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

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1. MOTIVATION

The **Alps**' severe thunderstorms are expected to **intensify** as climate change progresses (Menegoz et al., 2020).

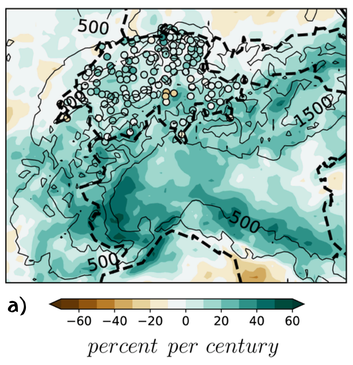
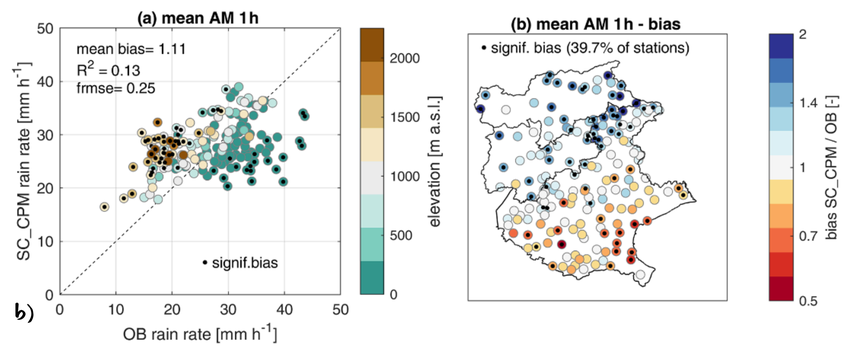


Fig 1. a) Summer maximum precipitation trends over the period 1903–2010. (Menegoz et al., 2020). b) Comparison of observed and simulated annual rain rate maxima at 1 h duration (Dallan et al., 2023)

In the Alps the **precipitation modelling** is biased due to the **orography**. (Dallan et al., 2023).



2. RESEARCH QUESTIONS

- Can model performances be **evaluated** using a Machine Learning (ML) framework over complex terrain?
- Are the **cloud classes** derived from the model similar to the ones derived from MSG/MTG observations?
- Can the differences among the cloud classes be quantified by **physical cloud properties**?

3. MACHINE LEARNING METHOD

We adopt a **self-supervised approach** to classify clouds: number of classes needs to be optimised (Dwaipayan et al., 2023)

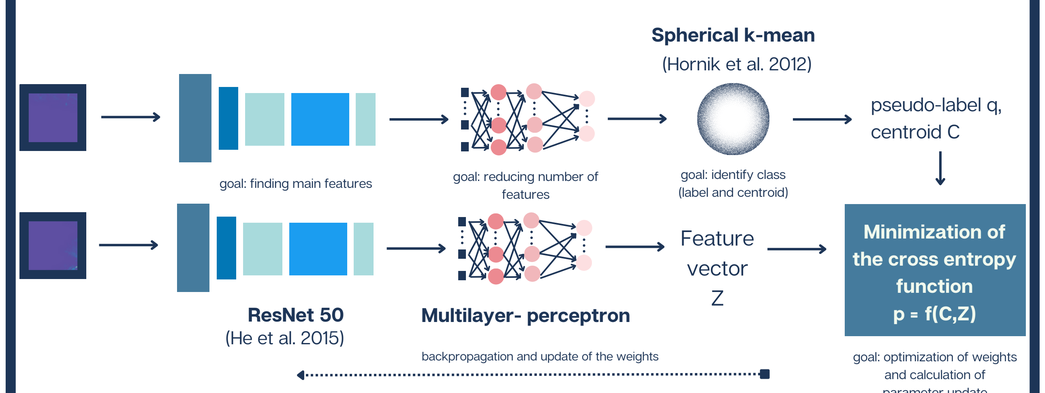
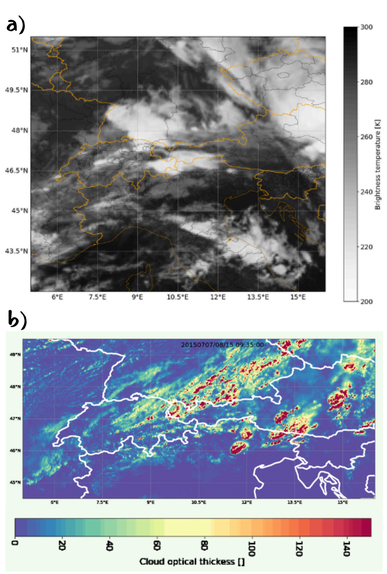


