Objective classification of cloud organisation with unsupervised neural networks

Leif Denby, School of Earth and Environment, University of Leeds

EUREC4A

UNIVERSITY OF LEEDS

Aim

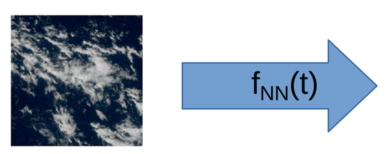
Produce software to **automatically segment and classify** a satellite image **into regions with differently organised convection** and through this **study how these types of organisation form**

Motivation

- Form of organisation affects radiative properties (albedo) and cloud-radiative feedback contributes **majority of climate sensitivity uncertainty** (Bony et al 2015 and many more)
- **Relative importance of local and large-scale** factors driving convection into specific forms of organisation are **unknown**
- **Use tool on satellite images** to identify where different forms of organisation occour and **correlate with environmental state** diagnosed from reanalysis data (e.g. ERA5)

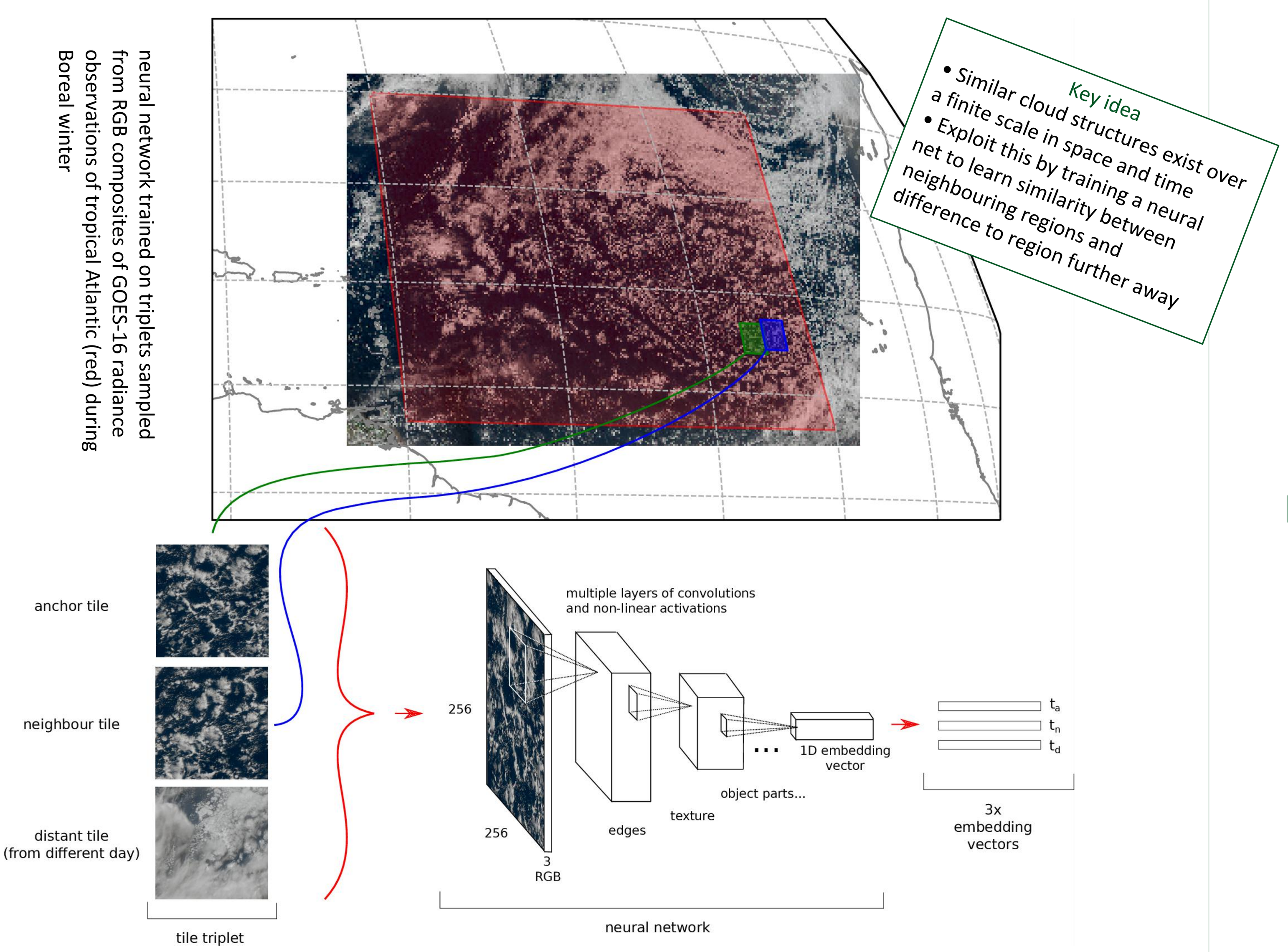
