Representation learning of cloud systems using energy-based deep learning neural networks

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What is the research gap that we try to fill?

- Cloud representation in NWP and climate models is critical
- Unmet need to fully exploit high resolution observations

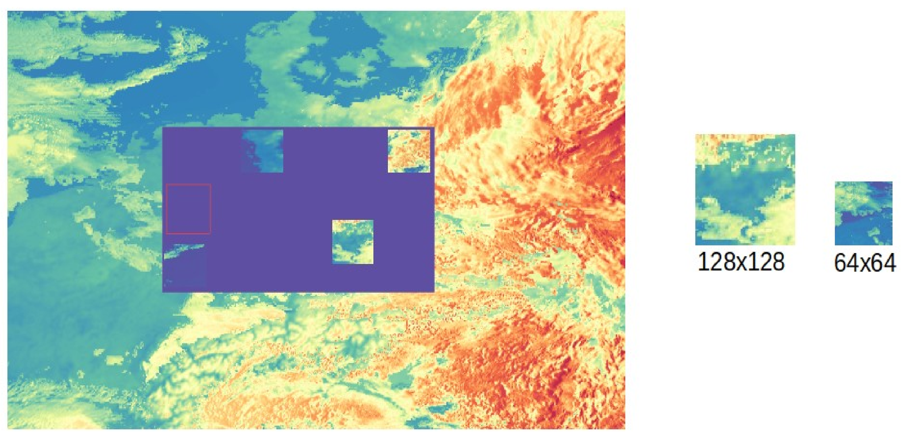
Goals of the project

- Develop new usages of geostationary sat data
- Exploit DL techniques to get new insight in mesoscale cloud organization:
  - case study 1 over land: learn to identify cloud systems with different radiative properties through representation learning
  - case study 2 over ocean: investigate the pseudo continuous (PC) order of cloud systems and exploit pseudo continuous feature space to approach discrete space
- Analyze the identified patterns with respect to:
  - large scale environmental conditions, physical processes, temporal variability, for renewable energy applications

I. First study: Over land

I.I Satellite data

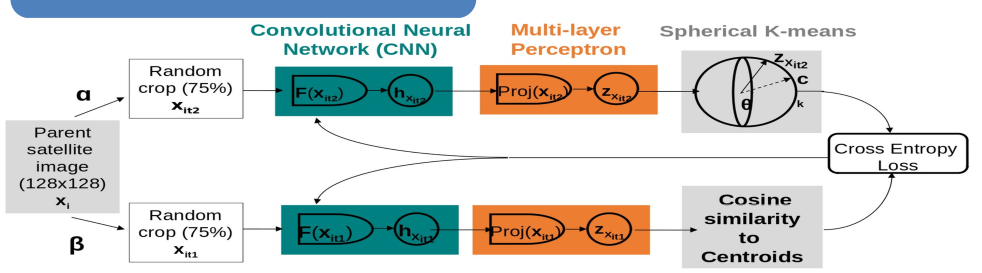
= central European domain



4 random crops at any instant

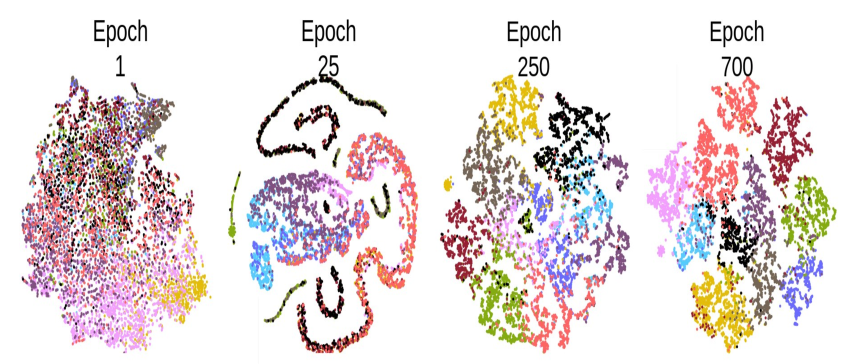
- Enhanced resolution MSG data set [5]
- Cloud optical depth (COD) and 10 additional retrieval products
- Period: April to July 2013, 2015
- Every 5 min between 6 and 18 utc
- 2.06 km × 1.07 km spatial resolution

