

# Analysis of Applying a Deep Learning Model for Prediction of WSR-98D Weather Radar Product Values

WeaMyL project is funded by the EEA and Norway Grants under the RO-NO-2019-0133. Contract: No 26/2020

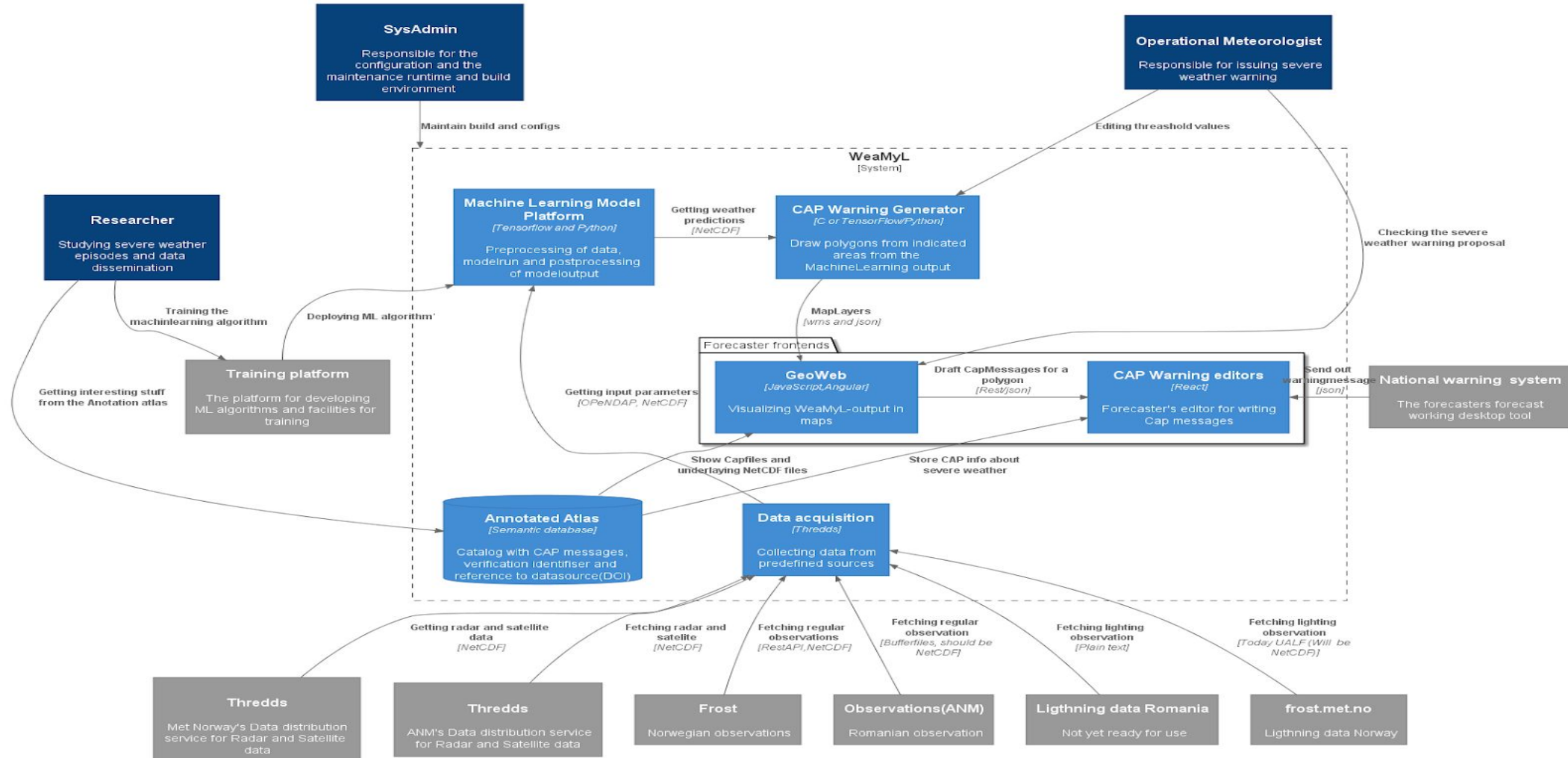
# WeaMyL project

Partnership between ANM, UBB Cluj and Met Norway

- 01.** Development and scientific validation of novel ML computational models and techniques specially tailored for accurate nowcasting
- 02.** Development and user evaluation of the Annotated Atlas of Meteorological Observations, a large database containing meteorological data
- 03.** Integration of the WeaMyL platform within the national weather warning systems of Norway and Romania.

# Activities in the first year of the project

- Establishing the functional specifications of the system
- Identify the state-of-the-art
- Setting the architecture of the system
- Identify the relevant data for ML models
- Developing and testing the data acquisition component
- Pre-processing of historical meteorological data
- Developing and testing the unsupervised and supervised models for data analysis
- Dissemination activities (7 published articles, workshop, website)

