DEEP LEARNING FOR QUANTITATIVE PRECIPITATION ESTIMATION

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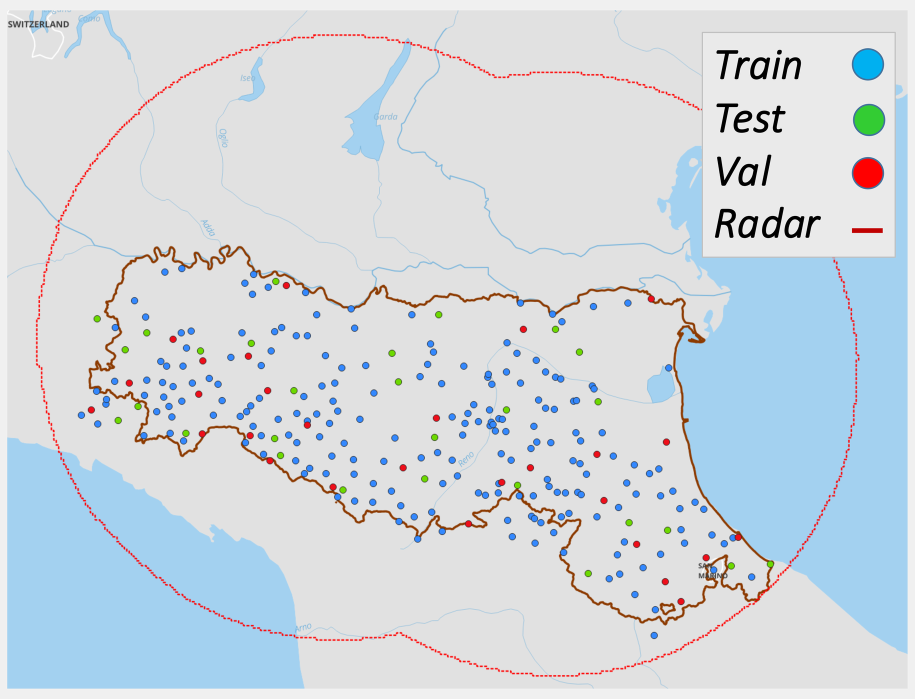
We present a comparison between machine learning and deep learning methods for **quantitative precipitation estimation**, by combining radar, gauges and topographical data at regional scale in Emilia Romagna, in the center of Italy.

DATA

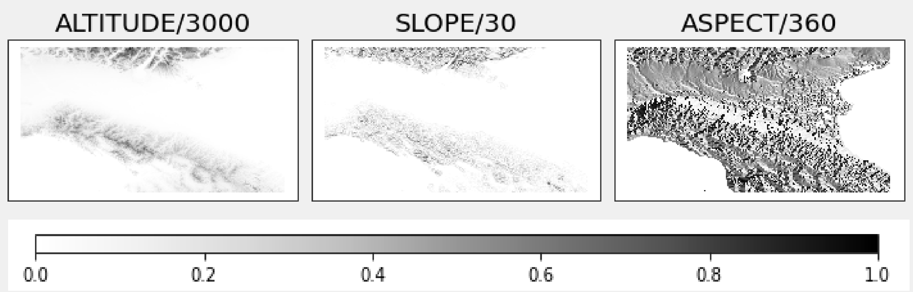
Data acquisition period : 14/01/2020 – 27/10/2020
Area: Emilia Romagna Region

ARPAE RAIN GAUGES NETWORK:
- 15' rainfall accumulation
- 266 rain gauges :
  - 210 training
  - 28 validation
  - 28 test (+temporal split)



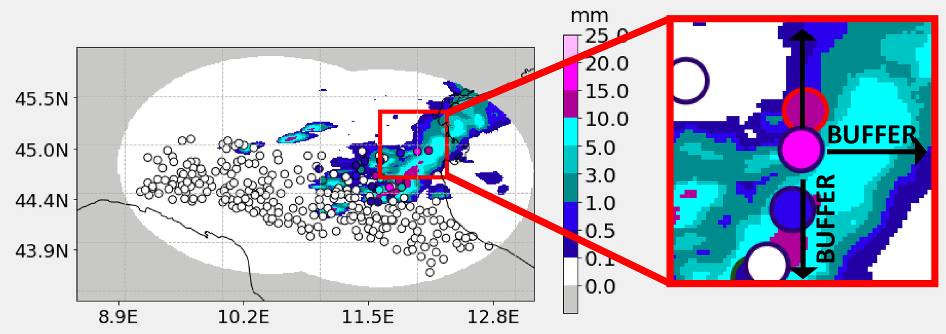
ARPAER RADAR COMPOSITE:
1 scan every 5', 290 x 373 matrix (1 km resolution)

