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Learning Convective Cloud Structures from Satellite Data for Severe Weather Analysis and Model Evaluation over the Alps

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Understanding the spatial organization and transitions of convective cloud systems over complex terrain remains a major challenge for both observation-based analysis and numerical weather prediction (NWP). This limitation affects our ability to accurately represent and predict extreme precipitation and hail events, which are expected to intensify over the Alpine region under climate change.

In this work, we present a data-driven framework based on self-supervised learning (SSL) to characterize convective cloud structures and their transitions using long-term geostationary satellite data records. By learning representations directly from infrared imagery without manual labeling, the model organizes cloud scenes based on their spatial and morphological similarities, providing a physically interpretable feature space of mesoscale cloud features. This learned representation is exploited in two complementary ways.

First, it enables the analysis of convective cloud structures and their transitions associated with severe precipitation events by identifying dominant pathways linked to intense rainfall and hail over the Alpine region. The most severe precipitation is predominantly observed either in association with long-lasting deep convective systems or during transitions from early-stage convection to a more mature regime, highlighting two key modes linked to extreme precipitation.

Second, the framework provides a novel tool for evaluating convection-permitting NWP simulations. By projecting synthetic satellite channels into the same feature space, it enables a direct comparison between modeled and observed cloud structures, both in terms of continuous embeddings and discrete cloud classes. Preliminary results indicate that ICON tends to overestimate the spatial extent of convective cells during their early development stages, suggesting biases in the representation of convective initiation and growth.

Overall, this approach demonstrates the potential of self-supervised learning to bridge satellite observations and model simulations, providing a flexible framework for studying convective processes and assessing their representation in high-resolution weather models over complex terrain.