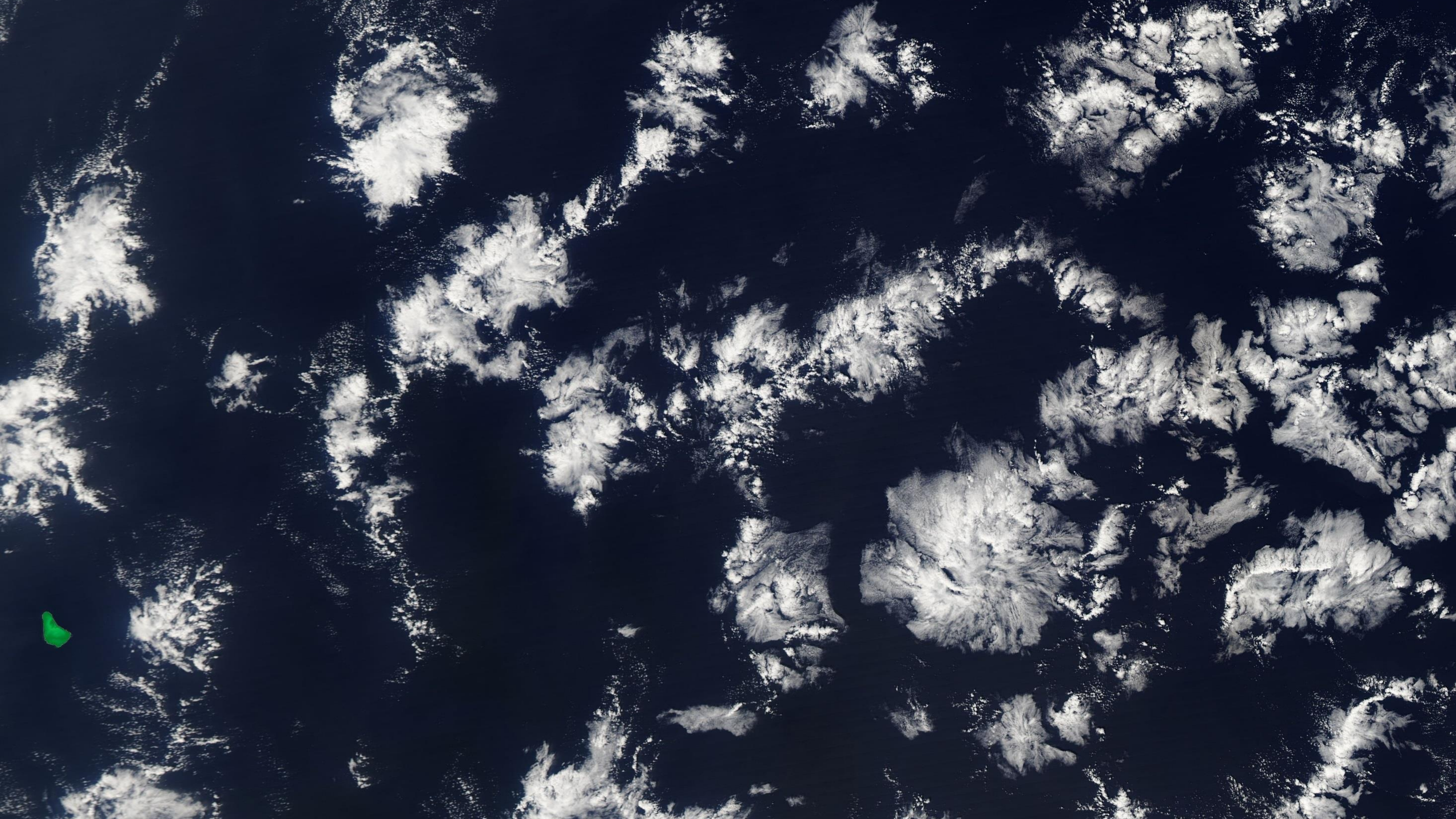
UNIVERSITY OF LEEDS

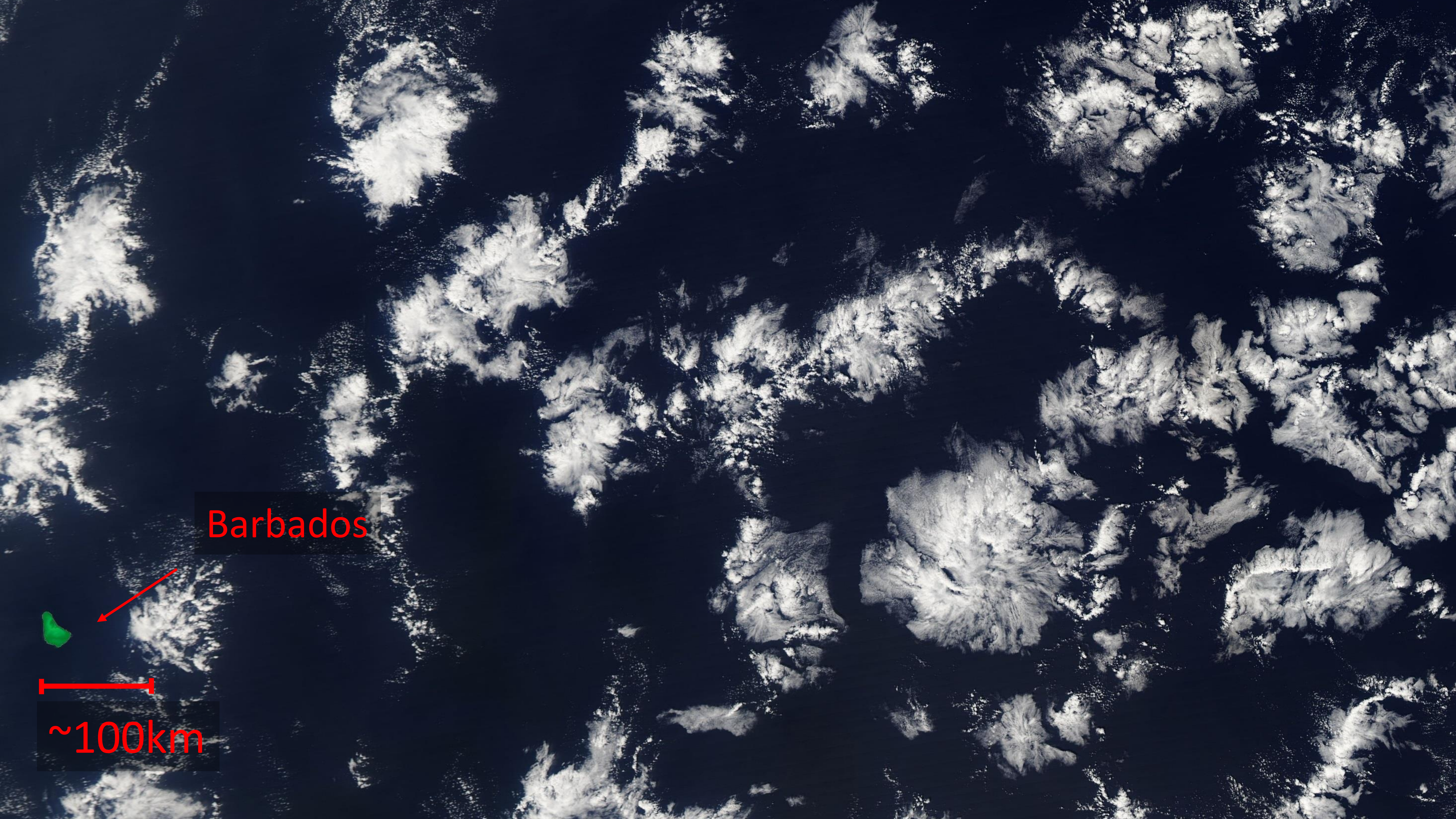
Studying convective organisation with Deep Learning