TOPOGRAPHY:
Altitude, Slope and Aspect data from dtm model at 1 km resolution



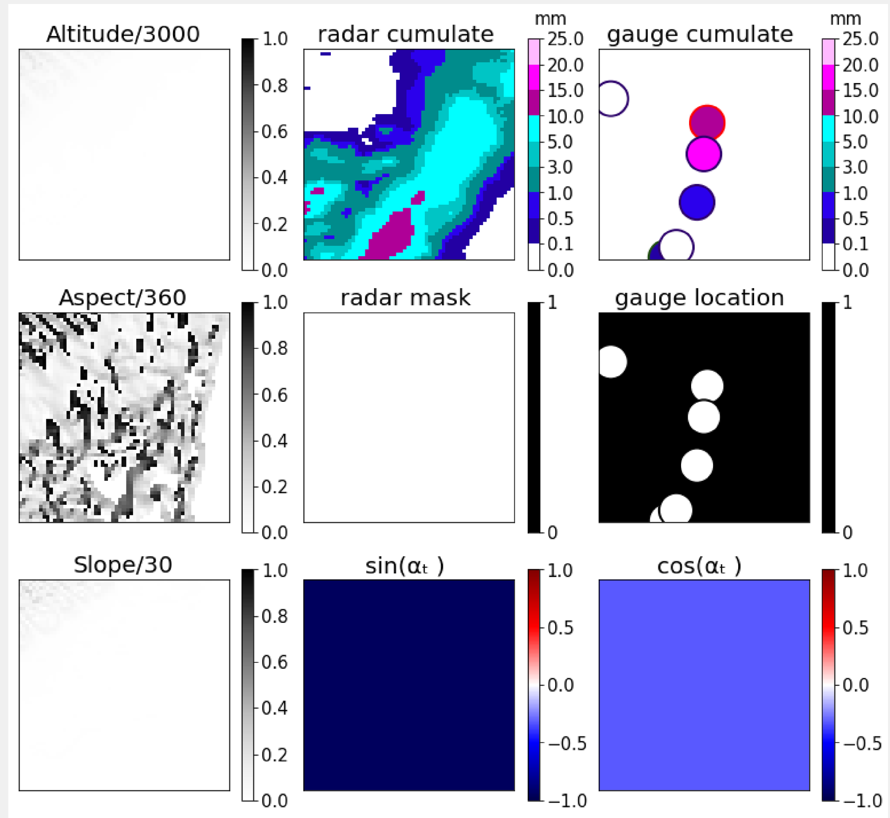
PREPROCESSING

Cumulative rainfall maps for radar and gauges:
- gauges location mapped on radar grid
- accumulation times: 15', 60', 3h, 6h, 12h, 24h



Tiles extraction for ML/DL models:
- 61x61 pixels box centered on each gauge (30 km buffer)
- 9 channels : topography, radar/gauge cumulates and masks, time of the day $\sin \alpha_t$, $\cos \alpha_t$