Method

- Produce for every tile (t) of a satellite image an *embedding*. A point in N-dimensional space



= [0.12, 0.82, ...]

- Enforce tiles with similar cloud structure to be close in this N-dimensional space
- Previous successful *embedding* method: Google's word2vec (Mikolov et al 2013): f("london") - f("england") ~ f("copenhagen") - f("denmark"). Here using technique of Tile2Vec (Jean et al 2018) which learnt land-use classification



neural network trained on triplets sampled from RGB composites of GOES-16 radiance observations of tropical Atlantic (red) during Boreal winter

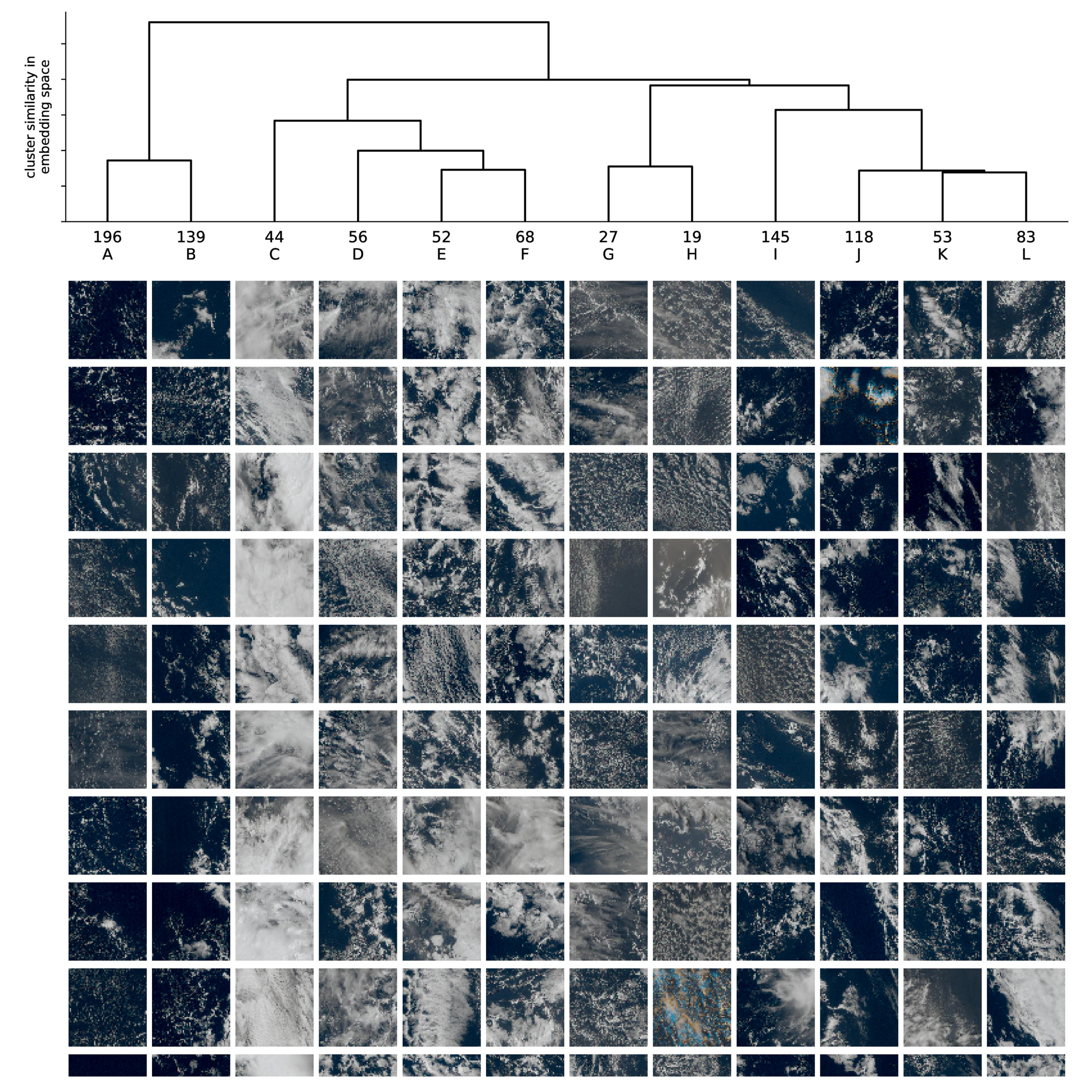
- Every training example consists of three tiles (triplet): the *anchor* (t_a), *neighbour* (t_n) and *distant* (t_d) tiles. All fed through NN (f_θ) simulatenously.
- Use loss function which optimises for *anchor* and *neighbour* tiles to be close in embedding space and *distant* tile to be far away (measured by Euclidian distance):

