High-resolution model evaluation with self-supervised neural network approach targeted on severe storms over the Alps

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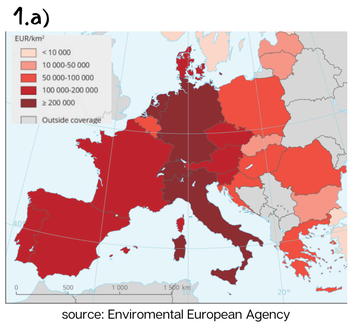
Deutscher Wetterdienst
Wetter und Klima aus einer Hand

UNIVERSITÄT ZU KÖLN

1. MOTIVATION

Extreme weather events are a serious **public safety hazard**

1.a)



source: Enviromental European Agency

Fig 1.a) Total economic loss per sq. km caused by weather-related extreme events in Europe (1980-2020) [Daniell et al. (2016)]

Severe **thunderstorms** are expected to intensify as **climate change** progresses.

1.b) 5 Year Return Value [SON]

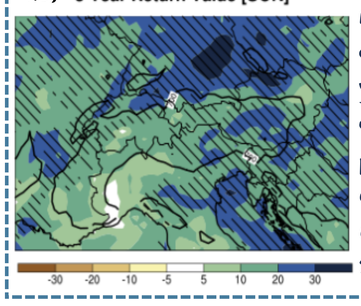


Fig 1.b) Projected changes (%) in 5-year return value of 1-day precipitation event during fall season (Gobiet et al., 2014).

In the Alps the **precipitation modelling** is biased due to the **orography**.

1.c)

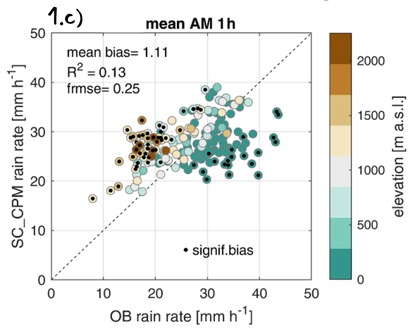


Fig 1.c) Comparison of observed and simulated annual rain rate maxima at 1 h duration (Dallan et al., 2023)

2. RESEARCH QUESTIONS

1. Can cloud regimes in the model be identified using a **Machine Learning** (ML) framework?
2. Can the differences among the cloud classes be quantified by **physical properties**?
3. Are the **cloud classes** derived from the model similar to the ones derived from satellite observations?

3. MACHINE LEARNING METHOD

We adopt a **self-supervised approach** to classify clouds without the use of labelled data. However, number of classes needs to be optimised

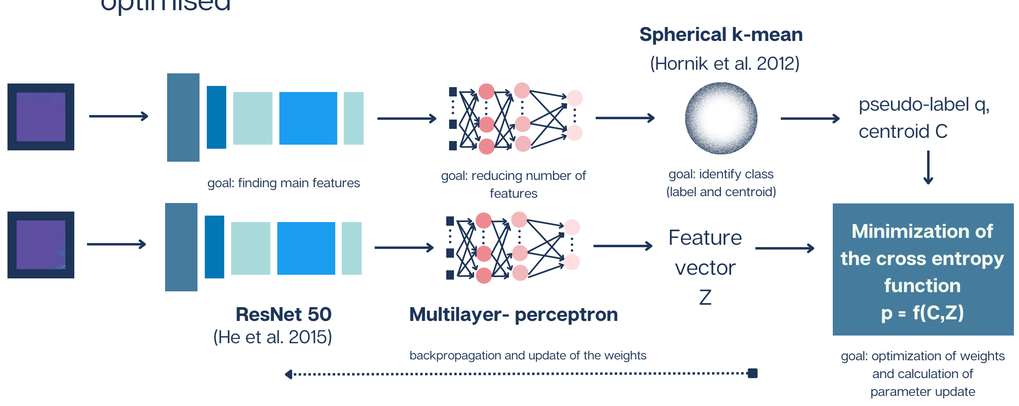


Fig 2. Architecture of self-supervised ML model adopted in Chatterjee et al., (2023).

4. DATASETS

- **MSG/MTG** brightness temperature/reflectances and derived products: ML training
- **ICON-GLORI** Model Output: evaluation
- **European Severe Weather Database** (ESWD), **radar** and **rain gauges** data: case studies selection
- **Environmental** (ERA 5), **Cloud** (CM SAF) and **topography** variables: cloud classes characterization.

