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Hazard-specific Thunderstorm Nowcasting Using Machine Learning with Satellite, Radar and NWP Data

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EUMETSAT AI/ML Seminar, 06 Oct 2021

Fellowship overview

- Swiss EUMETSAT Fellowship started in Oct 2020 at MeteoSwiss
- Objectives:
  1. Evaluate MeteoSat Third Generation (MTG) benefits for thunderstorm nowcasting
  2. Use advanced machine learning (e.g. convolutional neural networks) with MSG and MTG-like data
  3. Develop hazard-specific nowcasts for different hazards
- Heritage from previous nowcasting projects at MeteoSwiss (COALITION-2, COALITION-3, TRT)
- Collaborations: Alessandro Rigazzi (HPE), Olivia Romppainen-Martius (U. Bern), John Mecikalski (U. Alabama Huntsville)
- In communication with similar EUMETSAT fellowship at ZAMG (Vienna, Austria)

Motivation

- Thunderstorm hazards:
  - Highly localized and develop quickly
  - Hard to predict the time and location exactly using numerical weather prediction
  - ➢ *Nowcasting*: statistical prediction from latest measurement data
  - ➢ *Seamless* nowcasting: combining nowcasting with NWP forecast

- Machine learning has a lot of potential for nowcasting
  - Lots of data available, but what sources should one use?
  - Specifically, what will MTG be able to offer for thunderstorm nowcasting?

Goals of the current study

- Evaluate the contributions of various data sources to thunderstorm nowcasting
  - Provide guidelines for data source selection in later studies
- Nowcast concrete hazards: lightning, heavy precipitation, etc.
- Use the same machine-learning methodology for all hazards to facilitate comparisons

Rain

Hail

Lightning

Wind

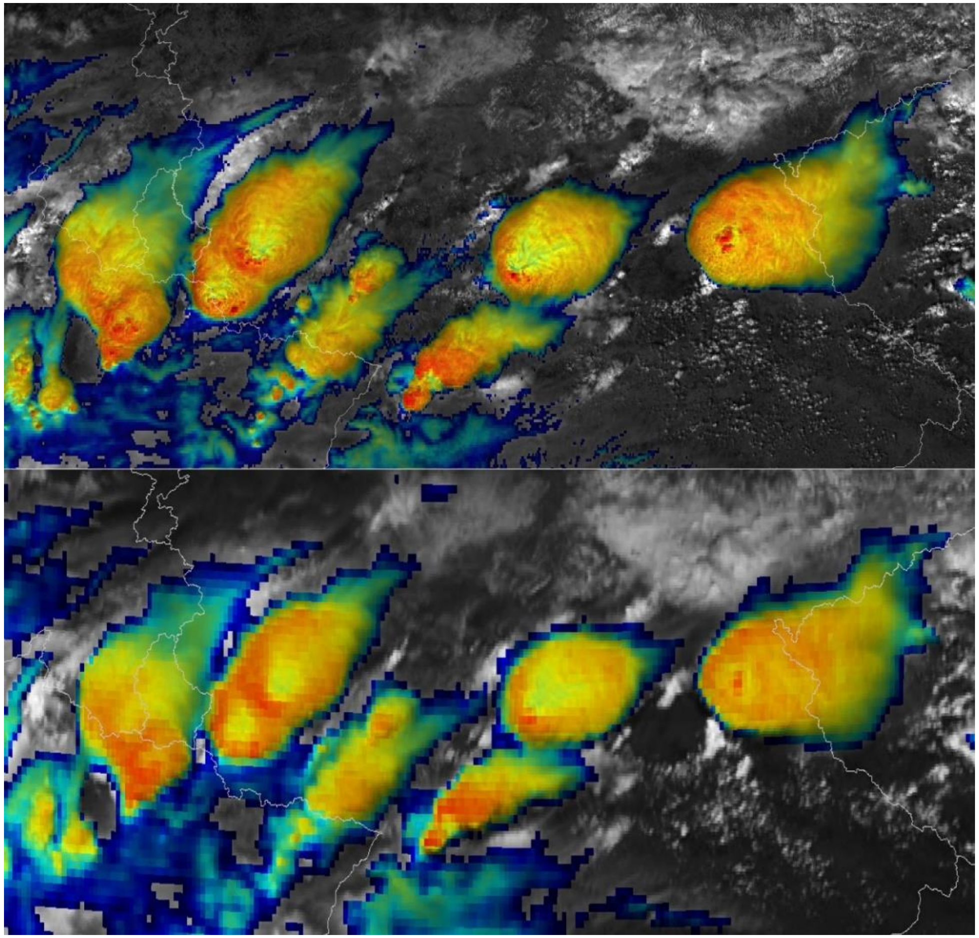
Tornado

MTG advantages

Compared to MSG, MTG has a higher-resolution imager with more channels (FCI) and a lightning imager (LI)

We perform a study in the USA where similar instruments are already operational in the GOES-R satellites

