Characterization of cloud variability through novel satellite-based observations

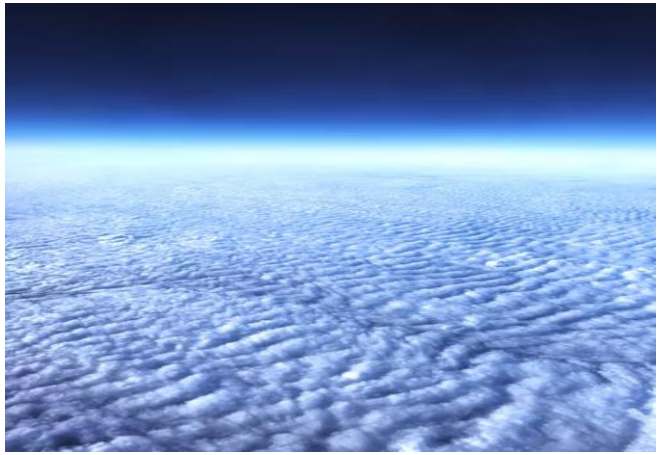
Dwaipayan Chatterjee, Hartwig Deneke, Susanne Crewell

Computational resources from

Motivation

Cloud system appearance (structure and distribution) results from complex interplay of physical processes and large-scale environmental conditions
→ large interest in cloud classification

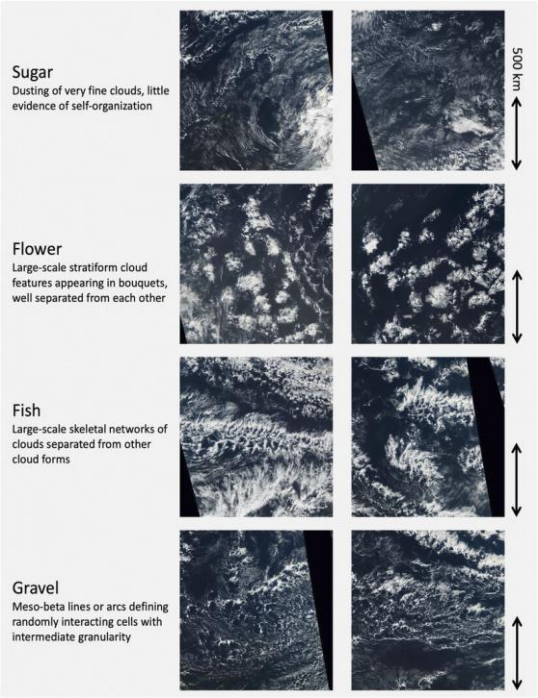


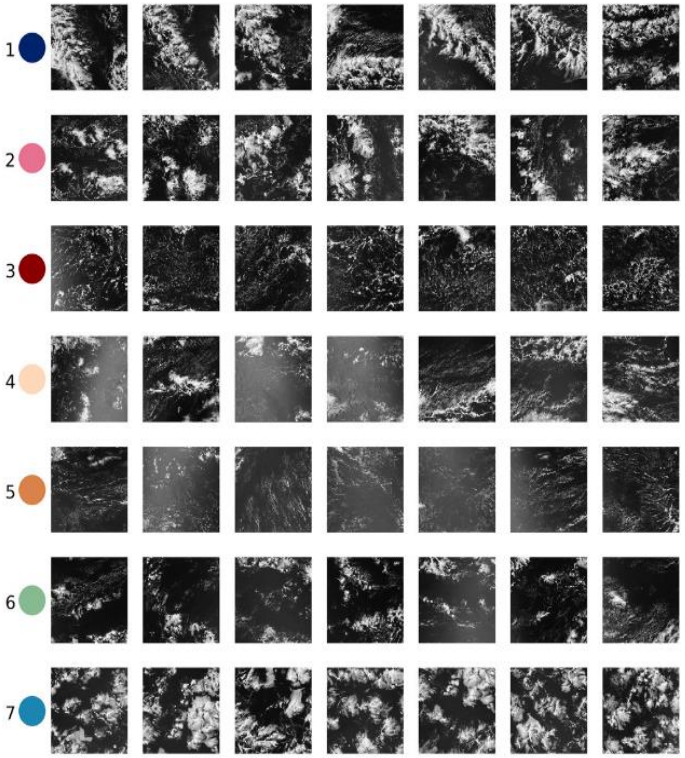
Cloud organization ⟷ cloud feedback ⟷ climate sensitivity



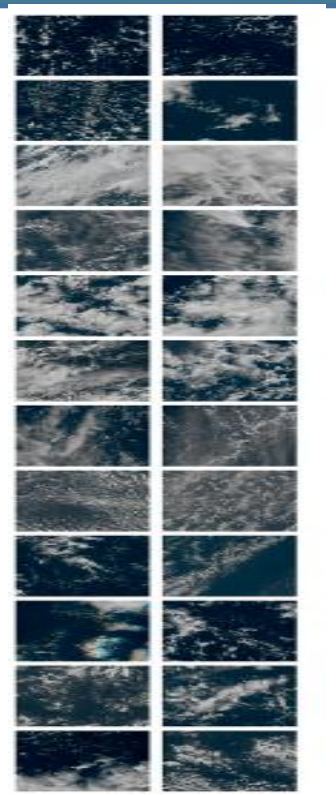
Previous Work



Visual inspection
Stevens et al., 2019



Traditional approach of using human-defined metrics
Janssen et al., 2019



Unsupervised machine learning
Denby, 2019

How can we classify cloud systems?

Our approach

Previous studies

- only consider tropical clouds over water
  → expand to central European domain
- make at least some use of human decisions
  → consider a purely data driven approach

Challenges

- Cloud systems transform continuously
  → categories are transient
- Likelihood of closeness should be assed by machine learning

Use a bottom-up approach where the network learns a suitable hidden representation of the data

Guiding Questions

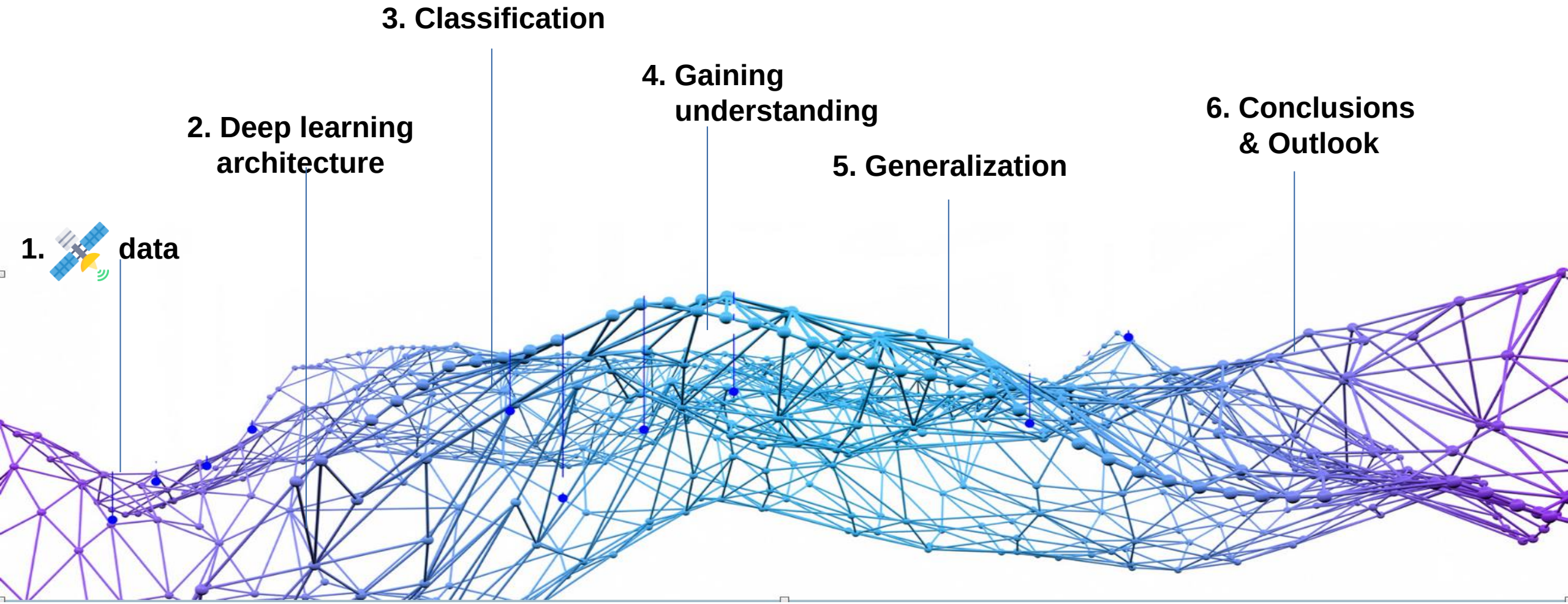
1. How can we use deep learning to identify different cloud systems?