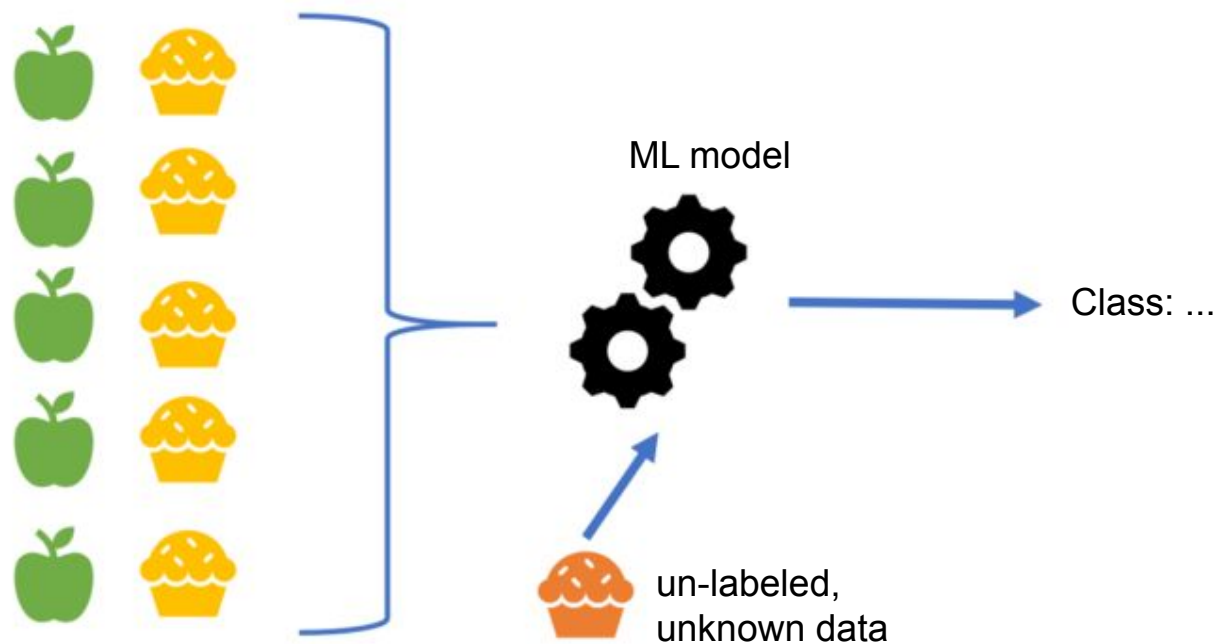


# NowDeepN Model

It is a supervised learning based regression model which uses an ensemble of deep artificial neural networks for predicting the values for radar products at a certain time moment.

# NowDeepN Model

**Supervised model** - a type of ML algorithm that aims to construct a function associating an input to an output based on labeled input-output examples.





# Research questions - RQ1

Are deep neural networks able to predict the values for a radar product at a given moment in a certain geographical location from the values of its neighboring locations from previous time moments? To what extent this holds for both normal and severe weather conditions?

# Research questions - RQ2

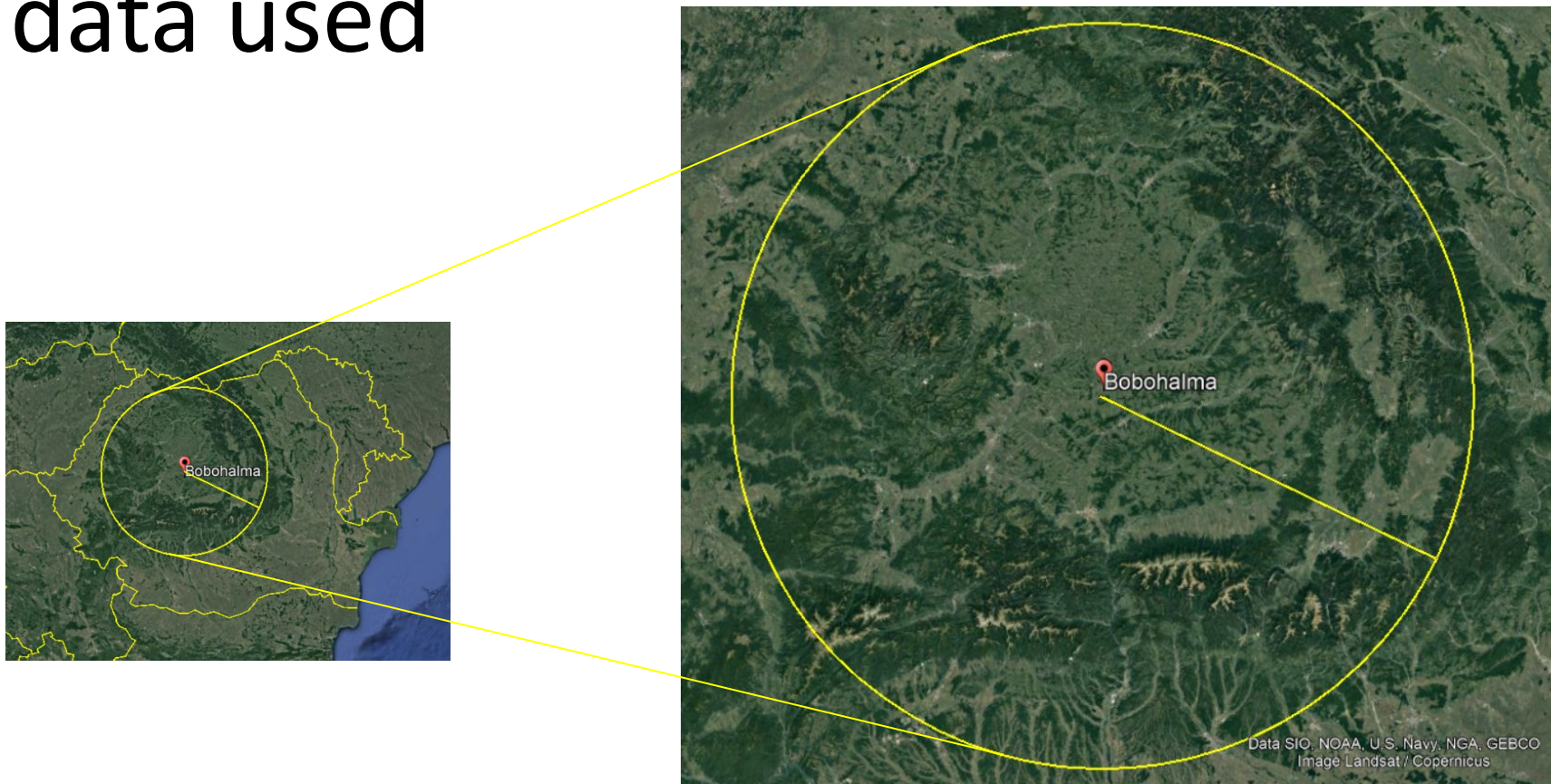
How does the data cleaning step introduced for correcting the erroneous input data impact the predictive performance of the NowDeepN model? In addition, to what extent is the proposed data cleaning step correlated with the meteorological perspective?



