RealPEP Phase 2:
Polara Benchmark Execution & PredRNN on Nowcasting
10.10.2024

Mst. Mahfuja Akter, Kai Mühlbauer, Raquel Evaristo, Julius Polz

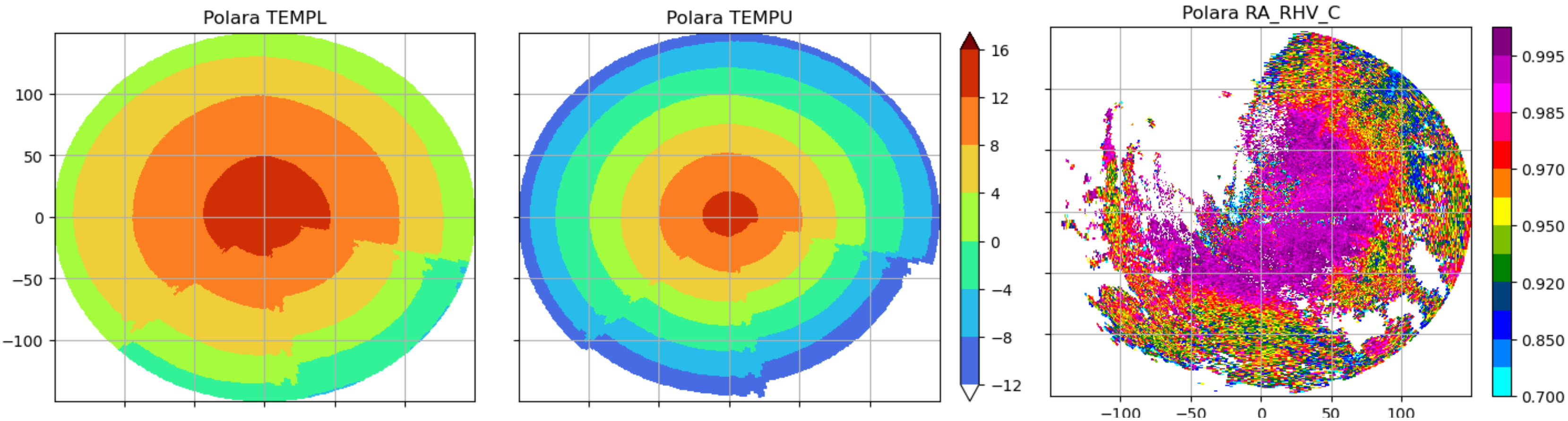
Dr. Silke Trömel

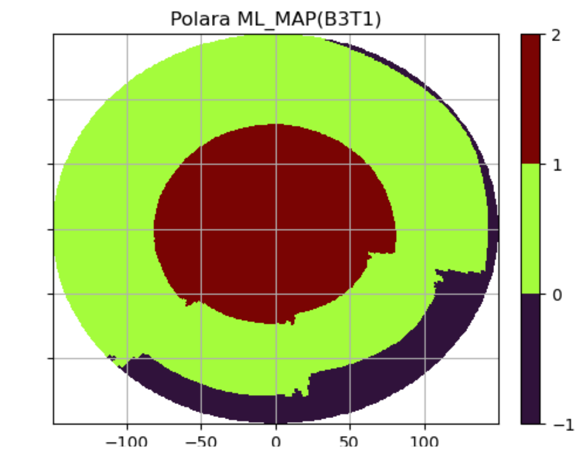
Meteorology Institute, University of Bonn

Polara Benchmark
Execution and Analysis

Melting Layer Detection from Temperature

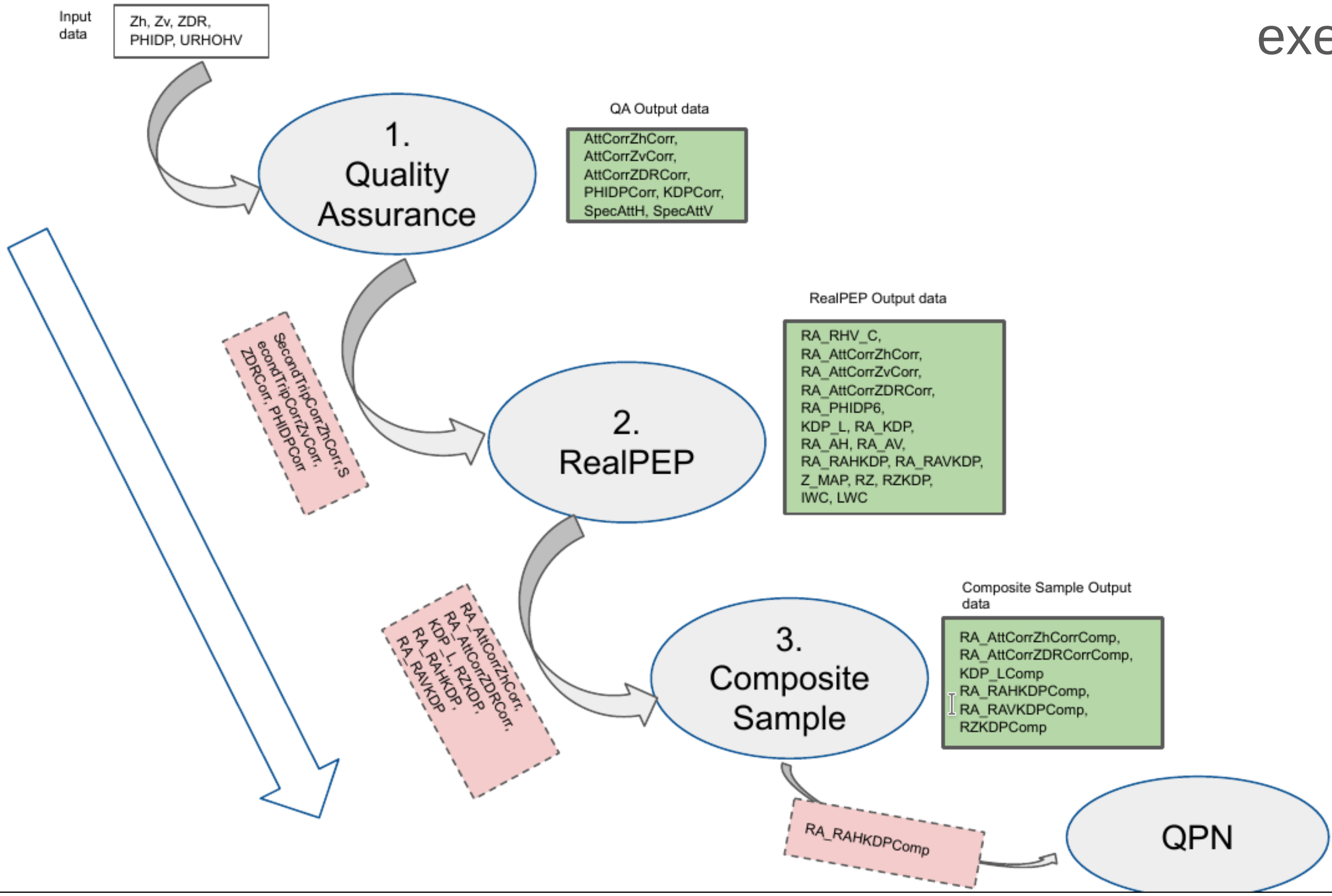
Time: 20170725 19:00
Radar: ESS
Stratiform case





- If TempU or TempL is within the range 3~1, then it is considered as melting layer