2. How can we physically interpret the identified classes?

3. What are the measures to identify the right number of classes?

4. Can the model generalise well on unseen data?

Overview


3. Classification
4. Gaining understanding
2. Deep learning architecture
6. Conclusions & Outlook
5. Generalization
1. data

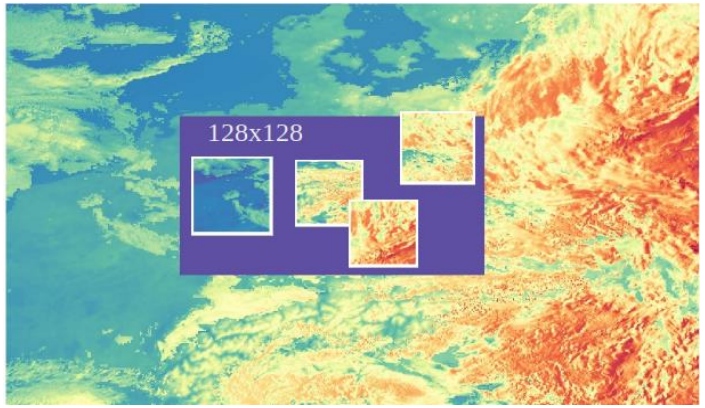
1. Satellite Data

Meteosat Second Generation (MSG) →  → Meteosat Third Generation (MTG)

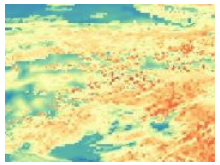
Satellite data

- Enhanced resolution MSG data set (Deneke et al., AMT, 2021)
- Cloud optical depth (COD) and 10 additional retrieval products, e.g. top of the atmosphere reflectivity, downwelling solar radiation
- April to July 2013 + 2015

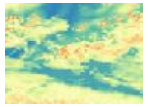
= central European domain



Two different sizes tested



128x128
= 256x256 km



64 x 64
= 128x128km

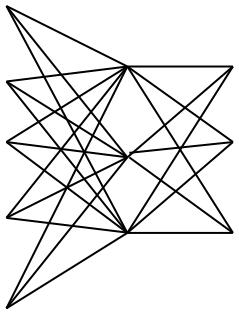
4 <u>random</u> crops at any instant

2. Deep Learning Architecture

Residual Network

Non Linear Projection

Input: COD Images



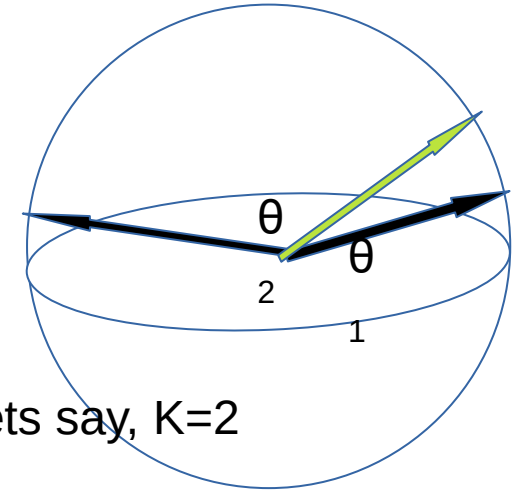
Forward Propogation

Back Propogation

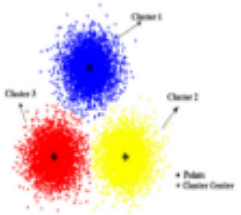
Contrastive Loss F(n)