- MTG FCI ↔ GOES ABI
- MTG LI ↔ GOES GLM



Study area

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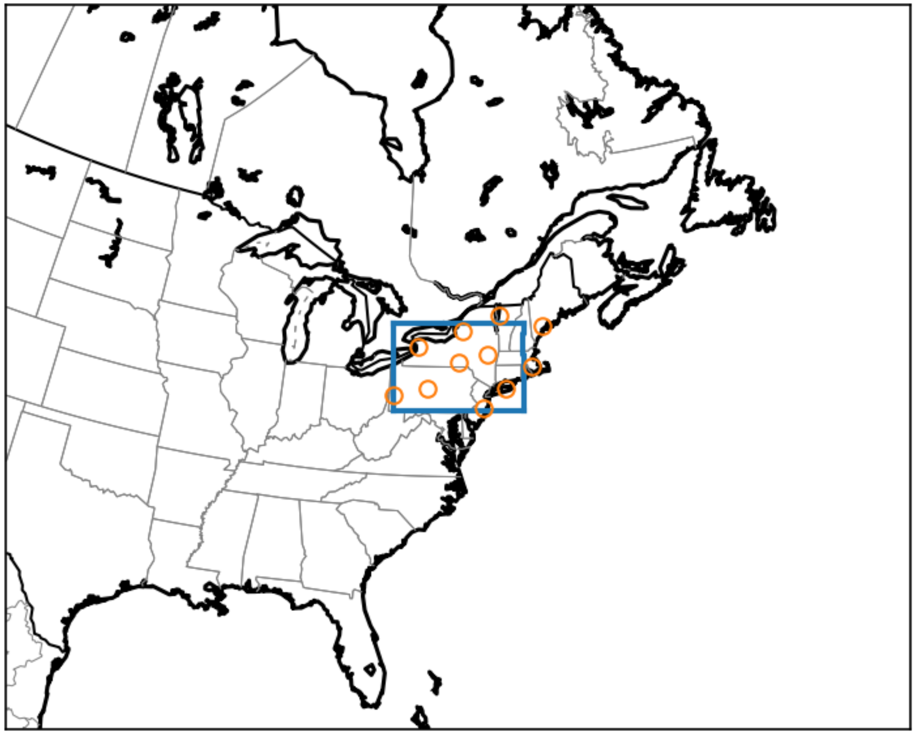
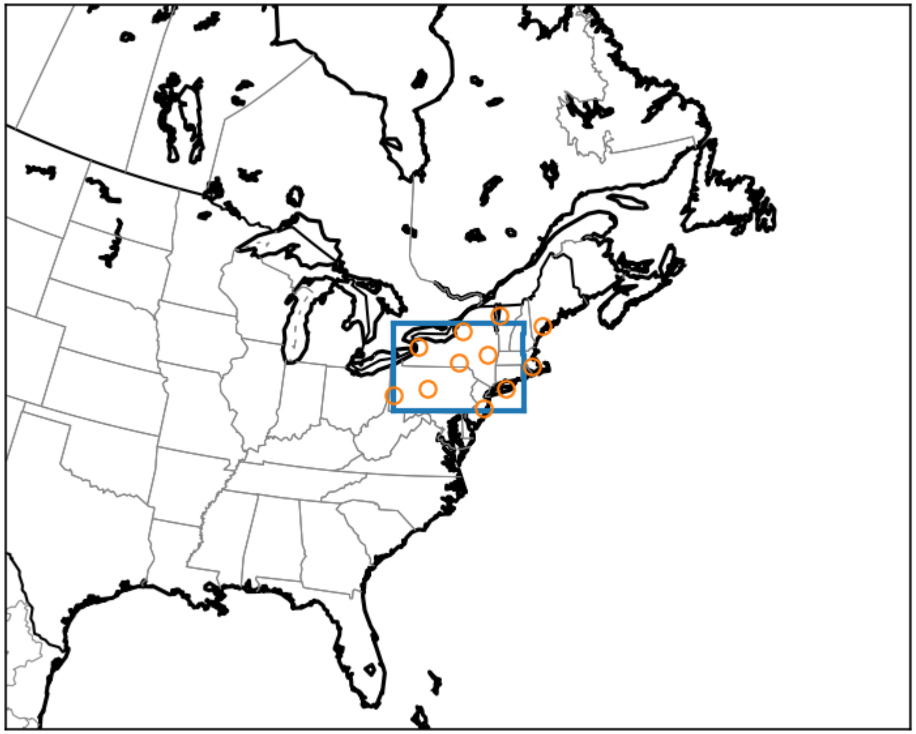


Data sources

- GOES ABI
- GOES GLM
- NEXRAD radar data
- ECMWF forecasts
- ASTER digital elevation model