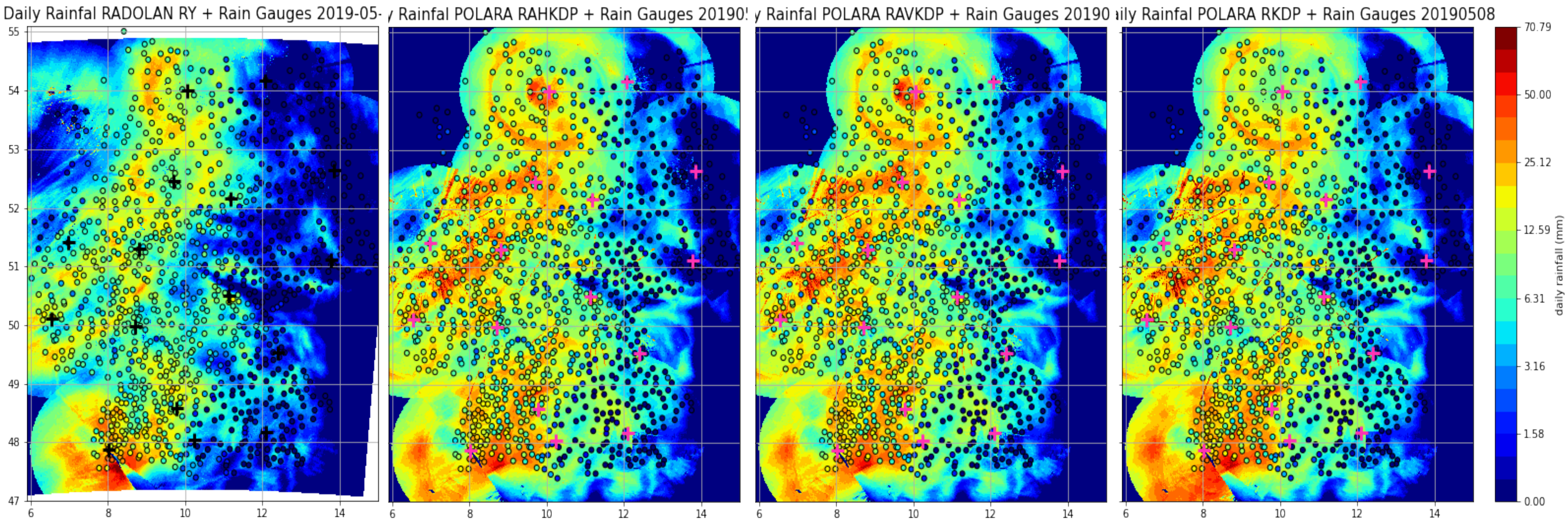
Workflow of Moment data



4 months benchmark data execution in Polara

- 2018.01
- 2019.05
- 2020.06
- 2021.07

Benchmark Analysis (Raquel)