$$L(t_a, t_n, t_d) = max(0, ||f_\theta(t_a) - f_\theta(t_n)||_2 - ||f_\theta(t_a) - f_\theta(t_d)||_2 + m)$$

f_θ is function of the neural net (θ representing the weights to be learnt) and $||\ldots||_2$ denotes the L2-norm (Euclidean distance) and m the target distance in Euclidean space.

Clustering and properties of 200km x 200km tiles

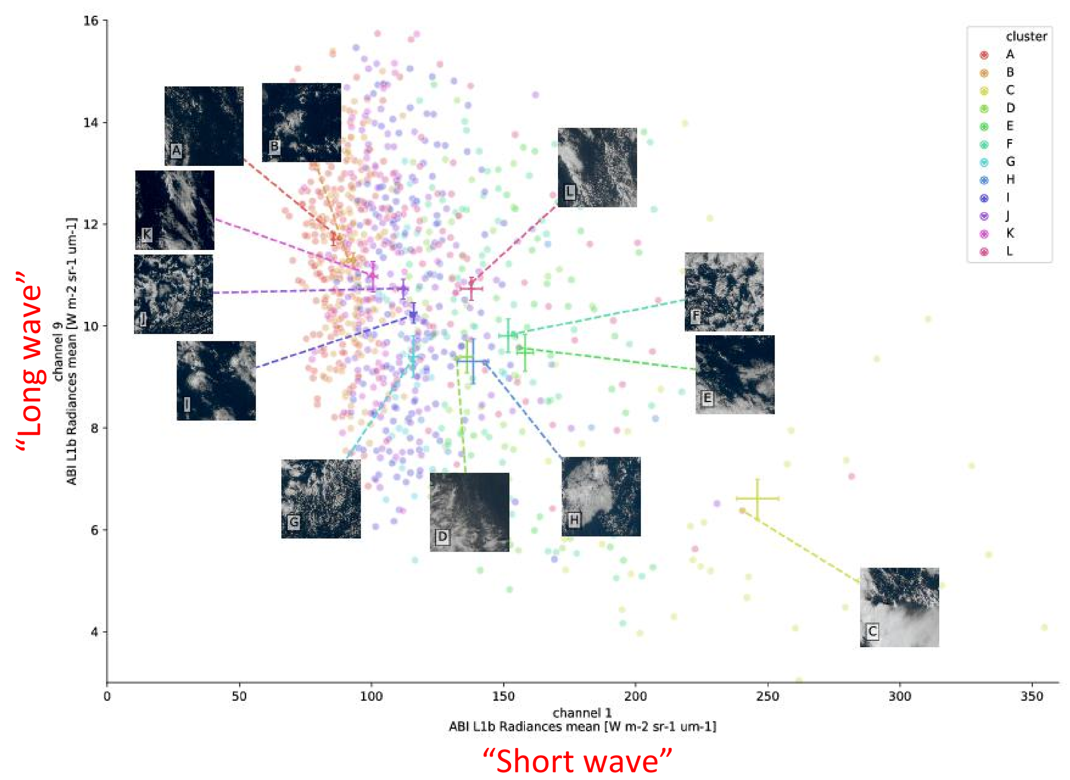
Clustering in the embedding space