I.II Methodology

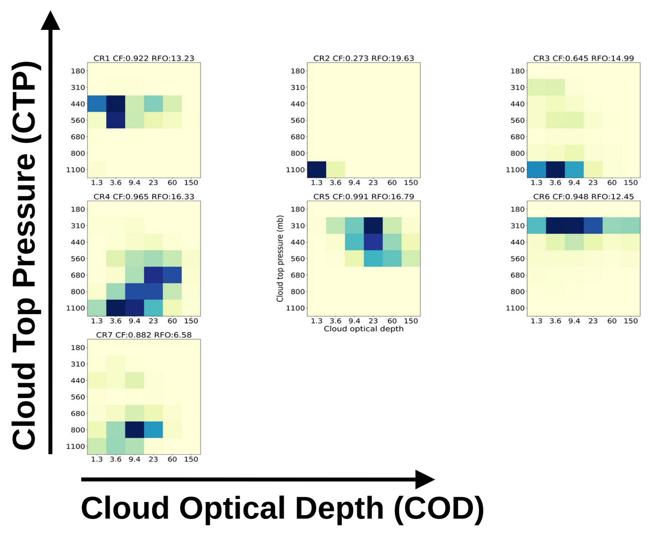


Cloud optical depth features act as signal to train self-supervised learning (SSL) approach[1,2] that classifies the satellite images into 'K' classes.

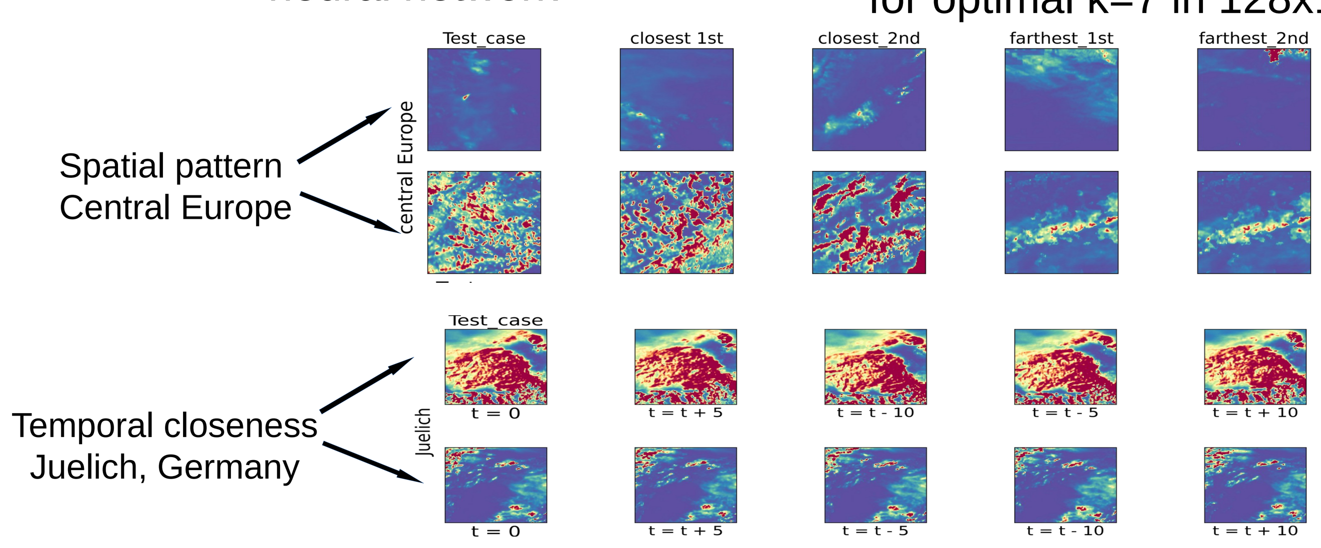
I.III Analysis of the feature space and main results



Progressive visualization of the feature space for 10 classes at a) 1 epoch, b) 25 epoch, c) 250 epoch, d) 700 epoch by the neural network

