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EGU23-15817: Evaluating the generalization ability of a deep learning model trained to detect cloud-to-ground lightning on raw ERA5 data

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Introduction

- Typical atmospheric conditions for lightning are represented by proxies like e.g. cloud top height or CAPE times precipitation.
- Proxies may need to be adapted for local conditions to perform well. This suggests that there is a need for more complex and holistic proxies.
- A neural network is trained and evaluated in Central Europe using ERA5 and lightning data. The model shows promising results for an unseen test year.
- This study questions whether the model can extend to a broader spatial domain.

Data for training

We use data from the summer months (June, July, and August) of the years 2010 through 2019 over the spatial domain of Central Europe.

1. **Features / Model input**: We use single spatiotemporal cells (30 km × 30 km × 1 h) with nine ERA5 parameters (ciwc, cswc, clwc, crwc, q, t, u, v, w) on 74 model levels. The cells are further enriched with altitude and hour of day information.
2. **Labels / Model output**: Cloud-to-ground lightning strikes as observed by the European Cooperation for Lightning Detection (EUCLID). If at least one flash has been detected in such a grid cell, then the cell is marked as a *lightning* cell, otherwise it is designated as a *no lightning* cell.

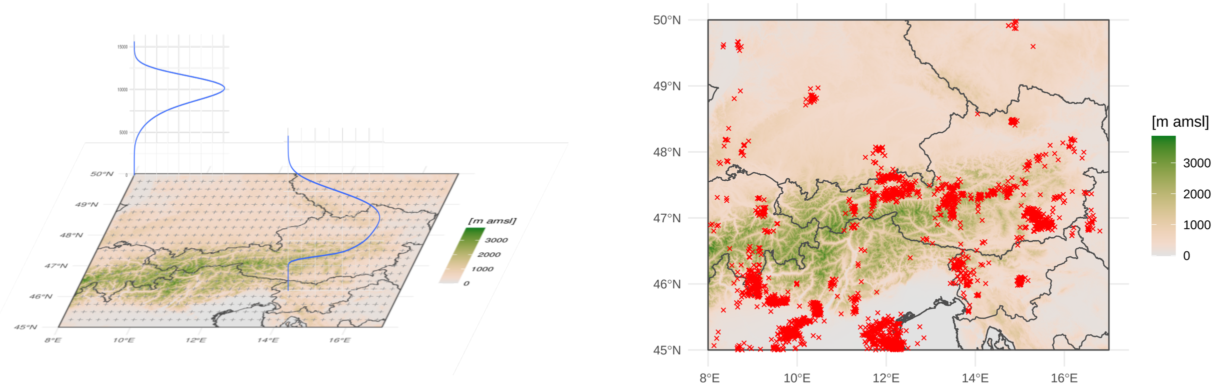
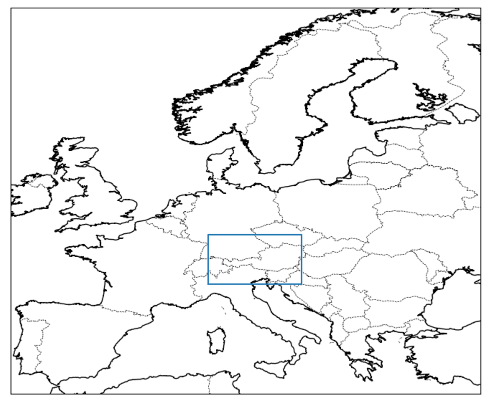


Figure 1: Visualizing ERA5 data (left) and EUCLID data (right)

Data for evaluation

To test the model's quality, we use data from summer 2020 across Continental Europe. The evaluation area is shown in the image to the right, with a small blue rectangle indicating the training area.



Results on the evaluation data

For classification tasks, it is important to note that the selection of the threshold can greatly affect the outcome.