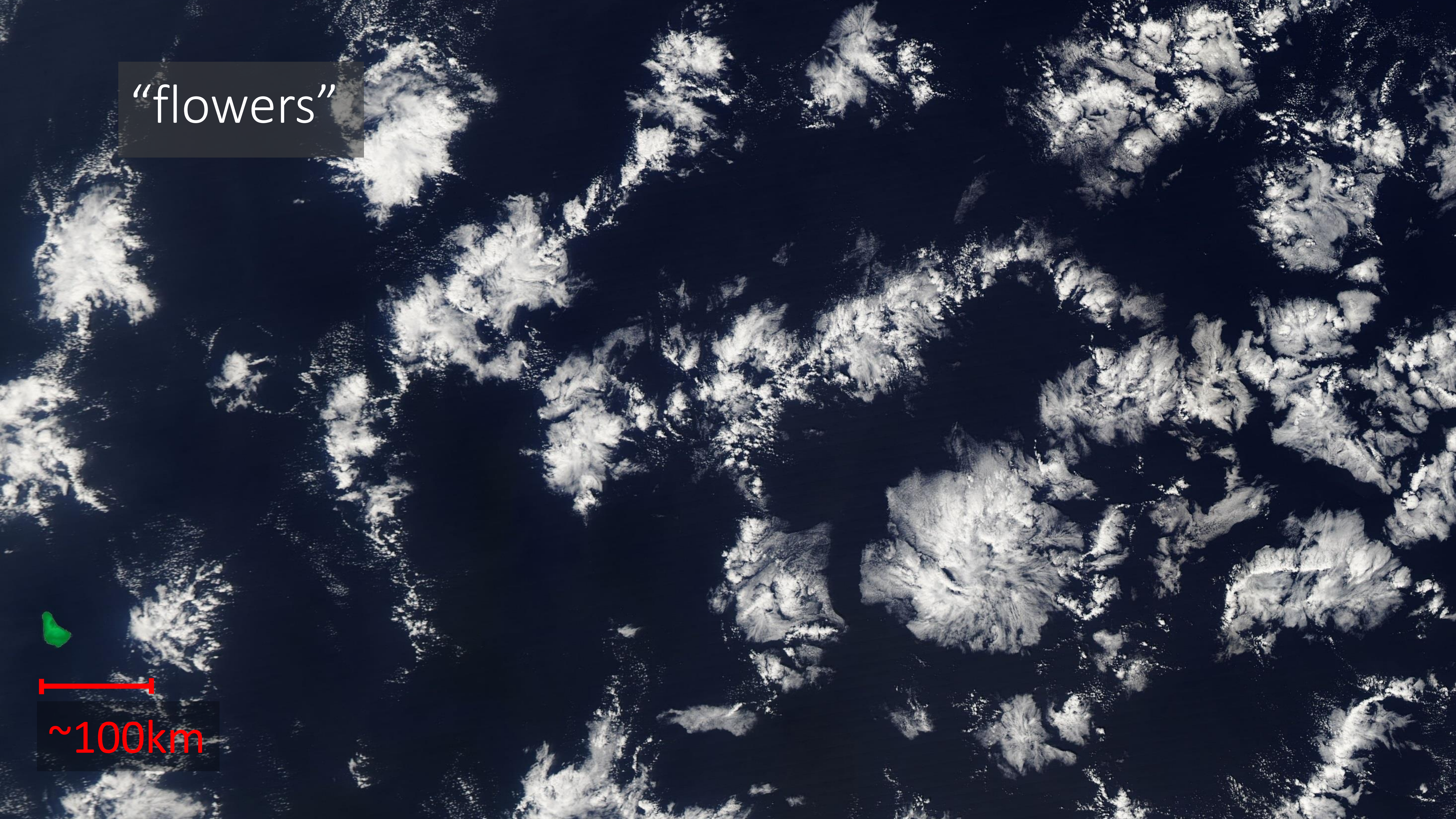
Leif Denby, ICAS, University of Leeds

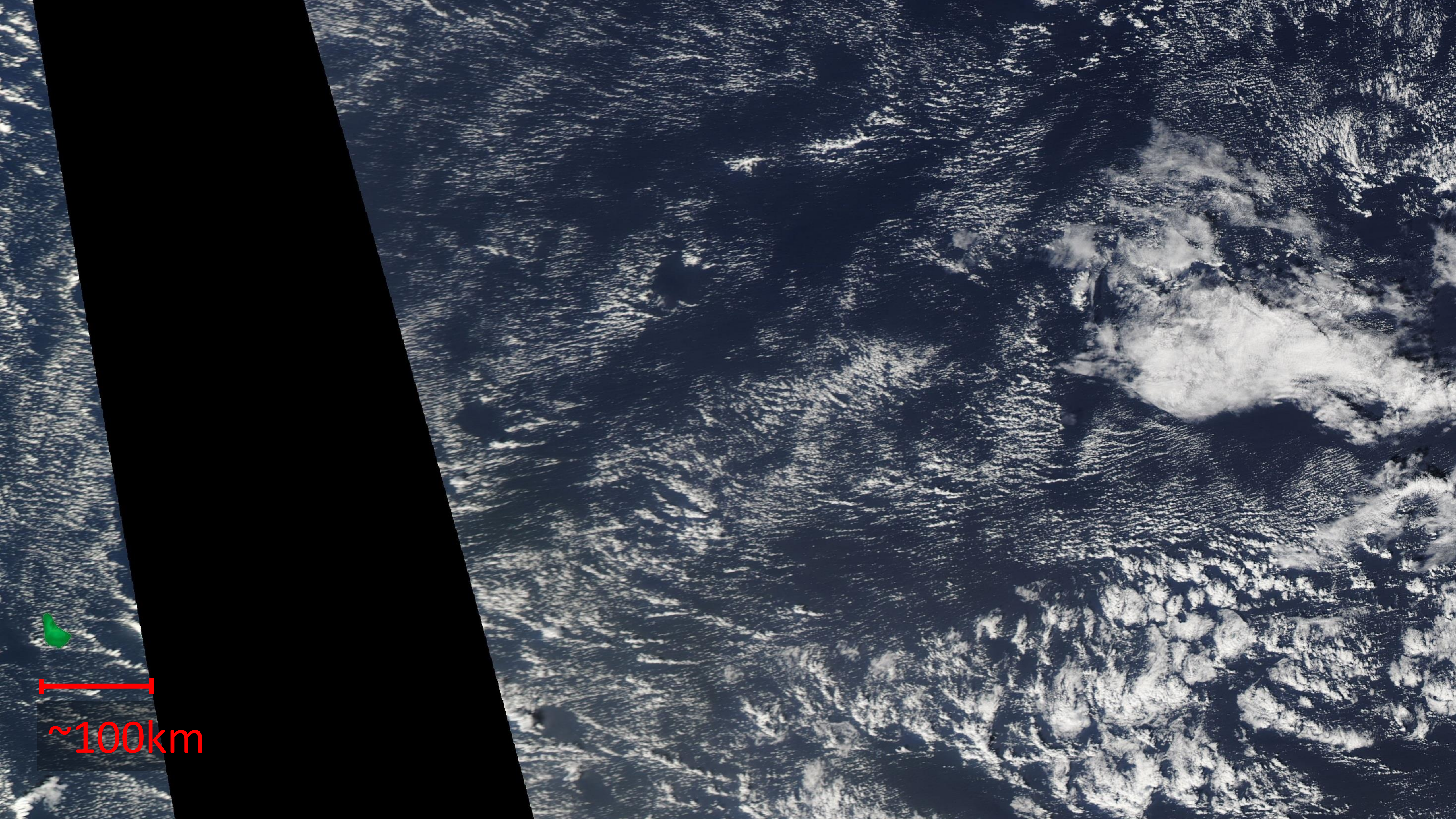
3/7/19

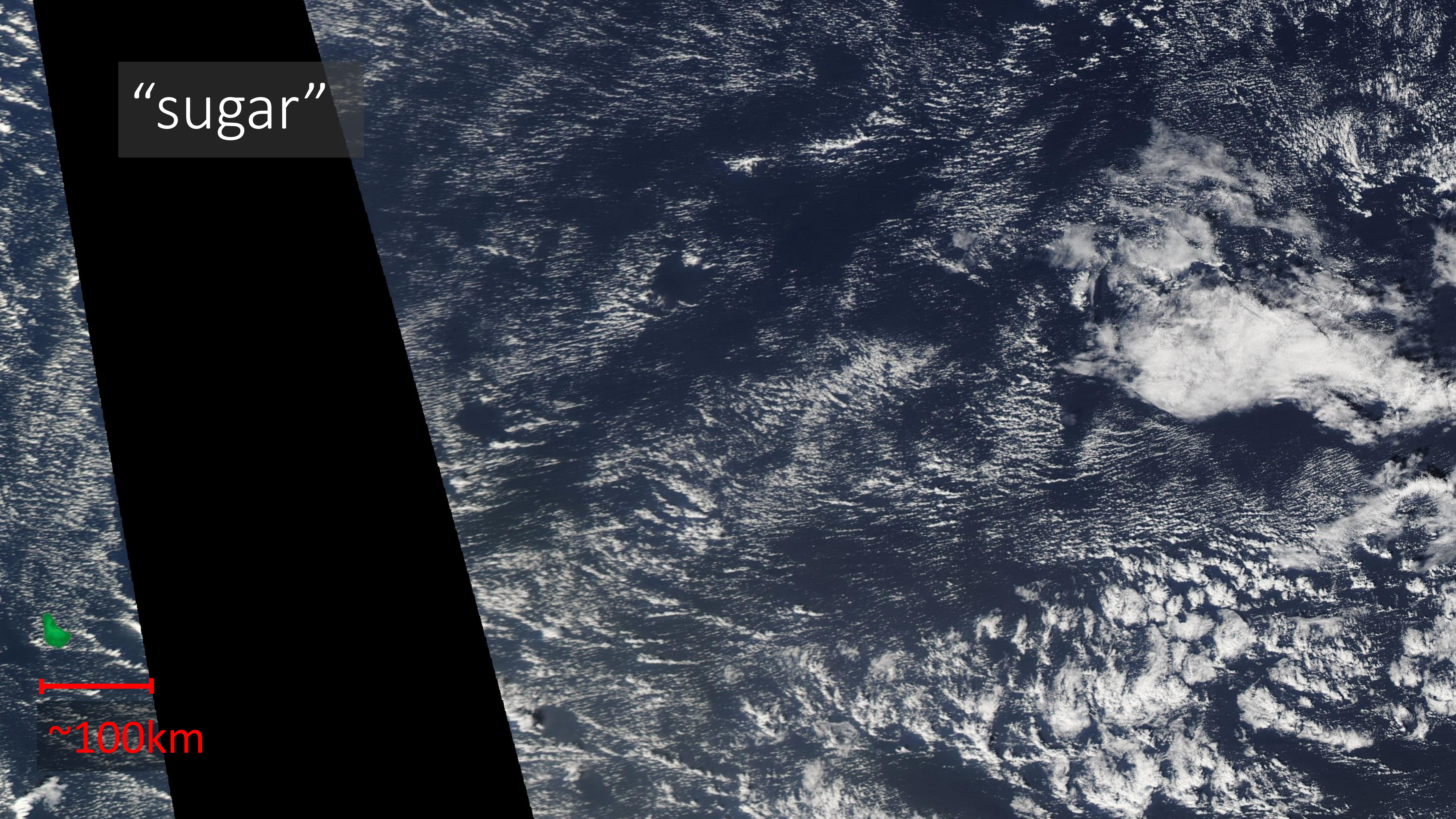
RMetS Atmospheric Science Conference

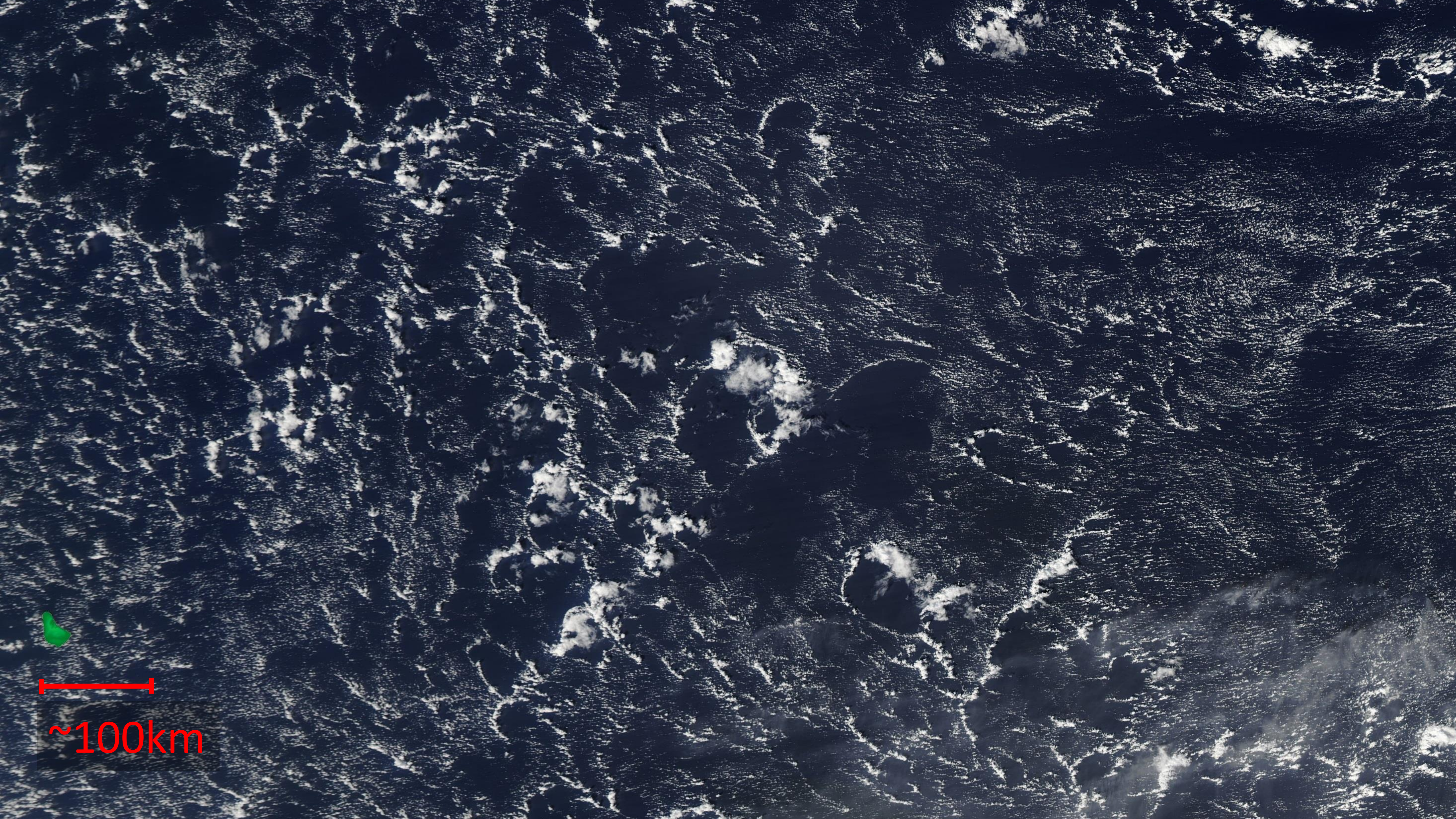


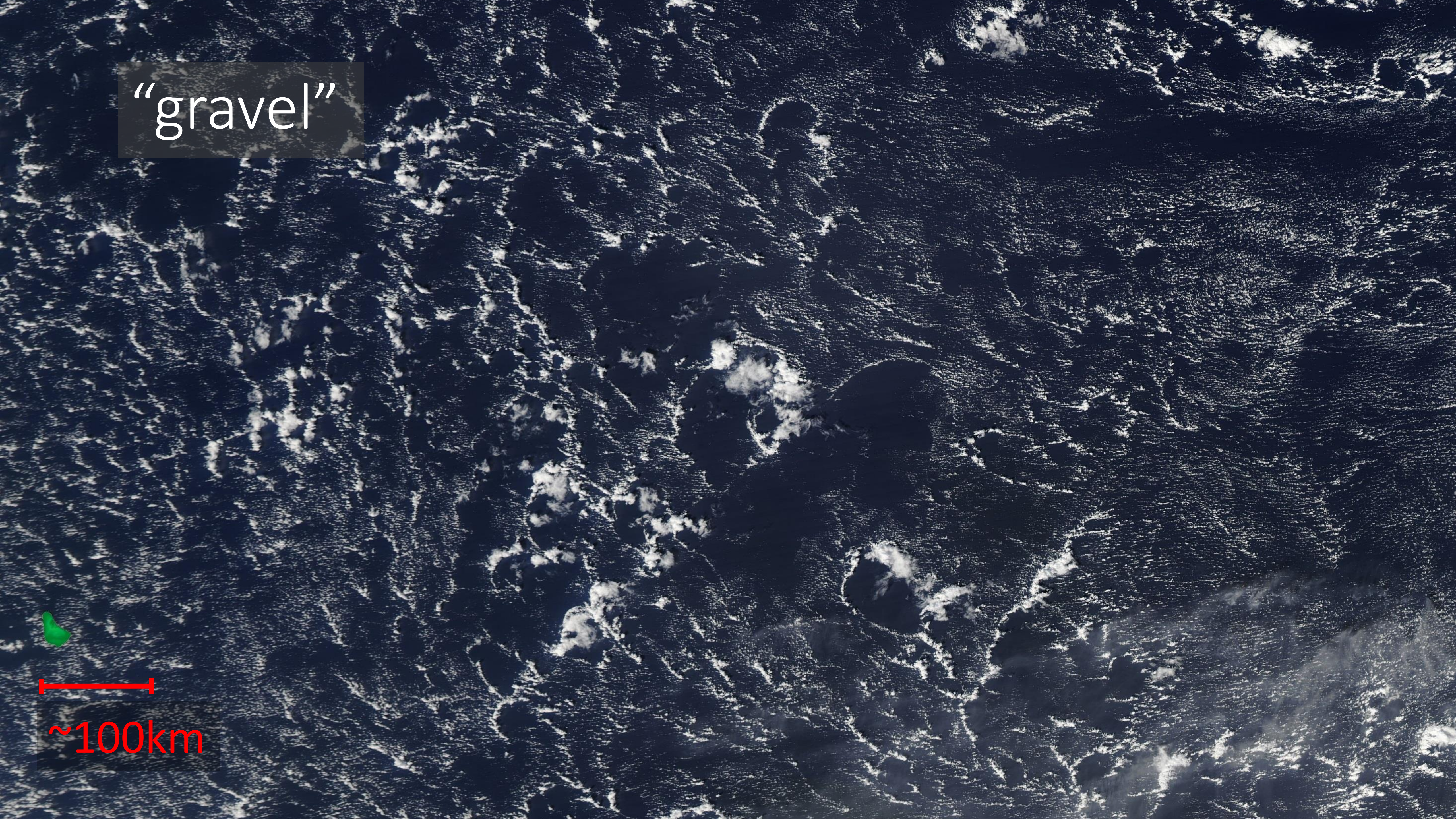

Barbados
~100km

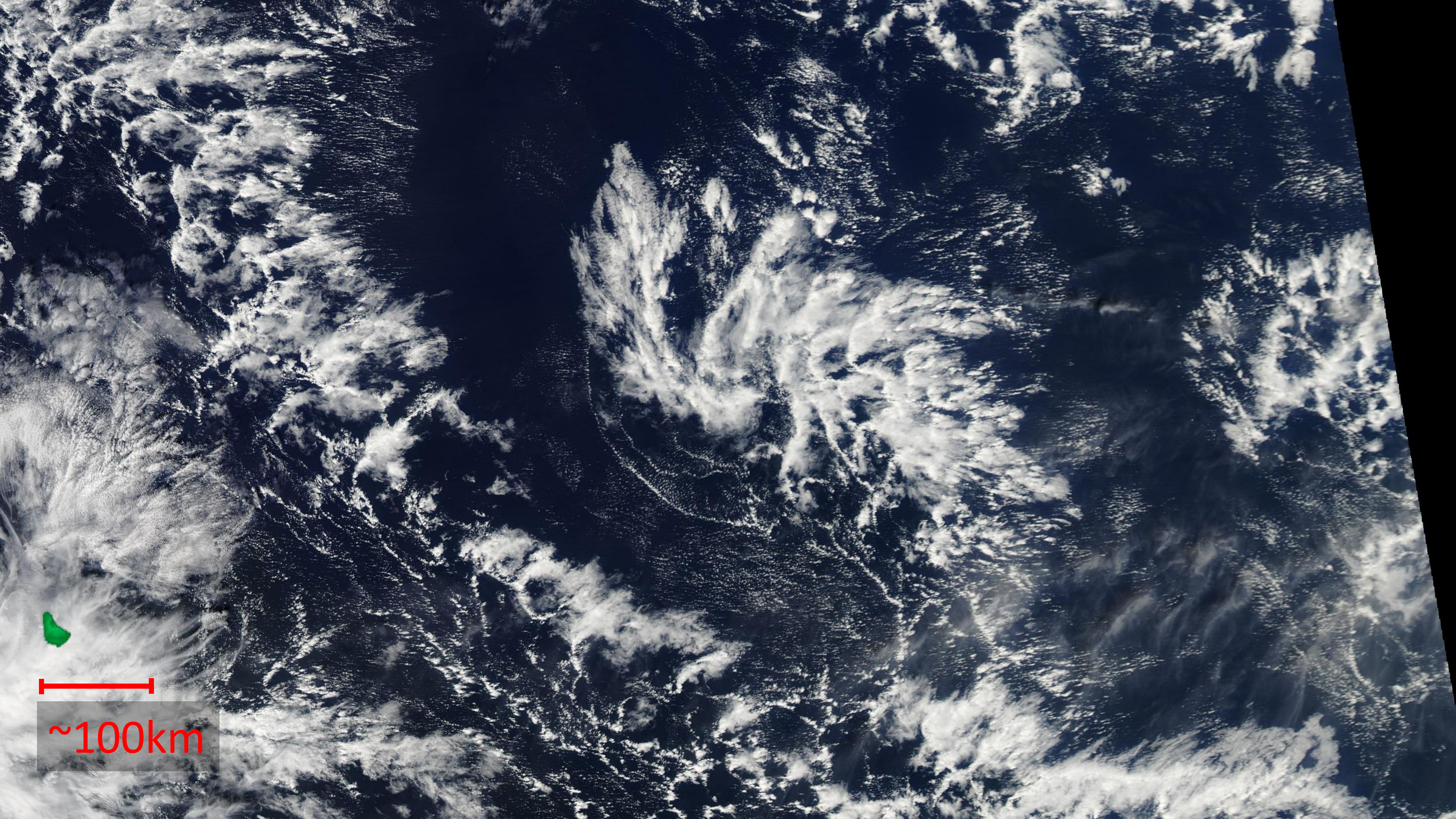

"flowers"
~100km

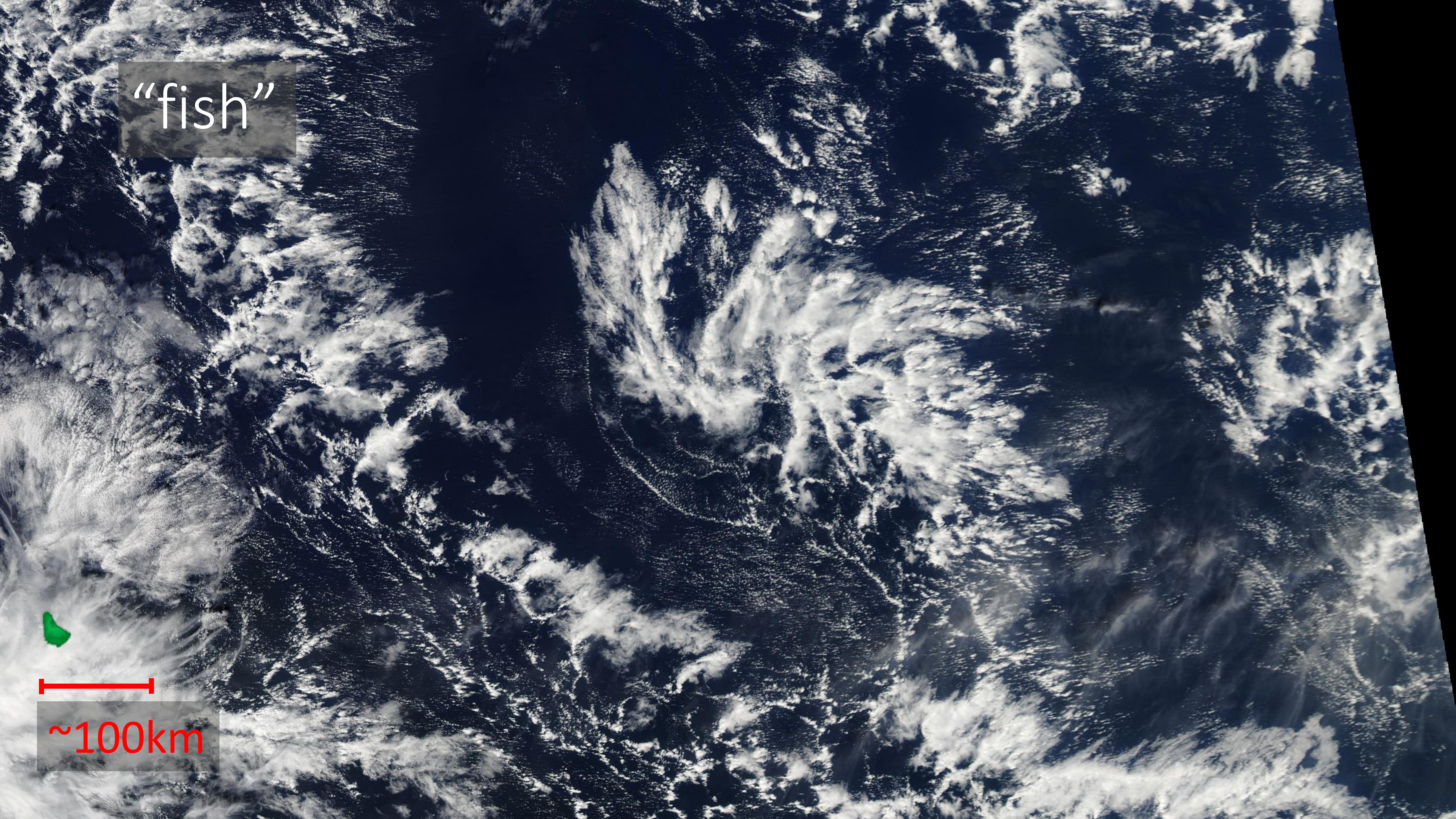

~100km


"sugar"
~100km


~100km


"gravel"
~100km


~100km


"fish"
~100km

Aim