$$\alpha_t = \frac{2\pi \; min\_day}{1440}$$
$$1 \leq min\_day \leq 1440$$

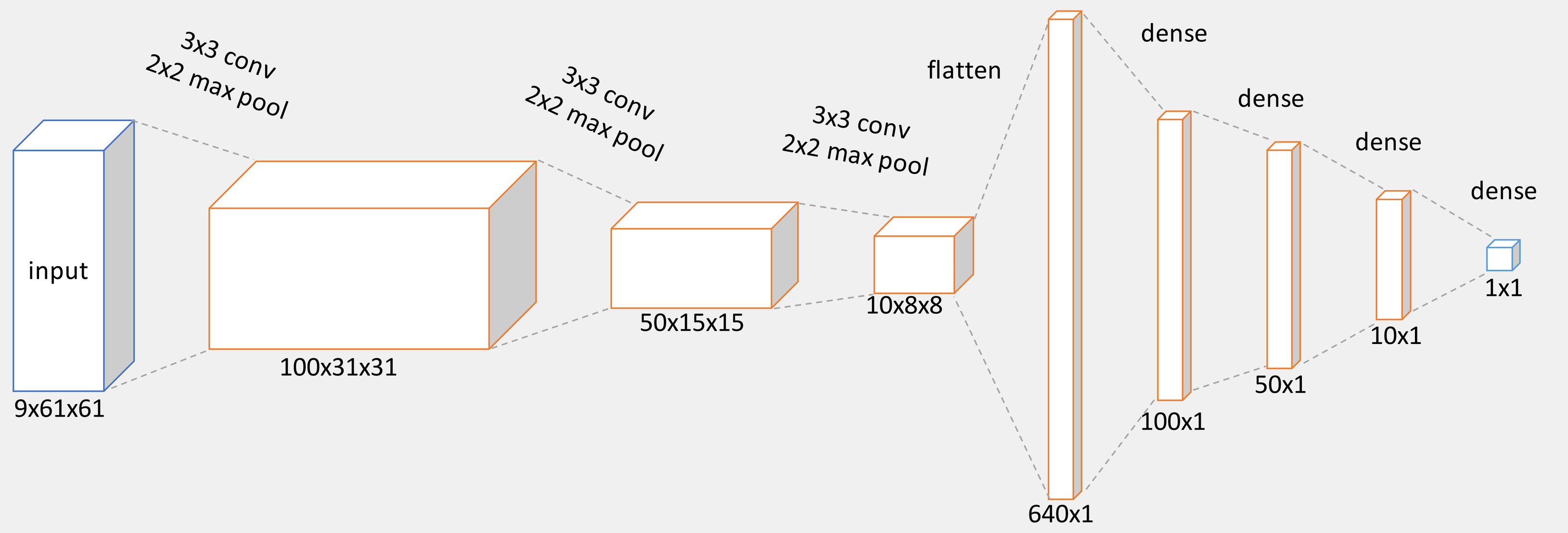


TESTED METHODS

DL : Convolutional Neural Network
- Input tiles: 9x61x61, target: accumulation value (central pixel)

ML : Regression Kriging (LightGBM regressor)
- Regressor input tile: 3x61x61 (radar/gauge cumulates and station mask), target: accumulation value (central pixel)

Ordinary Kriging of adjustment factor $f_{gauge} = \frac{median(9\,radar\,pixels)}{central\,gauge}$
- Input : radar and gauge cumulative rainfall estimation
- Output : radar cumulative rainfall estimation * kriged f_{gauge} map



RESULTS

- Critical success index (CSI) $\frac{hits}{hits + misses + false\ alarms}$
- False alarm rate (FAR) $\frac{false\ alarms}{hits + false\ alarms}$
- Probability of detection (POD) $\frac{hits}{hits + misses}$

CSI / FAR / POD computed by thresholding accumulation values and computing the contingency table

- Mean Absolute Error (MAE) $\frac{\sum_{i=1}^{N} |y_i - f(x_i)|}{N}$

CSI 15'

Threshold [mm]	CNN	RK	OK
0.2	0.56	0.47	0.42
1	0.46	0.35	0.40
5	0.18	0.12	0.20
10	0.12	0.06	0.13

CSI 60'

Threshold [mm]	CNN	RK	OK
1	0.67	0.56	0.67
5	0.55	0.38	0.66
10	0.34	0.21	0.55
25	0.21	0.09	0.40

CSI 3h

Threshold [mm]	CNN	RK	OK
5	0.69	0.52	0.79
10	0.60	0.42	0.75
30	0.24	0.1	0.62
50	0.35	0.07	0.66
70	0.27	0	0.85

CSI 6h

Threshold [mm]	CNN	RK	OK
5	0.74	0.57	0.84
10	0.66	0.52	0.83
30	0.47	0.24	0.79
50	0.31	0.11	0.79
80	0.18	0.05	0.70