Fig 2. Architecture of the Machine Learning model

4. DATASETS



- **MSG/MTG** radiances, products (COT): ML training
- **ICON-GLORI** Model Output: evaluation
- ESSL and **rain gauges**: case studies identification
- **Environmental** data: cloud classes characterization.

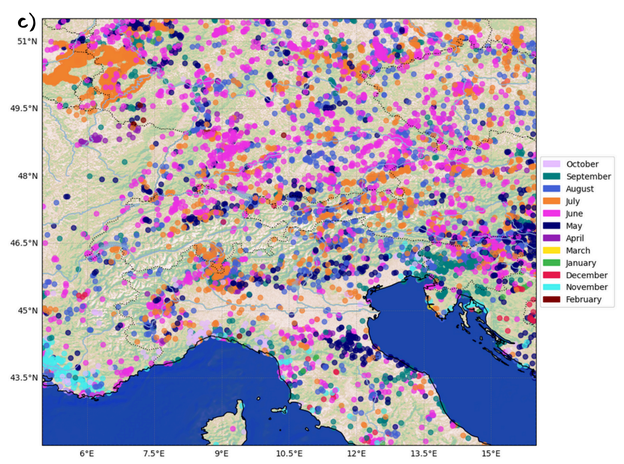
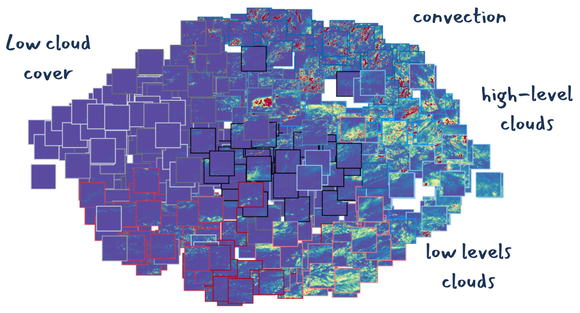


Fig 3. a) MSG example image of 10.8 micron radiance, b) Cloud optical thickness (COT), c) Heavy rain events location from ESSL , ranging from 01.01.21 to 31.10.2023

5. WORK PLAN

Observations Analysis

The **feature space** is created exclusively from the training of 1-year-long satellite observations. **Cloud classes** are identified and characterised using environmental information.



Model Evaluation

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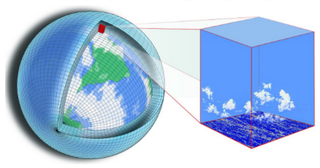
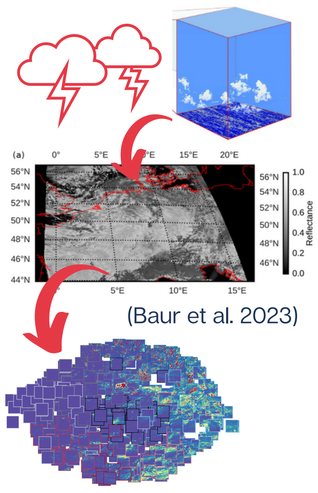