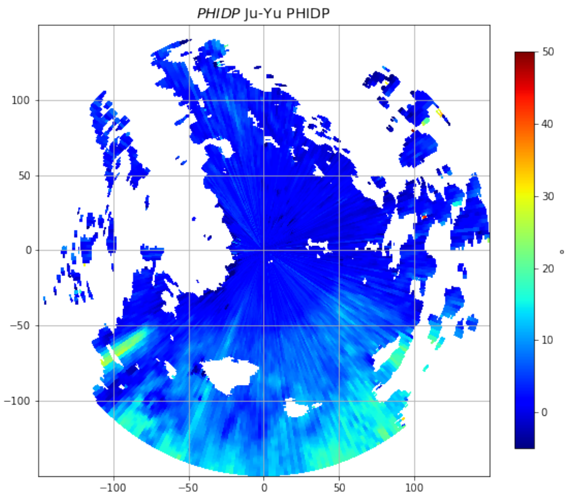


2019-05-08

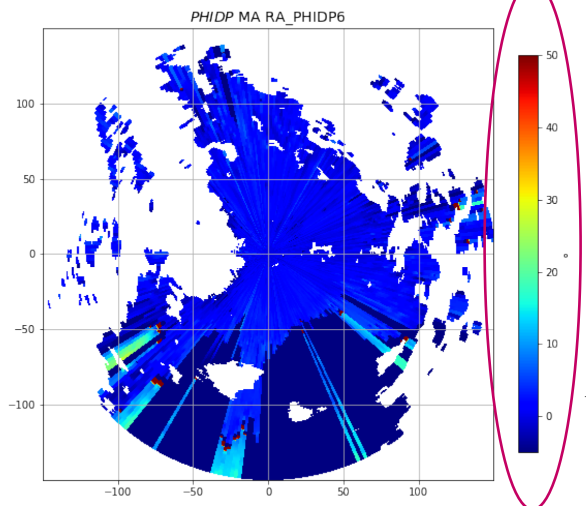
PhiDP 20190508 14:30UTC

Ju-yu

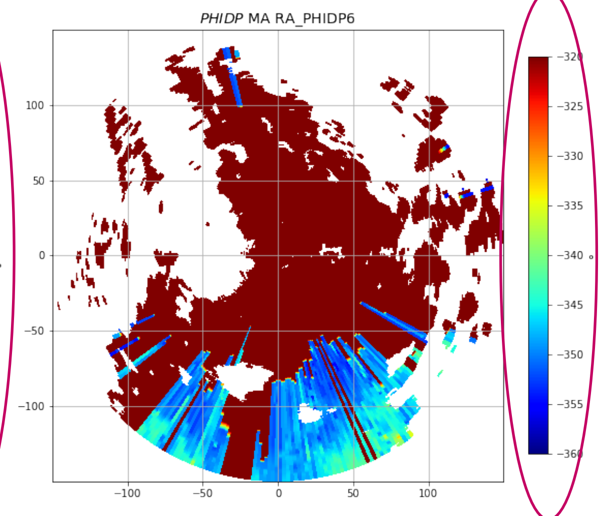
PHIDP 2019-05-08T14:30:04

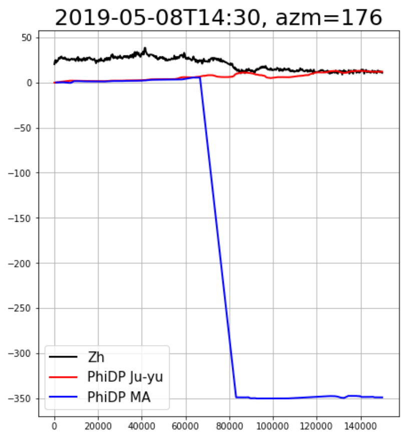


POLARA



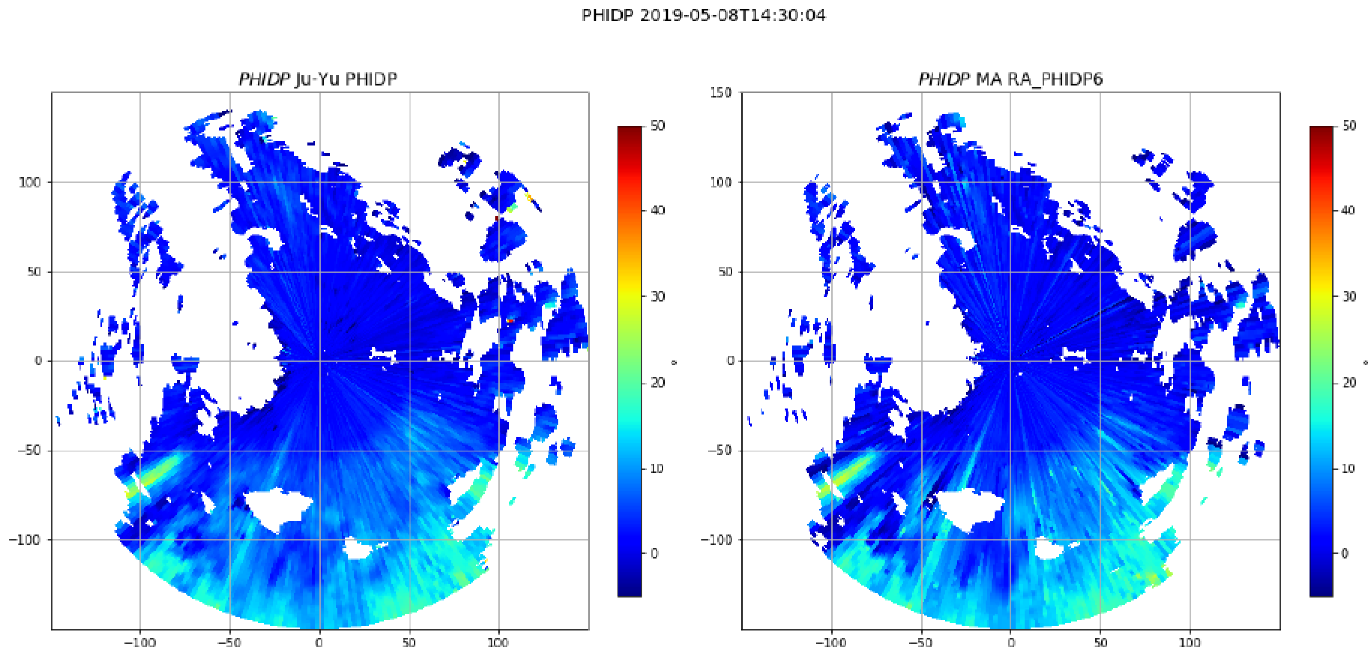
POLARA





Different color bar

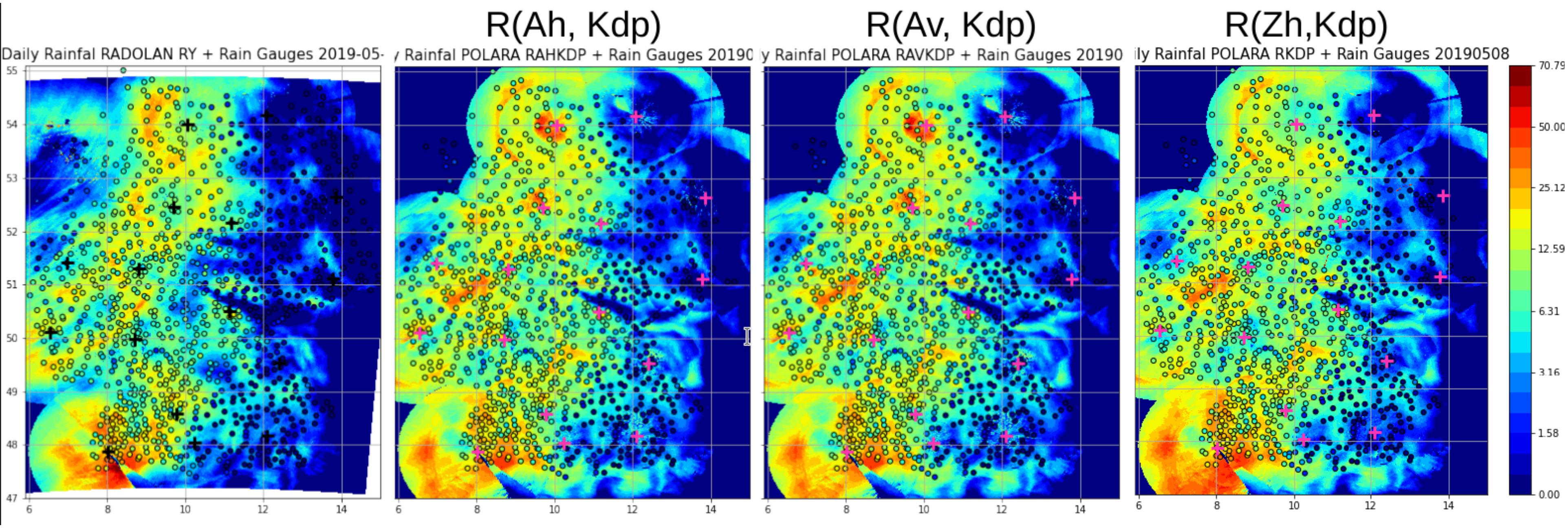
Fixed PHIDP issue



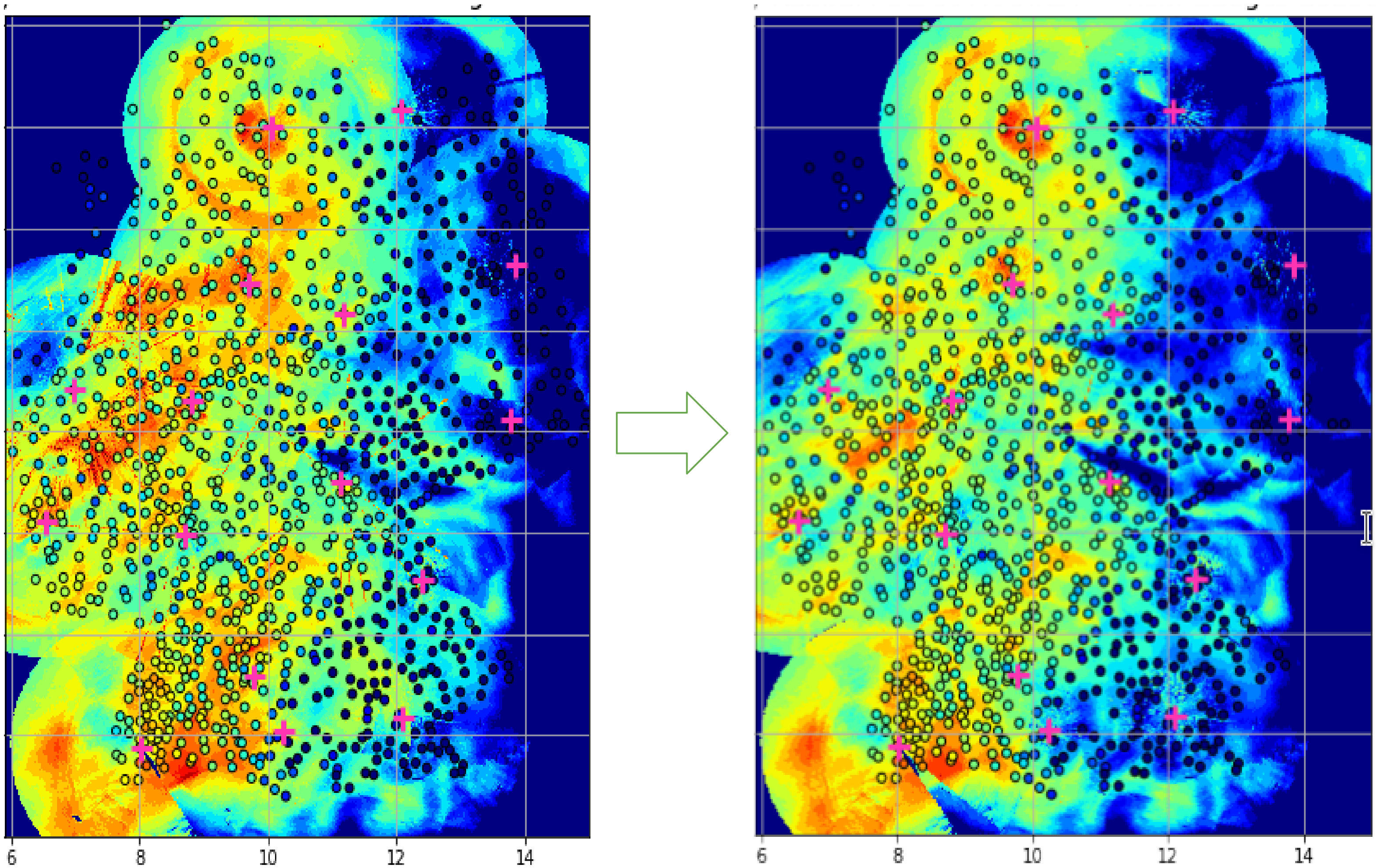

```
If (PhiDP < -10.)
  PhiDP +=360;
If (Diff(PhiDP) > 90.)
   Copy lastValidValue;
```

- Additionally we have updated Composite generation algorithm based on considering the value which has (MinMSL) minimum sea level length