- Data for April-September 2020
- All collocated to a single grid

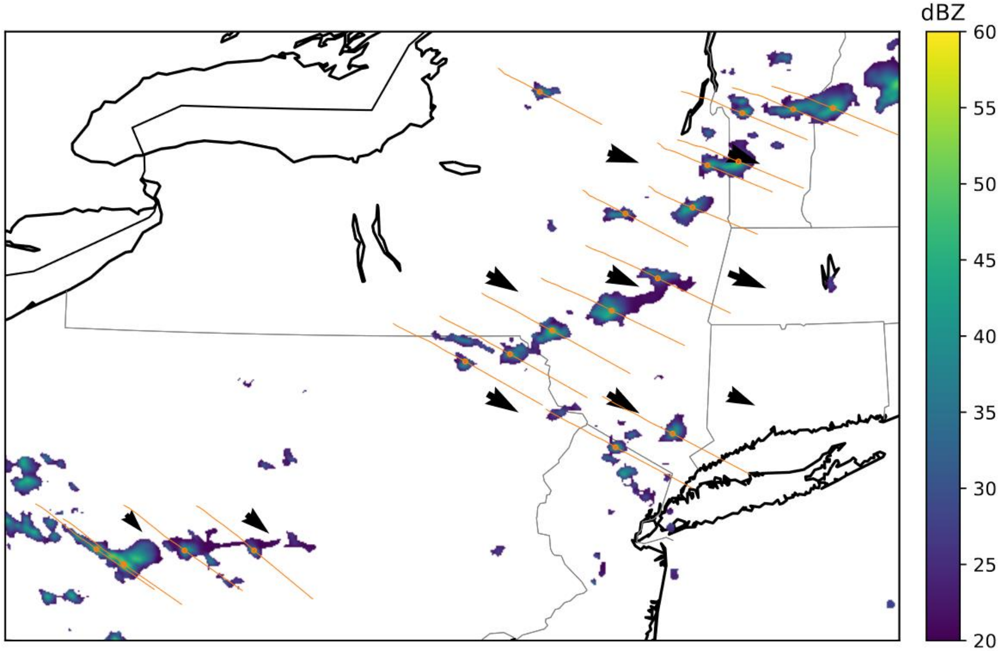


Strategy overview

1. Extract storm tracks
2. Compute features
3. Create training, validation and testing datasets
4. Train machine learning models to predict different hazards
5. Evaluate the importance of the data sources

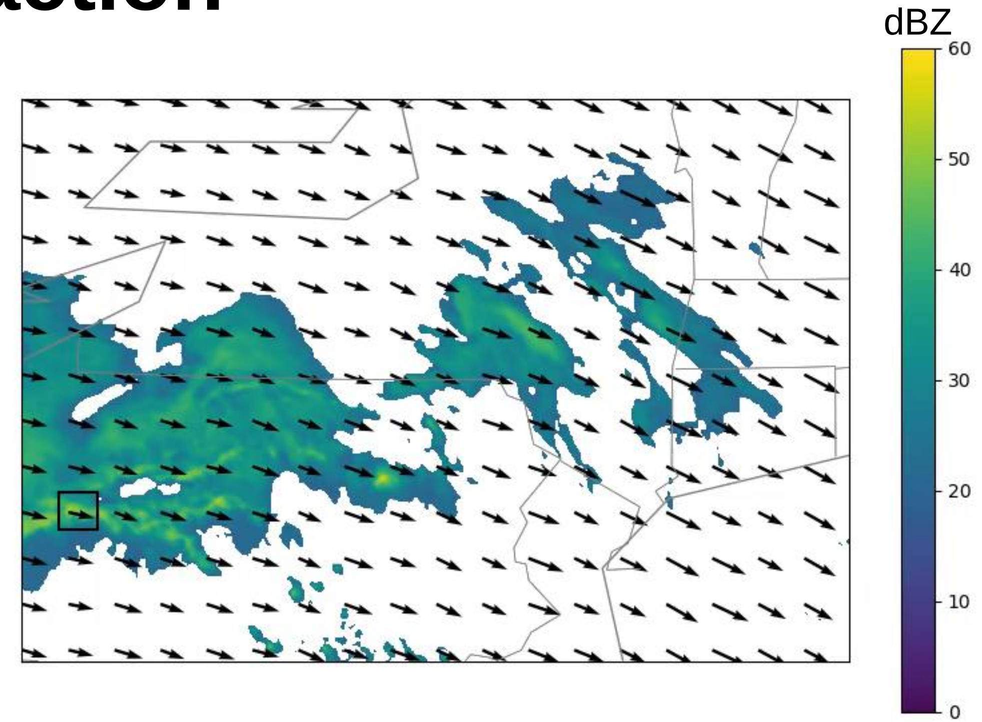
Storm tracks

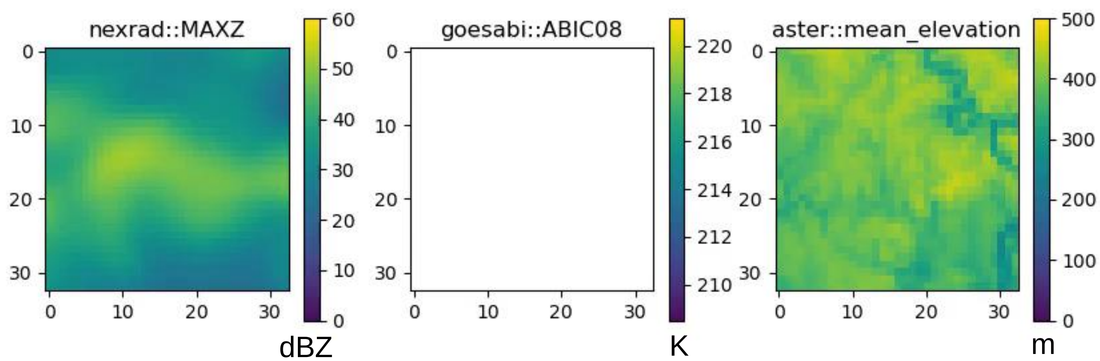
- Storm centers are local maxima of radar reflectivity based on a reflectivity threshold
- Tracks are computed using optical flow from PySTEPS



