Bayesian GMI precipitation retrievals with neural networks

CHALMERS
UNIVERSITY OF TECHNOLOGY

Teodor Norrestad[1], Patrick Eriksson[1], Simon Pfreundshuh[1], Christian Kummerow[2], David Randel[2]

[1]Chalmers University of Technology (Gothenburg, Sweden), [2]Colorado State University (Fort Collins, USA)

Abstract

This study aims to investigate the benefits of using a specific neural networks-approach to retrieve surface rain rates from passive microwave observations. Two main advantages are demonstrated:

- Improved accuracy of retrievals and
- better representation of the associated retrieval uncertainties.

Quantiles and QRNNs

Classical neural networks are typically not well suited for capturing case-specific errors. However, using so called Quantile Regression Neural Networks (QRNNs) have shown great results in predicting conditional posterior distributions in retrieval problems (Pfreundschuh et al., 2018). In this study, QRNNs are trained and tested on the GPROF observational a priori database (Kummerow et al., 2015) and compared with GPROF's retrievals. The quantile's relation to the posterior PDF and CDF are shown below.

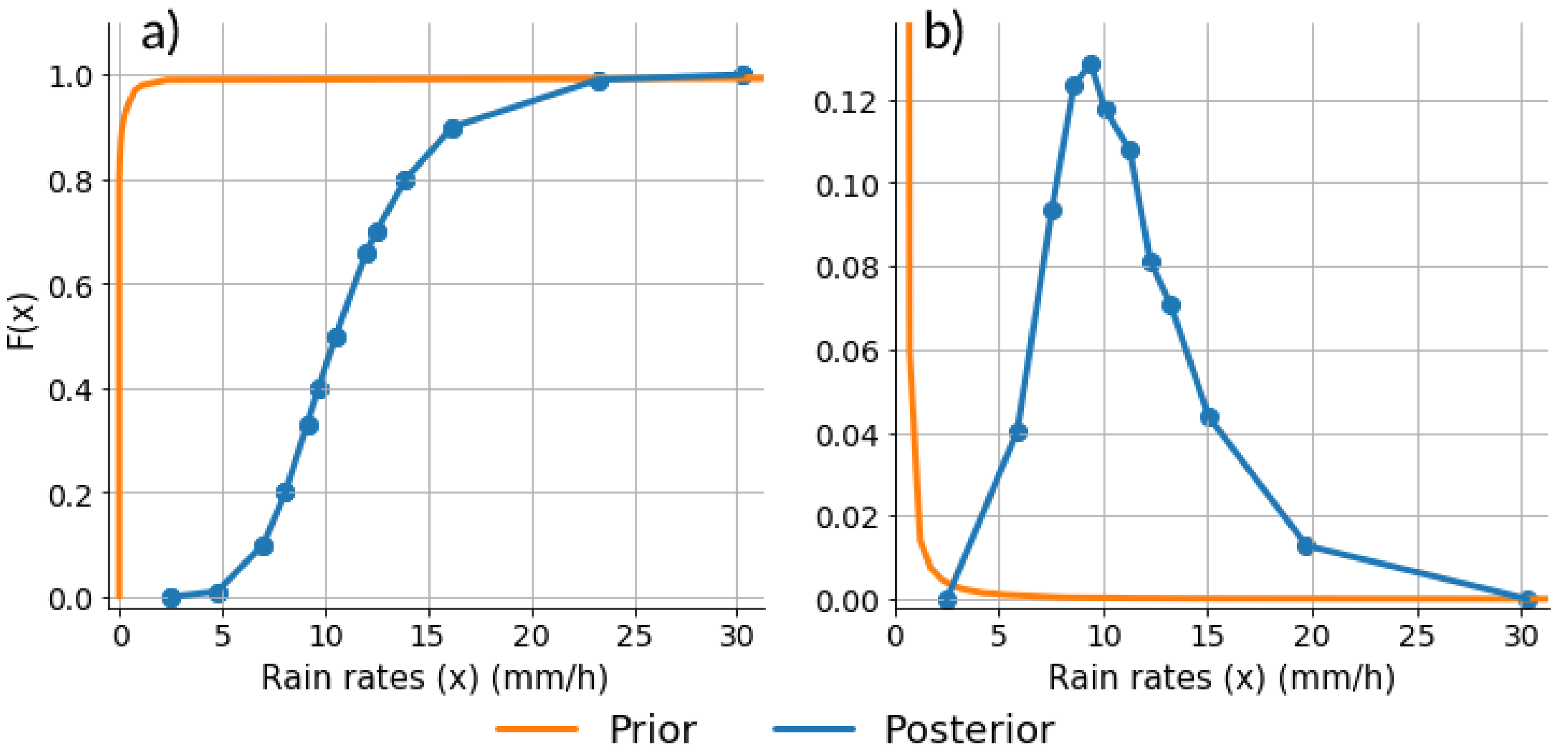

Figure 1: An example of the QRNN output for a single pixel retrieval. The dots are retrieved quantiles. Panels (a) and (b) show the approximated CDF and PDF, respectively, along with the priors of the database.

Model and data

Two different QRNNs are trained for retrievals over ocean and land with sizes **14** $\times$ **128** and **10** $\times$ **128** respectively. A training set of 12 million samples is taken from the GPROF a priori database.

Results over ocean

The QRNN is evaluated on the test set and compared with GPROF retrievals that are re-run without any post-processing. Based on the retrieved posteriors, two different point estimates are produced - the posterior mean and median. The Mean Squared Error (MSE) on the entire test set and Mean Absolute Error (MAE) on pixels with rain rate over 0.3 mm/h are shown in table.