Hierarchical clustering shows how tiles clump in *embedding space.* Here random tile examples are shown at point in hierarchy where 12 clusters exist

- *Nested* clusters share similar features
- Vertical distance in *dendrogram* (top) measures persistence of clusters

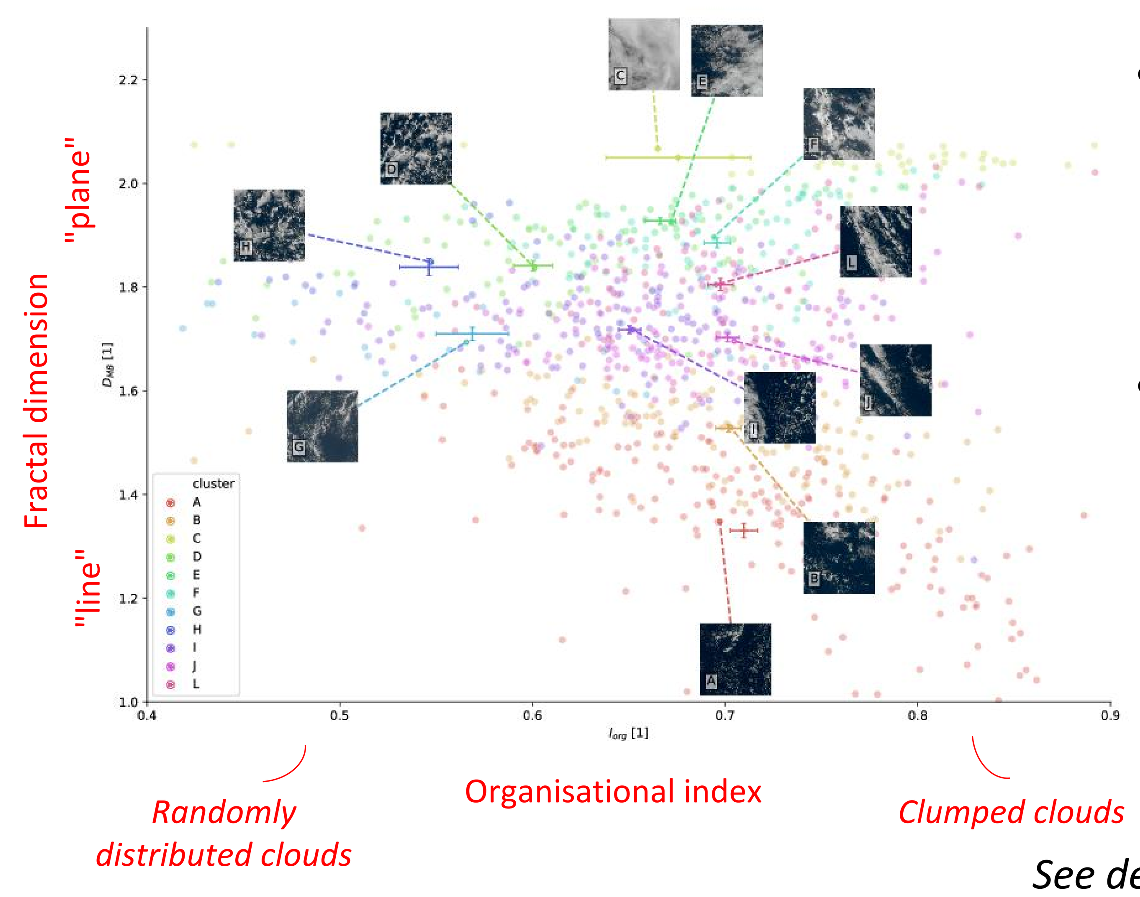
Radiative properties



Per-cluster mean of channel 1 (visible) and channel 9 (IR), error in the mean as error bars. Nearest tile to mean rendered as example