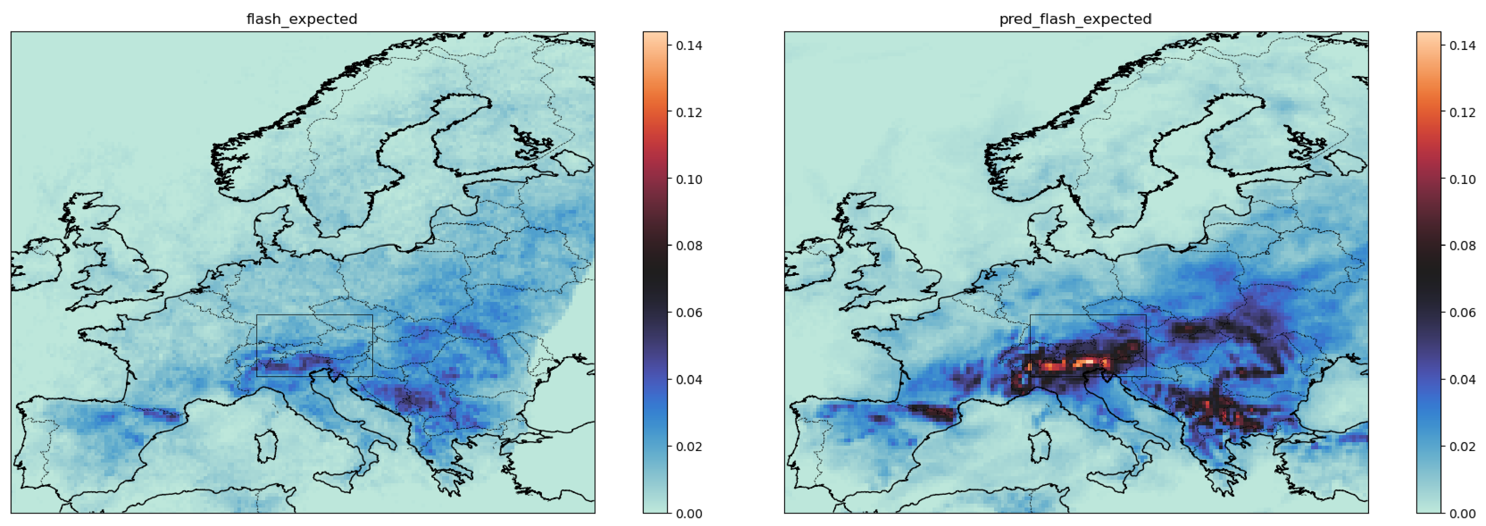


Figure 2: Left: Actual lightning activity. Right: Predicted lightning activity.

