Cloud state transitions at Ny-Ålesund: A machine learning supported statistical analysis

Andreas Walbröl[1], Nils Risse[1,2], Dwaipayan Chatterjee[3], Susanne Crewell[1], Kerstin Ebell[1]

[1] Institute for Geophysics and Meteorology, University of Cologne, Cologne, Germany
[2] European Centre for Medium-Range Weather Forecasts, Reading, United Kingdom
[3] Karlsruhe Institute of Technology, Karlsruhe, Germany

EGU 2026, 3 - 8 May 2026

Session: AS4.2: Clouds, moisture, and precipitation in the Polar Regions

Presentation type: Poster

Clouds are still a major source of uncertainty in projections of the future climate because of complex feedback mechanisms and their interplay with other atmospheric and surface properties (i.e., through solar and thermal-infrared radiation and precipitation). In the Arctic, where the climate is projected to warm the strongest, clouds pose a particular challenge to current climate and weather forecast models because of the difficulties in simulating the frequently occurring mixed-phase clouds and the sparsity of observational data.

In this study, we aim to improve our understanding of Arctic clouds on multi-annual time scales by performing statistical analyses of cloud states and their transitions using cloud radar data from the research site Ny-Ålesund, Svalbard. We have gathered nine years of comprehensive cloud and precipitation observations with the 94-GHz cloud radars, which were operated at the German-French Arctic Research Base AWIPEV observatory in synthesis with other in-situ and remote sensing instruments (i.e., microwave radiometers, lidar, disdrometers, ...). The additional meteorological measurements also allow us to study how atmospheric conditions affect the cloud states and transitions.

Modern machine learning algorithms are well suited to analyse big data sets and reveal features imperceptible to the human eye because of the complexity of the problem. We train a Vision Transformer [1-3] with height-resolved cloud radar reflectivities, Doppler velocities, ceilometer data and liquid water path-sensitive brightness temperatures at 89 GHz in a self-supervised framework. The Vision Transformer learns to identify distinct features in the training data and therefore find different cloud states without direct human intervention.

Here, we present our first steps focussing on the interpretation of the machine learning model output and fine tune the settings to better discern the cloud states. Different cloud macro- and microphysical properties are tested to understand the nature of each cluster the machine learning algorithm produced.

Later, we will apply the trained machine learning algorithm to synthetic radar data simulated with the Passive and Active Microwave radiative TRAnsfer (PAMTRA, [4]) model based on the output of the ICOsahedral Non-hydrostatic (ICON, [5]) model in large-eddy configuration. By comparing the observation-based analysis with the one performed on the simulated radar data we aim to further shed light on the strengths and weaknesses of ICON regarding cloud states and transitions.

Acknowledgement:

We gratefully acknowledge the funding by the Deutsche Forschungsgemeinschaft (DFG, German Research Foundation) – Project Number 268020496 – TRR 172, within the framework of the Transregional Collaborative Research Center „ArctiC Amplification: Climate Relevant Atmospheric and Surface Processes, and Feedback Mechanisms (AC)³“. We also acknowledge the support of AWIPEV for the project AWIPEV_0016.

References

[1]: Vaswani, A., et al., 2017: Attention is all you need, In I. Guyon et al. (Eds.), 31st Conference on Neural Information Processing Systems (NIPS), Advances in neural information processing systems, 30, Curran Associates, Inc. arXiv, 1706.03762, https://arxiv.org/abs/1706.03762.

[2]: Caron, M., et al., 2021: Emerging Properties in Self-Supervised Vision Transformers, *arXiv*, 2104.14294, https://arxiv.org/abs/2104.14294.

[3]: Chatterjee, D., et al., 2024: Capturing the Diversity of Mesoscale Trade Wind Cumuli Using Complementary Approaches From Self-Supervised Deep Learning, *Geophys. Res. Lett.*, 51, 12, e2024GL108889, doi: 10.1029/2024GL108889.

[4]: Mech, M. et al., 2020: PAMTRA 1.0: the Passive and Active Microwave radiative TRAnsfer tool for simulating radiometer and radar measurements of the cloudy atmosphere, *Geosci. Model Dev.*, 13, 4229-4251, doi: 10.5194/gmd-13-4229-2020.

[5]: Zängl, G. et al., 2015: The ICON (ICOsahedral Non-hydrostatic) modelling framework of DWD and MPI-M: Description of the non-hydrostatic dynamical core, *Q. J. R. Meteorolog. Soc.*, 141, 563-579, doi: 10.1002/qj.2378.