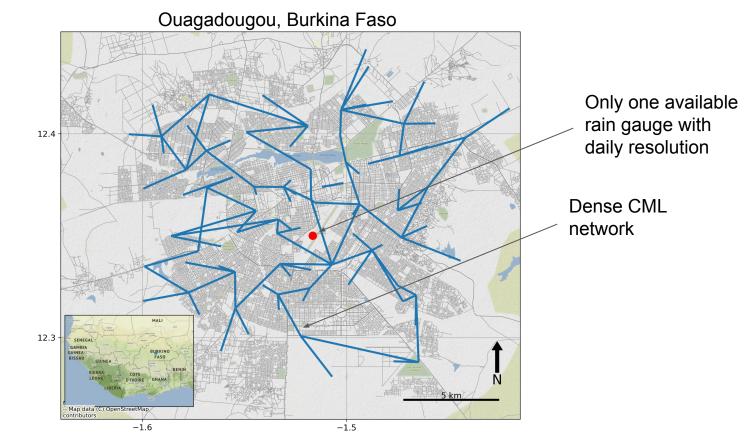
Moumouni Djibo, Christian Chwala, Maximilian Graf, Julius Polz, Harald Kunstmann, and François Zougmoré

Online Publication: 09 Aug 2023

DOI: https://doi.org/10.1175/JHM-D-23-0015.1

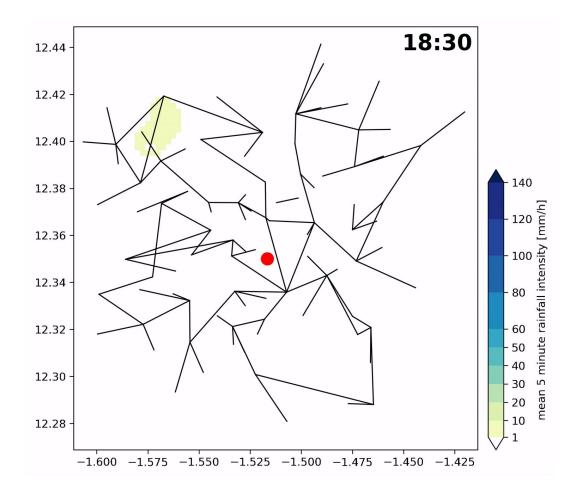


### High resolution rainfall maps for West Africa





## High resolution rainfall maps for West Africa



## Thank you!

**Questions?** 