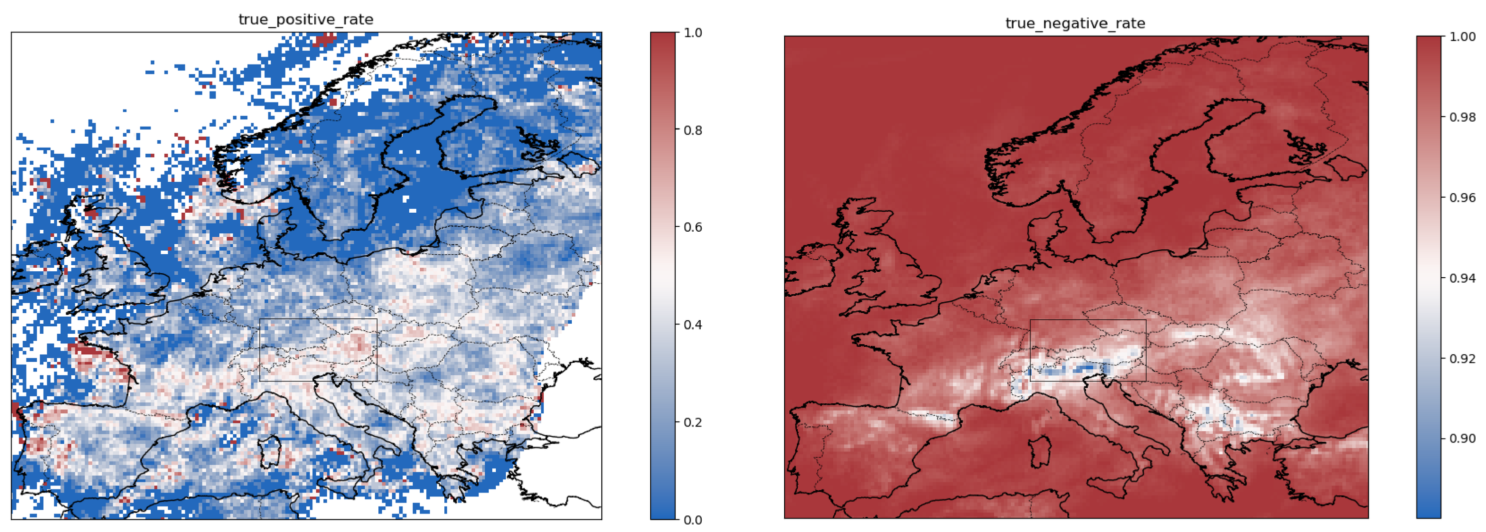


Figure 3: Left: True positive rate. Right: True negative rate.

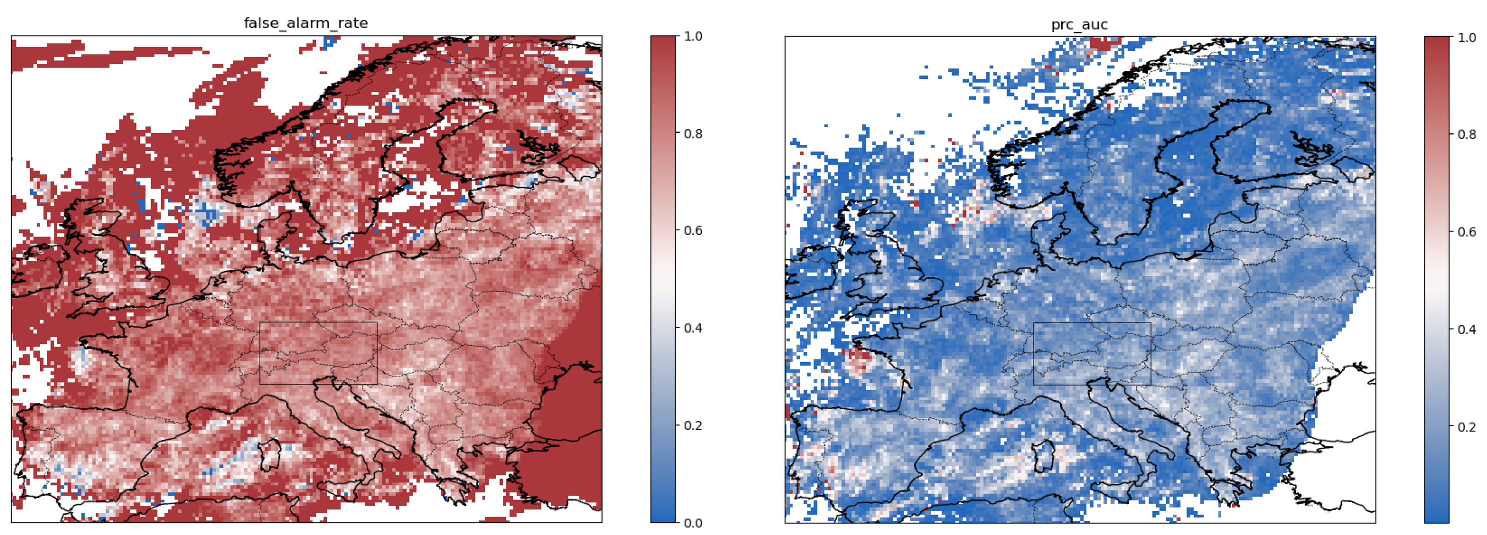


Figure 4: Left: False alarm rate. Right: area under the precision recall curve which is not influenced by the choice of threshold.