- produce software to **automatically segment and classify** a satellite image **into regions with differently organised convection**

Motivation

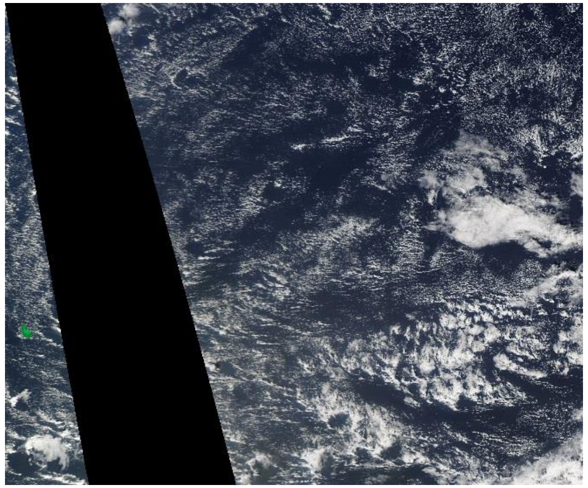
- Form of organisation affects radiative properties (albedo) and cloud-radiative feedback contributes **majority of climate sensitivity uncertainty** (Bony et al 2015 and many more)

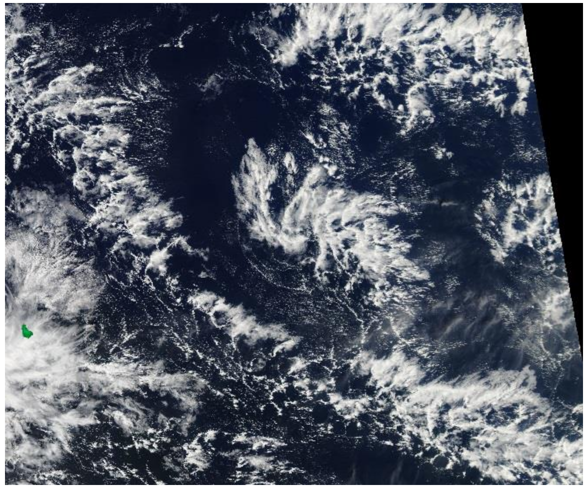
- **Relative importance of local and large-scale** factors driving convection into specific forms of organisation are **unknown**