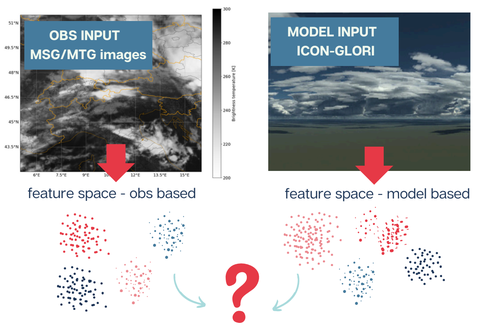
The feature space obtained can be used to **evaluate** the ICON-GLORI model output in two different ways:

Approach 1



Relevant **cases studies** of extreme precipitation will be identified and reproduced by the model. Then, the machine learning framework will determine the location of these case studies within the observation-based feature space.

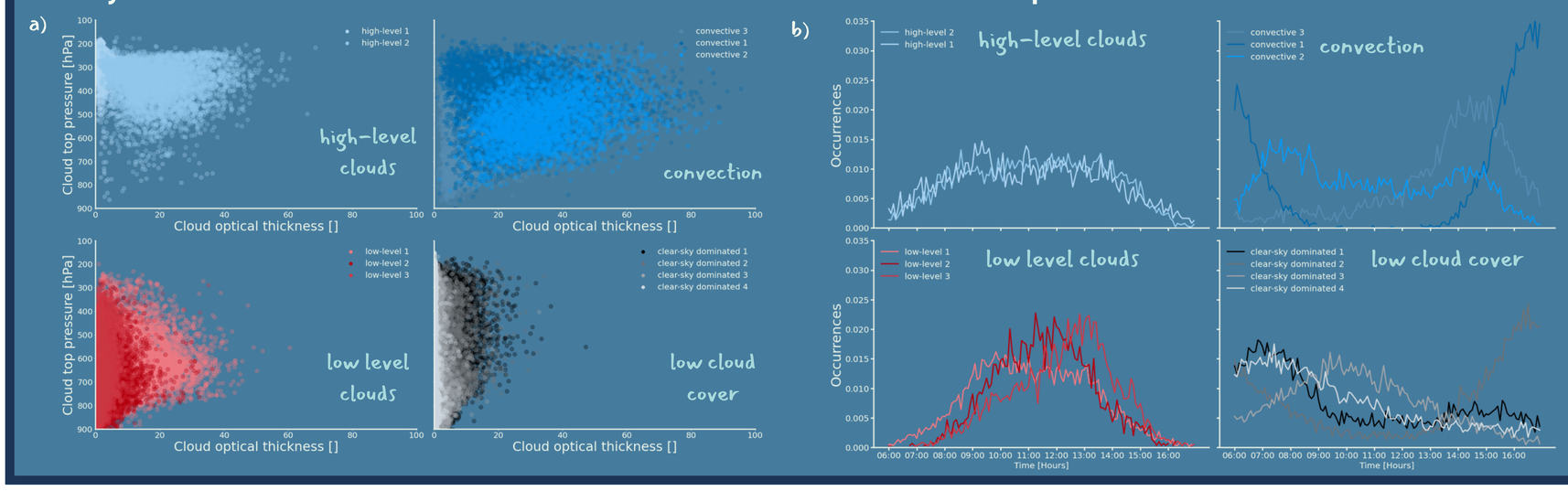
Approach 2



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

6. PRELIMINARY RESULTS

Analysis of the cloud classes obtained with the observation-based feature space



- We identified four **cloud type groups** by clustering classes with similar behavior in optical thickness relative to cloud top pressure.
- We examined the **diurnal cycle**, noting that high-level clouds are present throughout the day, whereas low-level clouds and those with low cloud fraction peak around 11 AM, with convection also evident in the early afternoon.

Fig. 5: a) Scatterplots illustrating the relationship between cloud optical thickness and top pressure for various cloud classes. b) Diurnal cycle patterns of cloud class occurrences. Analysis based on 2015 COT data, sourced from Deneke et al., 2021.

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