- Separation of clusters indicate each has specific radiative properties

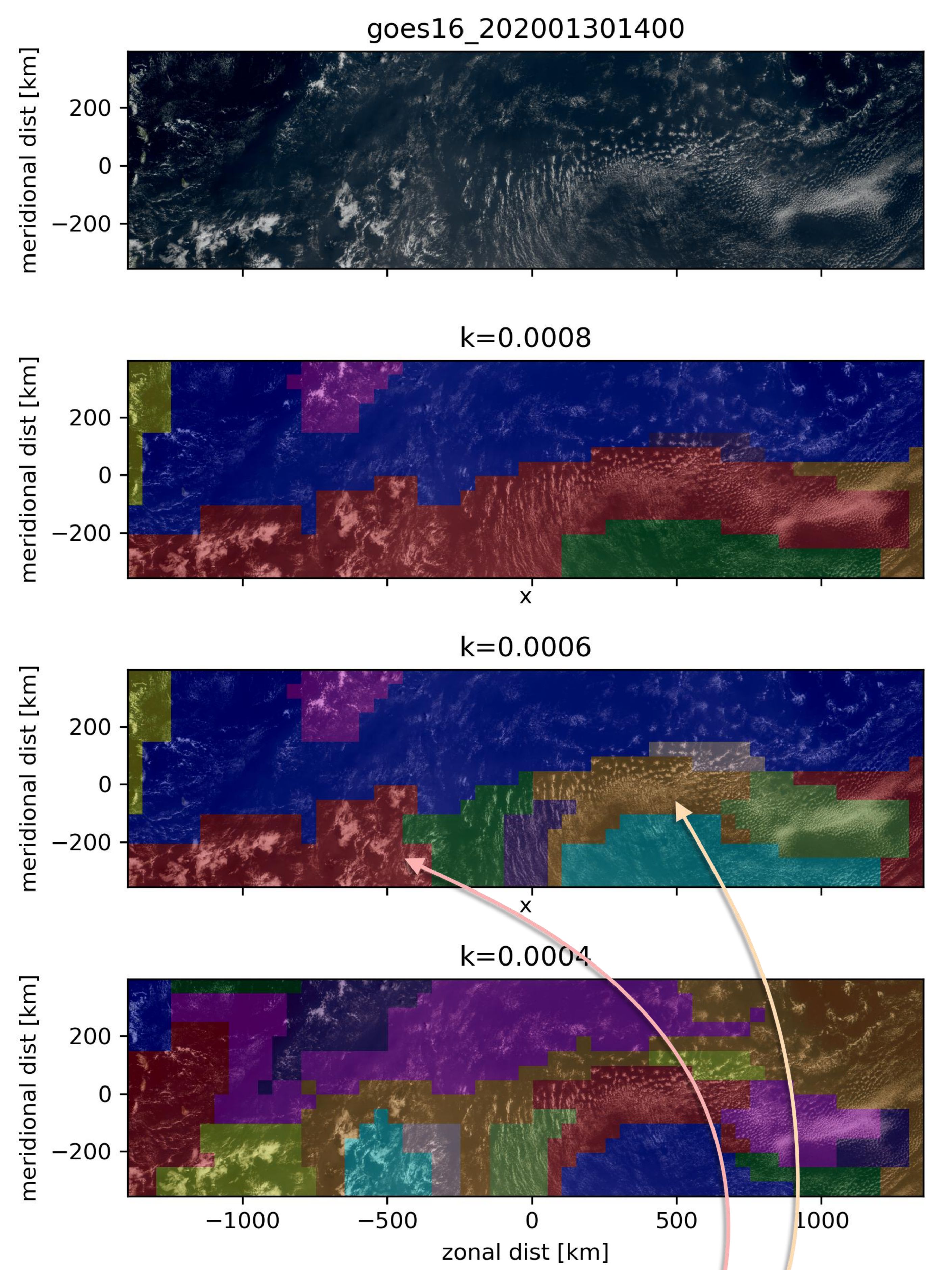
Morphological properties



- Forms of organisation identified by neural network clearly distinct => the neural network have identified distinct types of organisation
- Some organisation types are only separable when considering fractal dimension **and** organisational index (I_{org}, Tompkins & Simie 2017)

