PASC 2023
Davos, Switzerland
June 26 to 28, 2023

Deutscher Wetterdienst
Wetter und Klima aus einer Hand

Analysis and application of CNN to improve deterministic optical flow nowcasting at DWD

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At DWD deterministic optical flow nowcasting is used to compute forecasts of radar reflectivity and precipitation data for lead times up to two hours. The method uses Lagrangian extrapolation and assumes stationarity of the advected information and the flow field. The goal of the current work to explore the potential of deterministic CNN to address these issues. A multi-input UNet approach is considered and optimized.

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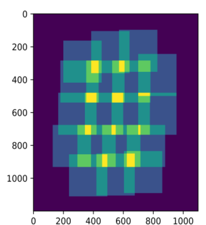
Goals

CNN postprocessing of optical flow reflectivity nowcasts

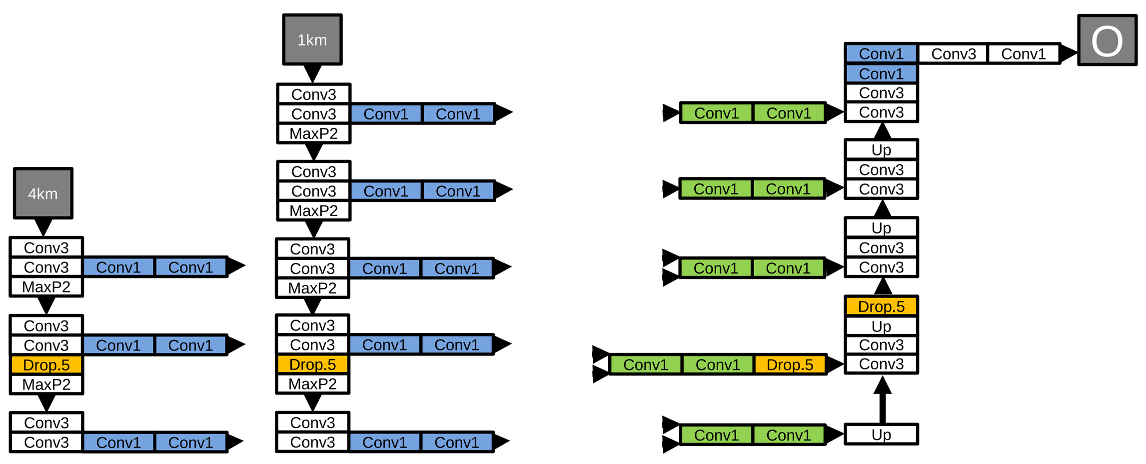
- Develop multi-input UNet for deterministic prediction of reflectivity at lead time
  - Setup of dataset and training environment
  - Explore model design choices and derive an optimized model
- Evaluate impact of different types of input data
- Determine the potential as a prediction method and technical stepping stone

Data



- 2019, 2020
- Every 5 min: Radar reflectivity composites, OF fields on 1km grid
- Orography on 1km grid
- Every 3h: ICONEU NWP data for reference time +0,+1,+2,+3 h
  - NWP data is interpolated to several heights and pressure levels, 5min timesteps and 4km grid
  - Parameter: mixed layer CAPE, specific humidity, height of 0°C isotherm, wind, temperature
- Data is split into days. Days are separated into train/val (90:10). 18 boxes with 256 km^2 are considered. On each box a 5min timestep is used, if the box is sufficiently filled

Model



Schematics of single 4km data encoder (left), single 1km data encoder (middle), decoder

Input Data
- 4 consecutive radar composites, 1 OF field, orography, 11 NWP parameter
  - The 4 radar reflectivity composites and optical flow are advected to target-time, NWP is evaluated at target-time

Output
- Predicted reflectivity at target-time = reference-time + lead-time
- One model for each lead time