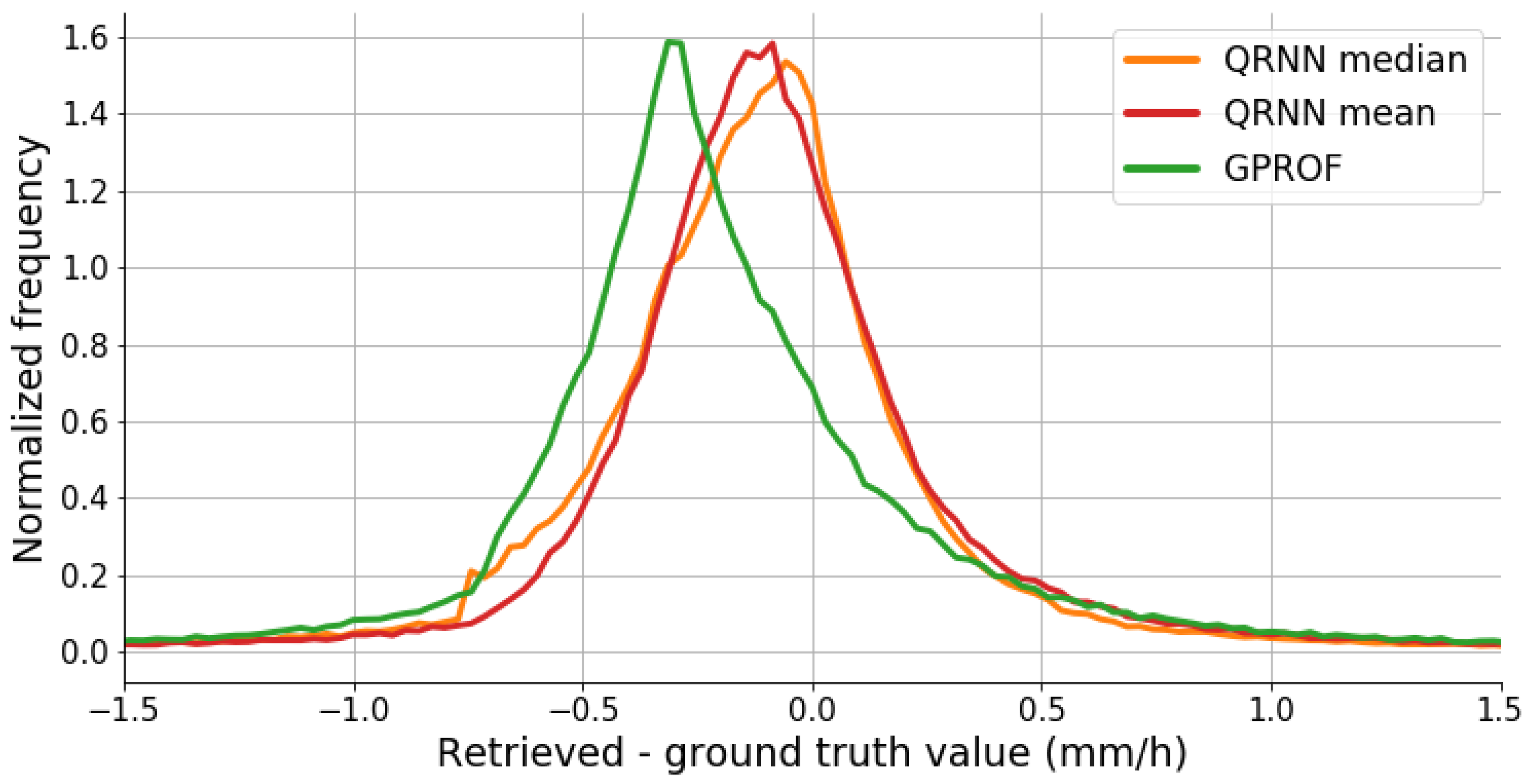

Figure 2: Distribution of retrieval errors (mm/h) for QRNN and GPROF. Pixels with surface rain below 0.3 mm/h are excluded.