After PHIDP correction and Composite Update



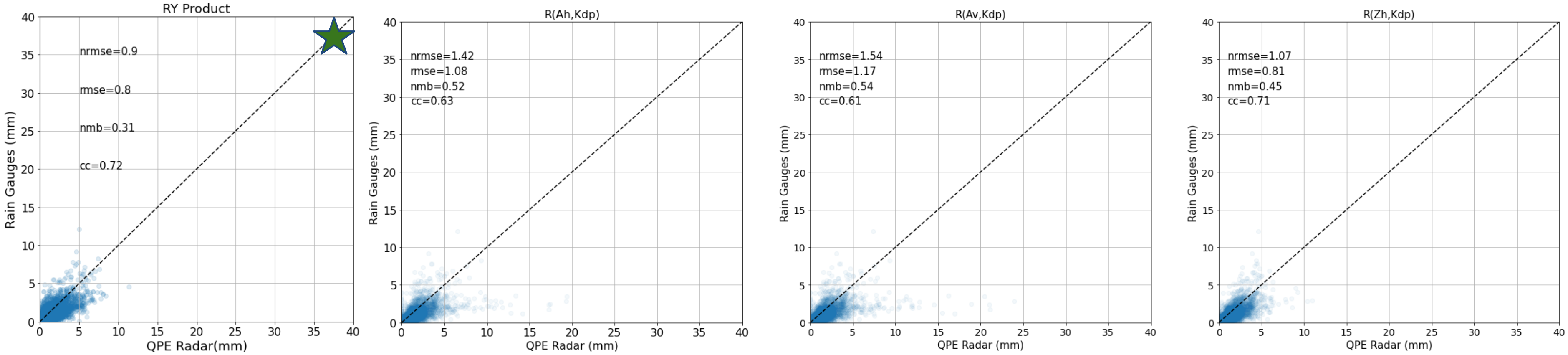
2019-05-08



2019-05-08

Day: 20190508

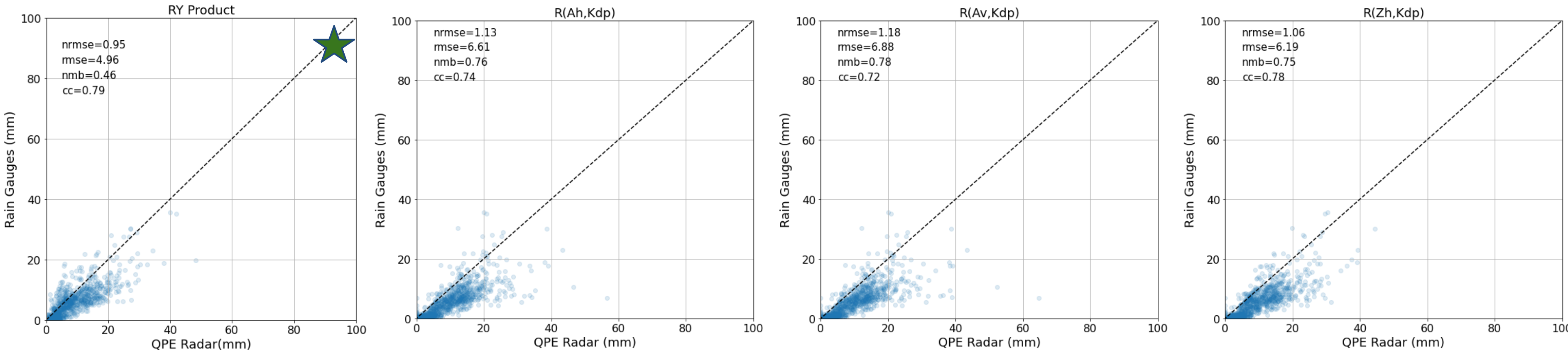
Hourly Accumulation 20190508



N=9683

N=7019

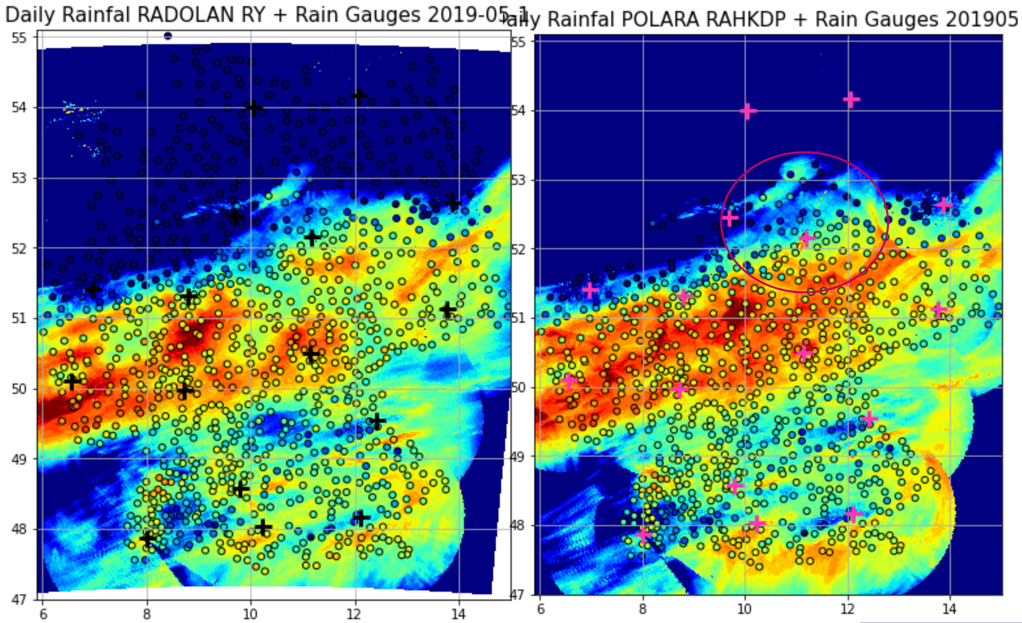
Daily Accumulation 20190508

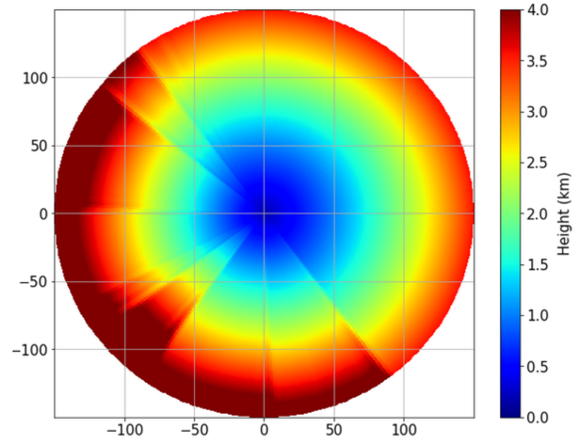


N=1020

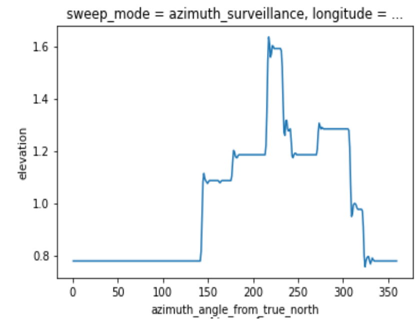
N=909

Issue on UMD radar

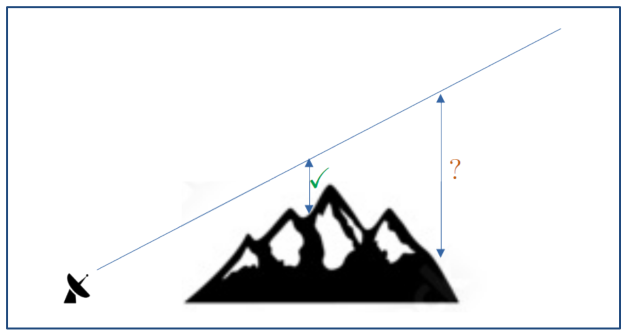