Feature extraction

- Features are computed from the neighborhood of storm centers
- We take the mean, standard deviation etc. of the neighborhood as scalar features
- Finally about 4000 features and 80000 samples



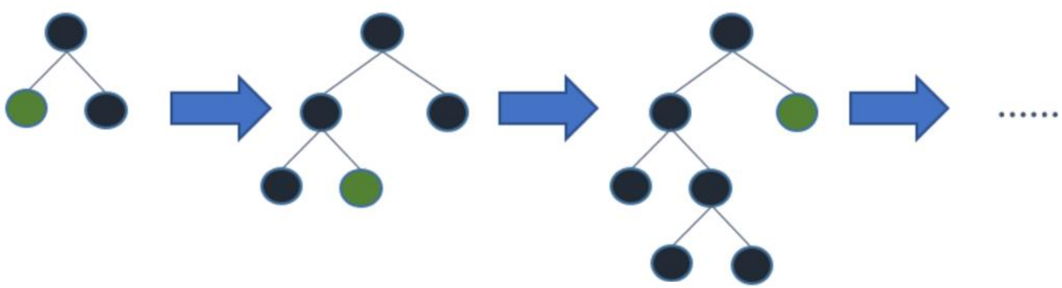


Machine learning

Gradient boosted trees:
Growing a series of regularized decision tree models to iteratively correct the error of previous models

We set up LightGBM to train gradient boosted trees

- Fast to train, even with many inputs
- Can easily compute feature importance



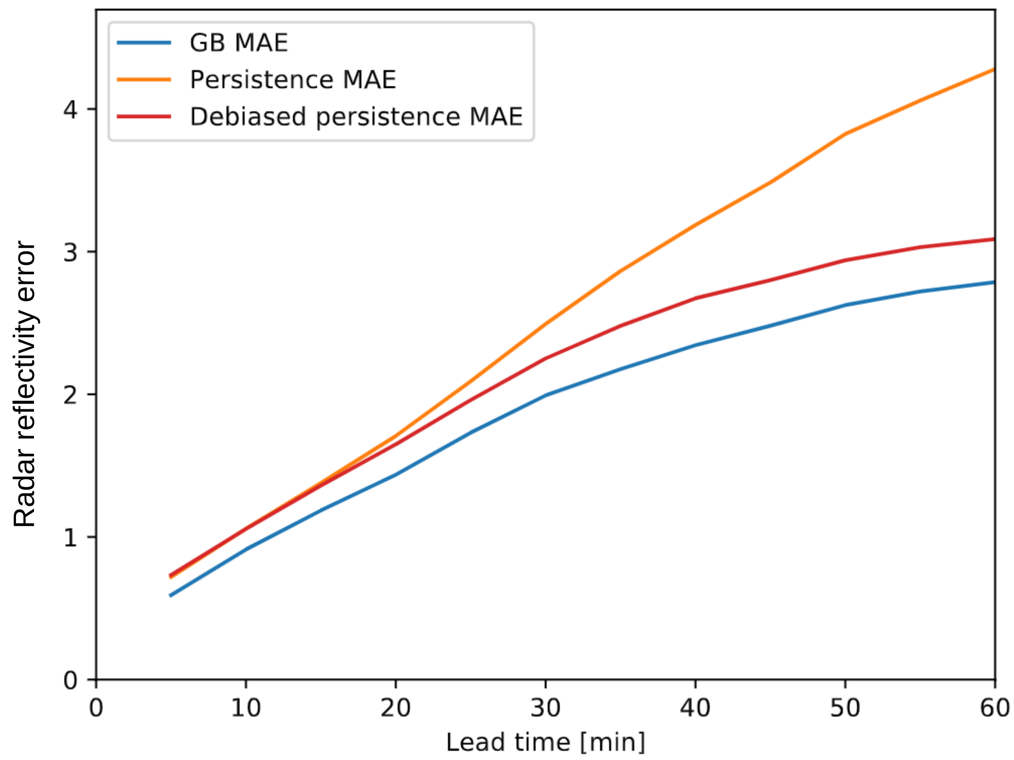
Machine learning targets

To cover multiple thunderstorm hazards, we use the following variables as ML targets:

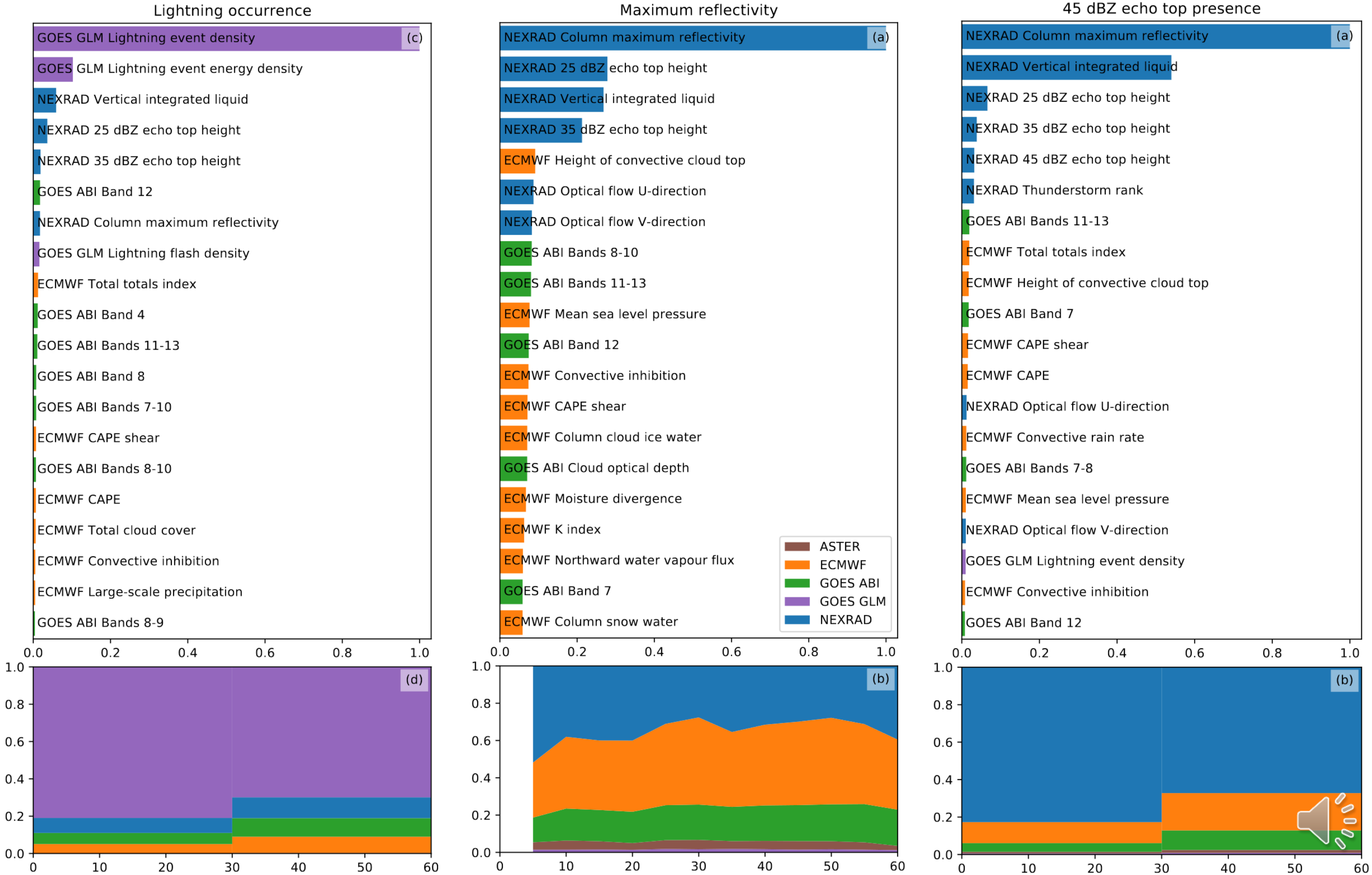
- Column maximum radar reflectivity (related to precipitation) for lead times 0-60 min
- Lightning occurrence from GLM at 0-30 min and 30-60 min from reference time
- Presence (and height) of a 45 dBZ echo (related to hail) at 0-30 min and 30-60 min

Predicting storm evolution

- Learning to predict the evolution of radar reflectivity seems difficult
- Bias correcting the persistence assumption already gives ok results
- Better results from predicting lightning occurrence (86% accuracy) and 45 dBZ echo top occurrence (87% accuracy)



Feature importance



Excluding data sources

- Also possible to look at performance by excluding sources
- This example shows the error rate on lightning prediction
- Combining row+column shows which data sources are used

Lightning occurrence

Lightning occ. cross-entropy

	ABI NEXRAD	NEXRAD	ABI	
ASTER ECMWF GLM	0.328	0.338	0.338	0.355
ECMWF GLM	0.325	0.336	0.336	0.355
ASTER ECMWF	0.356	0.407	0.375	0.492
ASTER GLM	0.329	0.335	0.354	0.371
ECMWF	0.357	0.407	0.381	0.487
GLM	0.332	0.335	0.352	0.367
ASTER	0.375	0.422	0.458	0.629
	0.370	0.415	0.457	

Lightning occ. error rate

	ABI NEXRAD	NEXRAD	ABI	
ASTER ECMWF GLM	0.143	0.153	0.146	0.156
ECMWF GLM	0.141	0.154	0.146	0.157
ASTER ECMWF	0.159	0.193	0.165	0.267
ASTER GLM	0.141	0.150	0.145	0.155
ECMWF	0.159	0.195	0.162	0.265
GLM	0.141	0.148	0.146	0.155
ASTER	0.156	0.203	0.212	0.387
	0.153	0.196	0.208	0.292

Excluding data sources

Lightning occ. error rate

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ASTER	0.156	0.203	0.212	0.387
	0.153	0.196	0.208	0.292