	GPROF	QRNN median	QRNN mean
MSE	0.1112	0.0822	0.0824
MAE	0.556	0.417	0.414

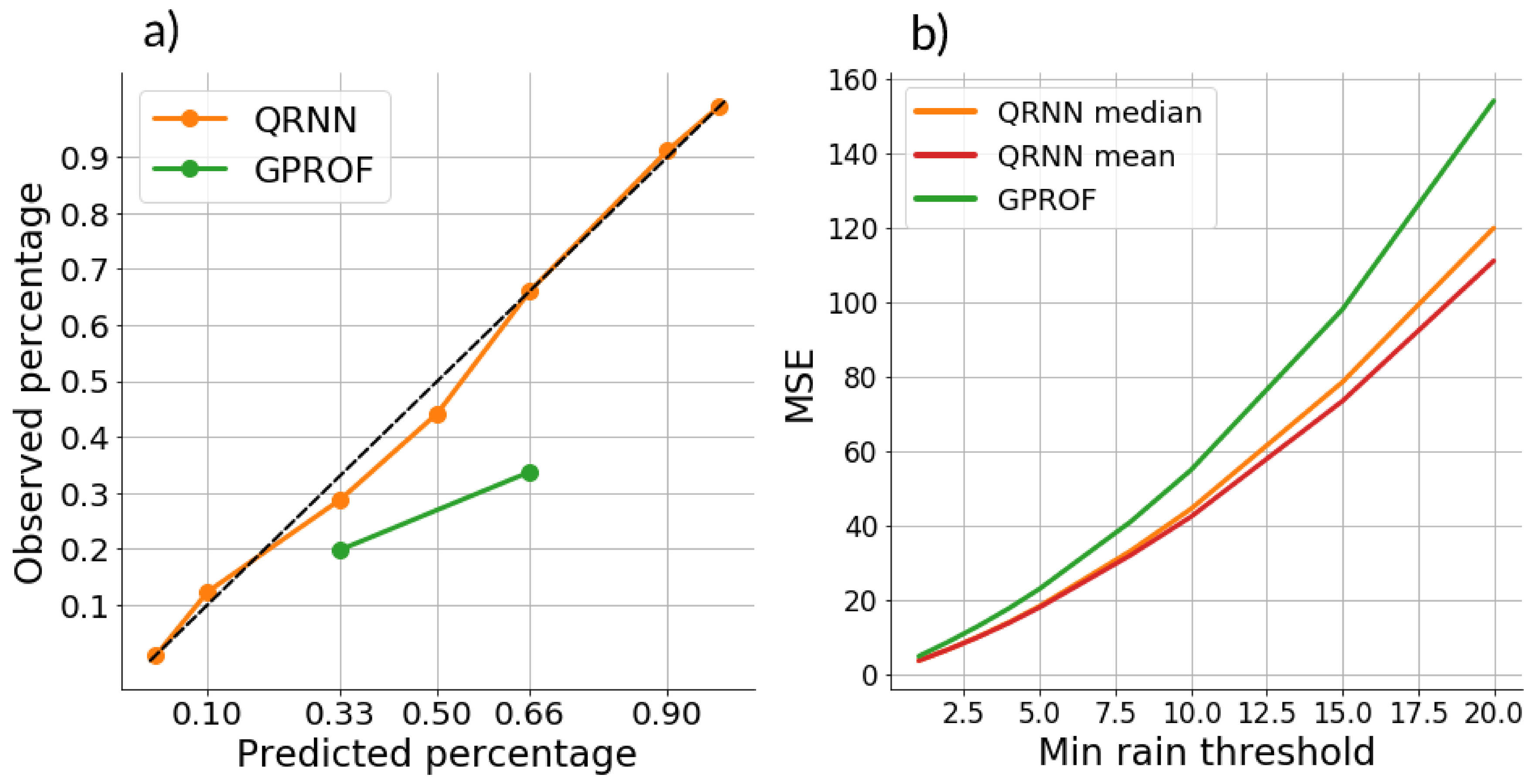

Figure 3: An assessment of the retrieved quantiles, a calibration plot, is shown in panel (a). The percentage of cases where the observed rain rate is below the quantile is compared to the quantile's predicted percentage. Alignment with the $y = x$ line indicates good calibration. For comparison, the 0.33rd and 0.66th quantiles produced by GPROF are added. In panel (b) the MSE is plotted for different subsets of the test data, obtained using increasing minimum rain thresholds.

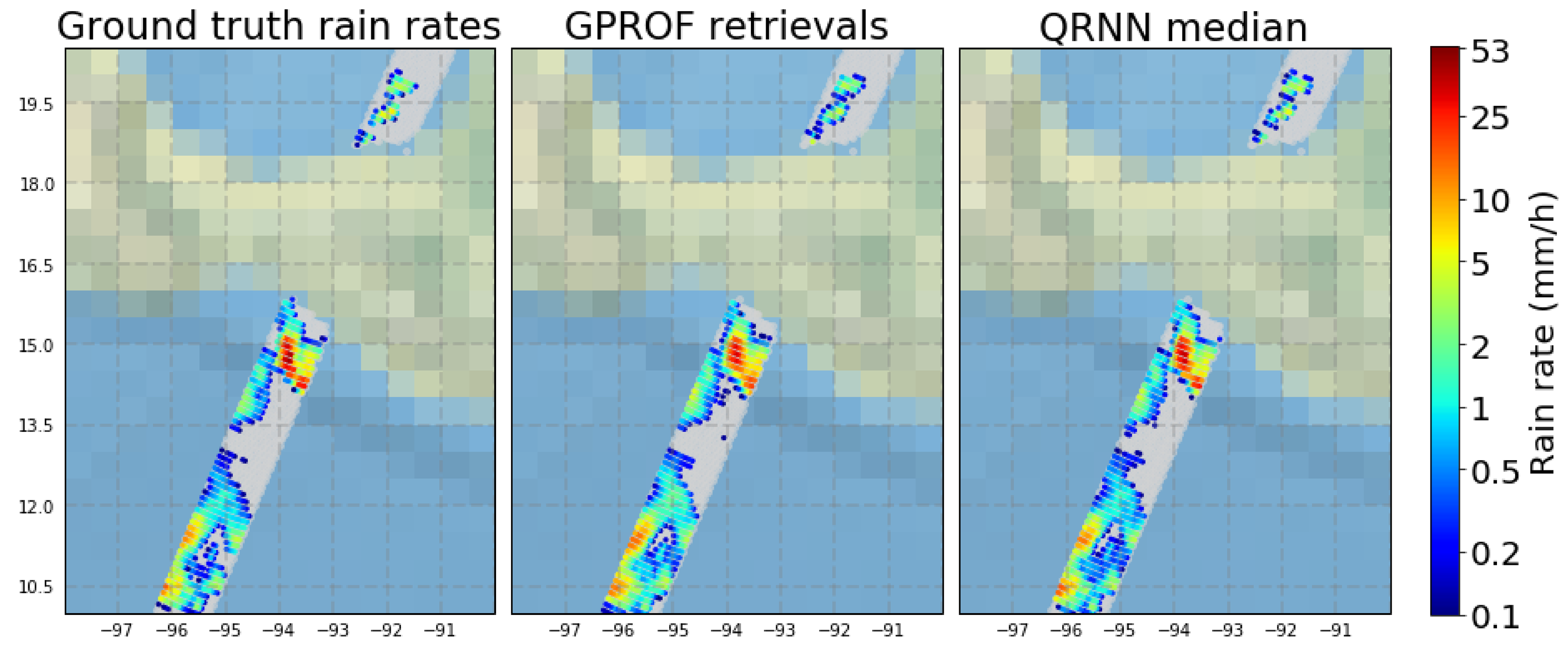

Figure 4: Example retrievals on a test scene taken from 2014-10-01 around 09:10 AM.