- **Use tool on satellite images** to identify times where different classes have formed and **correlate with large-scale state** diagnosed from reanalysis data (e.g. ERA-Interim)

“Archetypes” of convective organisation?

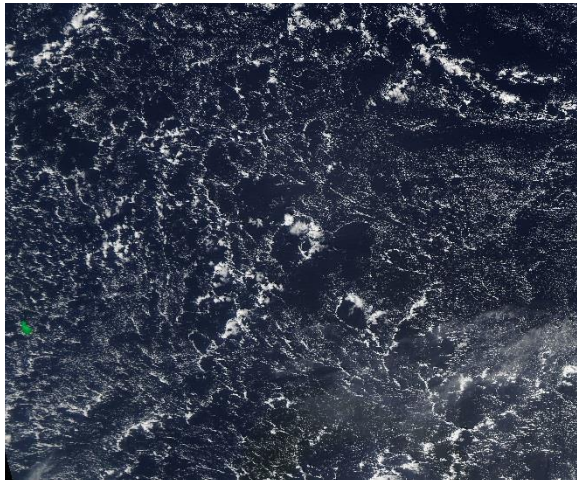
“sugar”

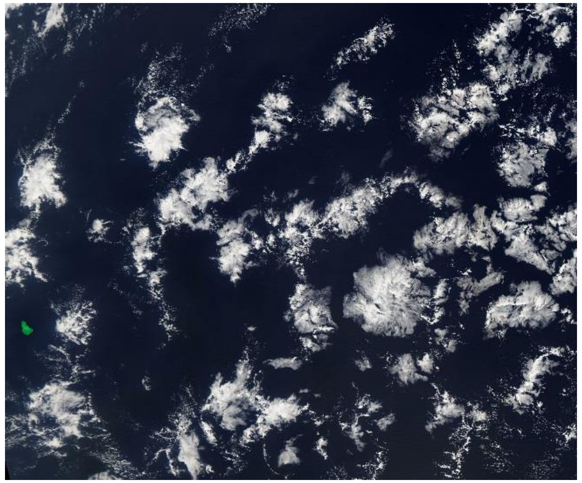




“fish”

“gravel”

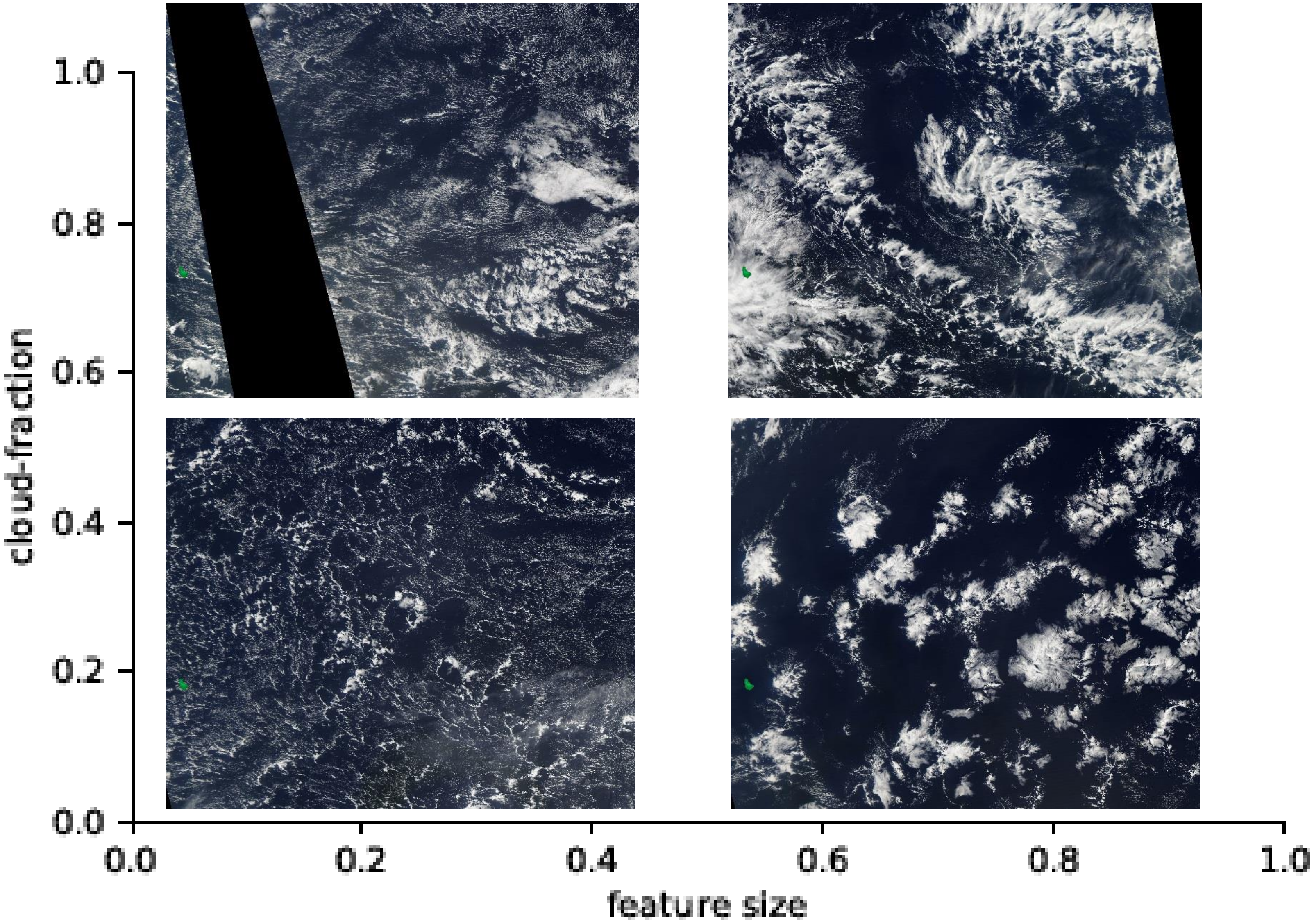




“flower”

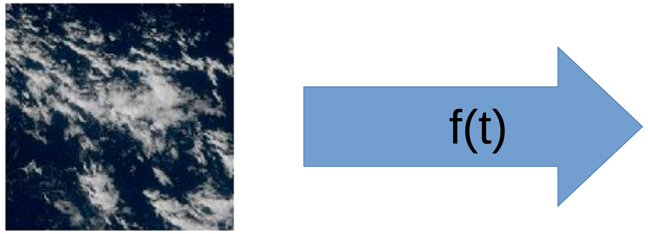
Stevens et al 2019, submitted

“Archetypes” of convective organisation?



