Evaluating the Spatial Structure of Convective Clouds in 500-m ICON Simulations during the TEAMx Campaign Using Self-Supervised Learning

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The severity of convective storms in the Alpine region are expected to increase under climate change. However, accurately predicting extreme precipitation in complex terrain remains a major challenge for current numerical weather prediction (NWP) models. In this study, we propose a novel approach to evaluate the realism of simulated cloud spatial structures using a self-supervised deep learning framework trained on satellite observations.

The framework is trained on long-term MSG SEVIRI brightness temperature observations at 10.8 µm, enabling the model to learn cloud representations without the need for manual labeling. The learned feature space clusters cloud scenes in classes based on semantic and structural similarities. We characterize such cloud classes using independent satellite-derived cloud properties, including cloud cover, cloud optical depth, cloud-top height, and precipitation estimates.

The trained model is applied to high-resolution (500 m) forward simulated satellite channels obtained from ICON simulations conducted during the TEAMx observational campaign over the Alps in 2024–2025. By projecting simulated satellite channels into the learned feature space, we quantitatively compare synthetic model output with satellite observations for selected convective case studies. This approach allows us to assess the spatial structures of convective cloud systems in both observations and model simulations, highlighting strengths and deficiencies in the representation of cloud structure and organization. For additional validation, the model-derived liquid water paths and precipitation amounts are evaluated against the profiling ground-based observations deployed during the campaign.

Our results demonstrate the potential of self-supervised learning as a powerful tool for evaluating convection-permitting NWP simulations over complex terrain.