Abstract
Severe hailstorms are becoming more frequent in Central Europe, showing increasing interannual variability. The Pre-Alpine and Alpine region is significantly affected due to its complex terrain, which initiates convection and can intensify many hail-favoring processes. In particular, large hail events are often very local phenomena and are becoming increasingly intense. Ground-based observations from weather radars are the most reliable for detecting hail; however, they are challenging in the Alpine region due to interference at mountain ranges.

Passive Microwave satellite observations offer a valuable alternative for detecting hail: a hail probability can be directly derived from Passive Microwave channels with a high spatial coverage. However, this data is only available at certain times during satellite overpasses, thus capturing only snapshots of a few of these events. Visible, near-infrared, and infrared data from MSG give the highest spatial and temporal coverage. Though not directly sensitive to hail, its high spatiotemporal resolution can identify early stages of severe storm development leading to large hail formation by peculiar characteristics in their spatiotemporal evolution.

Whereas various ML approaches already classify spatial cloud patterns from satellite measurements, the temporal component of cloud development remains less explored. This work aims at classifying the evolution of typical cloud patterns leading to severe storms over the Alpine region. In particular, learning about formation of hail storms and the conditions in which they develop.

We initially adopted a **supervised** deep-learning framework for classifying spatiotemporal cloud evolution patterns as hail and non-hail, obtaining better performance than a simple logistic regression. We trained the network using MSG timeseries displaying cloud evolution patterns and labeled the presence of hail using a hail probability product based on passive microwave radiometry. Then, we exploited the same architecture in a **self-supervised approach**, using the labeled dataset as fine-tuning to capture hail development characteristics better. We characterize such classes of cloud developments in a spatiotemporal embedding, exploiting its characteristics and investigate the physical properties of the classes with ancillary datasets.