EGU22-5058
EGU General Assembly 2022

Can satellite images provide supervision for cloud systems characterization?

Dwaipayan Chatterjee[1], Hartwig Deneke[2], and Susanne Crewell[1]
[1]Institute for Geophysics and Meteorology, University of Cologne, Germany (dchatter@uni-koeln.de)
[2]Department of Remote Sensing of Atmospheric Processes, Leibniz Institute for Tropospheric Research, Leipzig, Germany

With ever-increasing resolution, geostationary satellites are able to reveal the complex structure and organization of clouds. How cloud systems organize is important for the local climate and strongly connects to the Earth's response to warming through cloud system feedback.

Motivated by recent developments in computer vision for pattern analysis of uncurated images, our work aims to understand the organization of cloud systems based on high-resolution cloud optical depth images. We are exploiting the self-learning capability of a deep neural network to classify satellite images into different subgroups based on the distribution pattern of the cloud systems.

Unlike most studies, our neural network is trained over the central European domain, which is characterized by strong land surface type and topography variations. The satellite data is post-processed and retrieved at a higher spatio-temporal resolution (2 km, 5 min), enhanced by 66% compared to the current standard, equivalent to the future Meteosat third-generation satellite, which will be launched soon.

We show how recent advances in deep learning networks are used to understand clouds' physical properties in temporal and spatial scales. In a purely data-driven approach, we avoid the noise and bias obtained from human labeling, and with proper scalable techniques, it takes 0.86 ms and 2.13 ms to label an image at two different spatial configurations. We demonstrate explainable artificial intelligence (XAI), which helps gain trust for the neural network's performance.

To generalize the results, a thorough quantified evaluation is done on two spatial domains and two-pixel configurations (128x128, 64x64). We examine the uncertainty associated with distinct machine-detected cloud-pattern categories. For this, the learned features of the satellite images are extracted from the trained neural network and fed to an independent hierarchical - agglomerative algorithm. Therefore the work also explores the uncertainties associated with the automatic machine-detected patterns and how they vary with different cloud classification types.