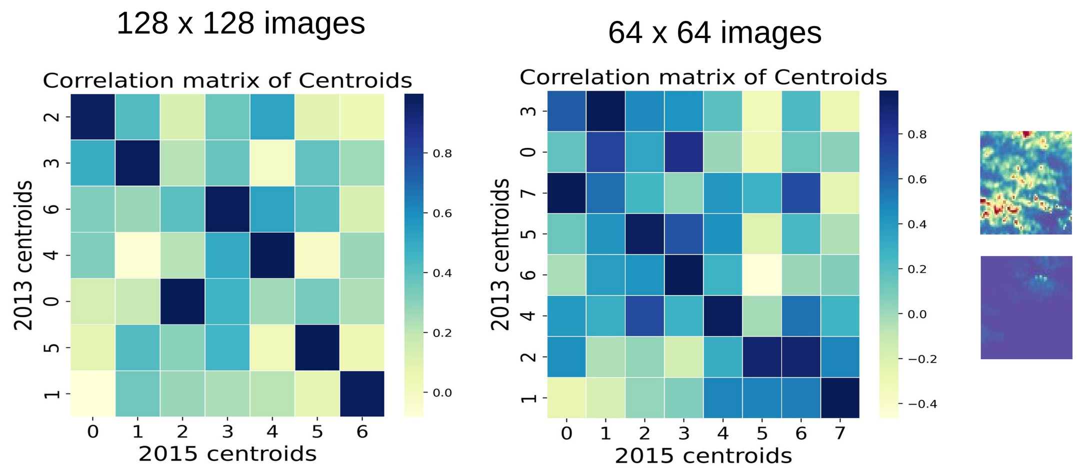


Centroid joint histogram of COD vs CTP for optimal k=7 in 128x128 configuration.



Good understanding of different cloud patterns and changing cloud patterns

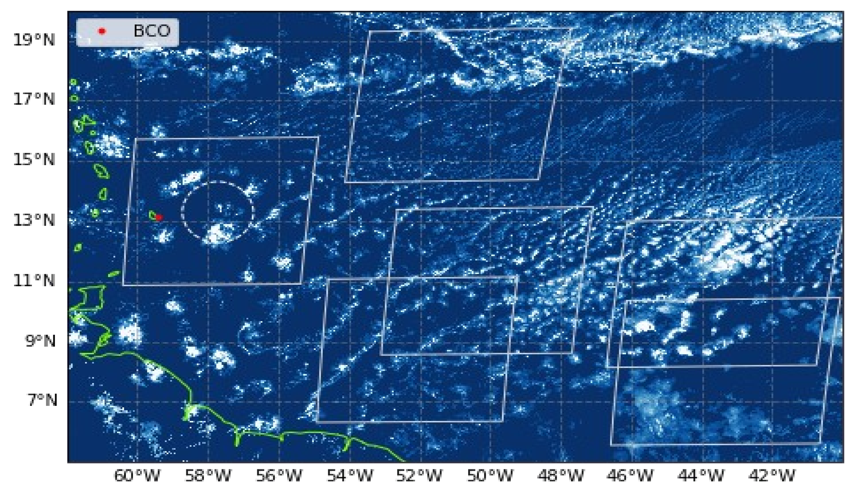
Row one and two, top two nearest and two farthest images when compared with the test image features in 128 x 128 configuration. Row 3 and 4 transfer learning the trained network over Juelich domain area for understanding the evolution of cloud systems



- For larger (128x128) domain, algorithm determined from 2013 produces the same distinct clusters for 2015
- For the smaller sized domain (64 x64) difficult to generalize for **two** unique cloud systems → larger training data set needed

II. Second study: Over ocean

II.I Satellite data

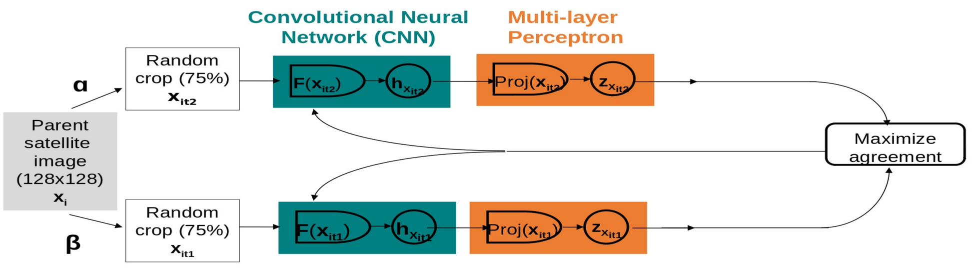


5 random crops at any instant

Cloud optical depth (COD) product[6]

