Volcano Monitoring using Deep Learning

Matthew Gaddes, University of Leeds, UK

esa

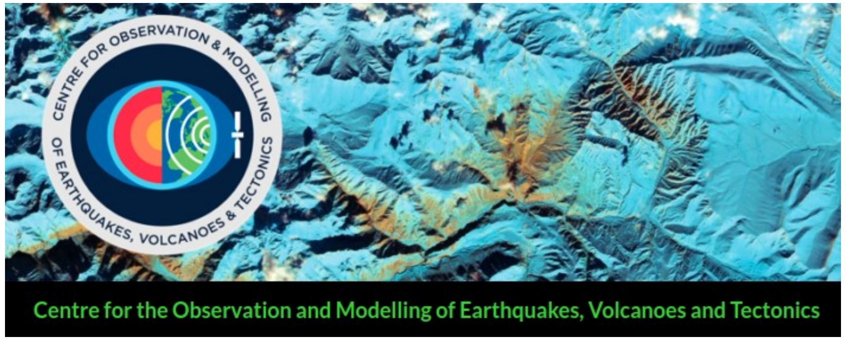
LIVING PLANET FELLOWSHIP

LITHOSPHERE

Acknowledgements

- I've previously worked on similar problems as a PhD student funded by the "Looking Inside the Continents from Space" (LiCS) grant, and as a COMET postdoc:

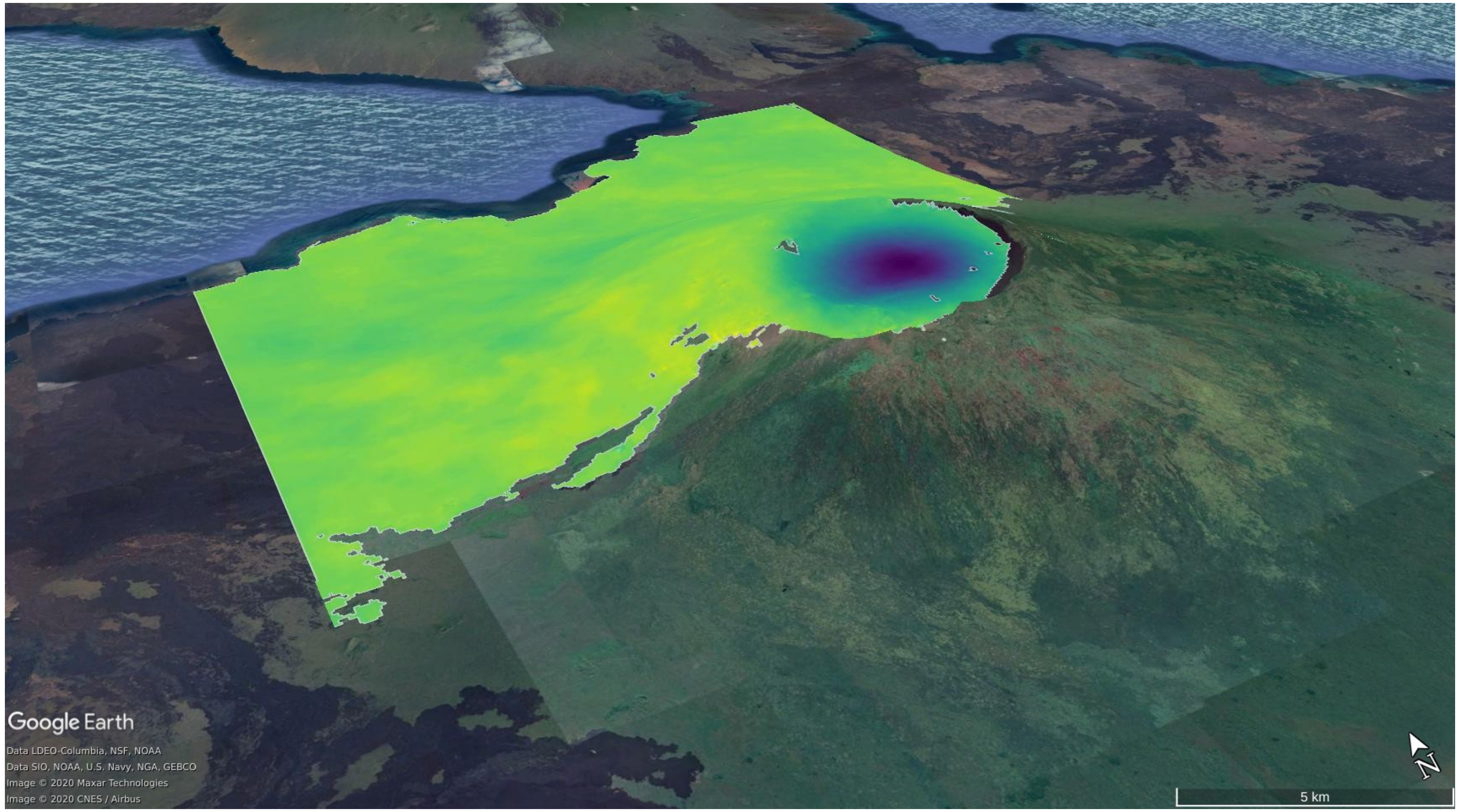
LiCS
LOOKING INSIDE THE CONTINENTS FROM SPACE