Maximum reflectivity MAE

	ABI NEXRAD	NEXRAD	ABI	
ASTER ECMWF GLM	3.296	3.393	3.471	3.541
ECMWF GLM	3.281	3.371	3.425	3.492
ASTER ECMWF	3.221	3.336	3.534	3.530
ASTER GLM	3.321	3.376	3.369	3.449
ECMWF	3.282	3.319	3.476	3.536
GLM	3.292	3.295	3.379	3.459
ASTER	3.282	3.341	3.436	3.526
	3.291	3.342	3.417	3.536

45 dBZ ET presence error rate

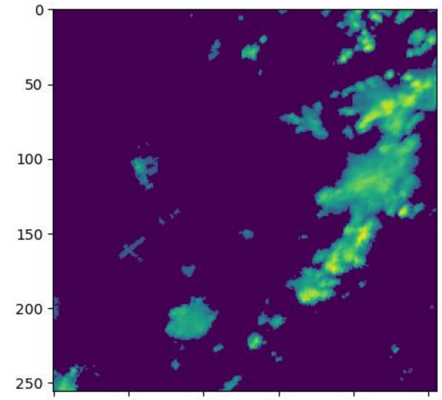
	ABI NEXRAD	NEXRAD	ABI	
ASTER ECMWF GLM	0.128	0.128	0.200	0.211
ECMWF GLM	0.128	0.129	0.200	0.210
ASTER ECMWF	0.126	0.127	0.221	0.277
ASTER GLM	0.125	0.125	0.201	0.214
ECMWF	0.127	0.130	0.219	0.278
GLM	0.125	0.125	0.209	0.214
ASTER	0.125	0.126	0.240	0.455
	0.127	0.125	0.253	0.383

Multi-source Nowcasting with RCNNs

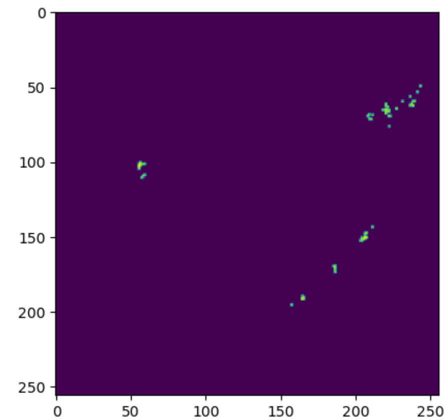
- Second project in the fellowship
- Differences from first project:
  - Nowcasting directly on a grid without object tracking
  - Using Swiss data for ease of use and access, portability to operations
  - Using recurrent-convolutional neural networks instead of gradient boosting for explicit modeling of time evolution

Data sources

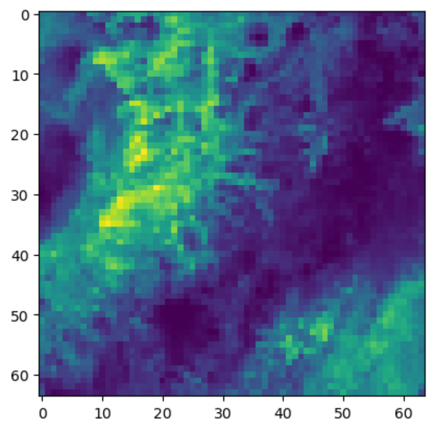
- Swiss operational radar
- Swiss lightning observations
- MSG + NWCSAF products
- COSMO NWP forecasts
- Digital Elevation Model