Machine learning modelling aim

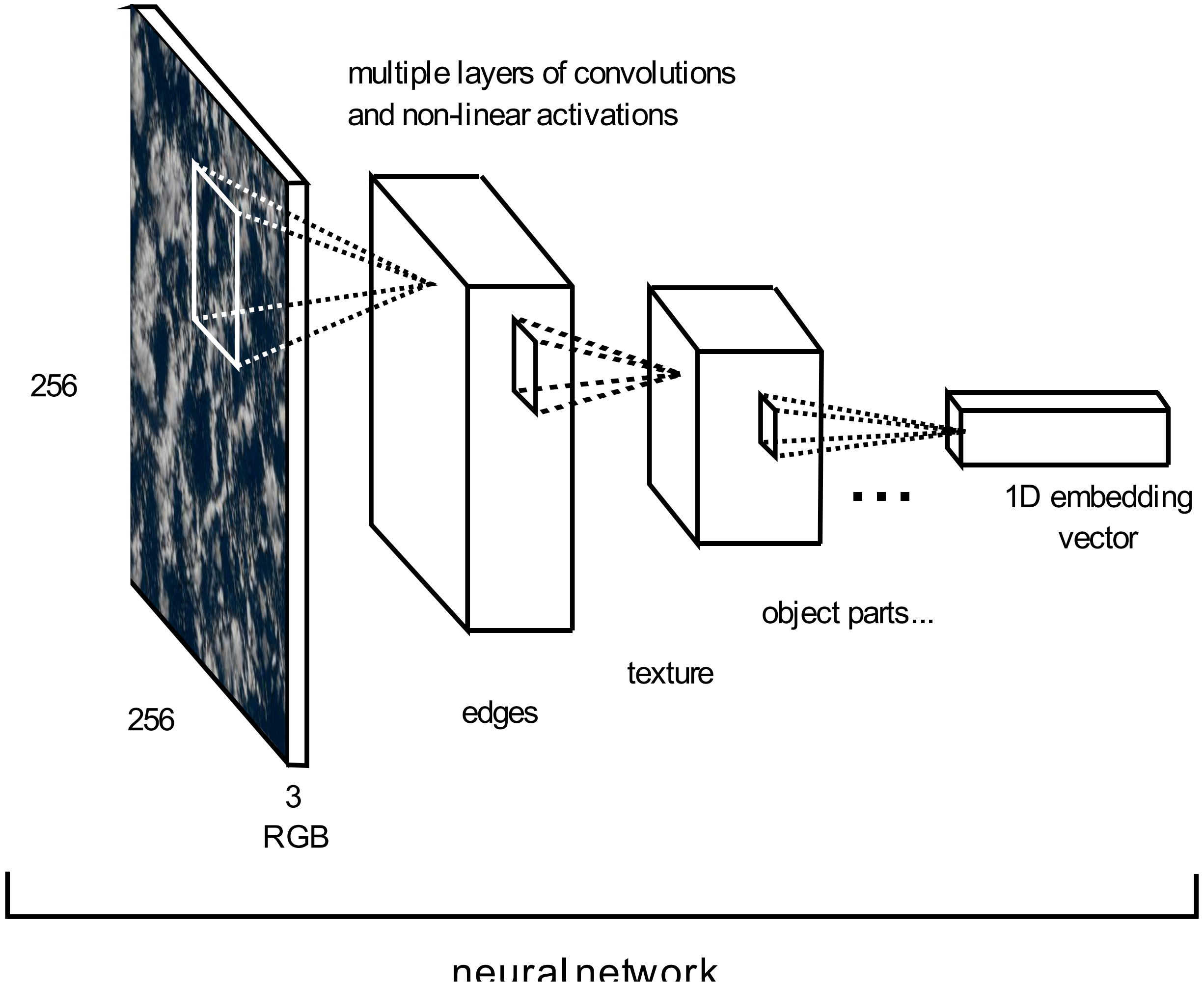
- Produce for every tile (t) of a satellite image an *embedding*. A point in N-dimensional space



= [0.12, 0.82, ….]

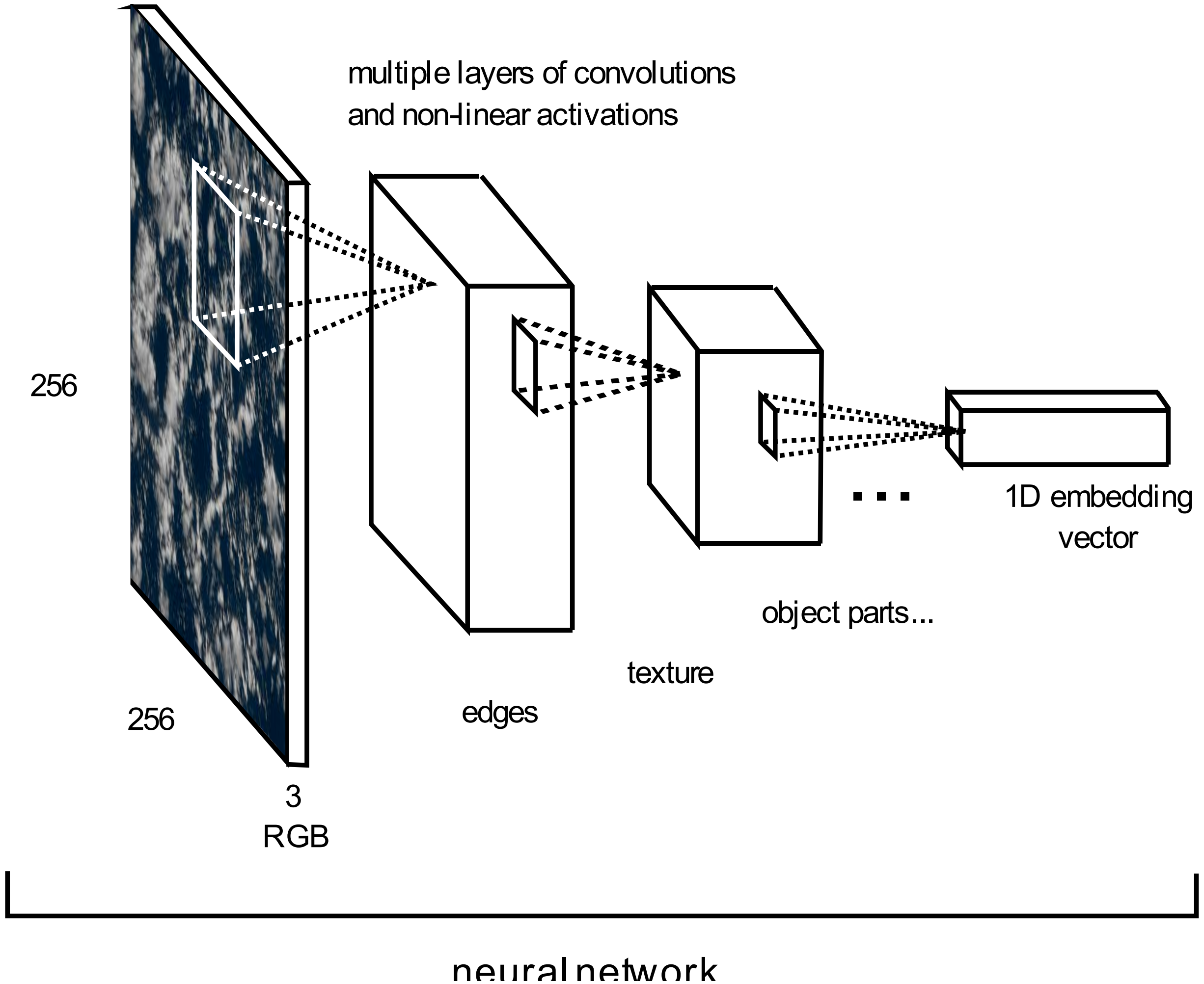
- Enforce that tiles with similar cloud structure a close in this N-dimensional space
- Previous successful application in Google's word2vec (Mikolov et al 2013):
  - f("santa") - f("christmas") ~ f("man")
  - f("london") - f("england") ~ f("copenhagen") - f("denmark")
- Using technique of Tile2Vec (Jean et al 2018) which learnt land-use classification

Using convolutional network to produce embedding



- Training done with `fastai` (built on `pytorch`)
- Use pre-trained Resnet34
- Replace last layer by fully connected layer
- Currently using N_d=100 embedding length