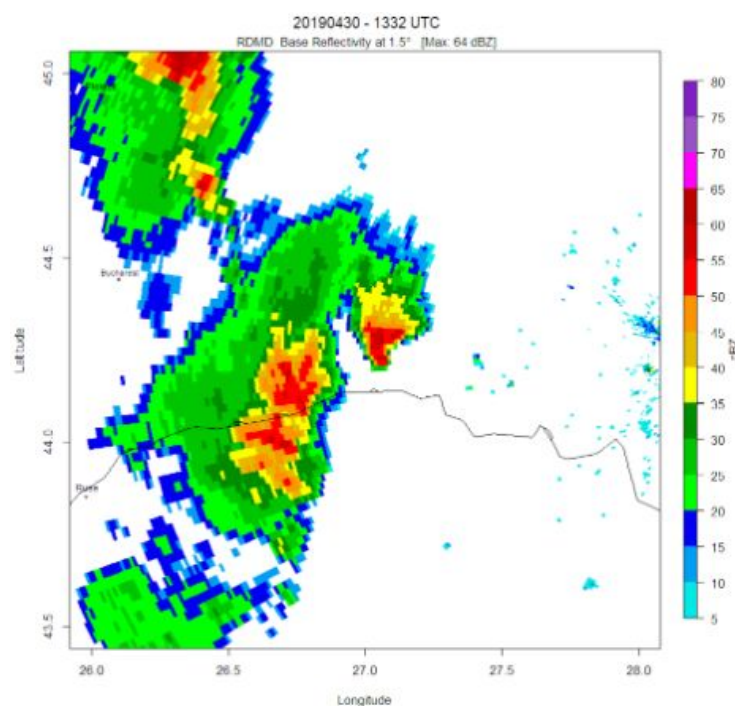
# Research questions - RQ3

How relevant are the features considered in the supervised learning task?  
More specifically, are the radar products' values from the neighboring area of a certain geographical location  $l$  at time  $t-1$  relevant for predicting the radar products' values on location  $l$  at time  $t$ ?

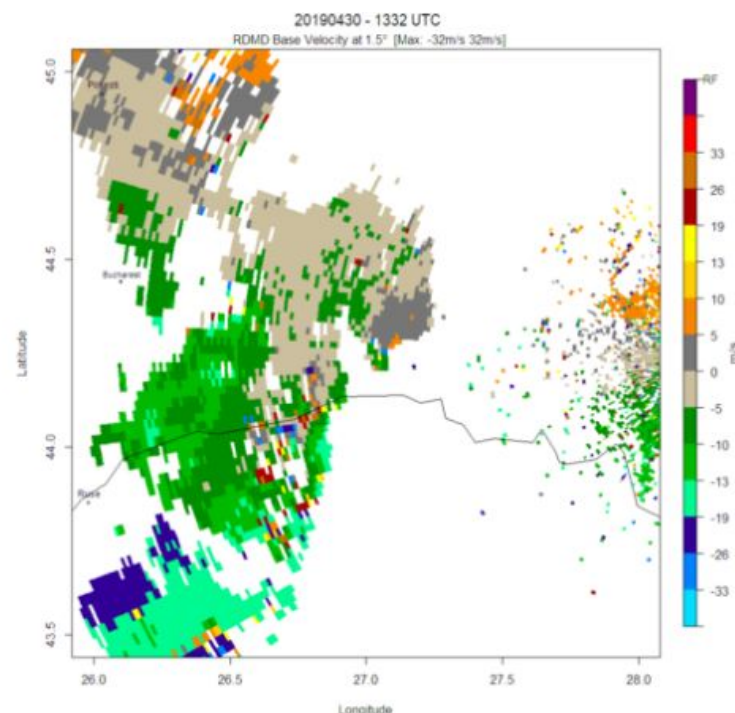
# Radar data used



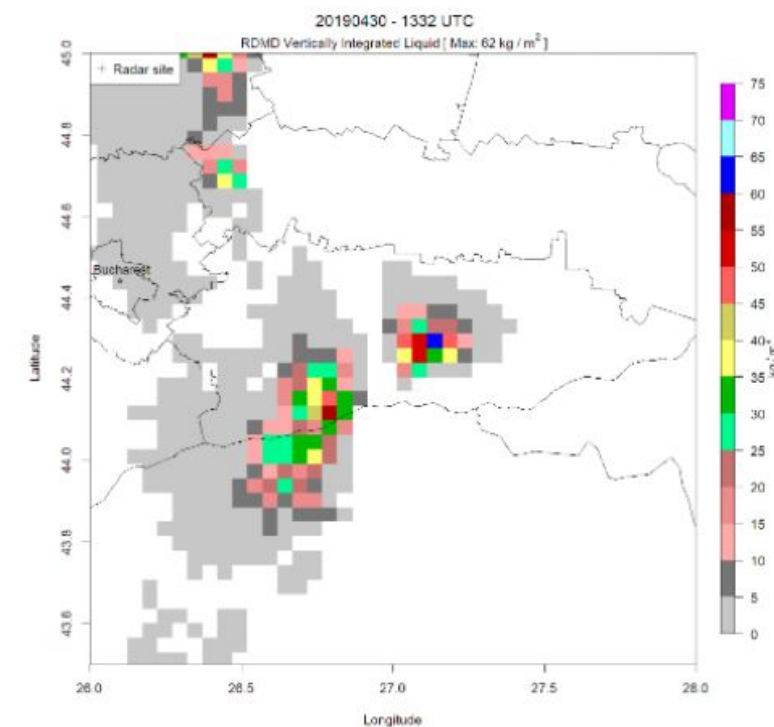
# Radar data used



Reflectivity R01-R07



Doppler speed V01-V07

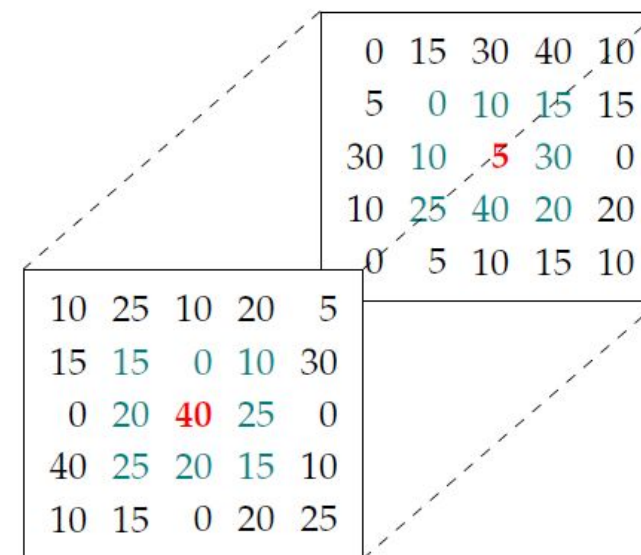
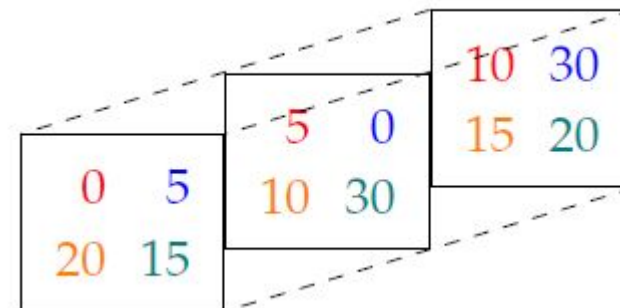