CSI 12h

Threshold [mm]	CNN	RK	OK
5	0.76	0.63	0.70
10	0.68	0.55	0.61
30	0.57	0.39	0.44
50	0.55	0.34	0.35
80	0.35	0.30	0.20

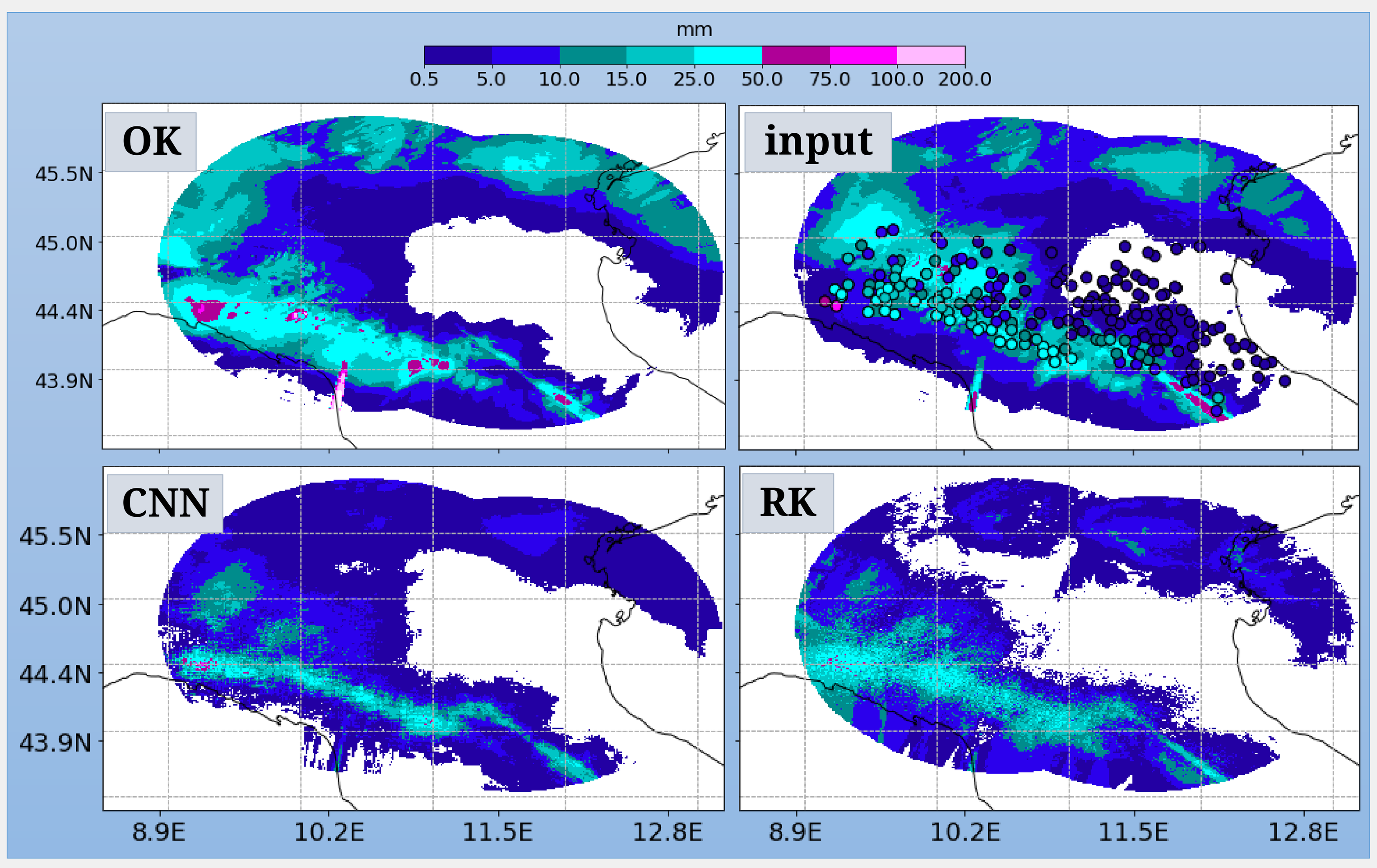
CSI 24h

Threshold [mm]	CNN	RK	OK
5	0.77	0.66	0.76
10	0.65	0.56	0.71
30	0.69	0.51	0.57
50	0.58	0.37	0.62
80	0.50	0.41	0.42
150	0.14	0.50	0.22