Using convolutional network to produce embedding

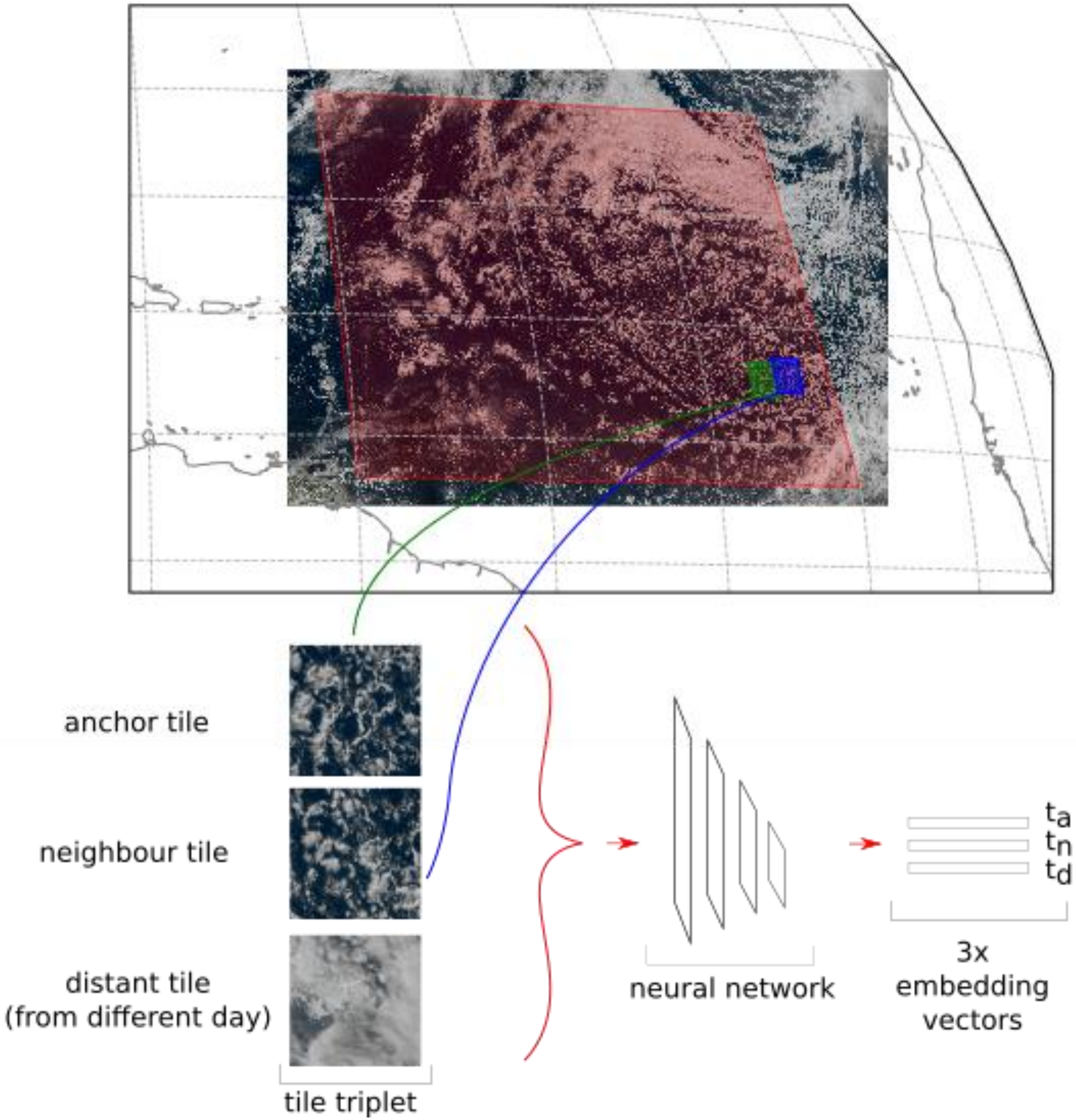


- Training done with `fastai` (built on `pytorch`)
- Use pre-trained Resnet34
- Replace last layer by fully connected layer
- Currently using N_d=100 embedding length

- How does this work?
  - See workshop in next session

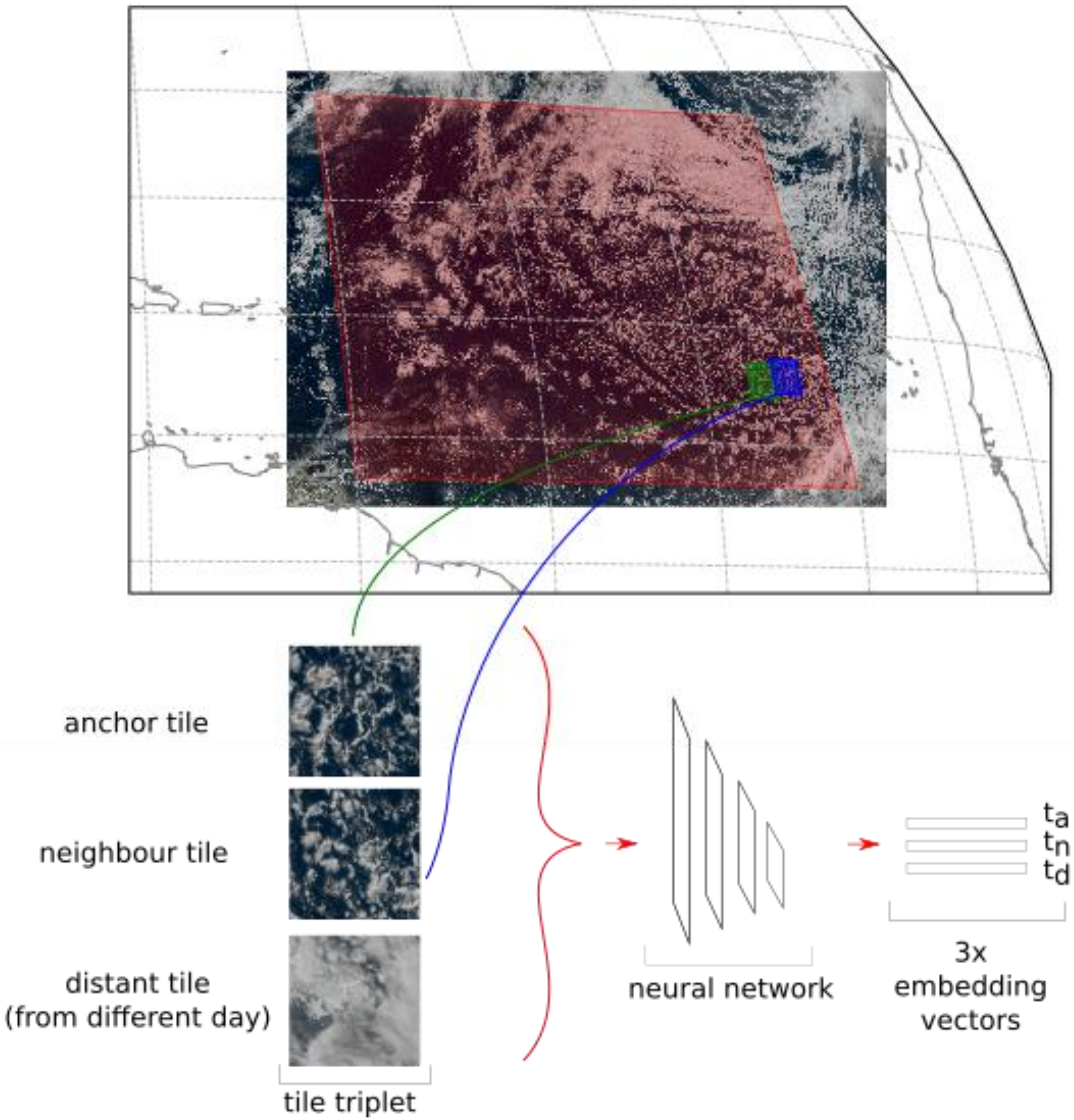
Model training

- Every training example consists for three tiles (triplet) the *anchor* (t_a), *neighbour* (t_n) and *distant* (t_d) tiles.



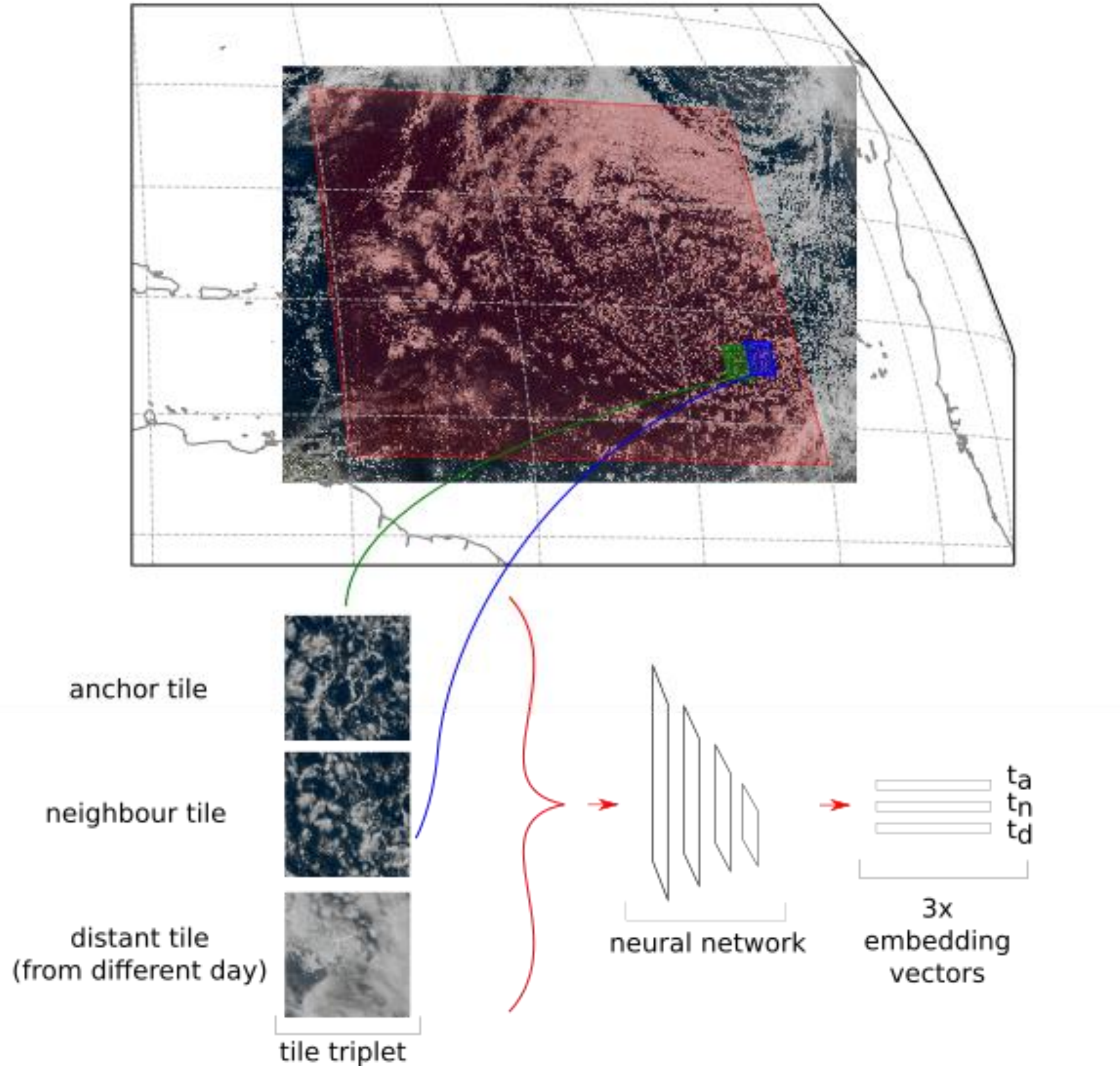
Model training

- Every training example consists for three tiles (triplet) the *anchor* (t_a), *neighbour* (t_n) and *distant* (t_d) tiles.
- Use loss function which optimises for *anchor* and *neighbour* tiles being close in embedding space and *distant* tile being far away (measured by Euclidian distance):



Model training

- Every training example consists for three tiles (triplet) the *anchor* (t_a), *neighbour* (t_n) and *distant* (t_d) tiles.
- Use loss function which optimises for *anchor* and *neighbour* tiles being close in embedding space and *distant* tile being far away (measured by Euclidian distance):