VIL



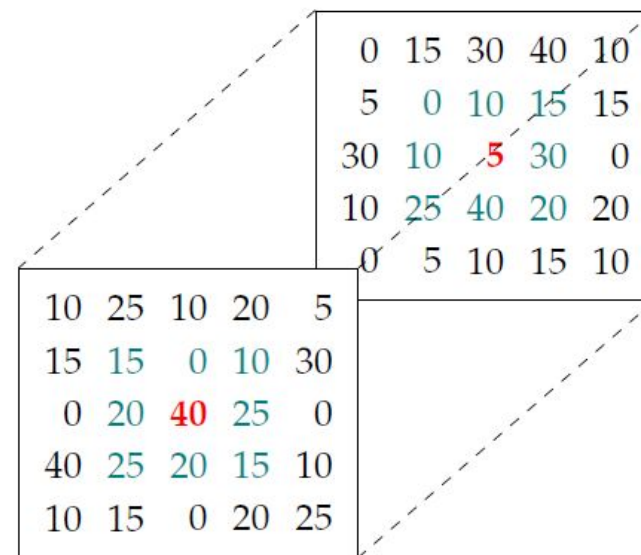
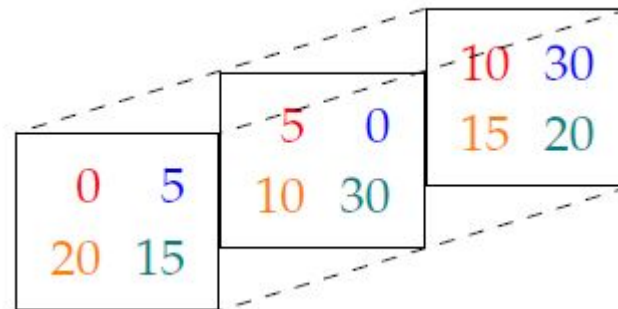
# Data model

- sequence of matrices of size  $m \times n$ ,  
each matrix corresponding to a given  
time  $t$  and a given weather product  $p$
- 240 matrices per day for each product
- normalised in pre-processing



# Data cleansing

- replacing the invalid values of V at a given point (i, j) by the weighted average of the valid values of V in a neighbourhood of length 13 surrounding that point

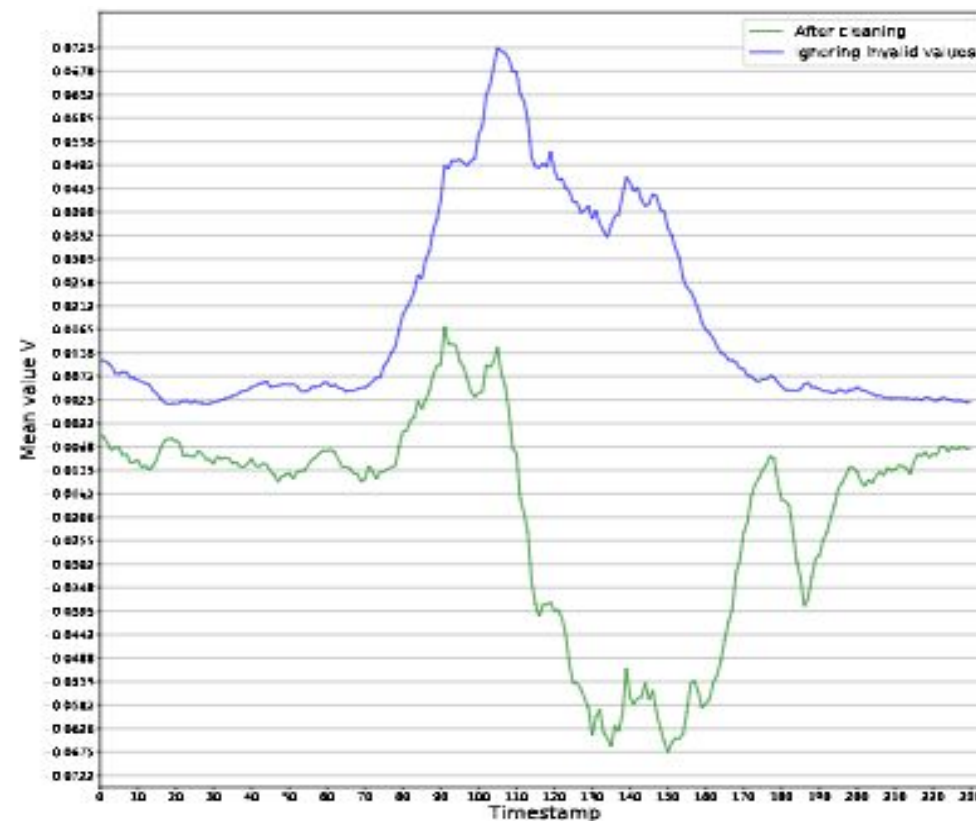
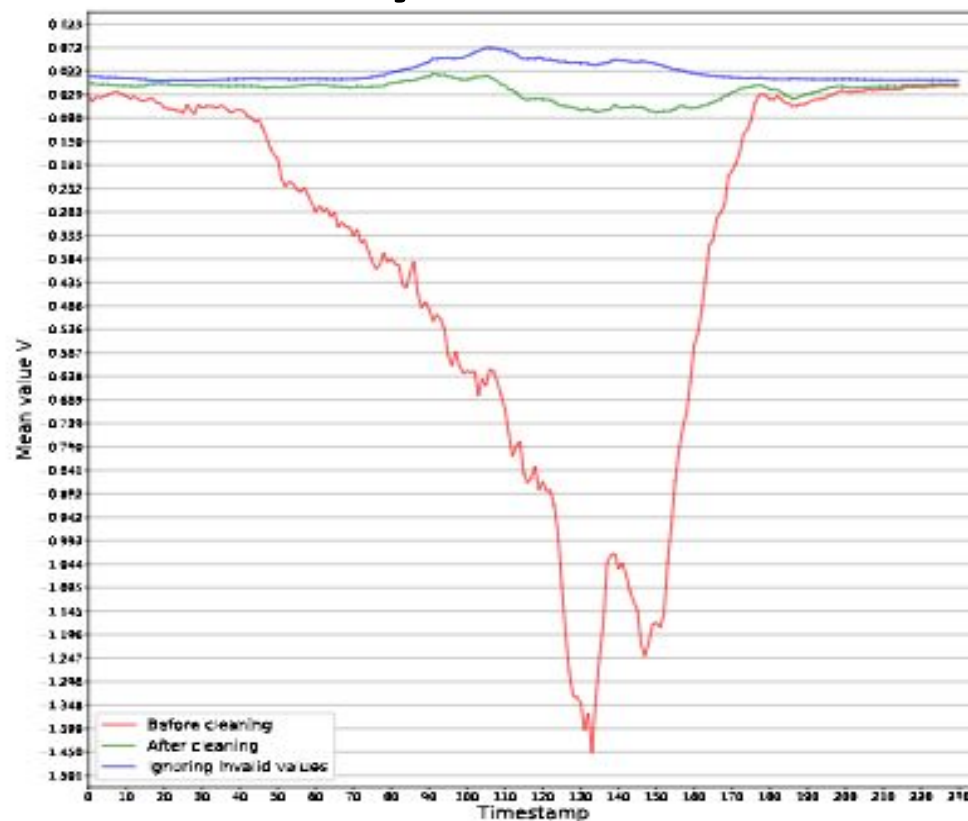