UMD



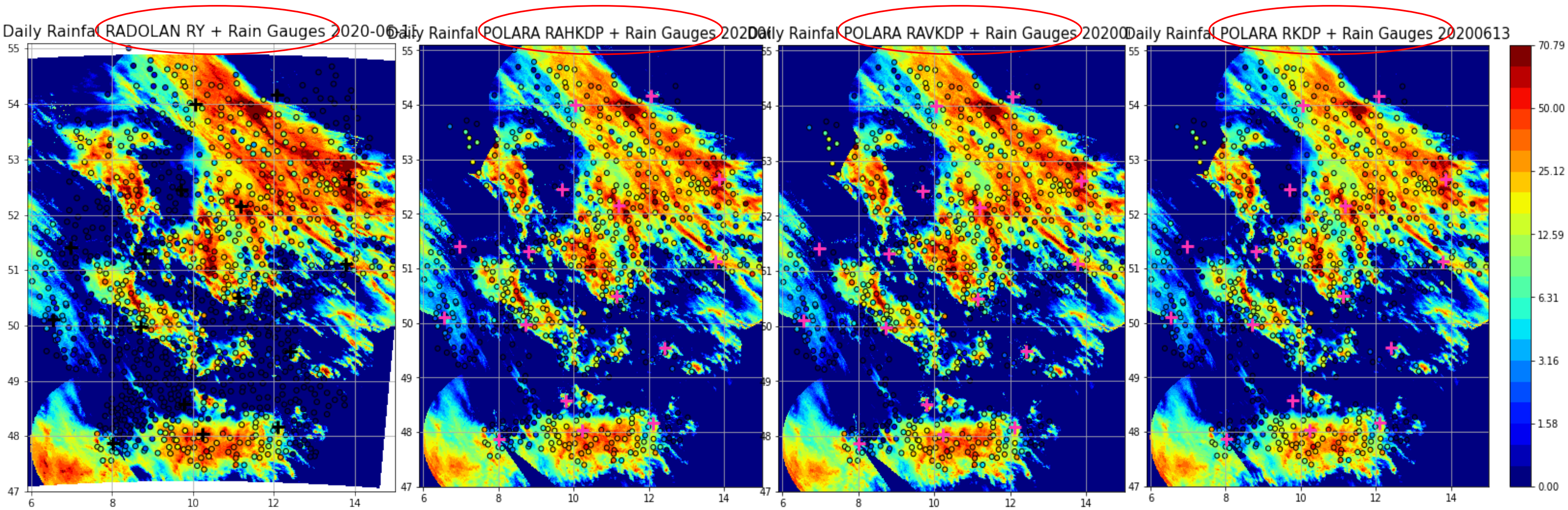
Day: 20190511



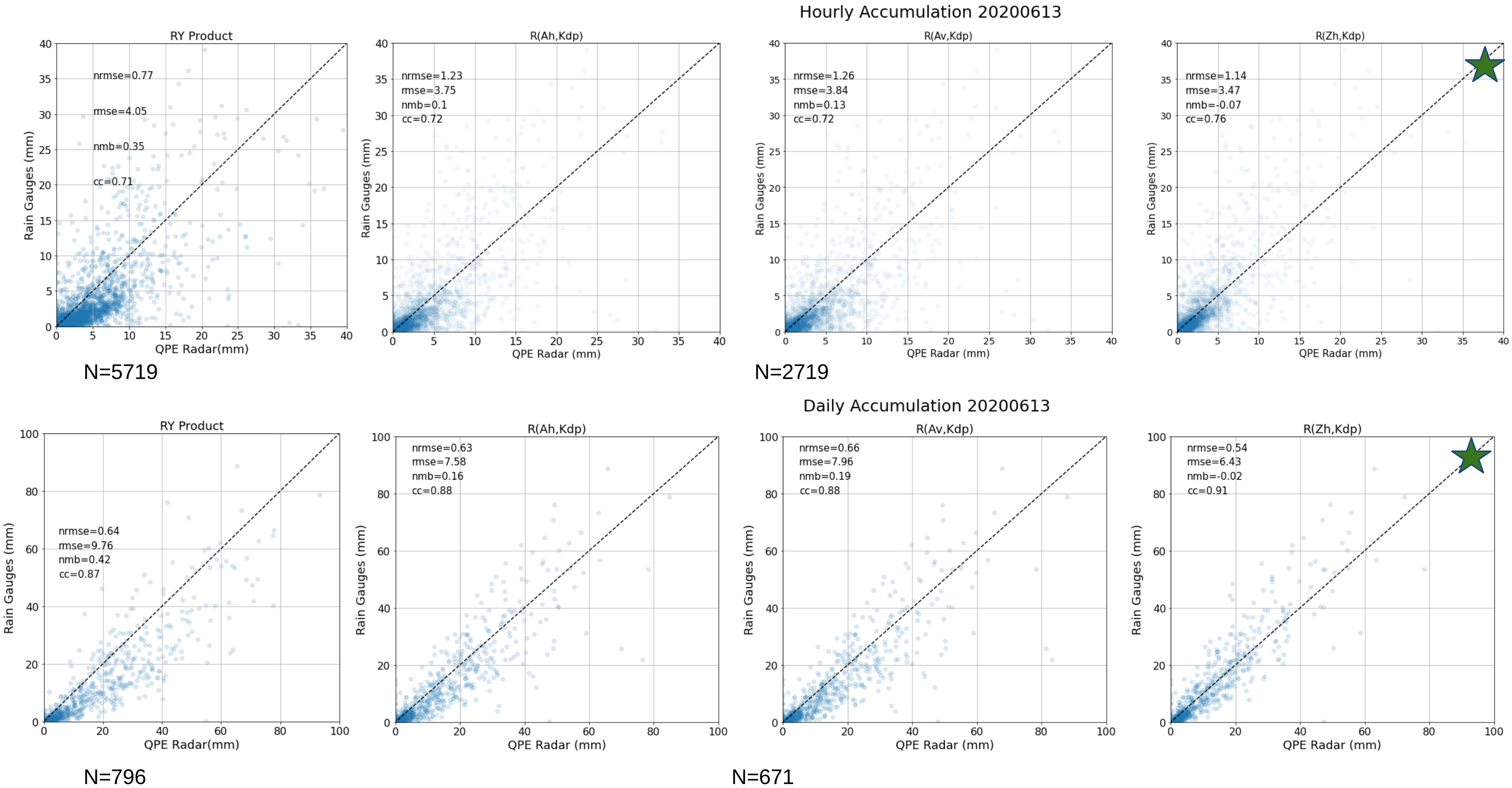
Problems on UMD radar:

- Elevation
- Height of the Beam
- Radar is sampling too far above the rain gauges

Day: 20200613



Day: 20200613



Benchmark Analysis (Julius)

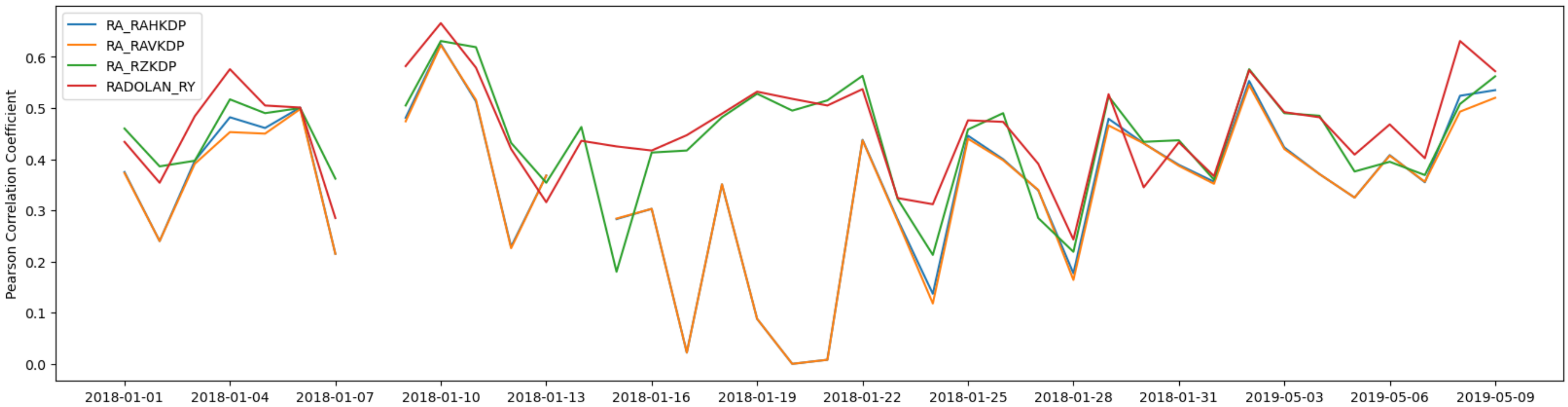
The composite data is from January 2018 and the first 10 days of May 2019

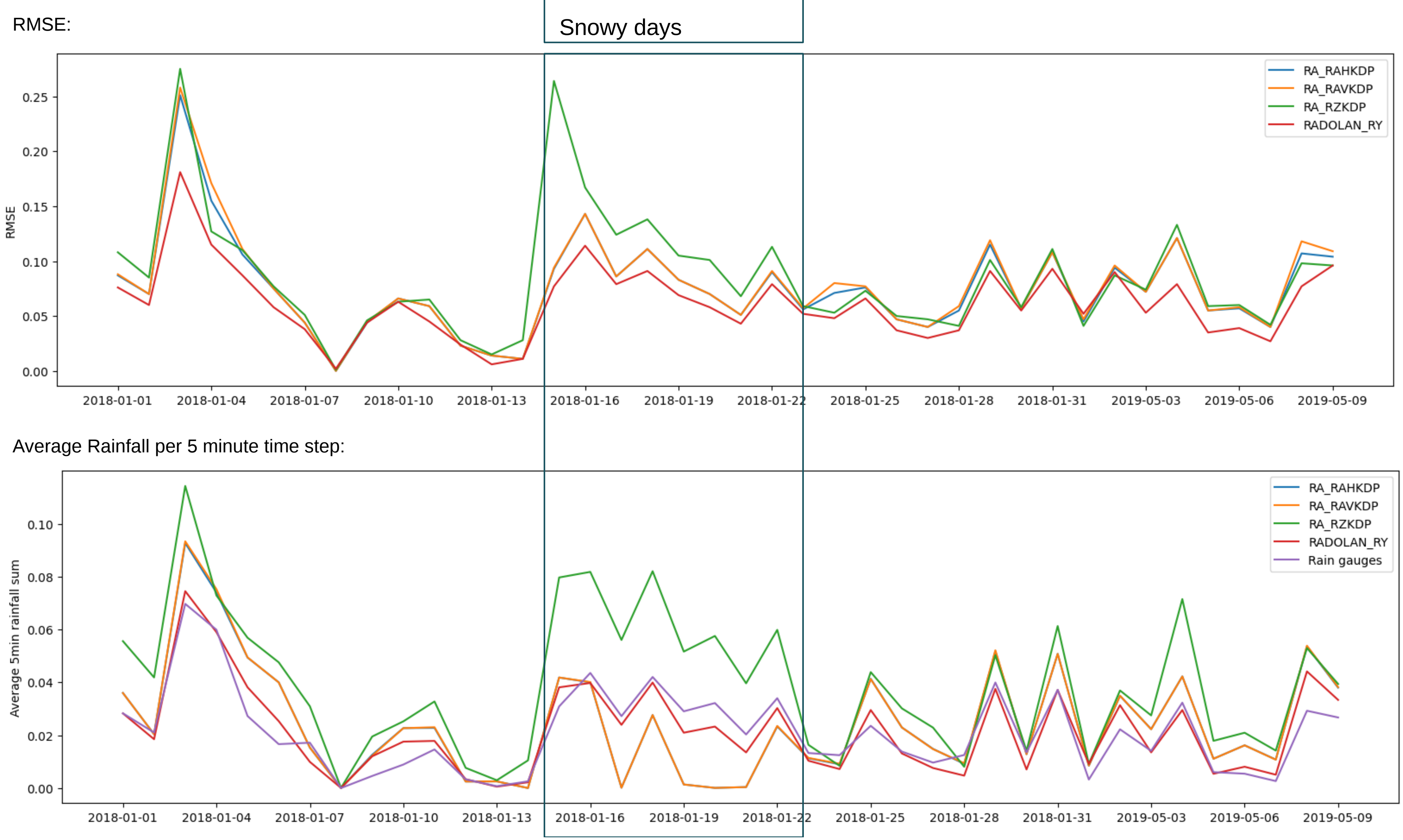
Data preparation:

1. A day is picked from daily composite files
2. For all rain gauges with a 1 minute resolution that are available on that day the radar pixel that contains the rain gauge is selected
3. Radar timestep **t** is compared to the sum of rain gauge timesteps **t, t+1min, ... , t+4min**
4. Scores are computed for all time steps where all radar products are available (not NaN)

Caution: the RealPEP radar data does have zeros for actual zeros and NaNs

Pearson Correlation Coefficient:




RMSE:
Snowy days
RMSE
0.00
0.05
0.10
0.15
0.20
0.25
2018-01-01
2018-01-04
2018-01-07
2018-01-10
2018-01-13
2018-01-16
2018-01-19
2018-01-22
2018-01-25
2018-01-28
2018-01-31
2019-05-03
2019-05-06
2019-05-09
RA_RAHKDP
RA_RAVKDP
RA_RZKDP
RADOLAN_RY
Average Rainfall per 5 minute time step:
Average 5min rainfall sum
0.00
0.02
0.04
0.06
0.08
0.10
2018-01-01
2018-01-04
2018-01-07
2018-01-10
2018-01-13
2018-01-16
2018-01-19
2018-01-22
2018-01-25
2018-01-28
2018-01-31
2019-05-03
2019-05-06
2019-05-09
RA_RAHKDP
RA_RAVKDP
RA_RZKDP
RADOLAN_RY
Rain gauges

Predictive Recurrent Neural Network on Benchmark data

PredRNN: A Recurrent Neural Network for Spatiotemporal Predictive Learning

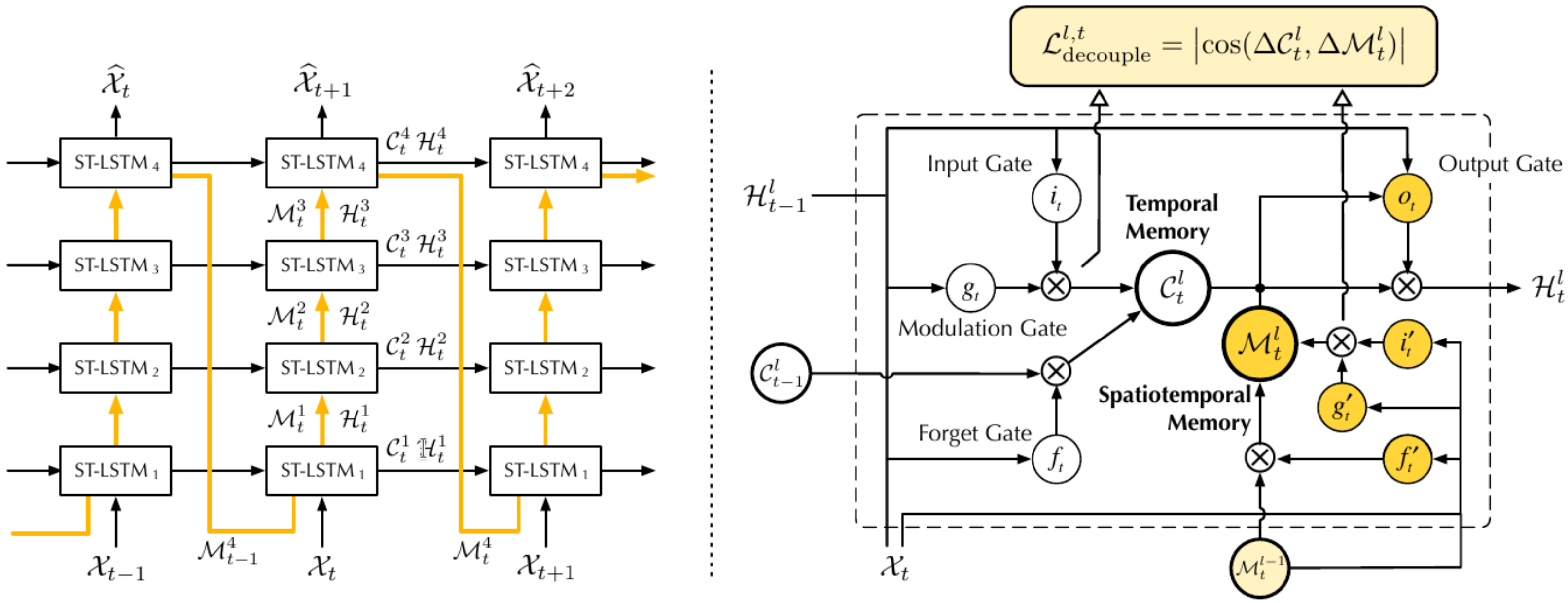


Fig. 2: **Left:** the main architecture of PredRNN, in which the orange arrows denote the state transition paths of $\mathcal{M}^l_t$, namely the spatiotemporal memory flow. **Right:** the ST-LSTM unit with twisted memory states that serves as the building block of the proposed PredRNN, where the orange circles denote the unique structures compared with ConvLSTM.

Methods:

1. Spatio Temporal Memory Flow to learn and decoupled to cover long and short term dynamics of spatiotemporal variations.
2. Action conditioned PredRNN that allows simulating the spatiotemporal variations in decision making scenarios.

Benchmark Data Preparation:

- Took 15 days RAHKDP composite data from 2019.05 those have precipitation.

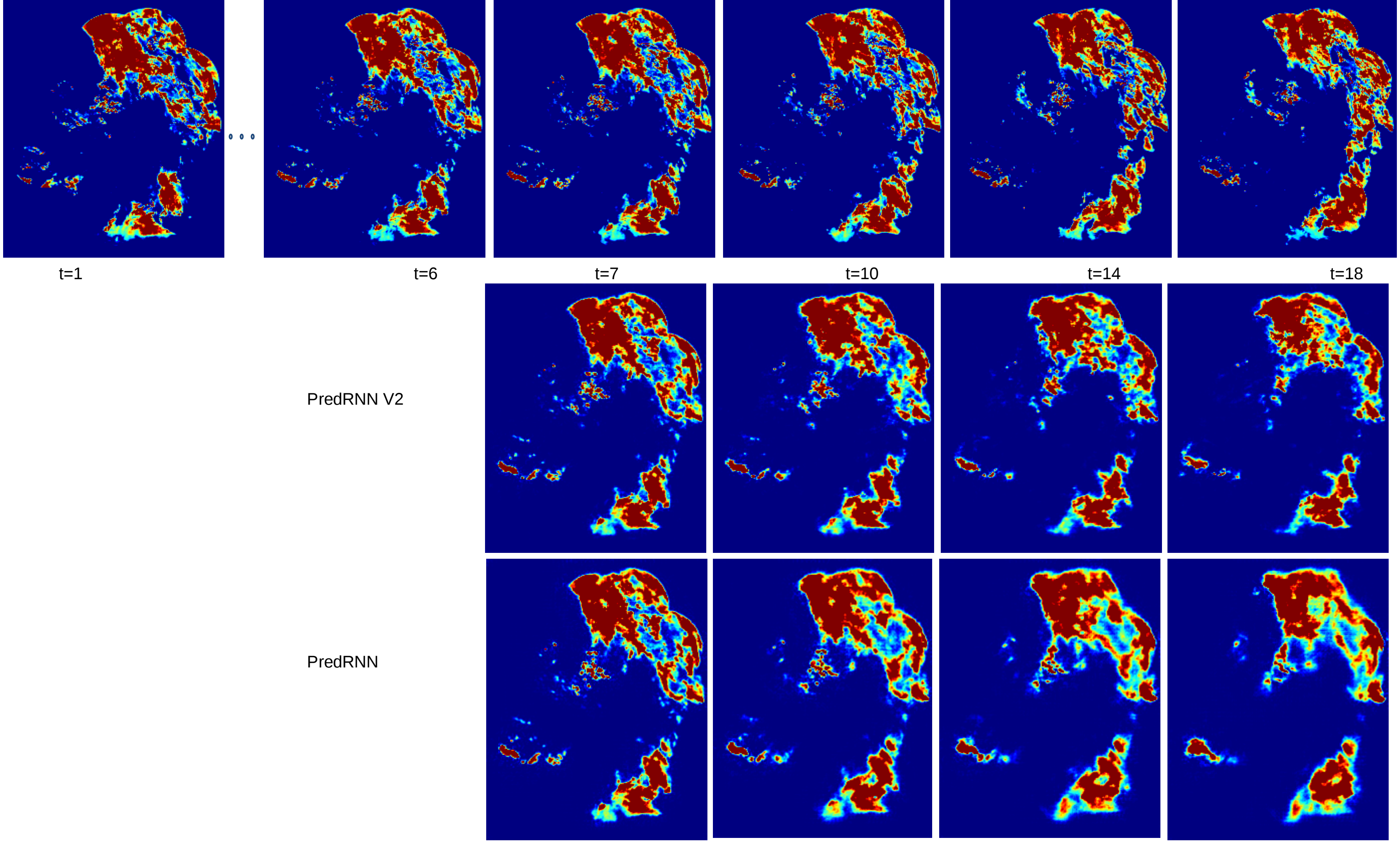
  Split 12 days for training and 3 days for test.