Supervised training phase

N =1,2,.....49,50

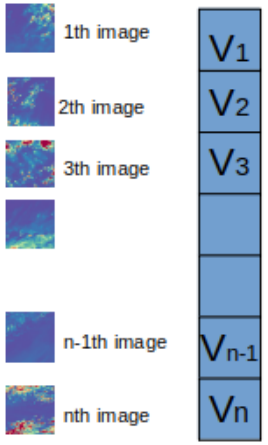


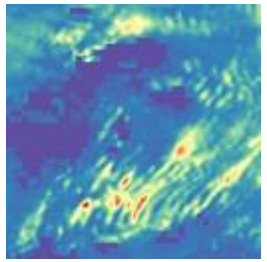
Lets say, K=2



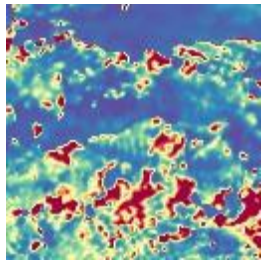
Spherical K-means_cluster

Assignment Phase





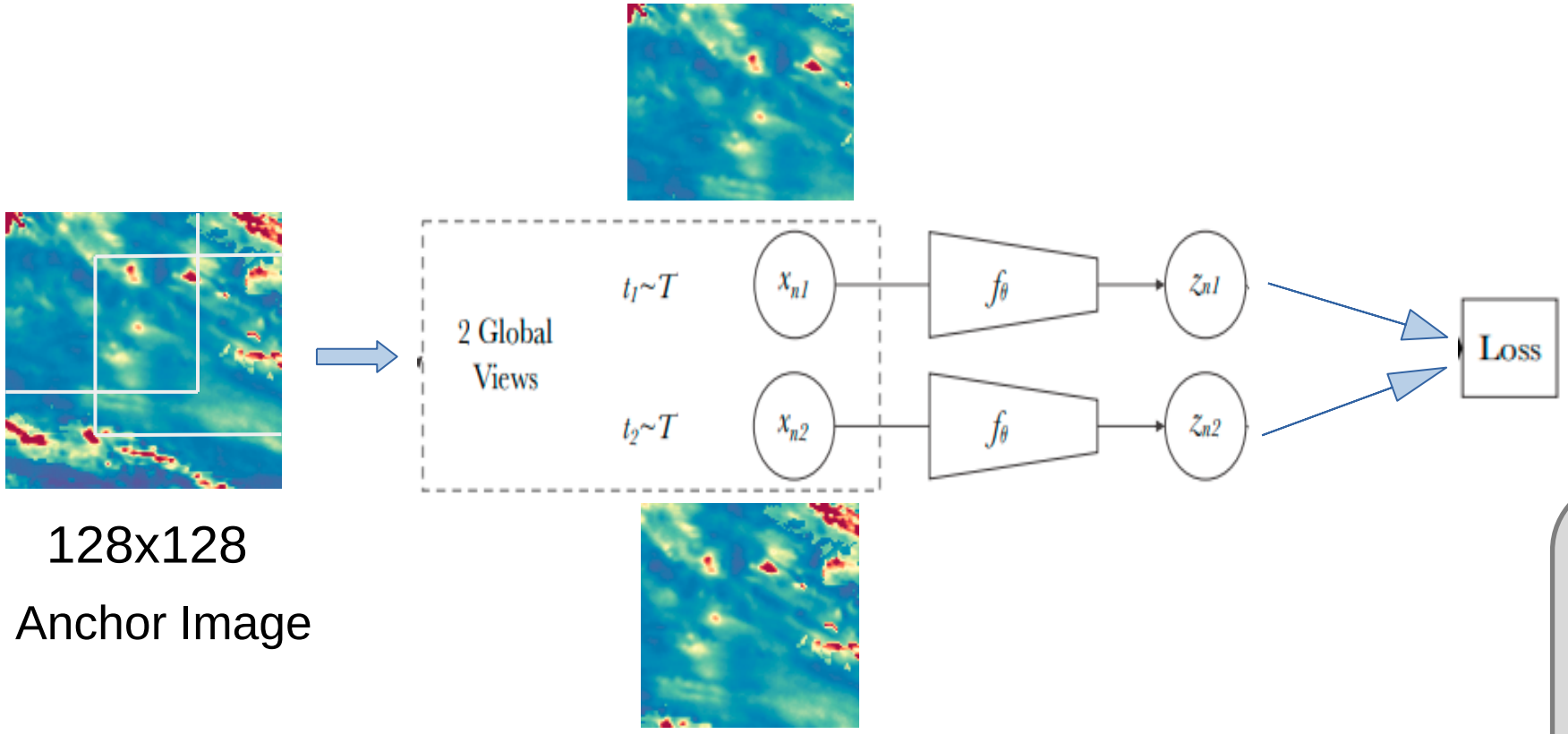
Class 1



Class 5

Facebook artificial intelligence research (FAIR) (Caron, 2018, 2021)
FAIR Open source Vision Self Supervised Learning (VISSL) library (Priya Goyal, 2021)

2. Deep learning architecture and data pipeline



128x128

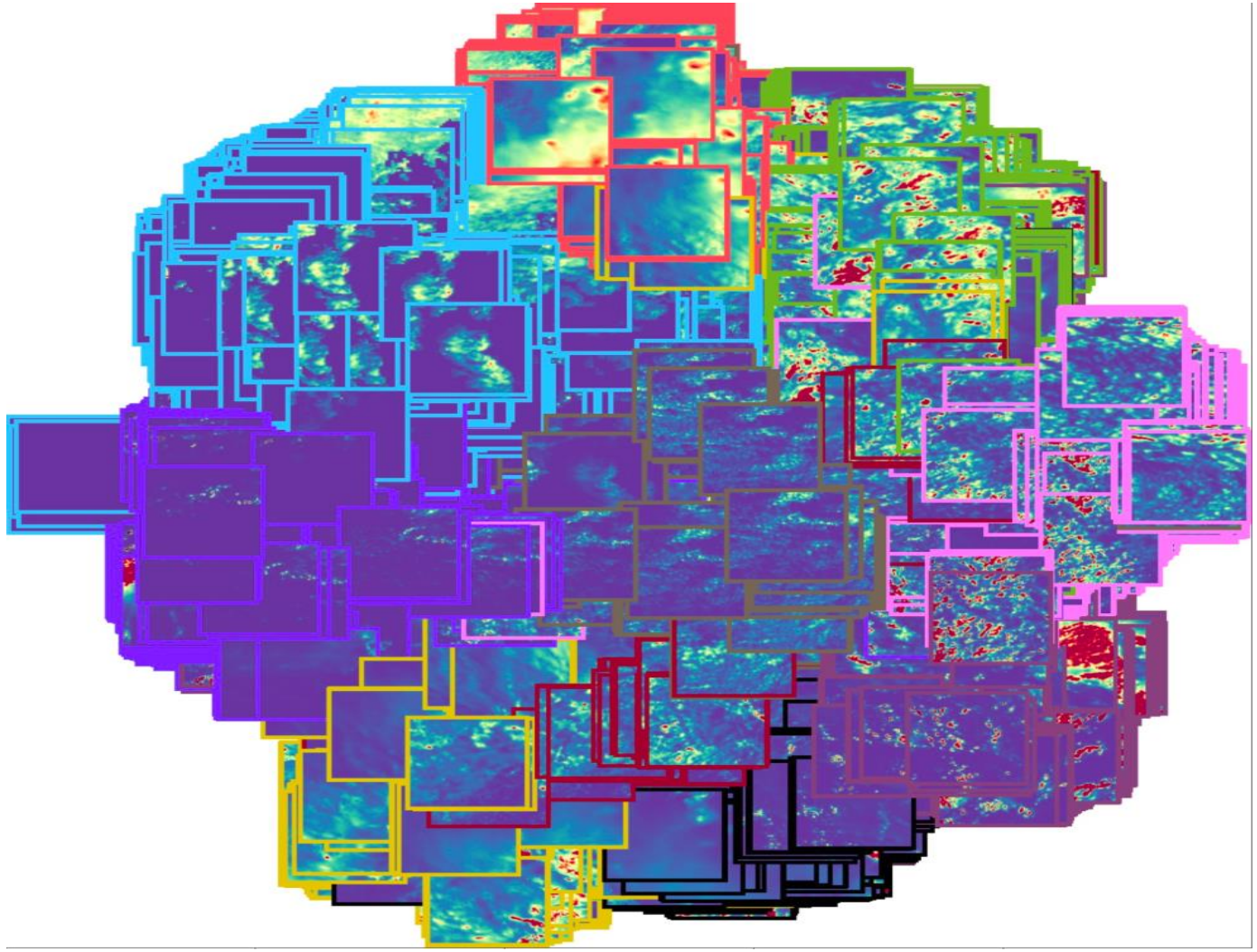
Anchor Image

Random_crops_96x96

global to global views

By using data augmentation such as random crops in our case, we discourage memorization and encourage generalization.

