Self-supervised cloud classification using infrared imagery for characterizing extreme precipitation events over the Alps

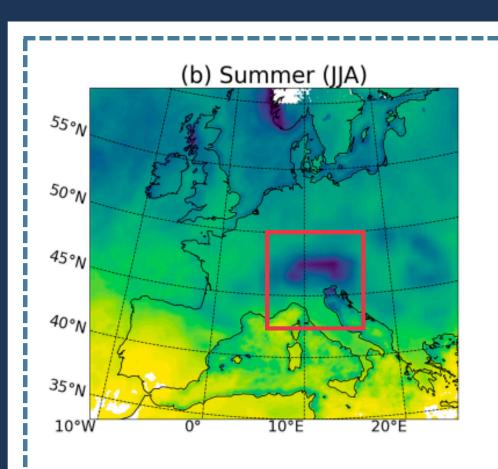
Daniele Corradini, Claudia Acquistapace, Paula Bigalke Institute of Geophysics and Meteorology, University of Cologne, Germany





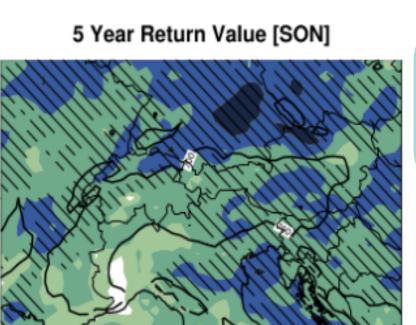


1. MOTIVATION



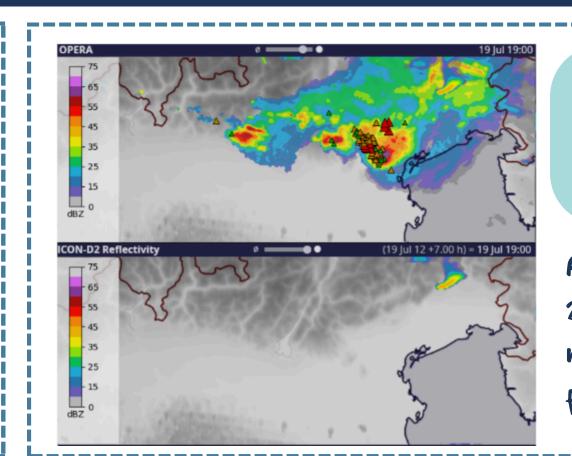
Intense precipitation in the Alpine region, particularly during the summer months

Fig. 1: Seasonal (JJA) precipitation climatology (2011-2020) from IMERG 10-year average data [Lombardo & Bitting, 2024].



Severe **storms** are expected to intensify as climate change progresses

Fig. 2: Projected changes (%) in 5-year return value of 1-day precipitation event during fall season (Gobiet et al., 2014).



Models still fail to capture precipitation over orography

Fig. 3: Severe hailstorm on 19 July 2023 in Northern Italy: OPERA radar reflectivity vs. ICON-D2 forecast. [Fischer et al., (2024)]

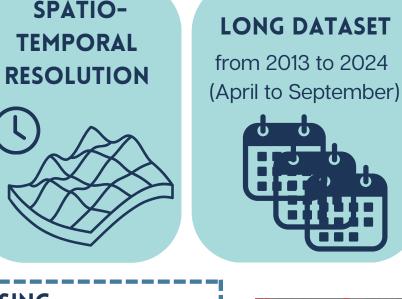
2. GOAL

Investigate the **spatial** structure and temporal evolution of cloud states associated with extreme precipitation events in the Alpine region using a selfsupervised deep learning (DL) model and infrared **images** from geostationary satellites

3. DATA

COVERAGE

Why 10.8 µm Infrared channel from Meteosat Second Generation (MSG)?



SPATIO-

TEMPORAL

PROCESSING

The data were **parallax corrected**

and interpolated into a regular grid

(0.04°x0.04°). Data are converted to

greyscale images with normalization

between 200 and 300 K



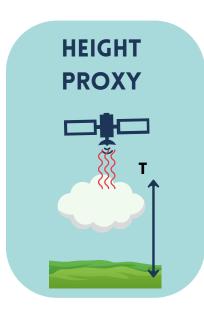


Fig. 4: Left: IR 10.8 channel image with CMSAF cloud mask (red) superimposed. Squares show the 128×128 pixels crops given to the ML