- Crop the data from 1200x1100 sized to 1120x880

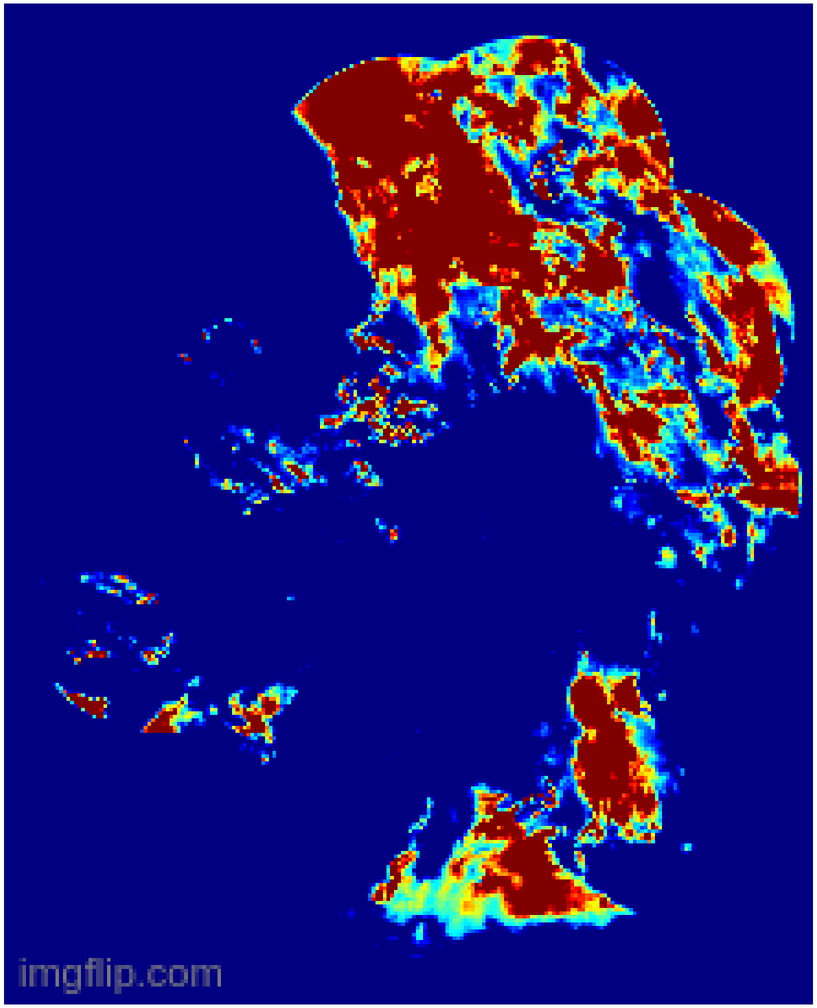
- Reshape the data into 280x220 by taking mean() of 4x4 cells

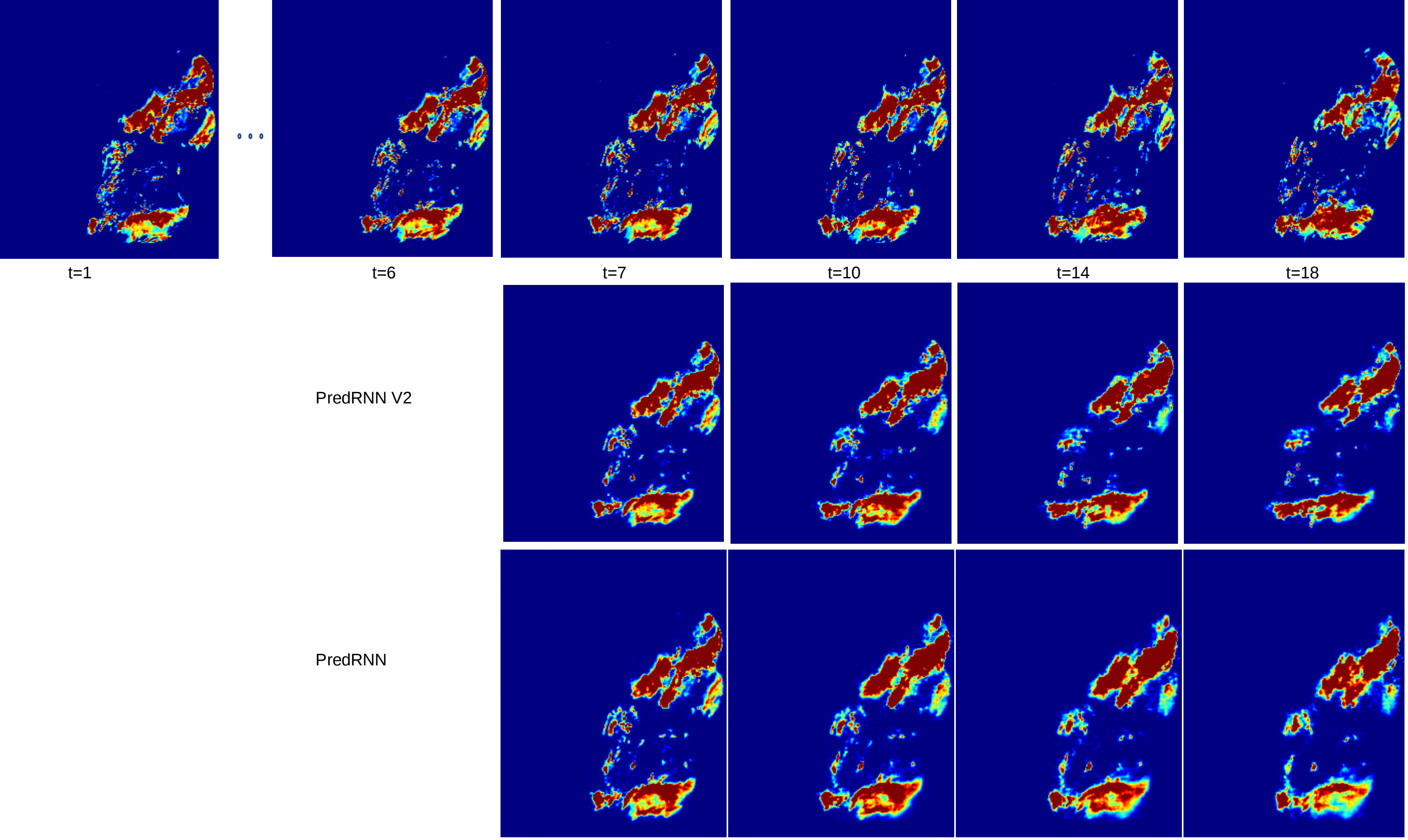
- Split the data based on a single day and take sequences based on total length 18.