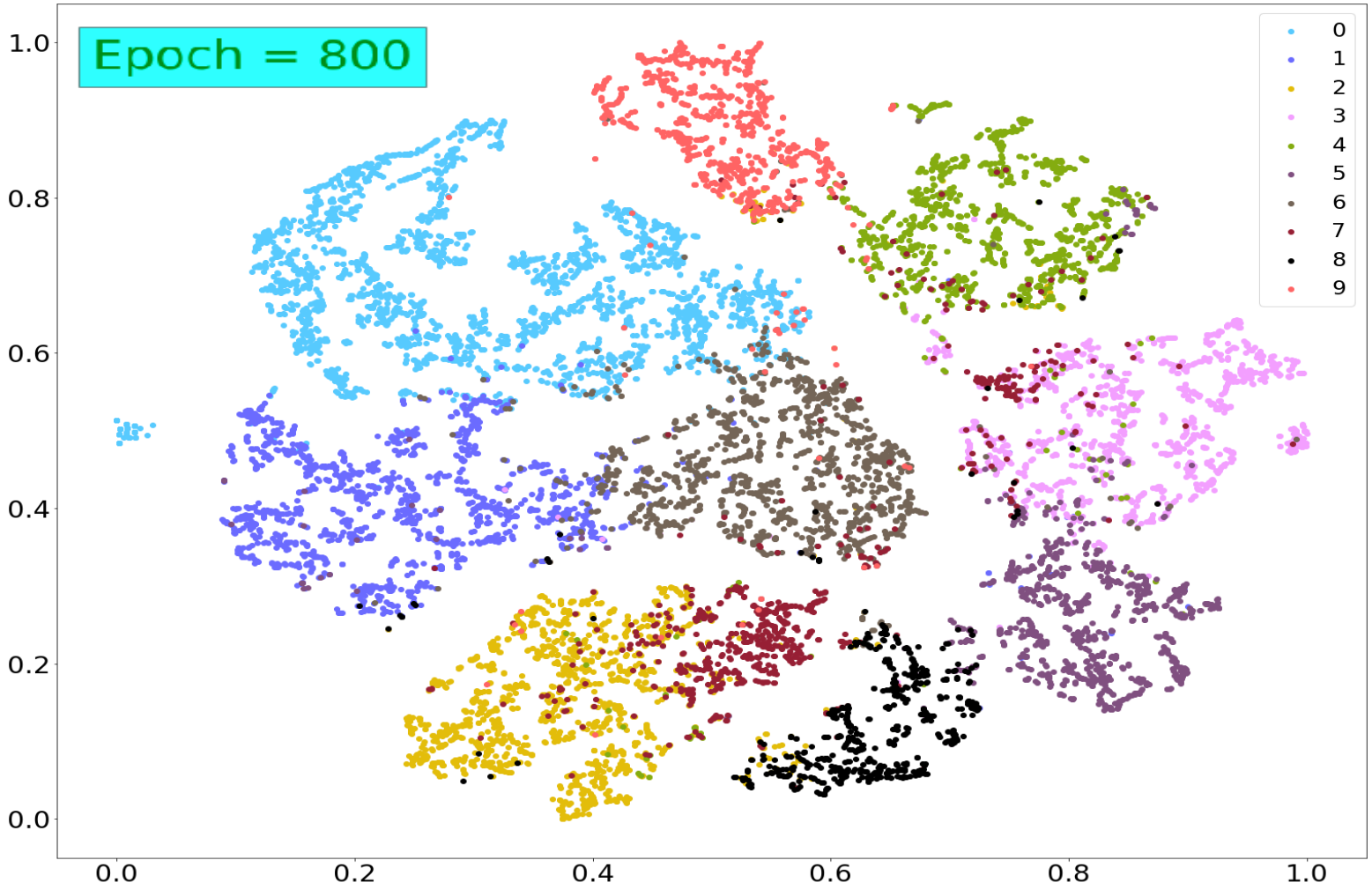
3. Classification result



Deep learning model assigns unique class (coloured frame) to each image

3. Classification

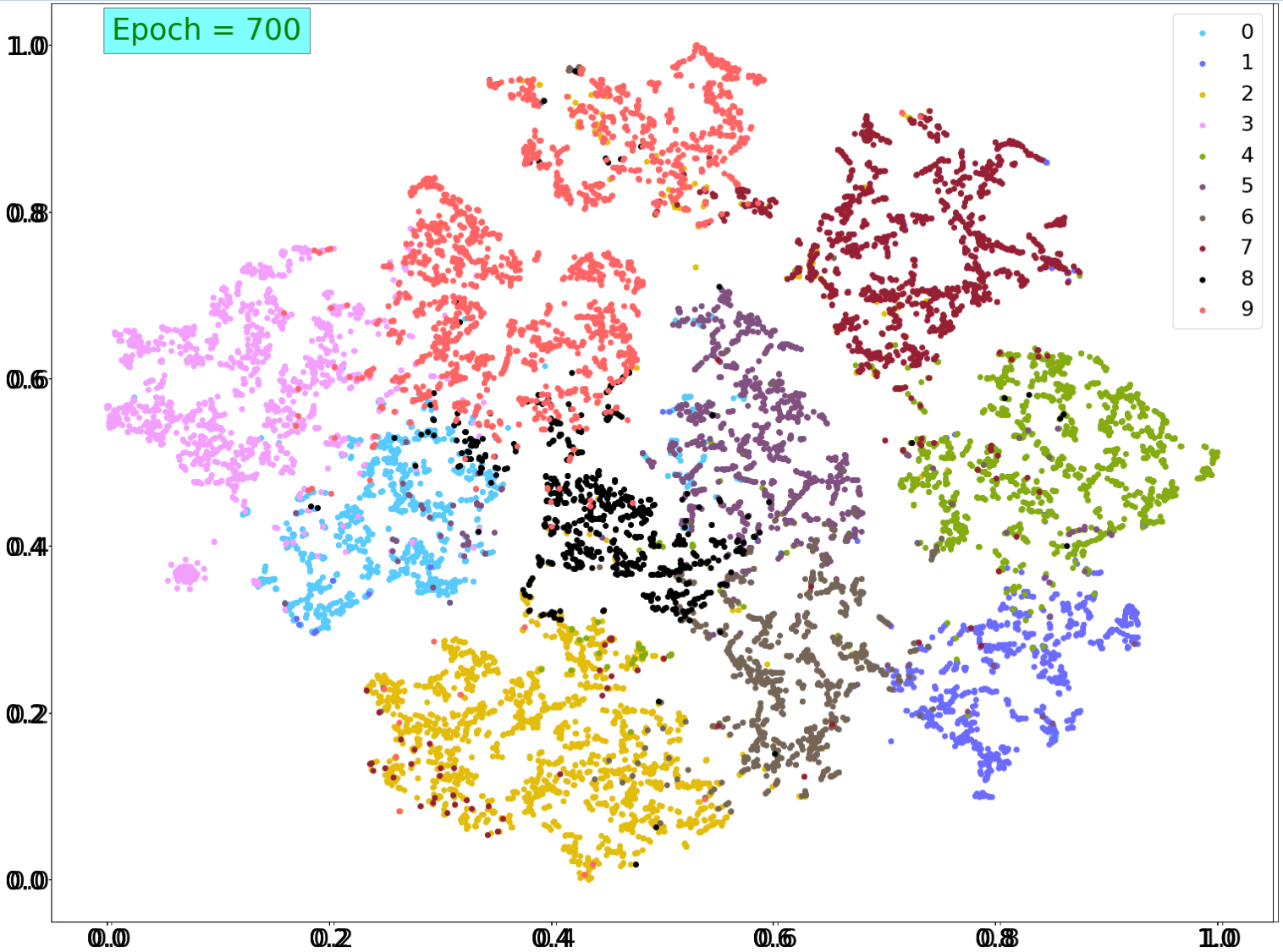
Evolution of understanding by the deep neural network