Results over land

The QRNN for land retrievals is trained on pixels in the database classified as any of the five types of vegetated land. The resulting MSE and MAE are shown in the table below. In general the same trends are seen over land as over ocean. The improvements of using QRNNs over land are, however, somewhat smaller.

	GPROF	QRNN median	QRNN mean
MSE	0.484	0.389	0.389
MAE	1.306	1.107	1.108

Outlook: can one QRNN be used for all surface types?

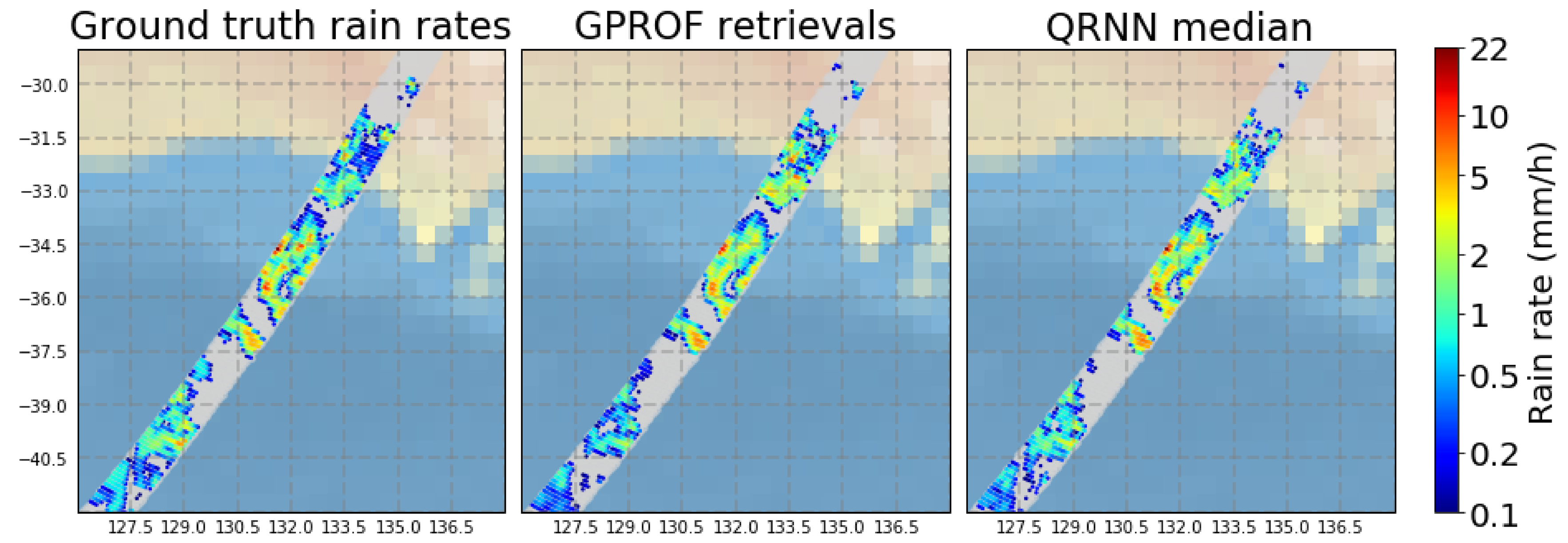

Figure 5: Another example scene retrieval, taken from 2014-12-01 around 10:20 PM. This QRNN is preliminary version of a network trained on retrieving over a variety of surfaces, including ocean, vegetated land, coastline and inland water. Snow and ice covered surfaces are excluded.

References

C. D. Kummerow, D. L. Randel, M. Kulie, N.-Y. Wang, R. Ferraro, S. Joseph Munchak, and V. Petkovic. The evolution of the goddard profiling algorithm to a fully parametric scheme. *Journal of Atmospheric and Oceanic Technology*, 32(12):2265–2280, 2015.

S. Pfreundschuh, P. Eriksson, D. Duncan, B. Rydberg, N. Håkansson, and A. Thoss. A neural network approach to estimating a posteriori distributions of bayesian retrieval problems. *Atmospheric Measurement Techniques*, 11(8):4627–4643, 2018.

Teodor Norrestad

teodorn@chalmers.se