4. DEEP LEARNING METHOD

Self-supervision is a form of unsupervised learning that does not require

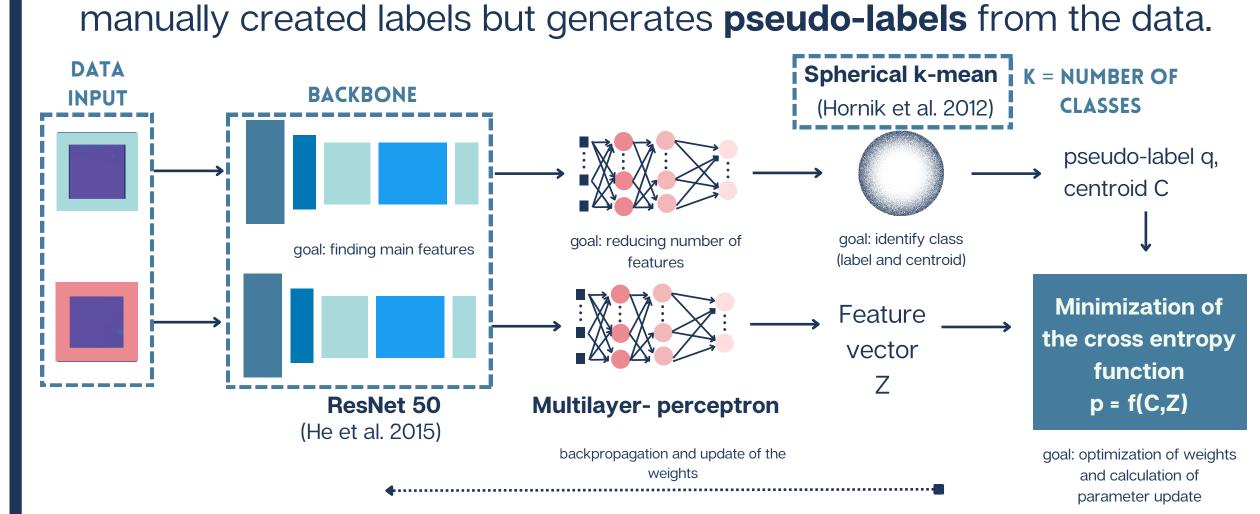


Fig. 5: Architecture of self-supervised ML model adopted in Chatterjee et al., (2023).

5. CLOUD CLUSTERING

The **feature space** consists of multidimensional ensemble of vectors of image semantic properties from multi-year satellite crops. To inspect it, dimensionality must be reduced to 2D.

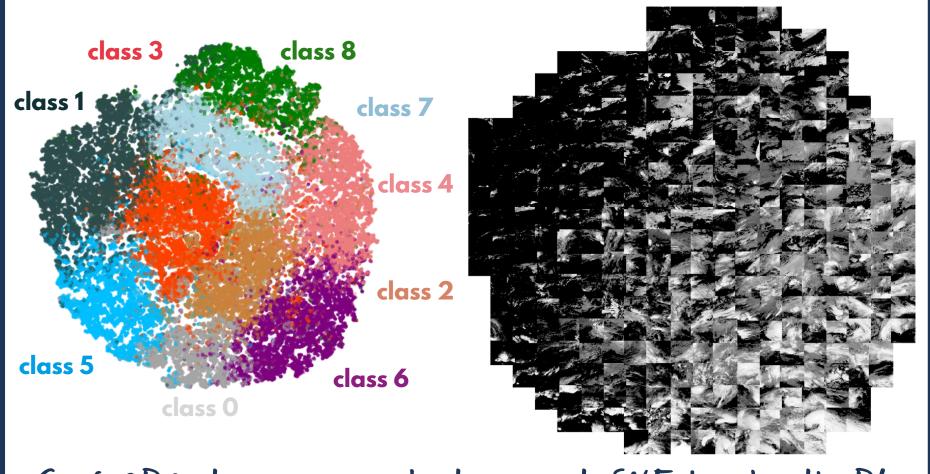
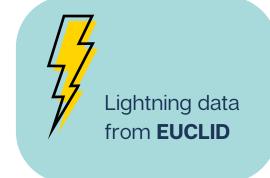


Fig. 6: 2D feature space visualization using t-SNE, based on the DL model trained with IR 10.8 image crops (including cloud masks) across 9 classes. Left: Feature representation with color-coded points for each class. Right: Feature space overlaid with sample image crops.

Classes need to be characterized by analyzing their diurnal occurrences and incorporating cloud physical properties from CMSAF and other ancillary datasets.