# Model construction

- 12 hidden levels (200 neurons, 2000 n, 5\*500 n and 5\*100 n)
- 1 output neuron containing the prediction for the product value
- training was done using 30 epochs and a batch of 1024 instances
- dataset divided into 5 subsets for training and testing

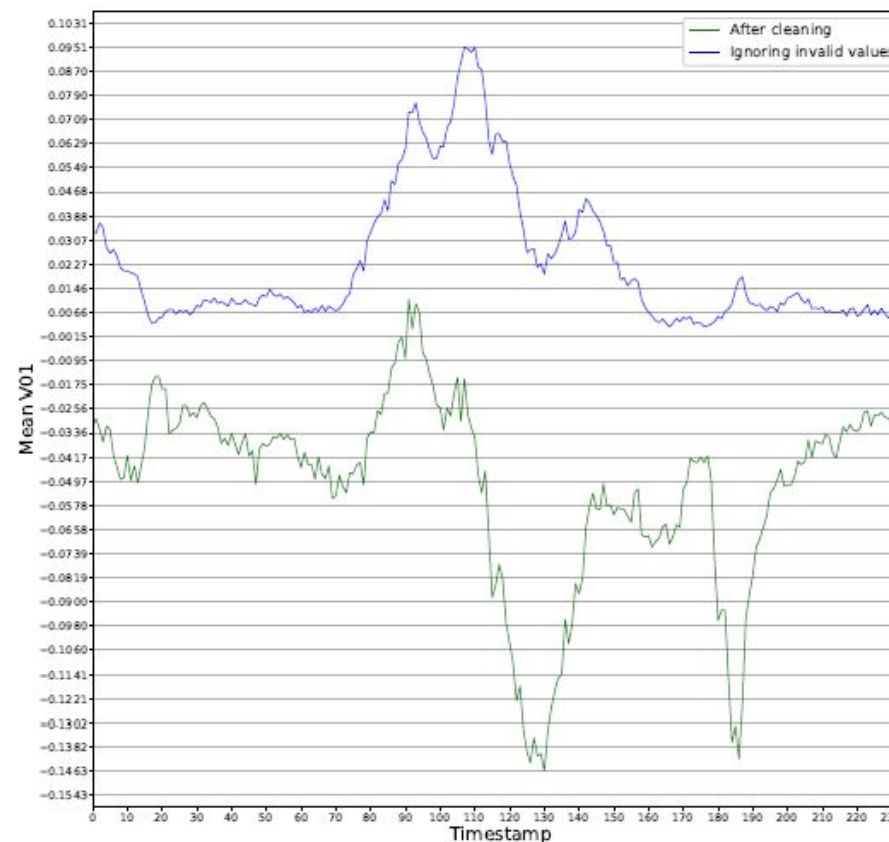
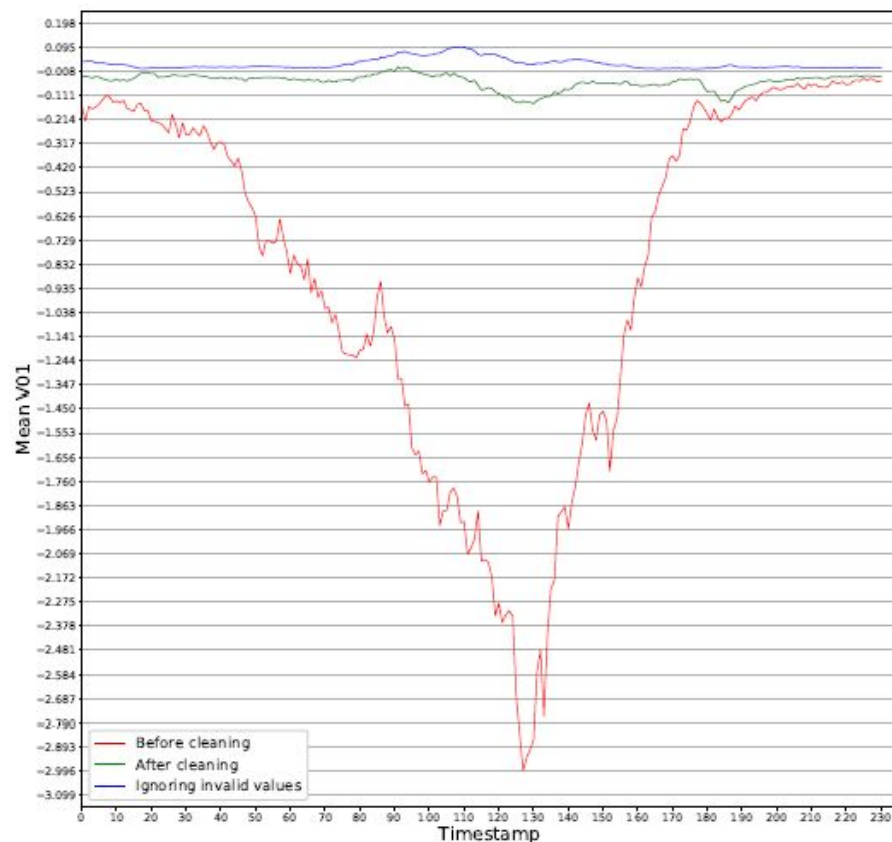