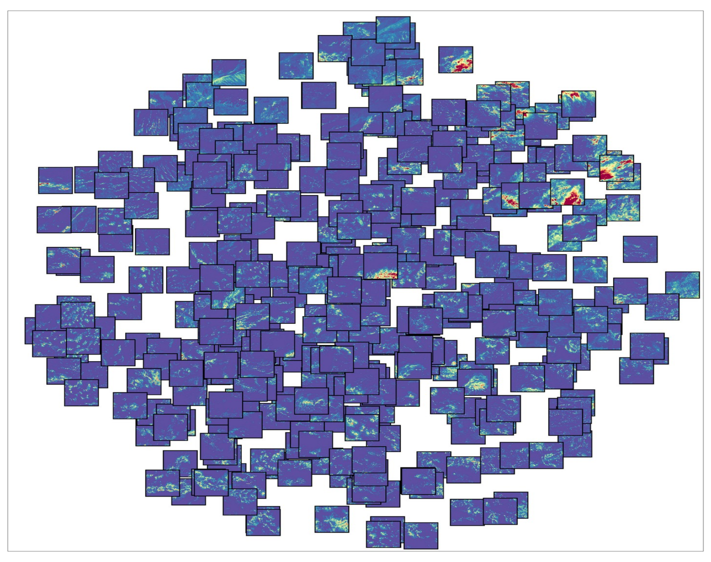
- 2 km horizontal resolution
- every 10-15 min between 9 and 15 local time
- Period: Nov - Apr 2017 – 2021
- Domain: 5-20°N, 40-60°W
- COD capped above 50

II.II Methodology

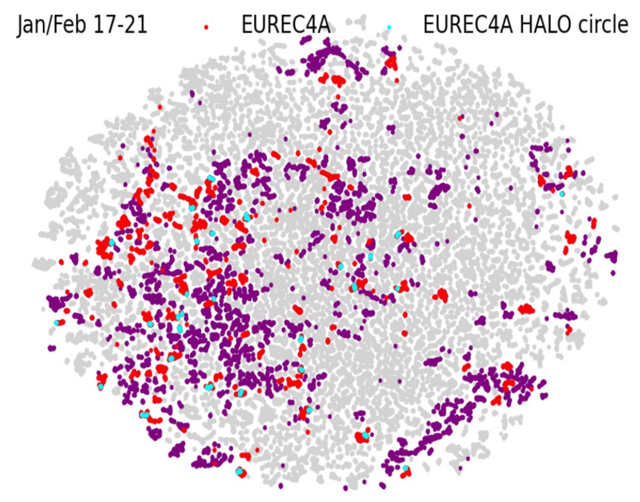


Neural network[3,2] uses cloud optical depth as input feature and puts similar cloud structure and distribution closer to each other in the feature space than dissimilar ones.

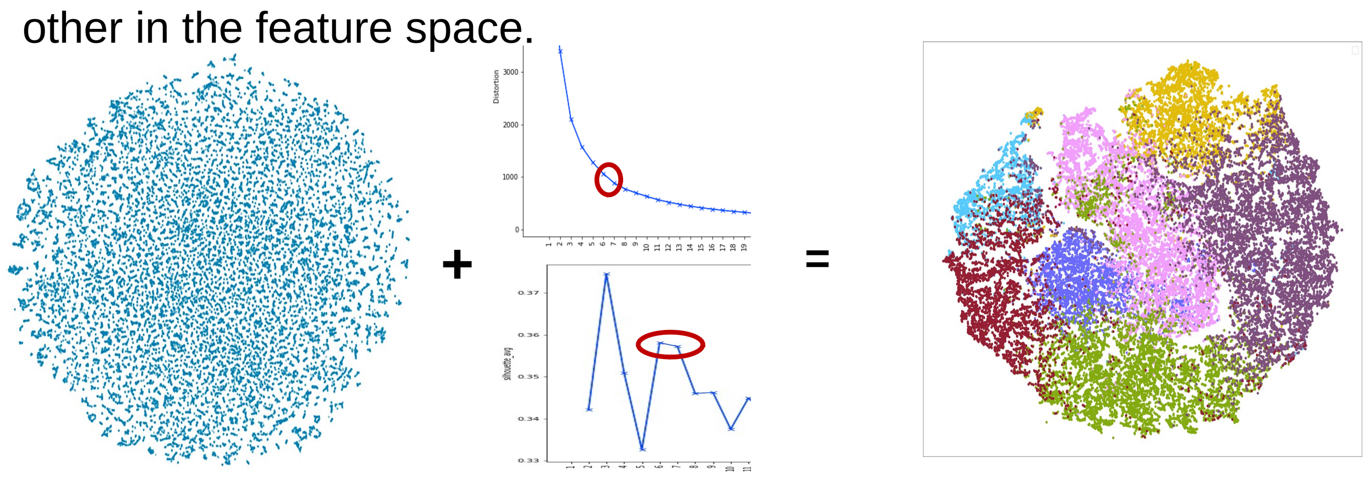
II.III Analysis of the feature space and main results