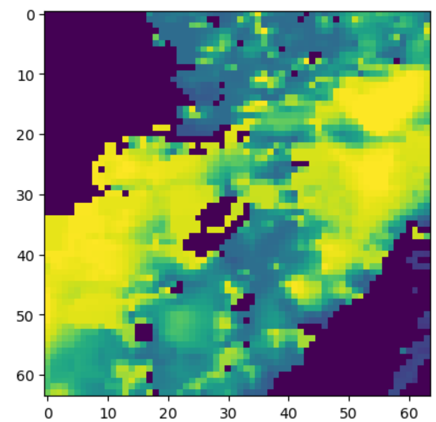
Radar precip rate



Lightning density



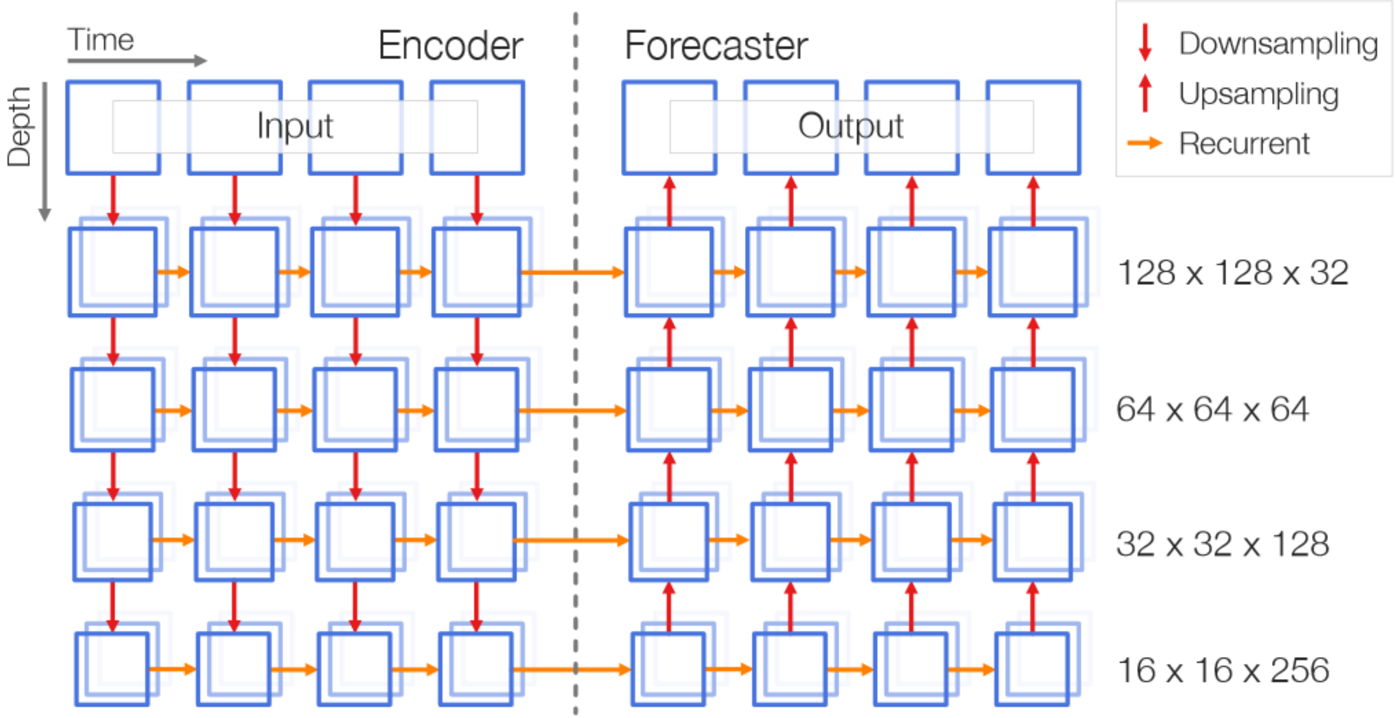
CAPE



Cloud top height

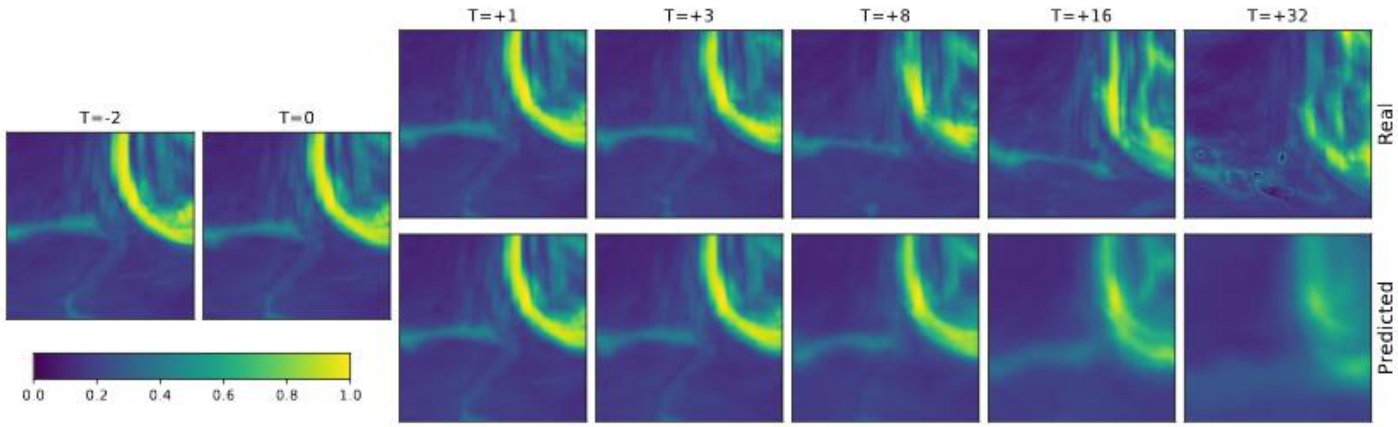
Model architecture

- Multi-scale recurrent-convolutional network
  (see e.g. Franch et al 2020, Ravuri et al 2021, Cuomo and Chandrasekar 2021)



Model architecture

- Multi-scale recurrent-convolutional network
  (see e.g. Franch et al 2020, Ravuri et al 2021, Cuomo and Chandrasekar 2021)
- Model tested in Weather4cast competition using NWCSAF products
  - 1st place in Stage 1