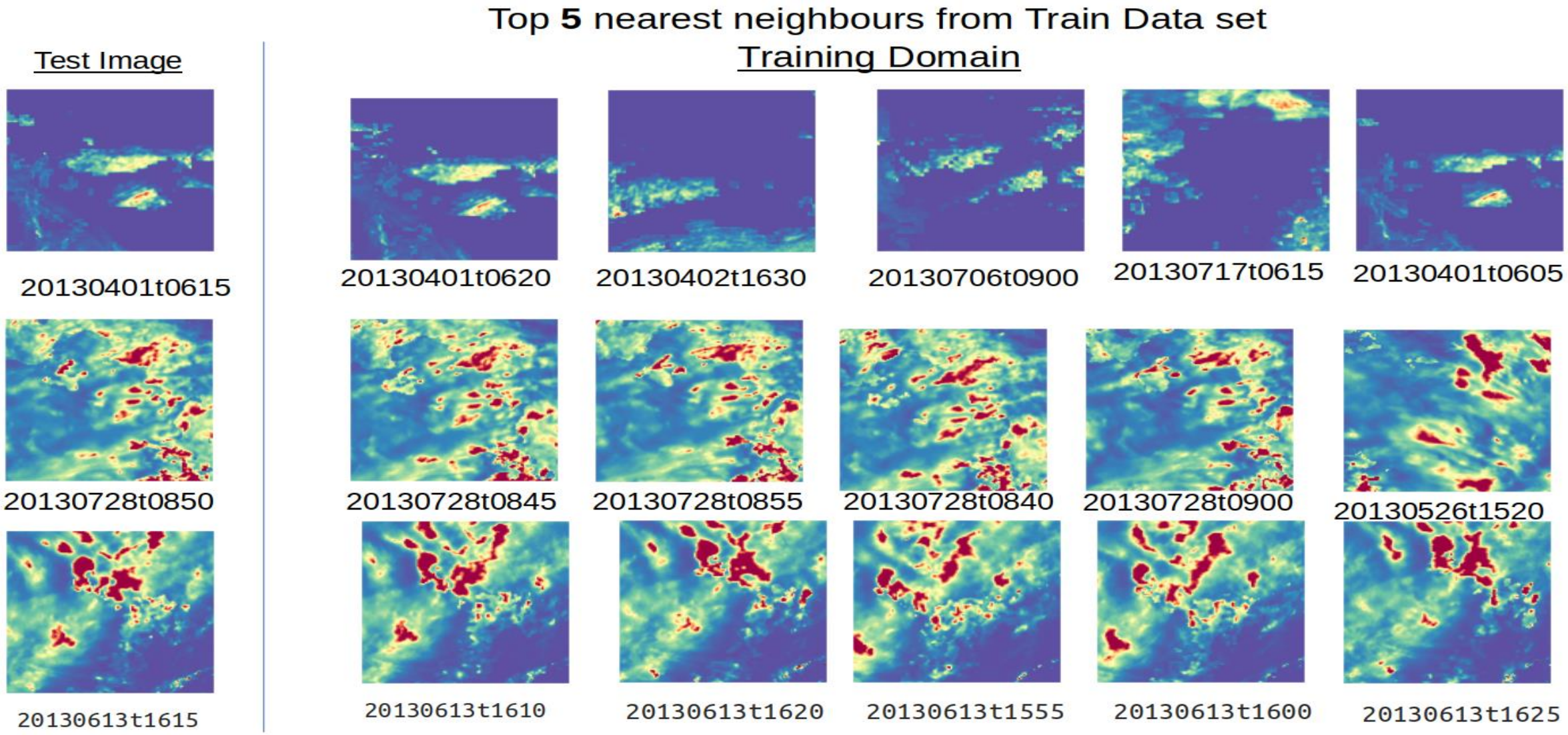
3. Classification

Good convergence achieved from 250 epoch

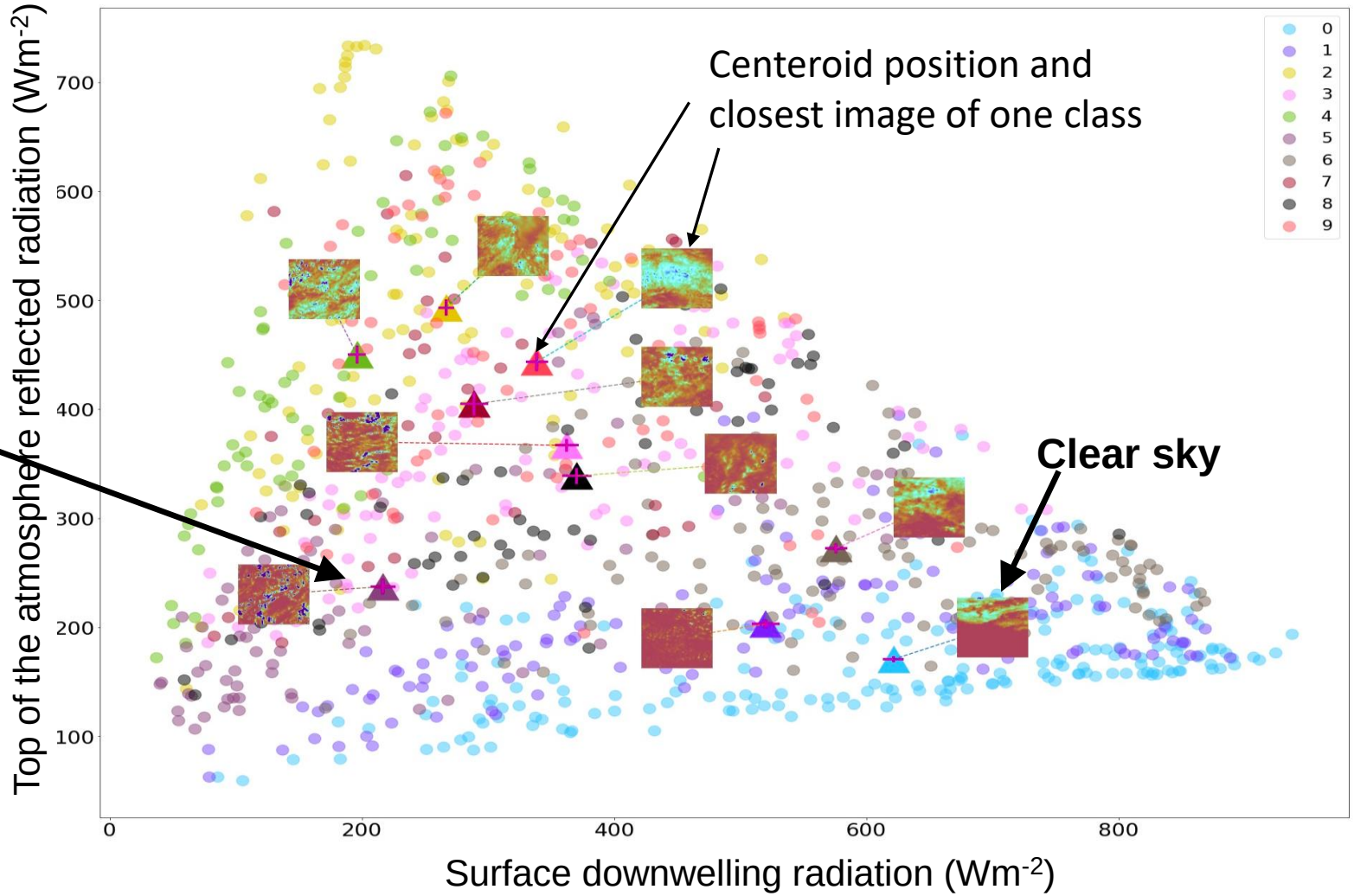
After 700 epoch clear segregation



3. Classification: Closeness

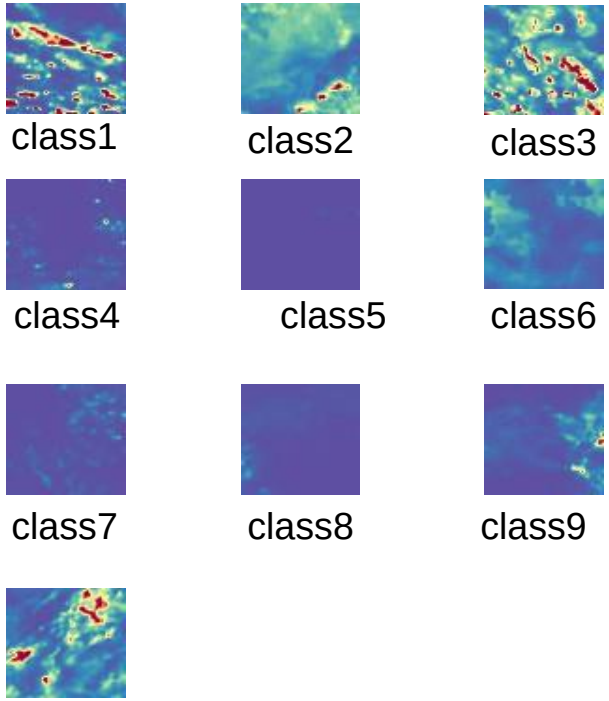


4. Gaining understanding: Physical significance