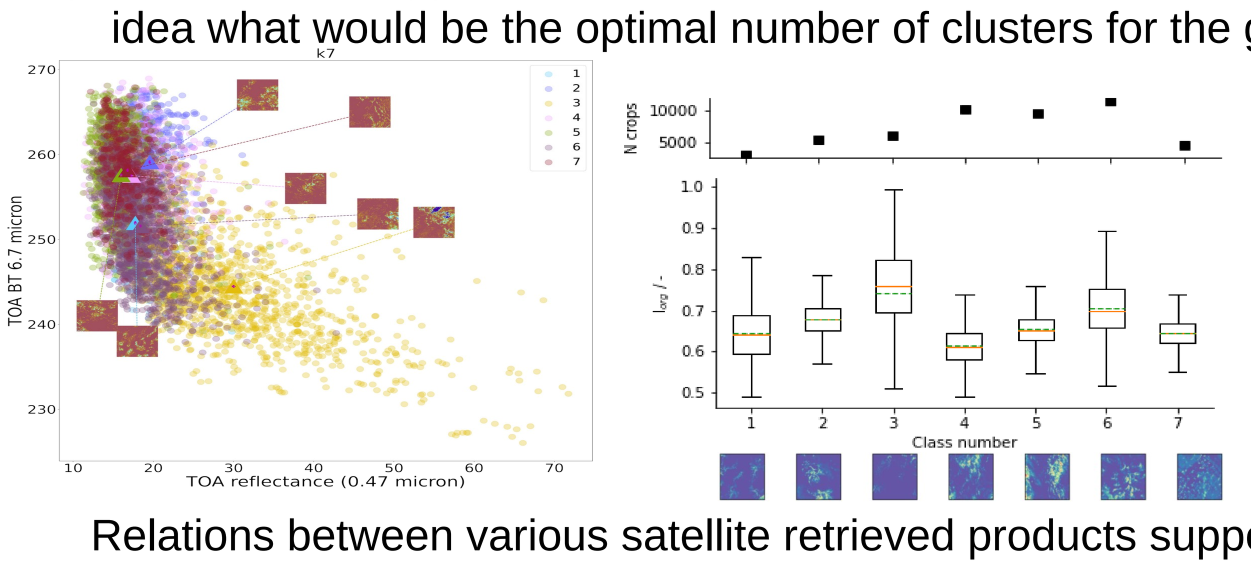
In the soft space, 300 random samples are shown. Similar cloud systems lie closer to each other in the feature space.



EUREC4A campaign core period similarly distributed as past years



Features of the samples trained using the pseudo continuous approach are used as an input in statistical approaches such as Elbow method and Silhouette method to get an idea what would be the optimal number of clusters for the given feature space



Different satellite measurement channels and cloud metrics[4] helps studying the physical properties of the cloud systems

Relations between various satellite retrieved products supports the physical interpretation of the identified cloud classes. Colors reveal separation of the different classes. Triangles mark centroids for which corresponding images are shown.

Take Home message:

I. The neural network is able to separate cloud structures and distributions and analysis with both cases provides a physical interpretation of the identified cloud systems.

II. Test of the algorithm from a different year show same clusters, confirming the reliability of the methodology

III. The generalization capacity of the deep neural network with unseen data is promising but depends on the spatial scale of cloud systems.

References:

[1] Caron, M., et al. (2020) doi: 10.48550/arXiv.2006.09882
[2] Goyal, et al. (2021) doi: 10.48550/arXiv.2103.01988
[3] Chen et al. (2020) https://doi.org/10.48550/arXiv.2002.05709
[4] Janssens, M., et al. (2021). doi: 10.1029/2020GL091001
[5] Deneke, H., et al. (2021) doi: 10.5194/amt-14-5107-2021
[6] Walther & Heidinger (2012) doi: 10.1175/JAMC-D-11-0108.1