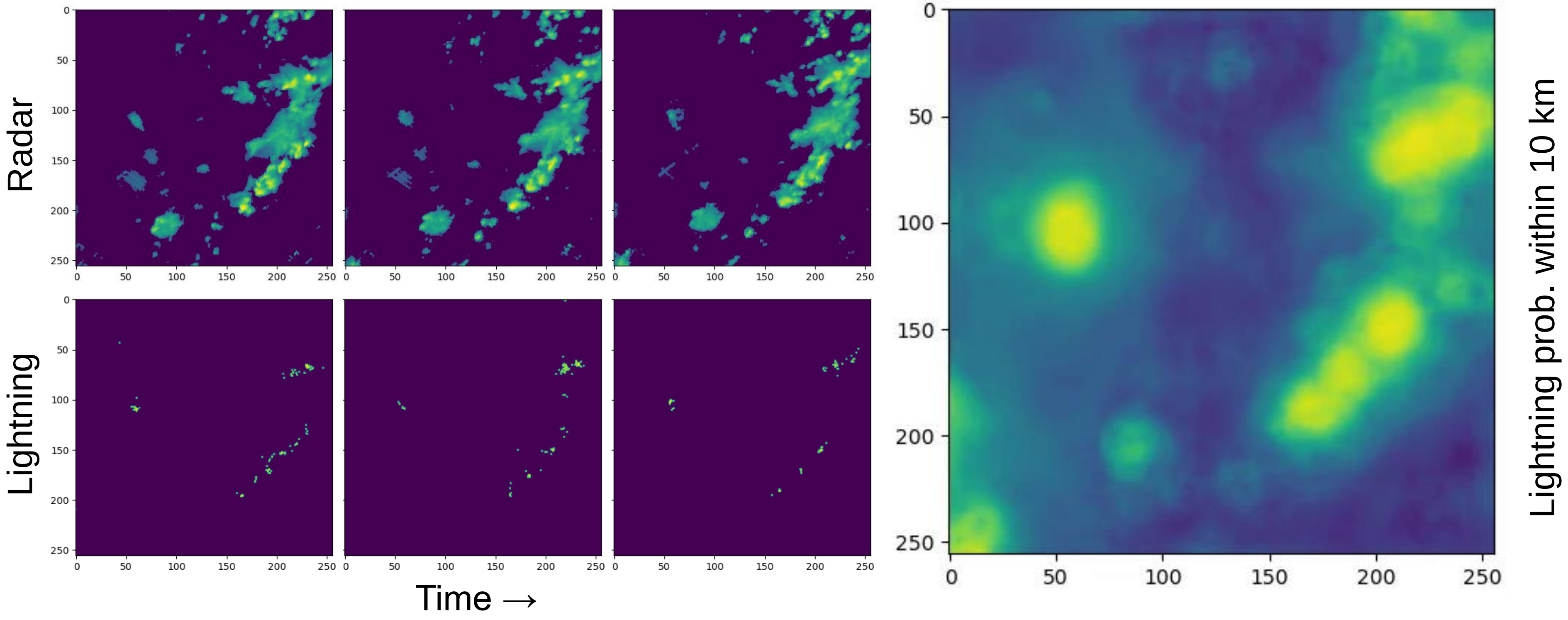


Model training

- Training data collected from April-October 2020
  - Will update data to 2021
- 5 min time resolution, predict next 60 min from previous 30 min
- Consider regions where radar reflectivity exceeds 35 dBZ somewhere in the area
- Trained with focal loss
- Rotation and mirroring for data augmentation
- Implemented in Tensorflow/Keras

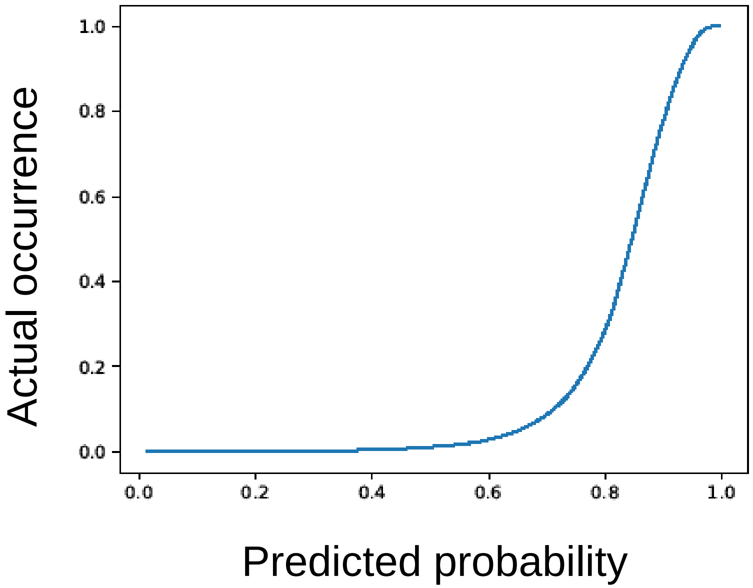
Application to nowcasting

- Target specific hazards
  (e.g. heavy precipitation, lightning, hail)
- Predict occurrence in a probabilistic manner



Challenges

- Image time series require large amounts of computation and GPU memory
  - ➢ Multi-GPU cluster
- CPU → GPU transfer speeds can be a bottleneck
- Extreme events are rare
  - ➢ Weighted loss function, requires recalibration of probabilities
- Best way to handle missing data?



Summary and current status

- Results of the initial study submitted as a paper, in review
  - https://doi.org/10.5194/nhess-2021-171
- Application to Weather4cast accepted as a workshop paper

Ongoing:

- Refining recurrent convolutional networks
- Developing postprocessing methods for analysis and calibration

Future:

- Next publication about thunderstorm hazard nowcasting with neural nets
- Operational applications in Switzerland, Europe and elsewhere