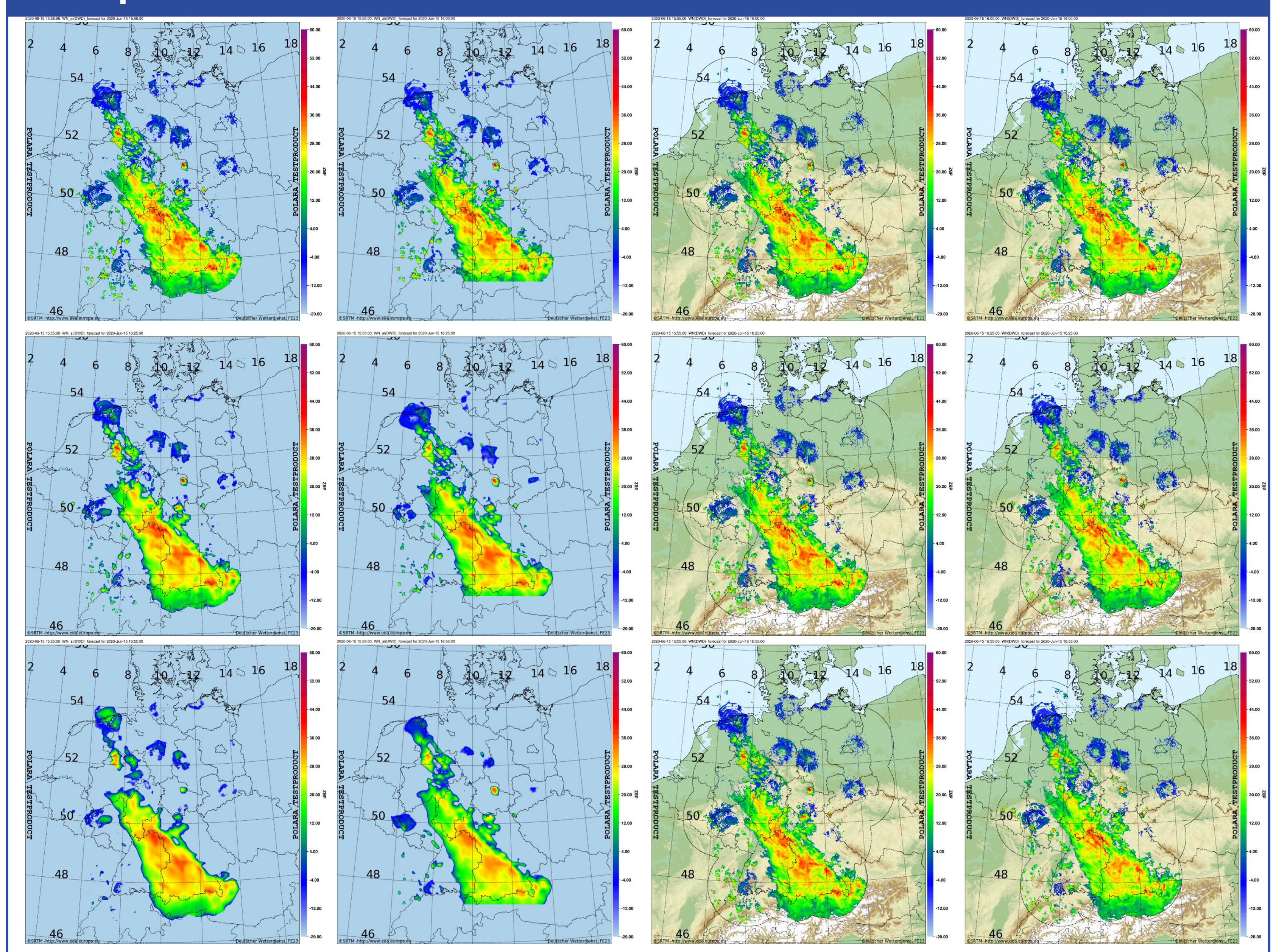
Experimental setups
- loss-function: *logcosh* or soft fractional skill score or combination of both
- Multiple encoder setups with individual or grouped data
  - Optimum 15 Encoder: 11xNWP data (4km); 1xradar reflectivity (4 consecutive timesteps, 1km), 1x orography (1km), 1xoptical flow (u,v, 1km)
- Data selection, 3 setups tested: 10% positions with at least 20dBZ, *2% with at least 35dBZ*, 1% with at least 40dBZ (490k, 196k, 118k samples)
- 30mio weights; 1 epoch takes 11h@NVIDIA A100 / 16h@RTX6000 (@European Weather Cloud)

Considered optimizations
- Vertical: *no modification* or additional residual/average-pooling connections; average-pooling or *max-pooling*; growth factor for number of channels with each level *1*,2; *upsampling* or transposed convolution
- 0,*2* or 4 Conv1x1 layer with or *without* residual connections as horizontal and/or final computation blocks
- Regularization with 0,1,2,*3* dropout-layer(0.5)
- Encoder combination : concatenation or affine linear modulation or *2 Conv1x1*
- Balance of DOF between encoder/decoder and 1km/4km data
  - Optimum depends on total number of DOF

Parameter	Error	Parameter	Error	Parameter	Error
Refl_0min	3,611	U&V_P500	1,047	T_0m	1,012
Refl_-15min	2,266	SpecHum_2km&4km&P750	1,035	T_2km	1,007
Refl_-5min	1,907	T_0m&1km&2km&4km	1,032	SpecHum_2km	1,007
Refl_-10min	1,427	U_P500	1,027	T_4km	1,007
Orography	1,268	T_0m&2km&4km	1,026	T_1km	1,005
OF_u&v,U&V_P500	1,117	SpecHum_2km&4km	1,026	CAPE_ML	1,004
OF_u&v	1,106	T_0m&1km&2km	1,025	SpecHum_P750	1,004
OF_u	1,074	V_P500	1,024	HZEROCL	1,003
OF_v	1,050	SpecHum_4km	1,016		

Relative increase of validation loss for 30min predictions when selected input parameters are permutated in time. Orography is permutated in space

Example 2020-06-15 15:55 UTC



From left to right: predictions with RainNet (Ayzel et al, '20), optimized UNet, OF nowcast, analysis at target-time; From top to bottom: lead-times 5,30,60 min, RainNet is applied recursively

Discussion

- The usage of temporal shifted inputs is crucial. Without this design choice, the fixed receptive field of the model would limit the highest meaningful lead-time. Further, the training task is significantly simplified, since the model only needs to address the OF residual error
- The new model provides nowcasts with dynamic properties and good spatial localization. High intensities are underpredicted. Using fractional skill score as loss function does not help here, as it introduces artifacts
- First dependent verification study for 06/2019 in the supplementary material
- The model is most sensitive to permutations of the radar based data. The most significant parameters are the first and last provided reflectivity. This may indicate learned dynamics and potential gains by using additional radar based inputs. Surprisingly, the height of the 0°C isotherm is the least important parameter. The high importance of orography may partly be due to the spatial permutation of this parameter
- Temporal continuity is not enforced and no significant problem
- The proposed model is trained to solve a regression problem in the context of prediction uncertainty. This puts limits on its performance as a nowcasting tool. However, as a technical tool for solving regression problems, the approach is quite optimized and may easily be extended by additional data sources. In the nowcasting context, the transfer to the case of generative predictions seems like the logical next step

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