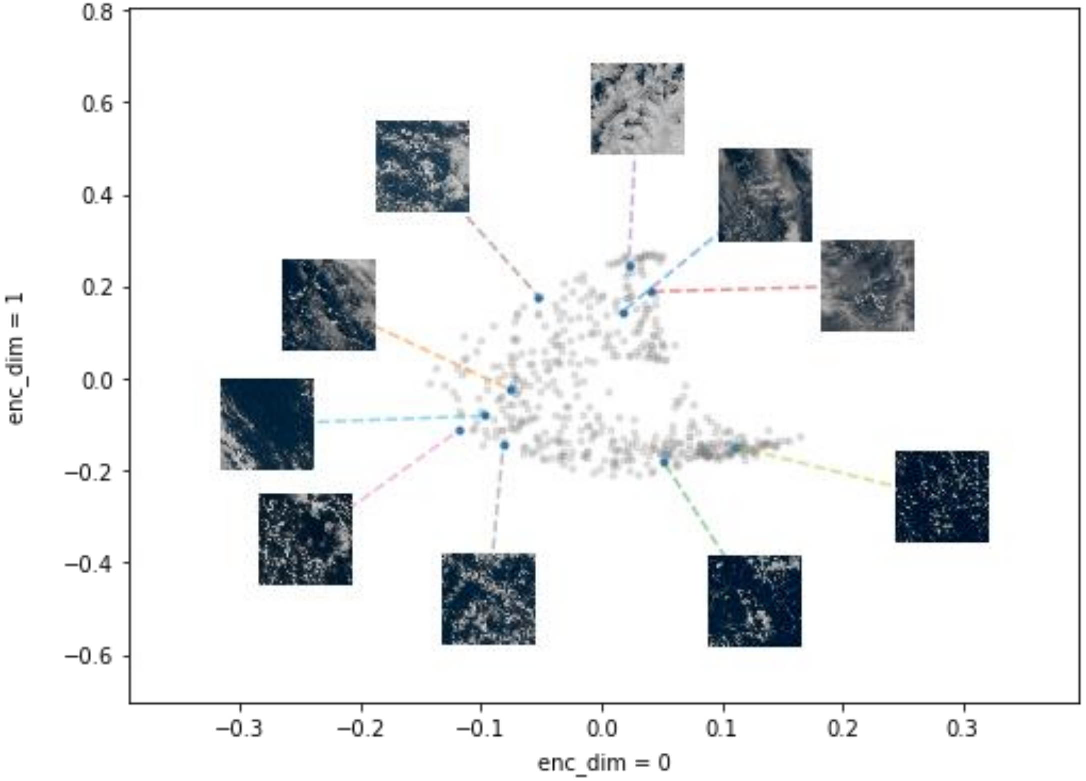


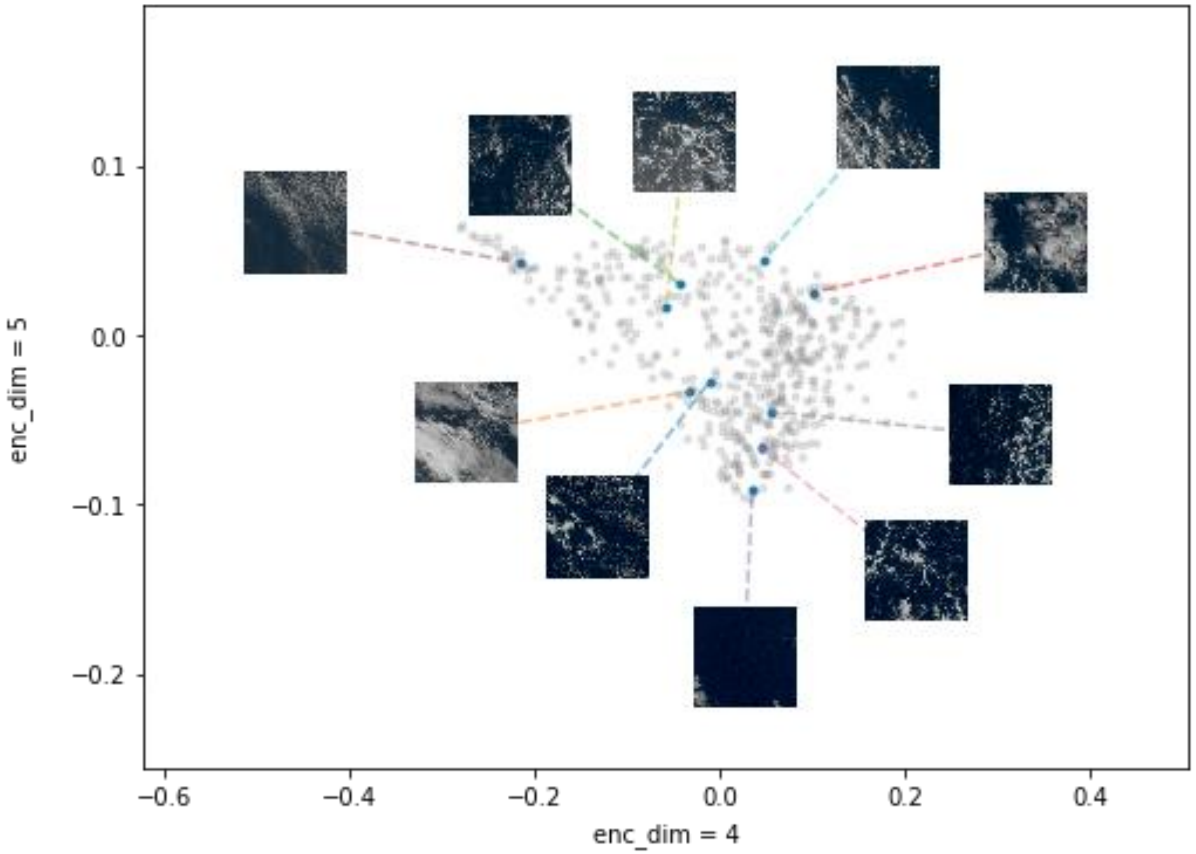
$$L(t_a, t_n, t_d) = max(0, ||f_\theta(t_a) - f_\theta(t_n)||_2 - ||f_\theta(t_a) - f_\theta(t_d)||_2 + m)$$

What does training data look like?

First 150 "anchor" tiles for a GOES-16 training dataset

What does this embedding look like?