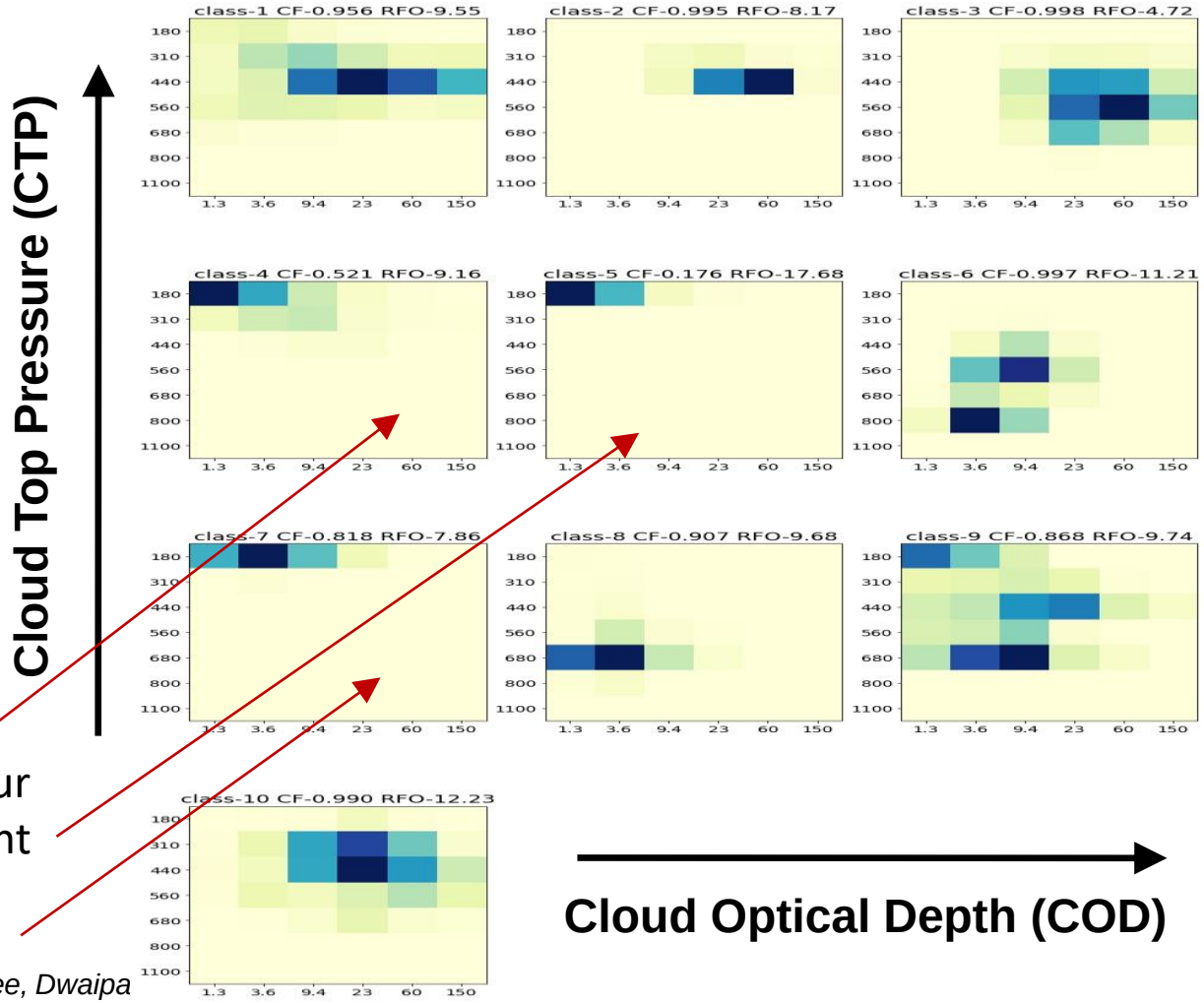


4. Gaining understanding: Number of classes

Centeroid images of 10 classes identified for small (64x64) region



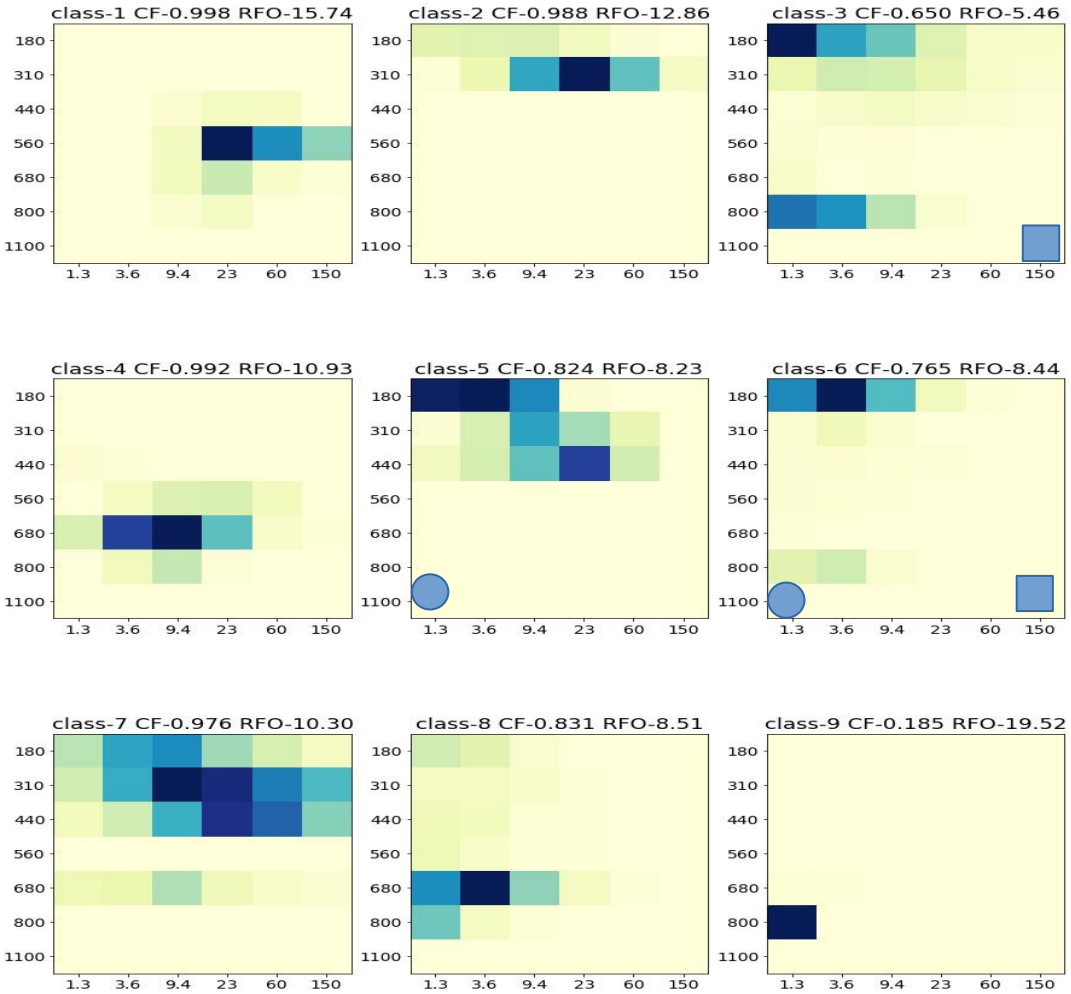
Frequency of occurrence in COD-CTP space following Oreopoulos et al., 2016