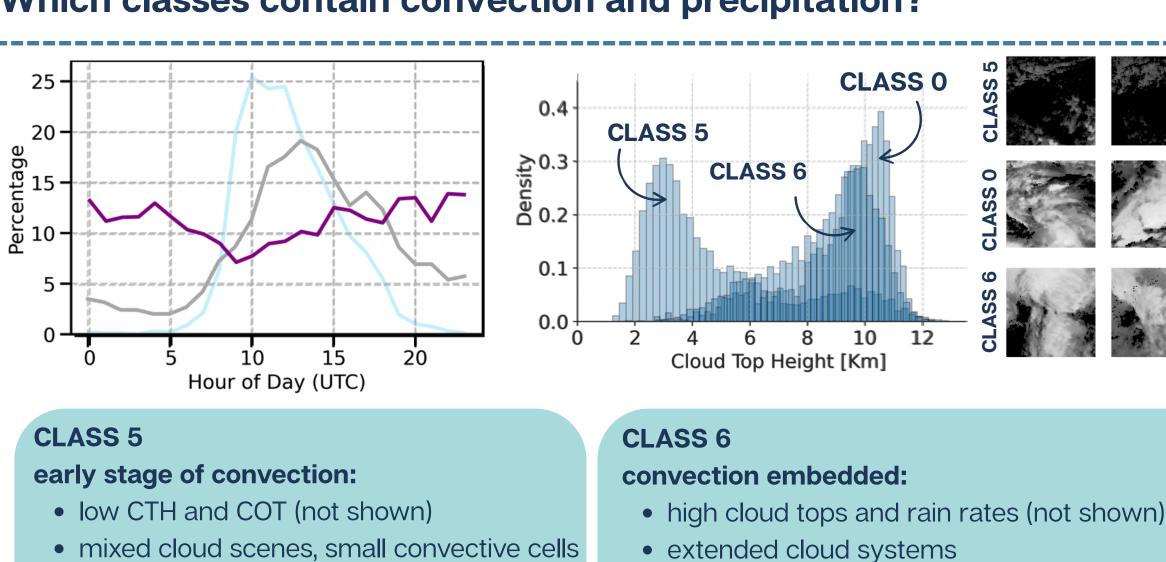
Cloud top height (CTH) and optical thickness (COT) from **CMSAF**

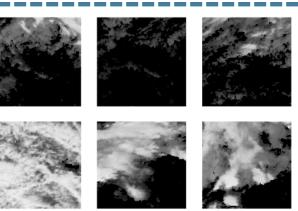
Rain rate from satellite (IMERG) and ground radar (OPERA)

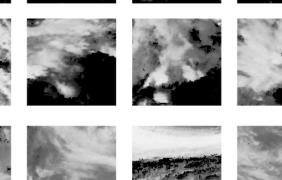


6. EXEMPLE OF CLASSES CHARACTERIZATION

Which classes contain convection and precipitation?







CLASS 0

mature convection:

- highest cloud tops and rain rates (not shown)
- afternoon convection peak
- large convective cells with complex cloud scenes

CLASS 2 SITASS 3 Cloud Top Height [Km] Hour of Day (UTC) CLASS 2 CLASS 3

bimodal cloud scene:

bimodal cloud top distribution

mostly noon (local time)

- low rain rates (not shown)
- large convective cells with complex cloud scenes

bimodal cloud scene

• lower COT and CTH compared to class 2

• large convective cells embedded in larger cloud patterns

- low rain rates (not shown)
- small convective cells with complex cloud scenes

Fig. 7: Classes characterization using diurnal occurrence plots and CTH distributions, along with the 10 image crops closest to the class centroids. Only classes exhibiting convective activity are shown.

7. OUTLOOK



Extreme events analysis

The feature space can be used to characterize selected case studies of intense rainfall and hailstorms in test mode. The DL model is currently being enhanced to improve its performance.

DATA INPUT

- Model now supports
- **NetCDF** input. Additional channels can be added, e.g.: 6.2-10.8 µm difference (proxy for overshooting tops).

BACKBONE

- Switched from ResNet to Vision Transformer (Vaswani et al., 2017).
- More powerful for capturing non-local features, especially with large datasets.

K OPTIMIZATION

- k needs adaptation to the new configuration.
- The one yielding better feature space clustering and lower inter-class correlation will be selected.

Model Evaluation

Extreme event case studies can be compared with ICON simulations to assess their performance in capturing cloud structures and evolution.

Fig. 8: Feature space example showing the trajectory of observed and simulated 10.8 Mm MSG data during the Marche (Italy) flood (09.2022)

8. REFERENCES

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