# Data analysis



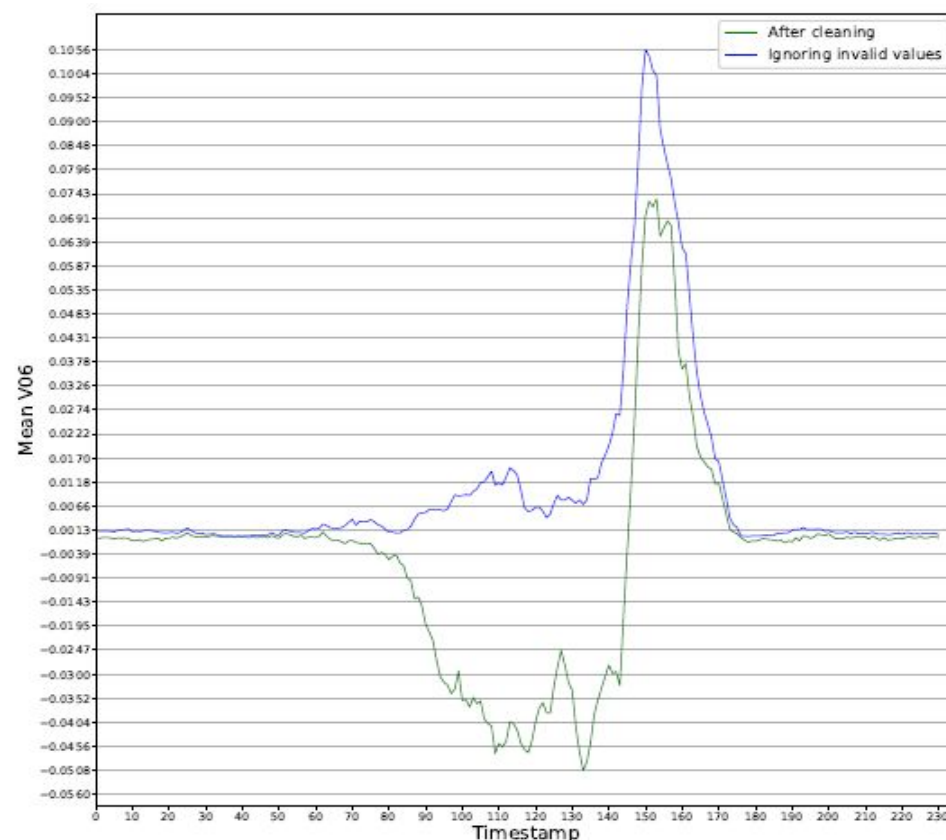
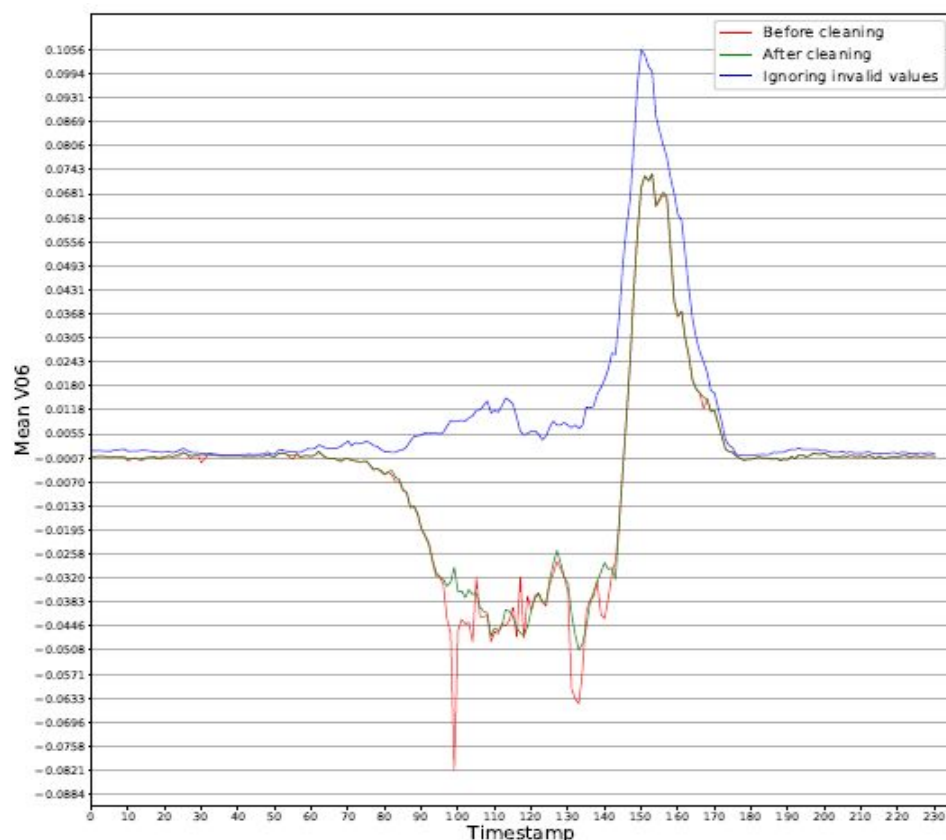
Histograms for mean values V - before and after cleaning, ignoring invalid values

# Data analysis



Histograms for V01 mean values - before and after cleaning, ignoring invalid values