See details in L. Denby 2020 (GRL)

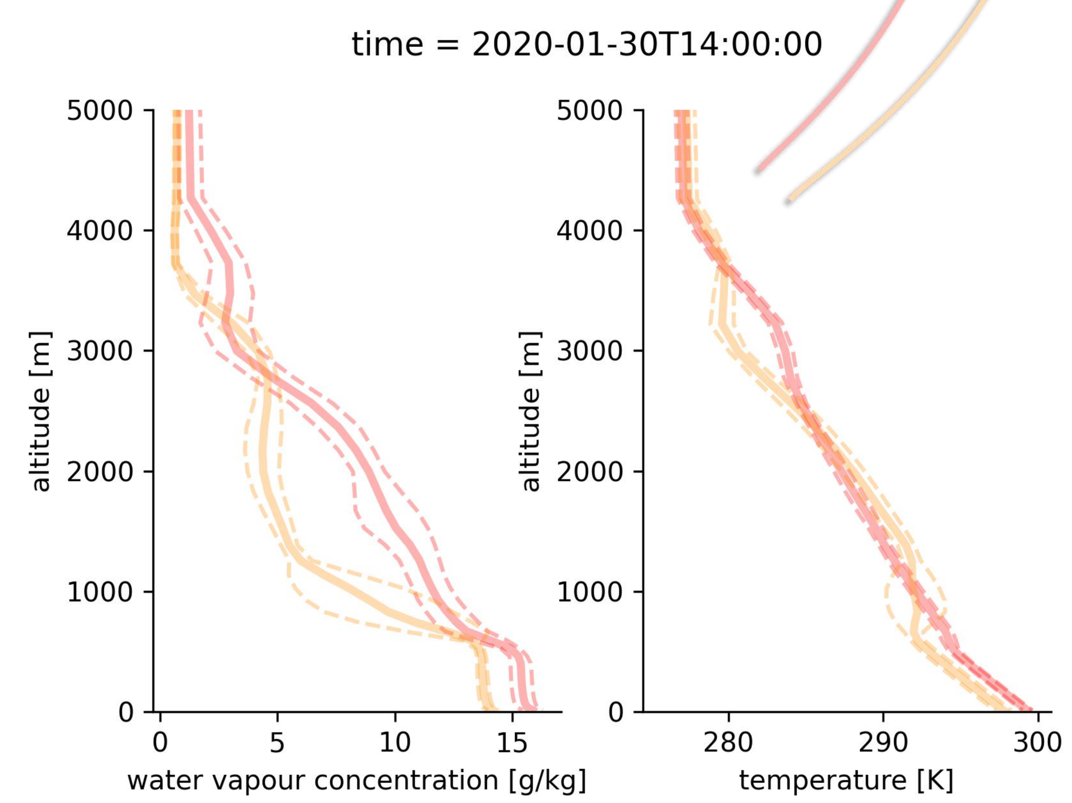
Spatial segmentation of organisation in tropical Atlantic



- produce embedding vector every 50km by applying neural network as a sliding-window
- segmented using spatial segmentation method (Felzenswalb 2009) with distance metric given by Eucledian distance in embedding space

Varying segmentation threshold (k) sets degree of similarity within clusters

ERA5 aggregated by segmentation



Compositing vertical profiles from ERA5 renanalysis using spatial segmentation from embedding space (dashed lines show standard deviation) we can study structure of atmosphere associated with different types of organisation

- Smaller scattered clouds associated with elevated dry layer, drier boundary layer and low-level inversion
- Larger "flower" clouds associated with lower trade inversion height and moister boundary layer

code available on https://github.com/leifdenby/convml_tt