Case studies

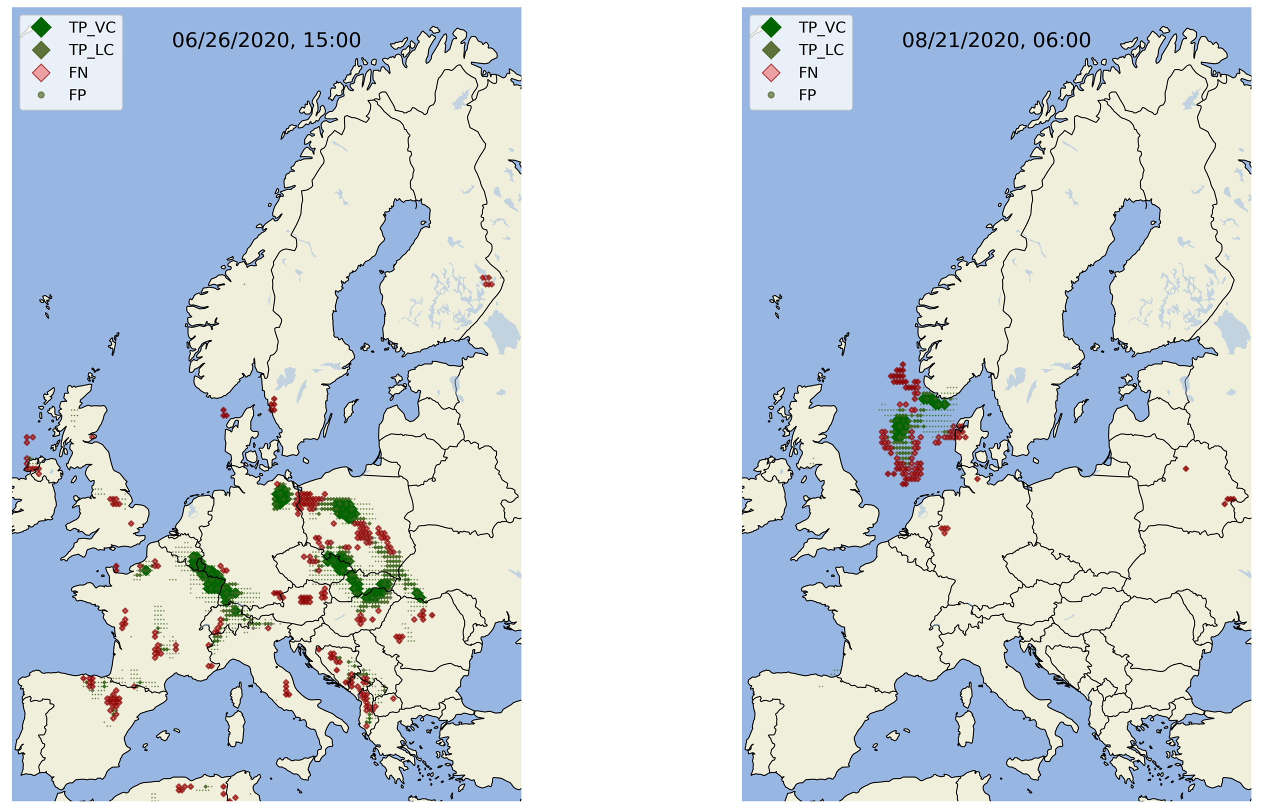


Figure 5: Figures show classification quality in two exemplary cases. True negatives have no marker.

Model details

A very simple fully connected neural network is used for modelling:

- 668 input nodes
- Ten hidden layers
- Leaky relu activation function
- Dropout 0.15
- Binary cross entropy loss function

Outlook

1. Enrich model input with data from neighbouring spatial cells (north, south, west, east) and neighbouring temporal cells (previous and next hour).
2. Train and evaluate a model on this enriched data set and compare with the one presented here.

References:

Ehrensperger, Gregor, et al. "Identifying Lightning Processes in ERA5 Soundings with Deep Learning." arXiv preprint arXiv:2210.11529 (2022).

Acknowledgements:

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