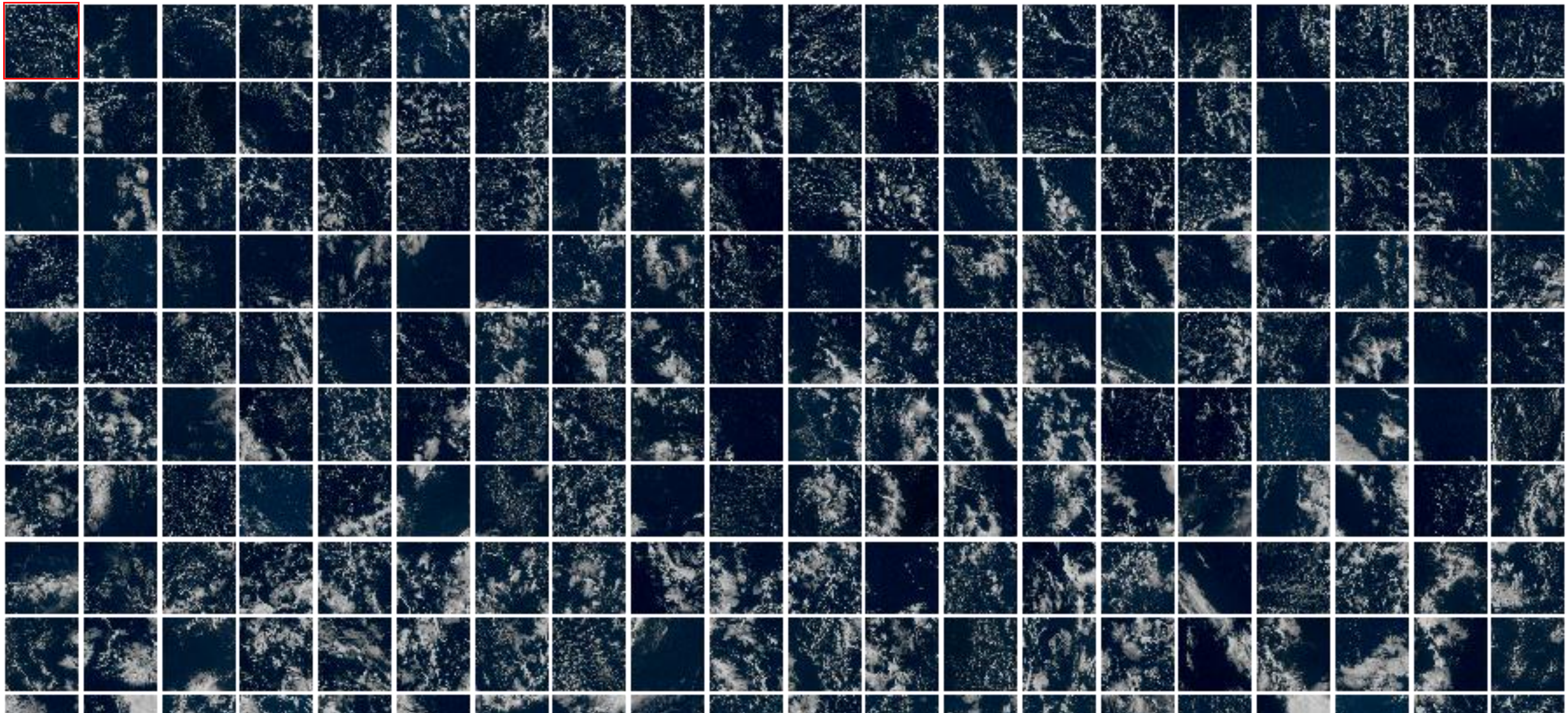


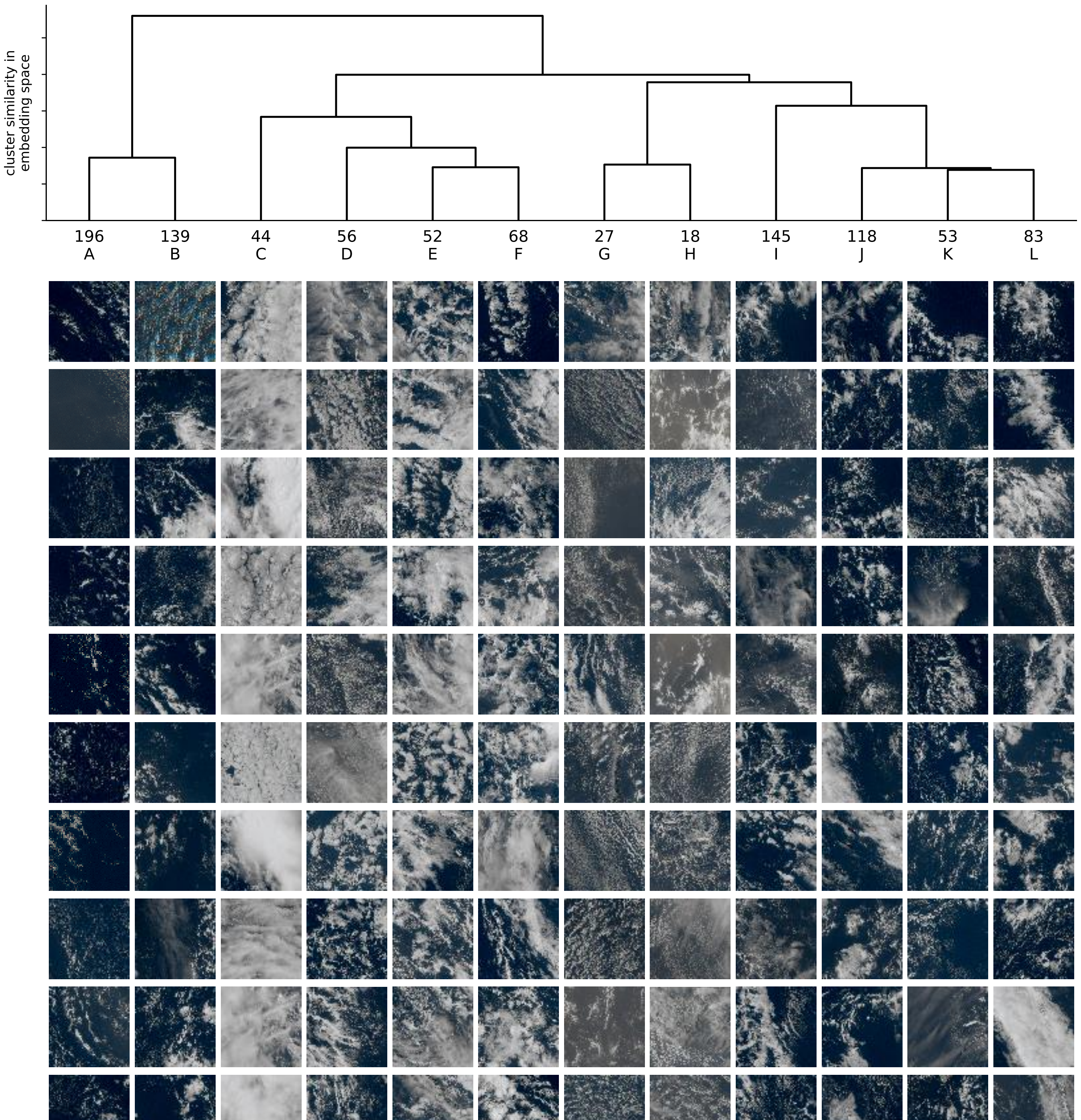


First four dimensions of embedding with a 10 random examples highlighted

So what does this embedding give us?

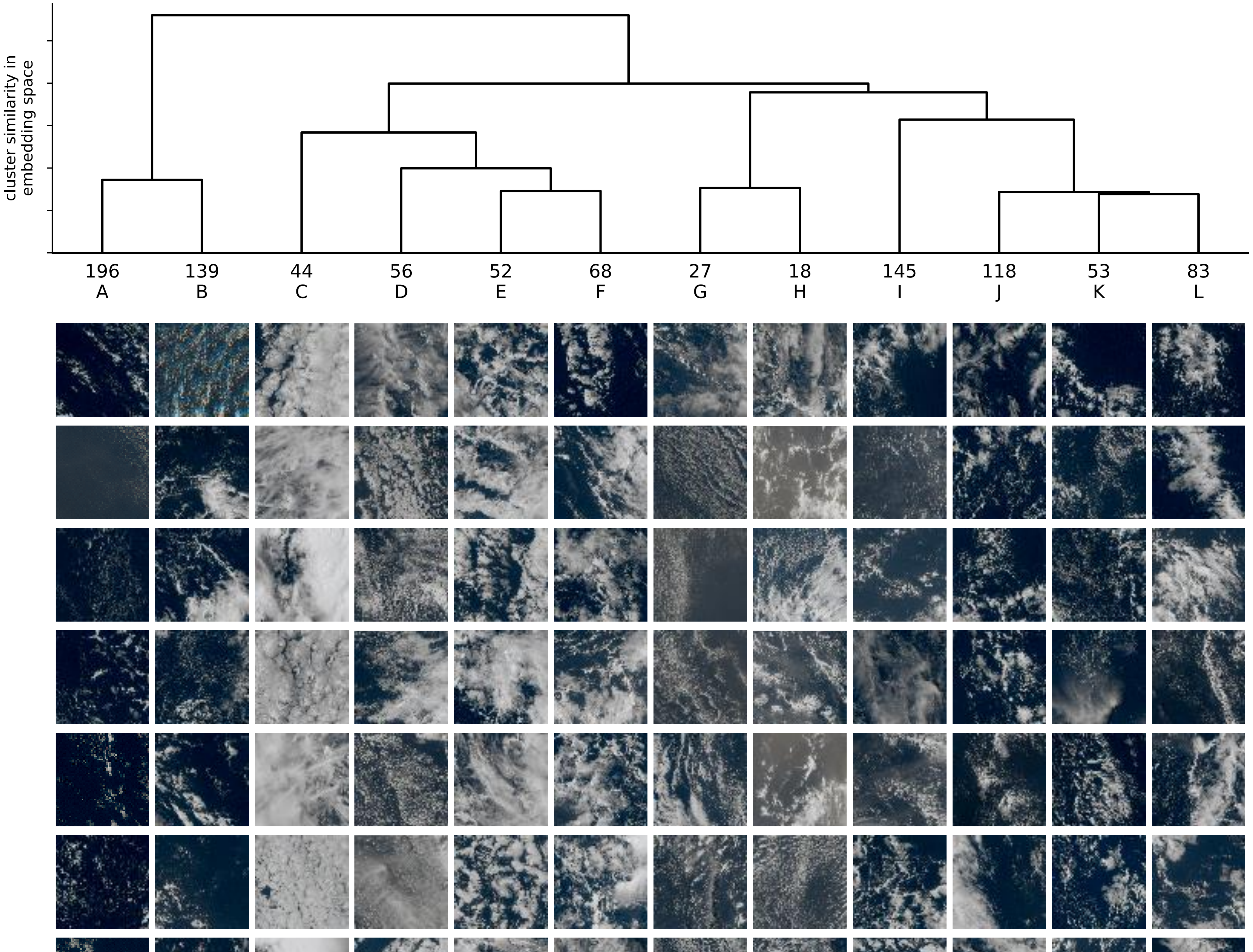
Can rank tiles by distance (in embedding space) to specific tile of interest (showing half of entire *study* set)



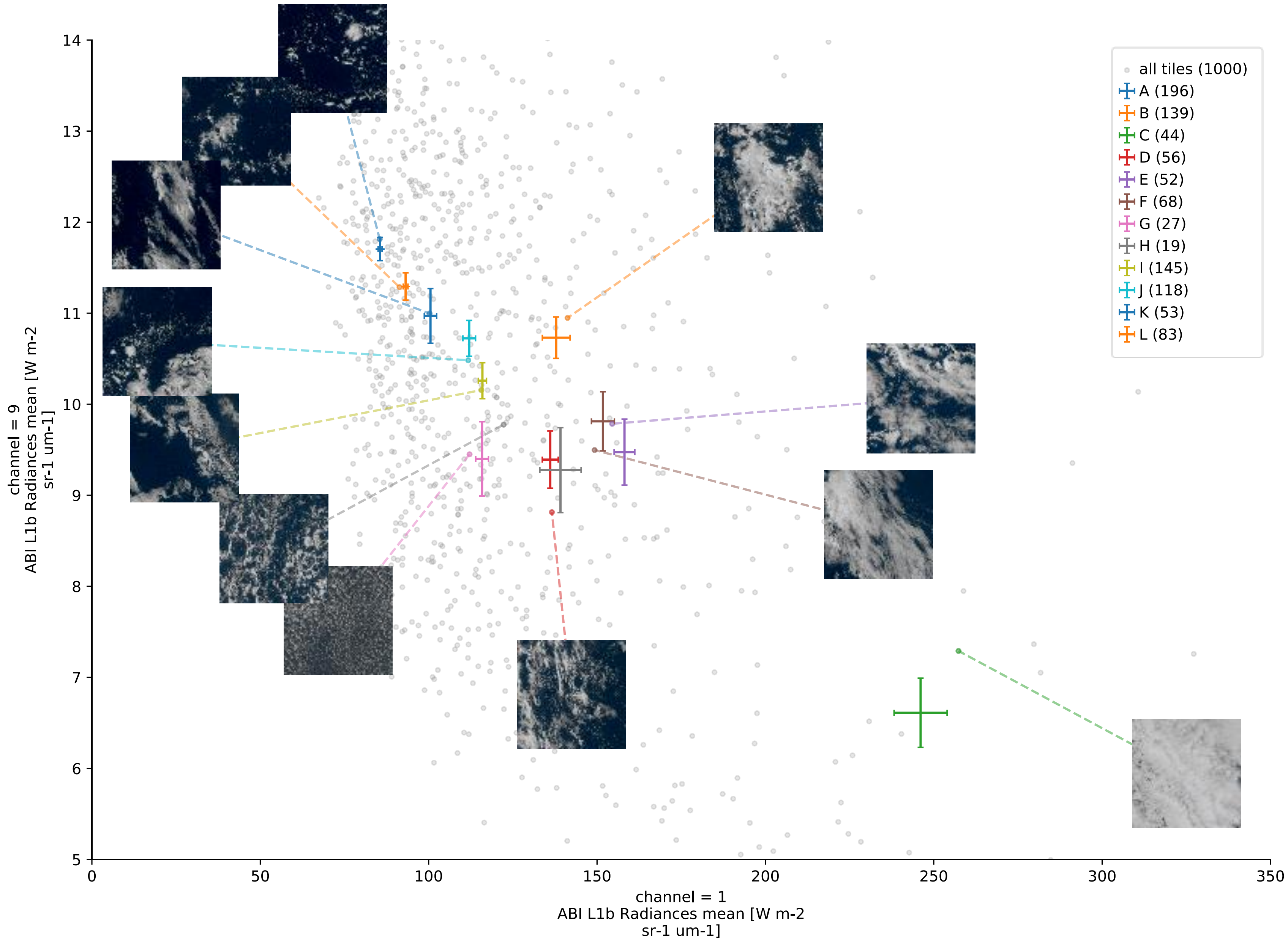


So what does this embedding give us?

- Can do (hierarchical) clustering to find out how tiles clump in *embedding space*
- *Nested* clusters share similar features
- Vertical distance in *dendrogram* measure of persistence of clusters


cluster similarity in embedding space
196
A
139
B
44
C
56
D
52
E
68
F
27
G
18
H
145
I
118
J
53
K
83
L

Do different cloud structures have different 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

Summary

- a neural network can, without labelled training data:
  - automatically discover different forms of cloud organisation
  - through this learn to group input images containing similar cloud structures together
- different cloud structures have distinct radiative properties
- benefits of unsupervised model:
  1. can be applied to any spatial dataset with limited effort as no hand-labelling is required
  2. automatically discovers the types of structures present in the input
  3. produces a representation of the similarity between these structures.

Thank you!

Questions?