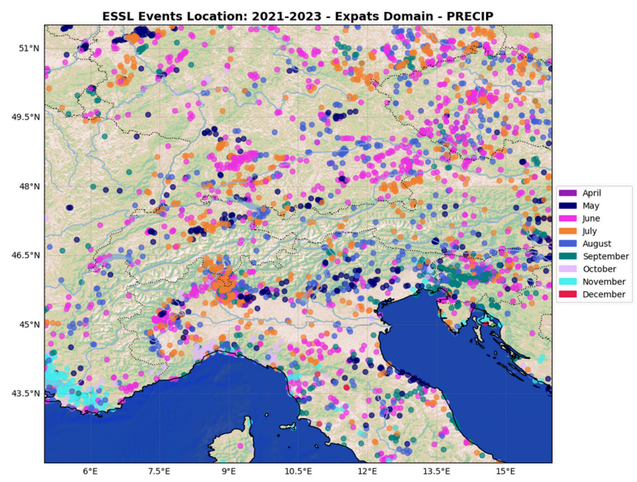
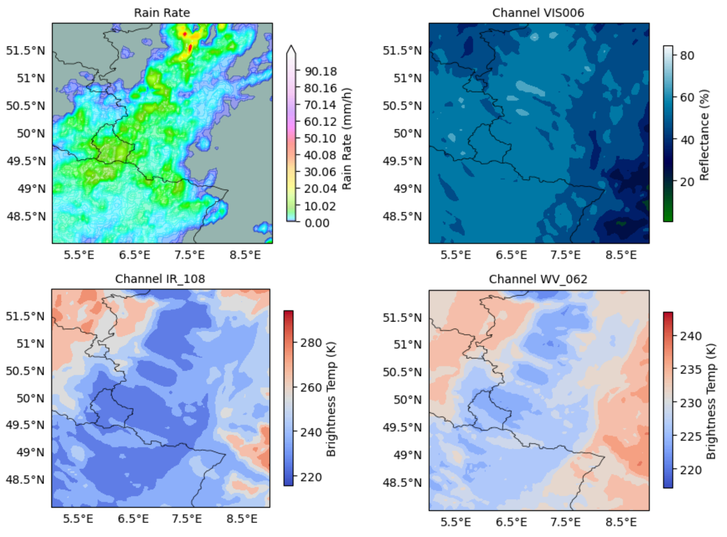


Fig 3. Heavy rain events location from ESWD , ranging from 01.01.21 to 31.10.2023

5. PRELIMINARY STEPS



- Characterize MSG channels to identify optimal inputs for the ML model.
- Evaluate both single channels and combinations, including cloud products like optical thickness (COT), against rain rate observations

Fig. 4: Snapshots of 4 MSG channels (0.6, 6.2, 10.8 μm) against rain rate map from the NIMROD dataset during the July 2021 Germany Flood.

6. CLOUD CLASSIFICATION

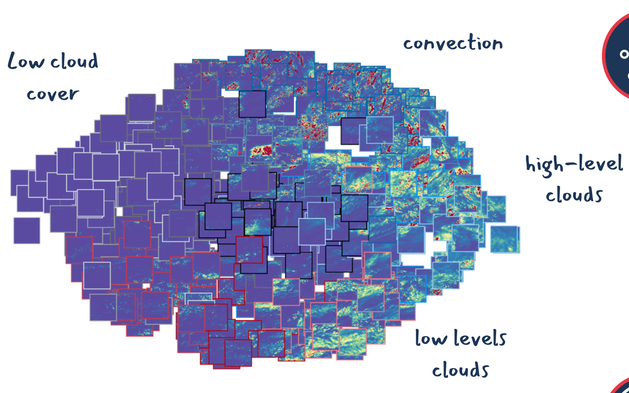
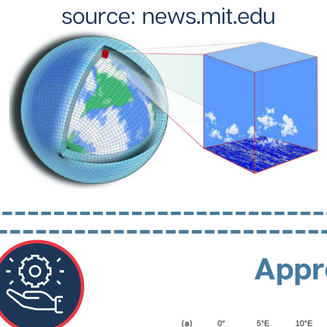


Fig. 5: Feature space representation of cloud classes derived from COT Images, visualized in 2D via t-SNE. Source: Chatterjee et al. (2023).

- The **feature space** represents multidimensional vectors of image semantic properties, derived from multi-year satellite observations.
- Cloud classes **characterization** with environmental variables.

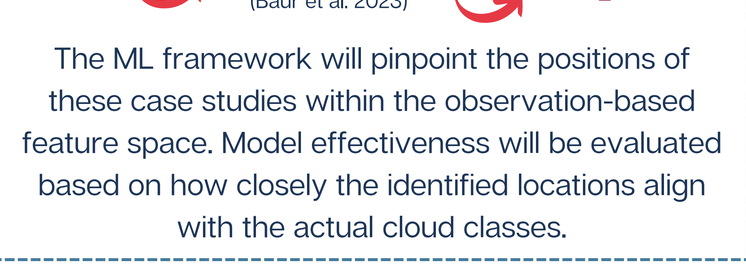
7. MODEL EVALUATION

source: news.mit.edu



- Relevant **case studies** of extreme precipitation will be selected and modeled to match the images used in training the ML model.
- The feature space obtained can be used to **evaluate** the ICON-GLORI model output in two different ways:

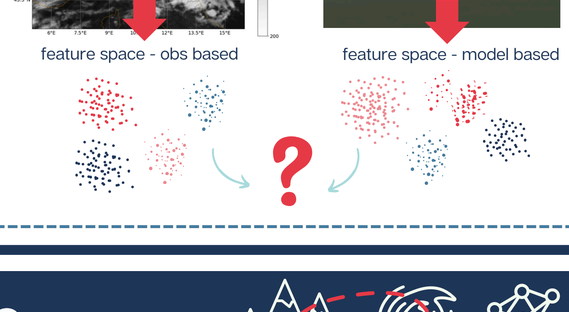
Approach 1



(Baur et al. 2023)

The ML framework will pinpoint the positions of these case studies within the observation-based feature space. Model effectiveness will be evaluated based on how closely the identified locations align with the actual cloud classes.

Approach 2



Another feature space is built based on ensemble model predictions and it is directly compared with the one obtained from satellite observations

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