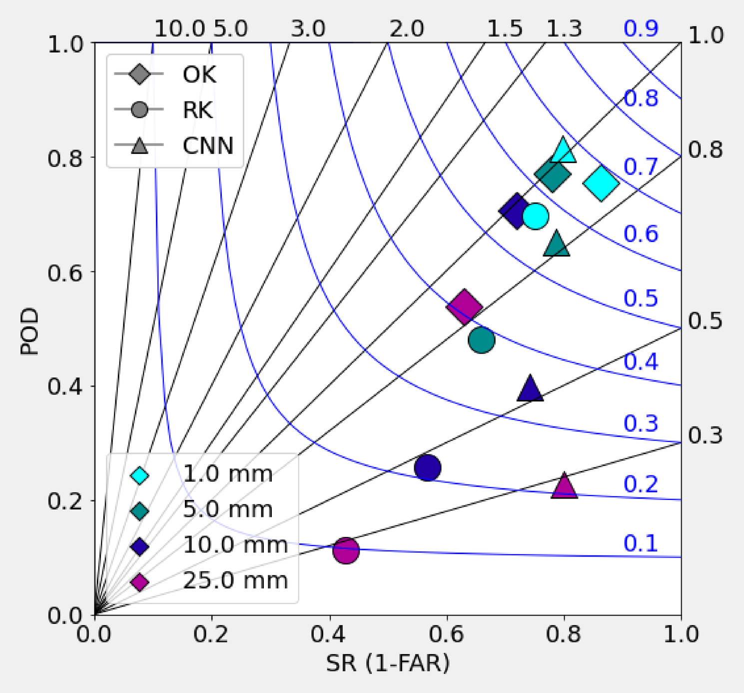
MAE

Model	15'	60'	3h	6h	12h	24h
CNN	0.07	0.18	0.48	0.9	1.66	2.91
RK	0.1	0.29	0.77	1.4	2.42	4.06
OK	0.08	0.17	0.32	0.45	2.48	3.20

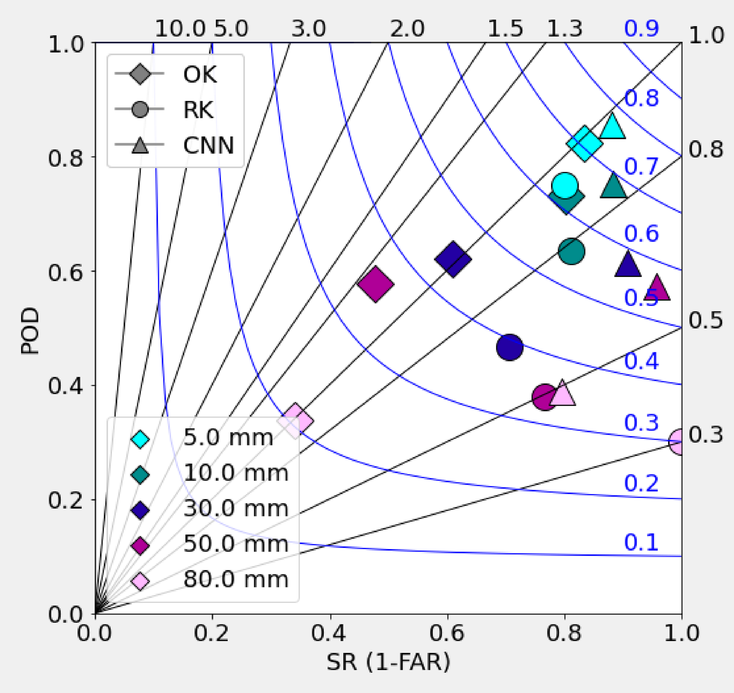
Example output 2020-03-02 15:15 UTC - 3h accumulation



Performance diagram 60'



Performance diagram 12h



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