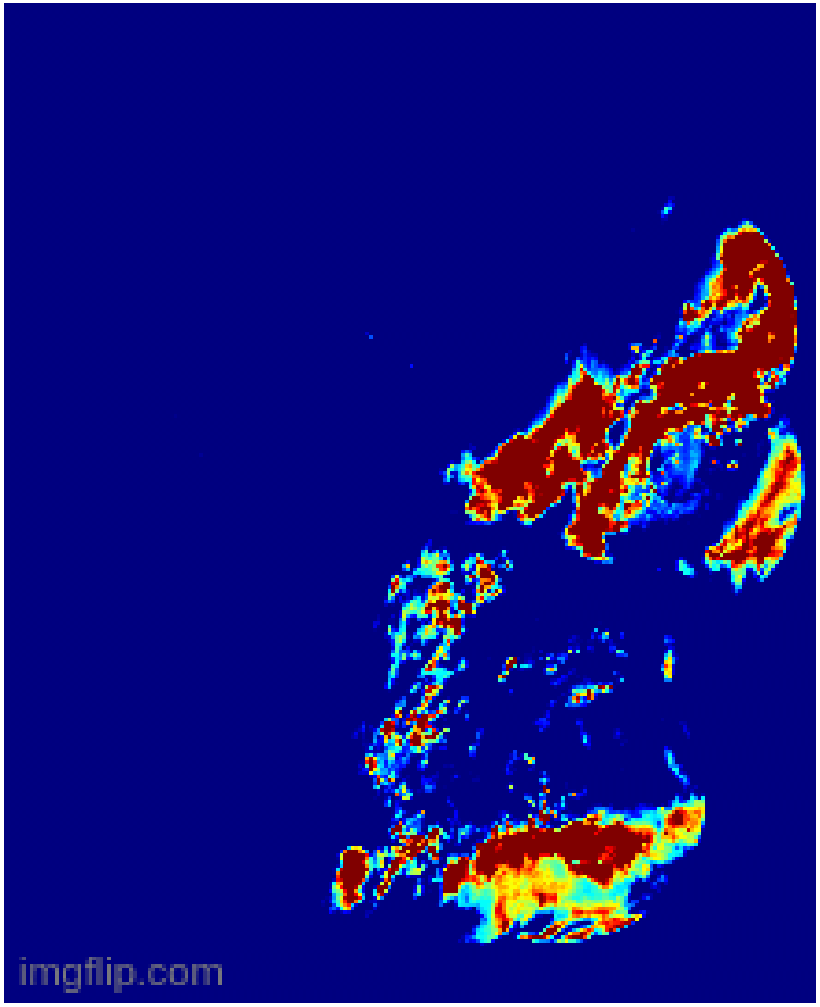
- Hyperparameter: input_length=6, total_length=18, img_height=280, img_width=220, img_channel=1, model_name='predrnn_v2', num_hidden='128,128,128,128', patch_size=4, reverse_scheduled_sampling=1, r_sampling_step_1=2500, r_sampling_step_2=5000, scheduled_sampling=1, lr=0.0001, reverse_input=1, batch_size=4, max_iterations=10000, display_interval=500, test_interval=500, snapshot_interval=1000, num_save_samples=10



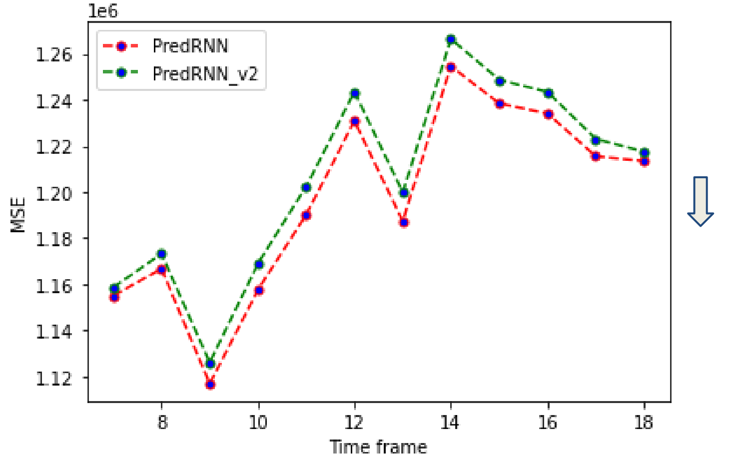
t=1
t=6
t=7
t=10
t=14
t=18
PredRNN V2
PredRNN

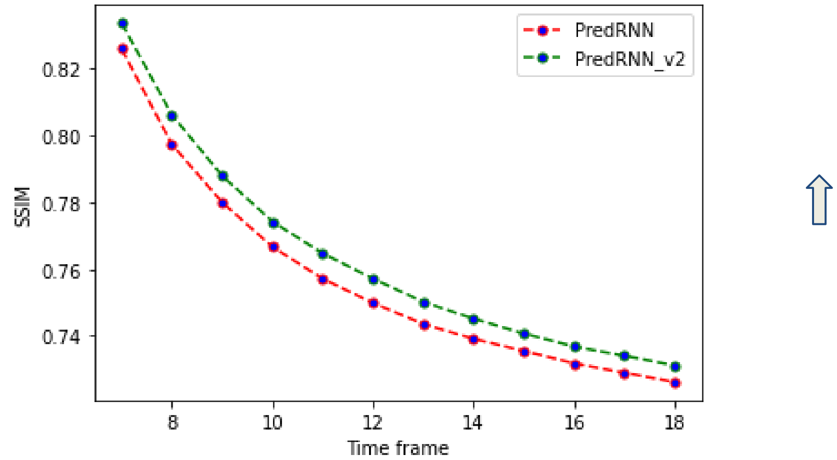

imgflip.com

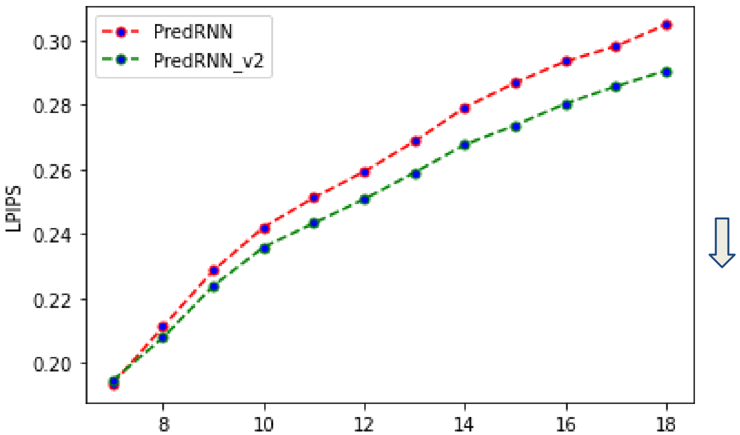

t=1
t=6
t=7
t=10
t=14
t=18
PredRNN V2
PredRNN


imgflip.com

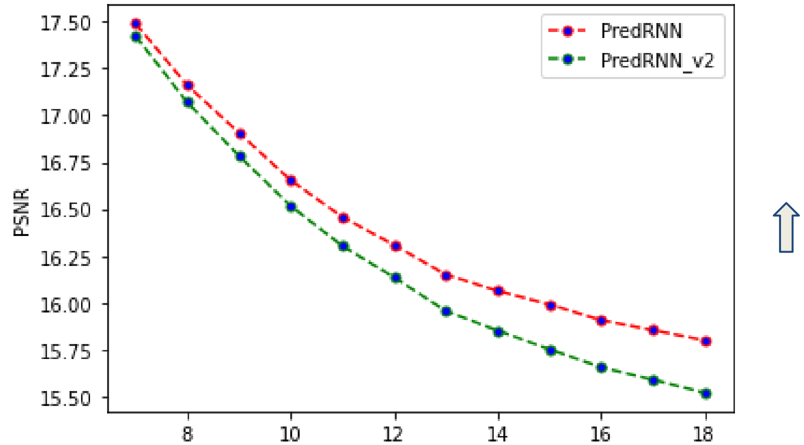
Framewise Prediction Evaluation:







Learned Perceptual Image Patch Similarity



Peak Signal to Noise Ratio

Future To-do’s:

- Improve QPE products by finding and fixing issues.
- Improve new PredRNN model by choosing best suitable hyperparam for benchmark data.
- Try PredRNN on new months data and more days.
- Adding more QPE moments besides RAHKDP into PredRNN model.
- Trying out different framework or approach to make better prediction of Benchmark data.
- Plugging satellite data into the framework.

References:

1. Giangrande, S. E., and A. V. Ryzhkov, 2008: Estimation of Rainfall Based on the Results of Polarimetric Echo Classification. *J. Appl. Meteor. Climatol.*, **47**, 2445–2462, https://doi.org/10.1175/2008JAMC1753.1
2. Yunbo Wang, Mingsheng Long, Jianmin Wang, Zhifeng Gao, and Philip S Yu. PredRNN: Recurrent neural networks for predictive learning using spatiotemporal LSTMs.In Advances in Neural Information Processing Systems, pages 879–888, 2017.
3. Yunbo Wang, Haixu Wu, Jianjin Zhang, Zhifeng Gao, Jianmin Wang, Philip S Yu, and Mingsheng Long. PredRNN: A recurrent neural network for spatiotemporal predictive learning, 2021.
4. Github Implementation: https://github.com/thuml/predrnn-pytorch