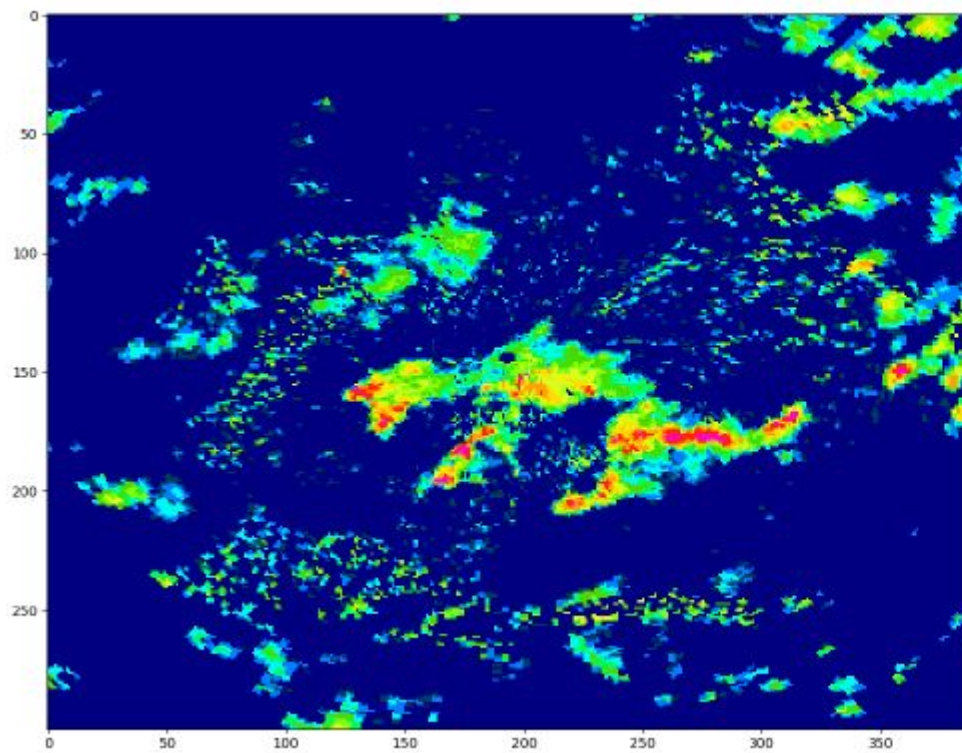
# Data analysis



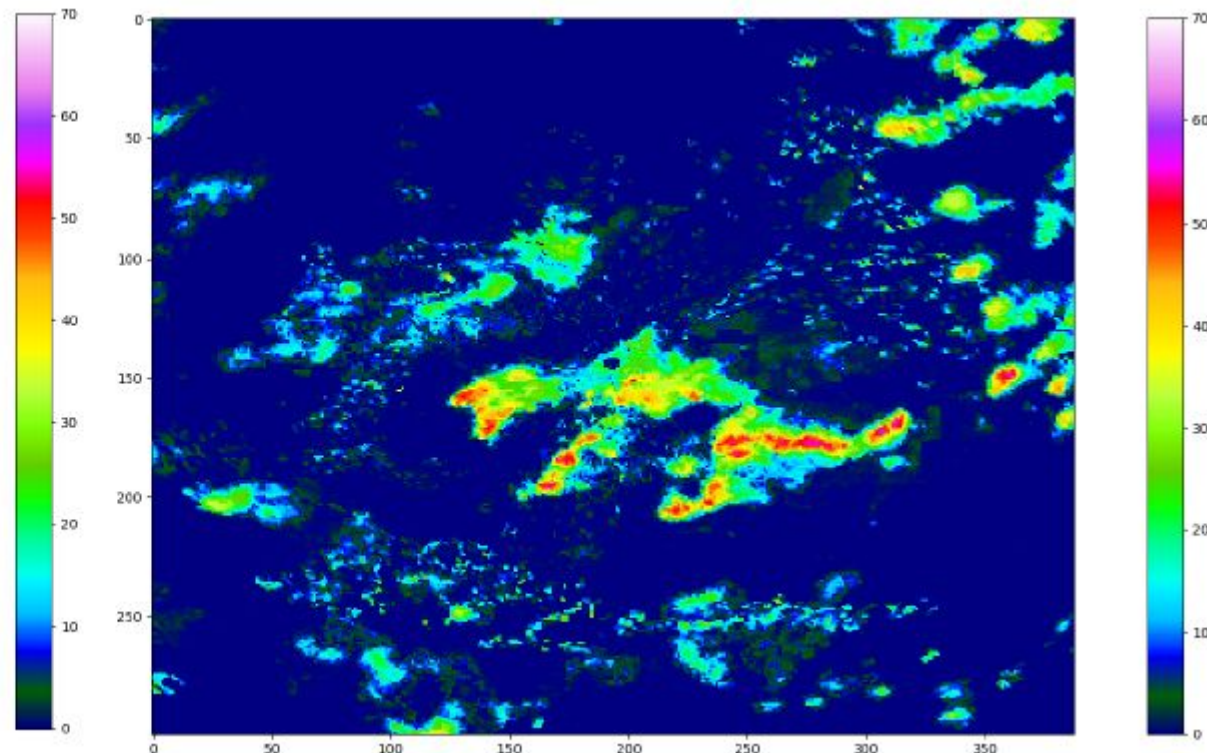
Histograms for V06 mean values - before and after cleaning, ignoring invalid values