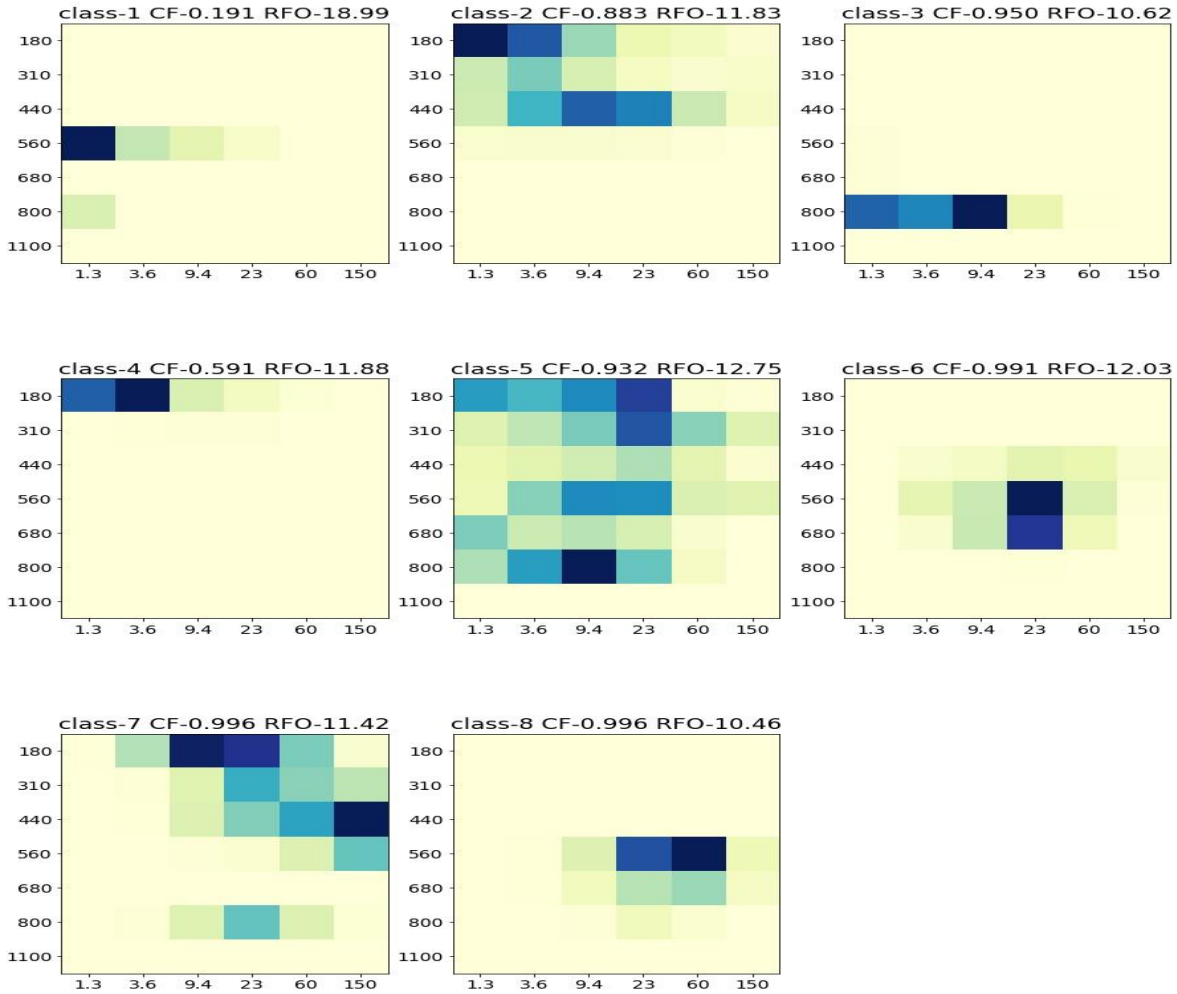
Similar behaviour found in different classes

4. Gaining understanding: Number of classes

N = 9



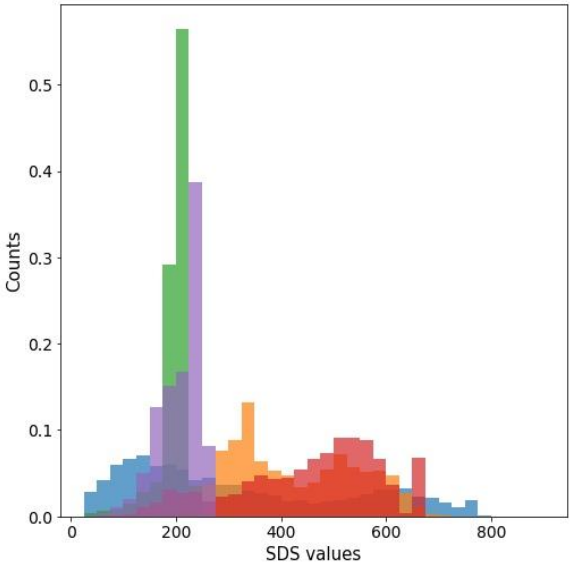
N = 8



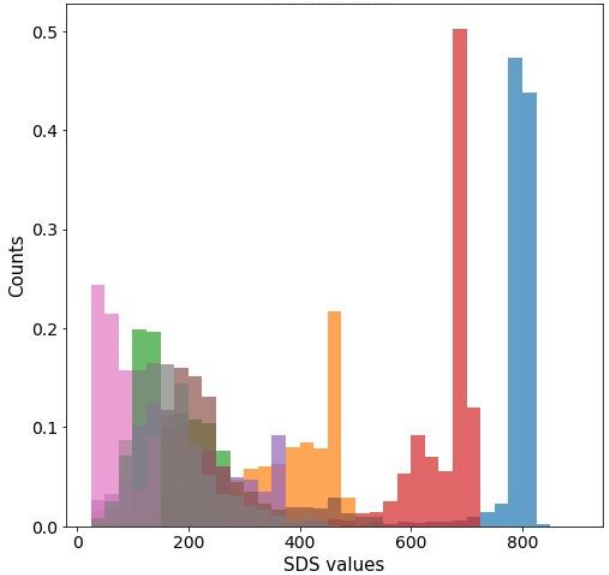
4. Gaining understanding: Targeted Parameter

Goal: Identification of highly variable conditions of solar energy

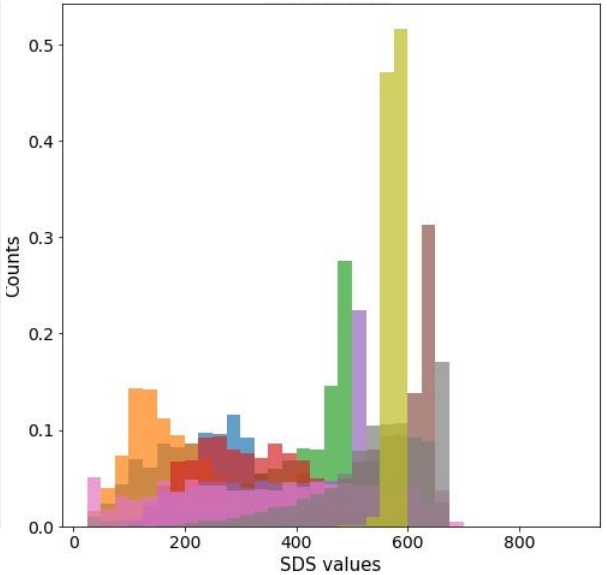
5 classes



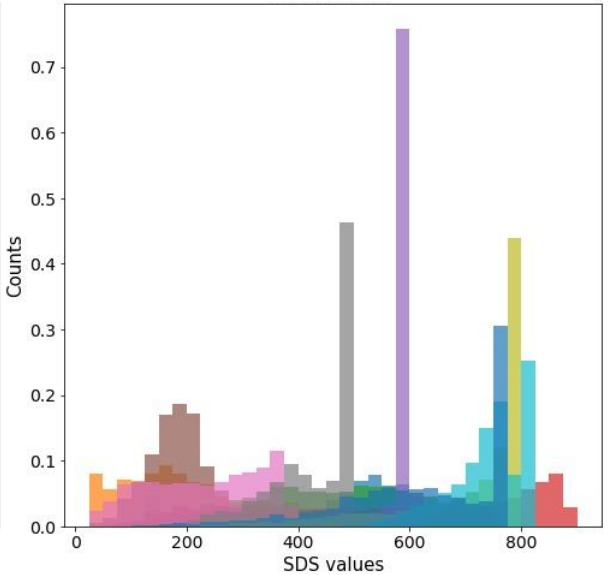
8 classes



9 classes



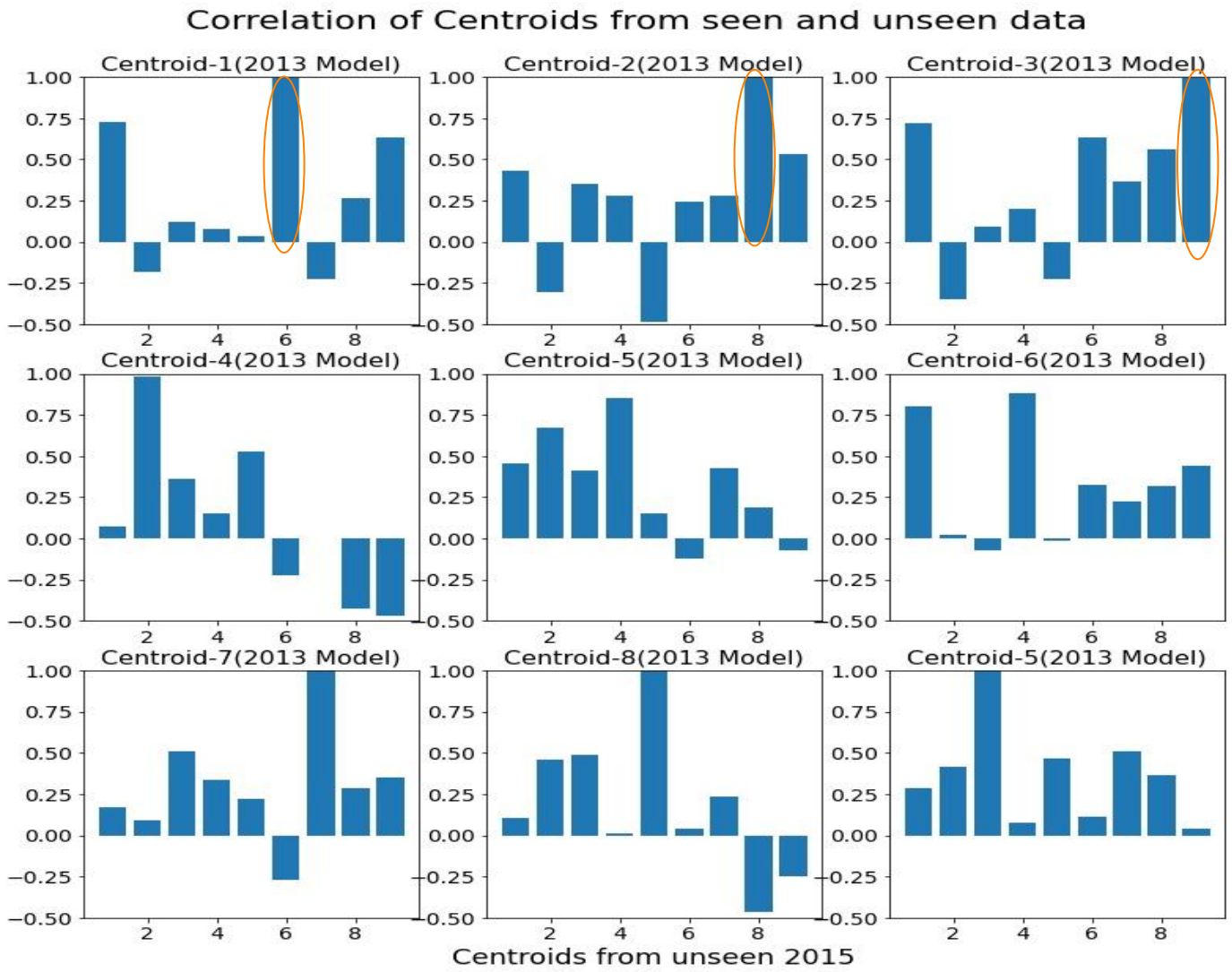
10 classes



Surface downwelling radiation (Wm^{-2})

Less representaion ⟷ **More classes Repetition**

5. Generalization

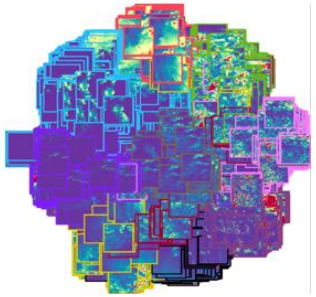


Inta Cluster distance of seen and unseen data from Centroids Which are closely related as 0.99 show good consistency in the spread

Conclusions

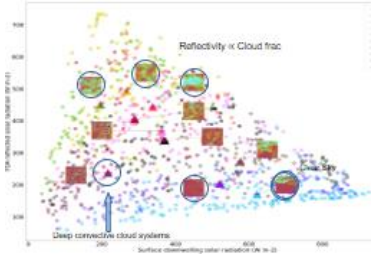
1. How can we use deep learning to identify different cloud systems?

DeepClusterV2 based self-supervised learning approach can identify distinct can cloud regimes in complex central European environment



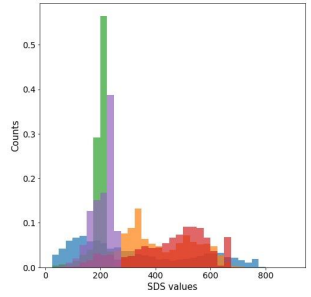
2. How can we physically interpret the identified classes?

Satellite retrieval products support the physical interpretations of identified cloud regime classes



3. What are the measures to identify the right number of classes?

Depending on purpose of classification different metrics can be used



4. Can the model generalise well on unseen data?

Generalisation tested with unseen data using centroid embeddings
→ correlations up to 0.99 and similar distance distributions