# Data analysis

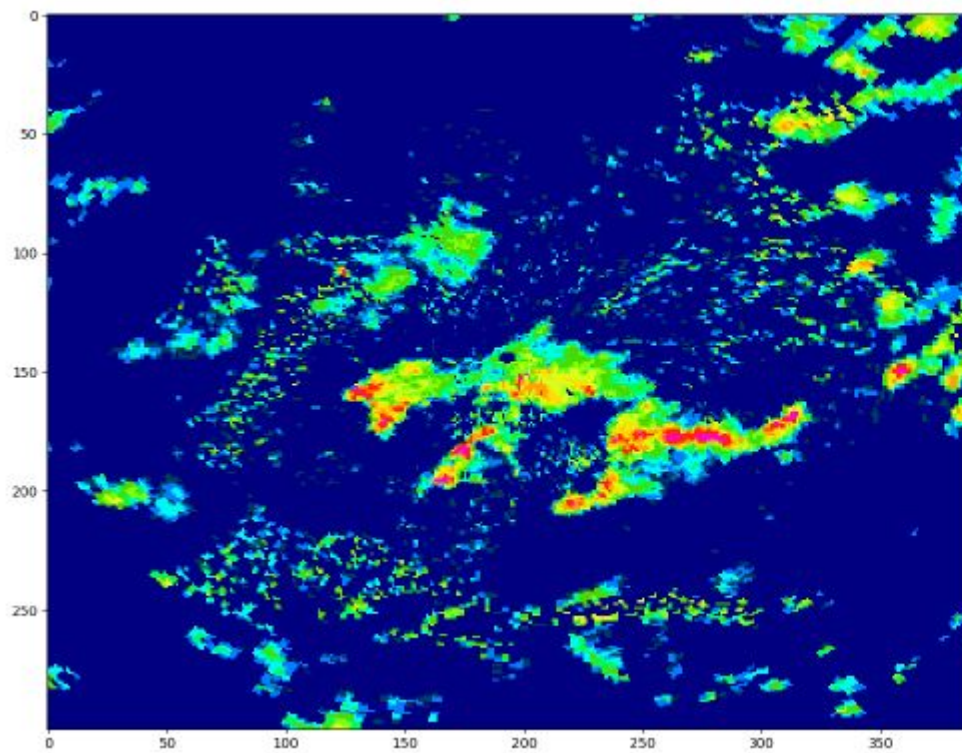


Real data for radar product R01 at t+1

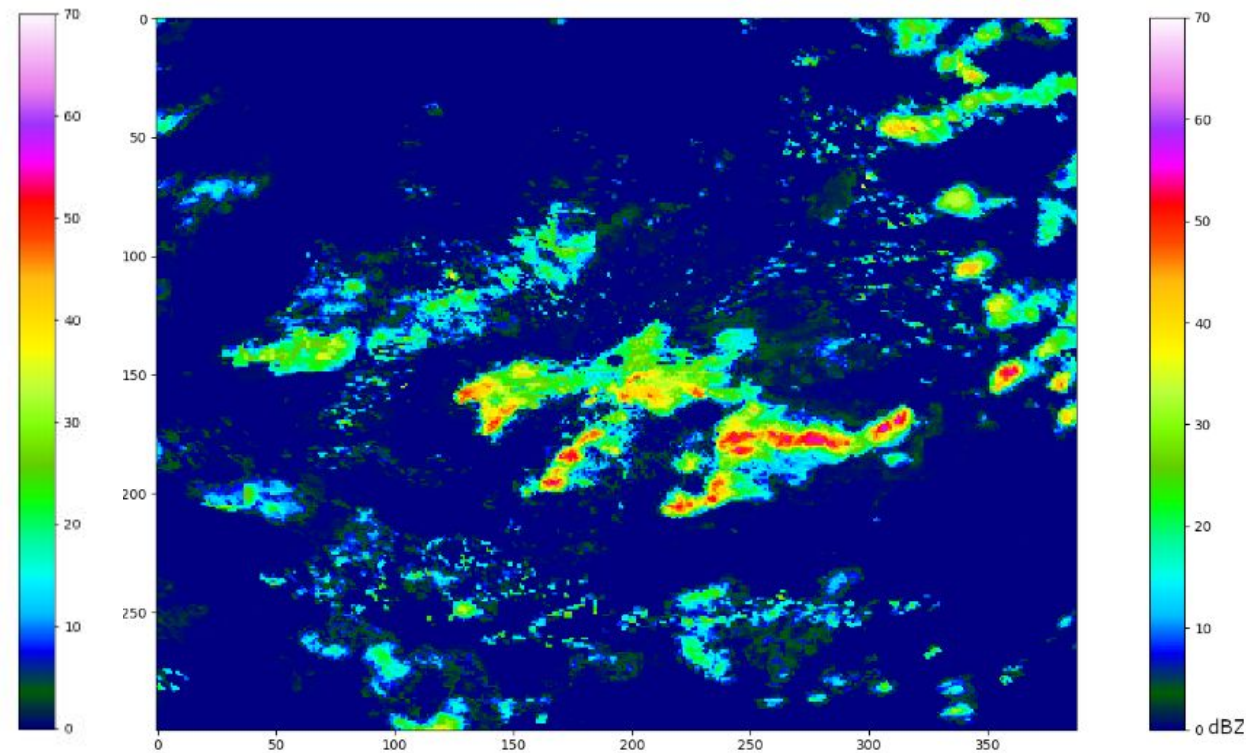


Estimated data for product R01 at t+1

# Data analysis



Real data for radar product R01 at t+1



Estimated data R01 at t+1 (uncleaned data)



# Data analysis

Evaluation measure	All 13 products	All R products	All V products	VIL
MAE	$0.58 \pm 0.02$	$0.76 \pm 0.03$	$0.41 \pm 0.02$	$0.53 \pm 0.02$
RMSE	$2.25 \pm 0.12$	$2.73 \pm 0.17$	$1.44 \pm 0.07$	$1.62 \pm 0.10$
NRMSE	$3.27\% \pm 0.17\%$	$3.91\% \pm 0.24\%$	$2.15\% \pm 0.11\%$	$2.32\% \pm 0.14\%$
$MAE_{non-zero}$	$4.02 \pm 0.12$	$5.51 \pm 0.17$	$2.73 \pm 0.12$	$2.89 \pm 0.04$
$RMSE_{non-zero}$	$5.93 \pm 0.14$	$7.63 \pm 0.15$	$3.50 \pm 0.15$	$3.9 \pm 0.18$
$NRMSE_{non-zero}$	$8.60\% \pm 0.21\%$	$10.91\% \pm 0.22\%$	$5.22\% \pm 0.22\%$	$5.63\% \pm 0.26\%$

Evaluation measure	All 13 products	All R products	All V products	VIL	Improvement (%) (cleaning step)
RMSE	$4.98 \pm 0.06$	$4.97 \pm 0.10$	$3.99 \pm 0.07$	$5.24 \pm 0.17$	55%
NRMSE	$7.27\% \pm 0.09\%$	$7.10\% \pm 0.15\%$	$5.95\% \pm 0.10\%$	$7.49\% \pm 0.24\%$	55%
$RMSE_{non-zero}$	$10.05 \pm 0.40$	$9.38 \pm 0.23$	$10.88 \pm 0.71$	$9.10 \pm 0.31$	41%
$NRMSE_{non-zero}$	$14.68\% \pm 0.59\%$	$13.40\% \pm 0.33\%$	$13.24\% \pm 1.06\%$	$13.00\% \pm 0.44\%$	41%



# Conclusions and future work

- Empirical demonstration that, under both normal and severe weather conditions, the values for a radar product at a given time, at a given location, can be determined based on the values at neighbouring locations at previous times
- NowDeepN will be further extended by increasing the dataset used for model training
- Extending the features used in the learning process by combining radar data with other features or data (e.g. satellite data, geographical and anthropogenic features).

**Czibula, Gabriela; Mihai, Andrei; Mihuleț, Eugen.** 2021. "*NowDeepN: An Ensemble of Deep Learning Models for Weather Nowcasting Based on Radar Products' Values Prediction*" Appl. Sci. 11, no. 1: 125, Special Issue Applied Machine Learning. <https://doi.org/10.3390/app11010125> (2020 IF=2.679, Q2)

<https://weamyl.met.no/>

Thank you!