- I've collaborated on this work with Andy Hooper (University of Leeds) and Fabien Albino (University of Bristol):

Project rationale

- Interferograms contain information about ground deformation, and this has strong evidential worth for assessing eruption potential (Biggs et al., 2014).
- Routine acquisition over subaerial volcanoes by the Sentinel-1 satellites could facilitate monitoring of many new volcanoes.
- An example of a deformation signal captured by the Sentinel-1 satellites: uplift of the caldera floor of Sierra Negra (Galapagos Archipelago, Ecuador), prior to the 2018 eruption.



Project rationale

- Howevever, with ~1500 active subaerial volcanoes and new interferograms being created every 6 or 12 days, searching for these signals manually is an onerous task.

- E.g. Consider Isabella Island in the Galapagos Archipleago:

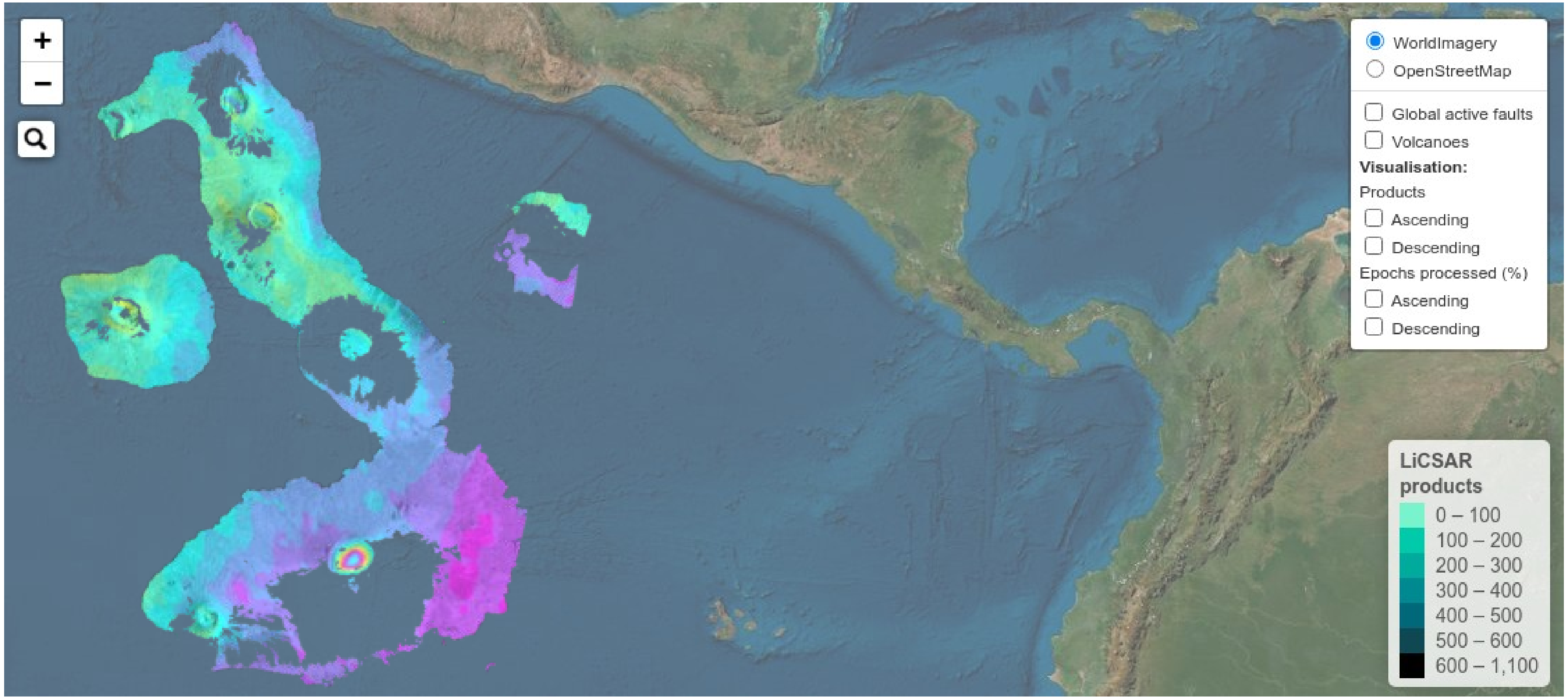


Figure: COMET LiCS portal

Project rationale

- Howevever, with ~1500 active subaerial volcanoes and new interferograms being created every 6 or 12 days, searching for these signals manually is an onerous task.
- E.g. Consider Isabella Island in the Galapagos, within the Eastern Pacific:

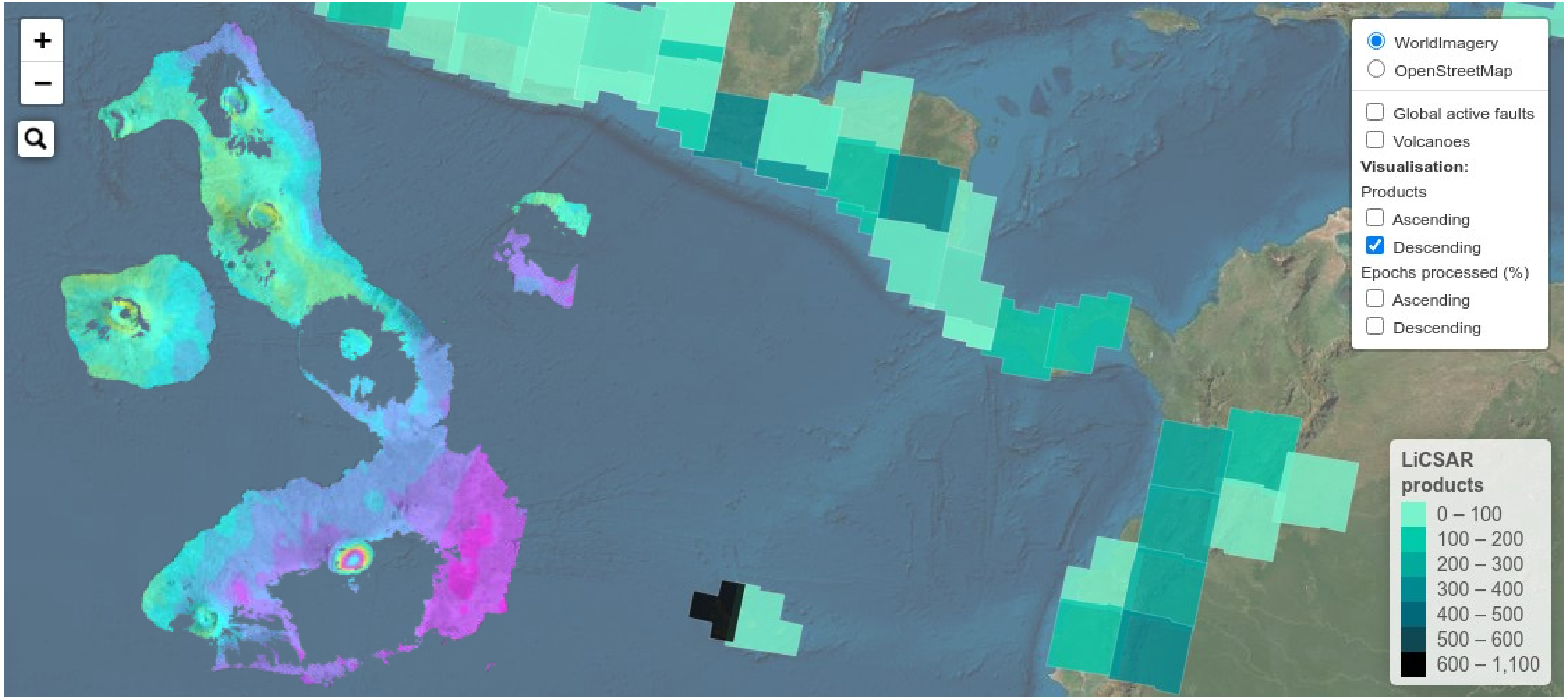


Figure: COMET LiCS portal

Project rationale

- Howevever, with ~1500 active subaerial volcanoes and new interferograms being created every 6 or 12 days, searching for these signals manually is an onerous task.

- E.g. Consider Isabella Island in the Galapagos, within the Eastern Pacific, and within the globe:

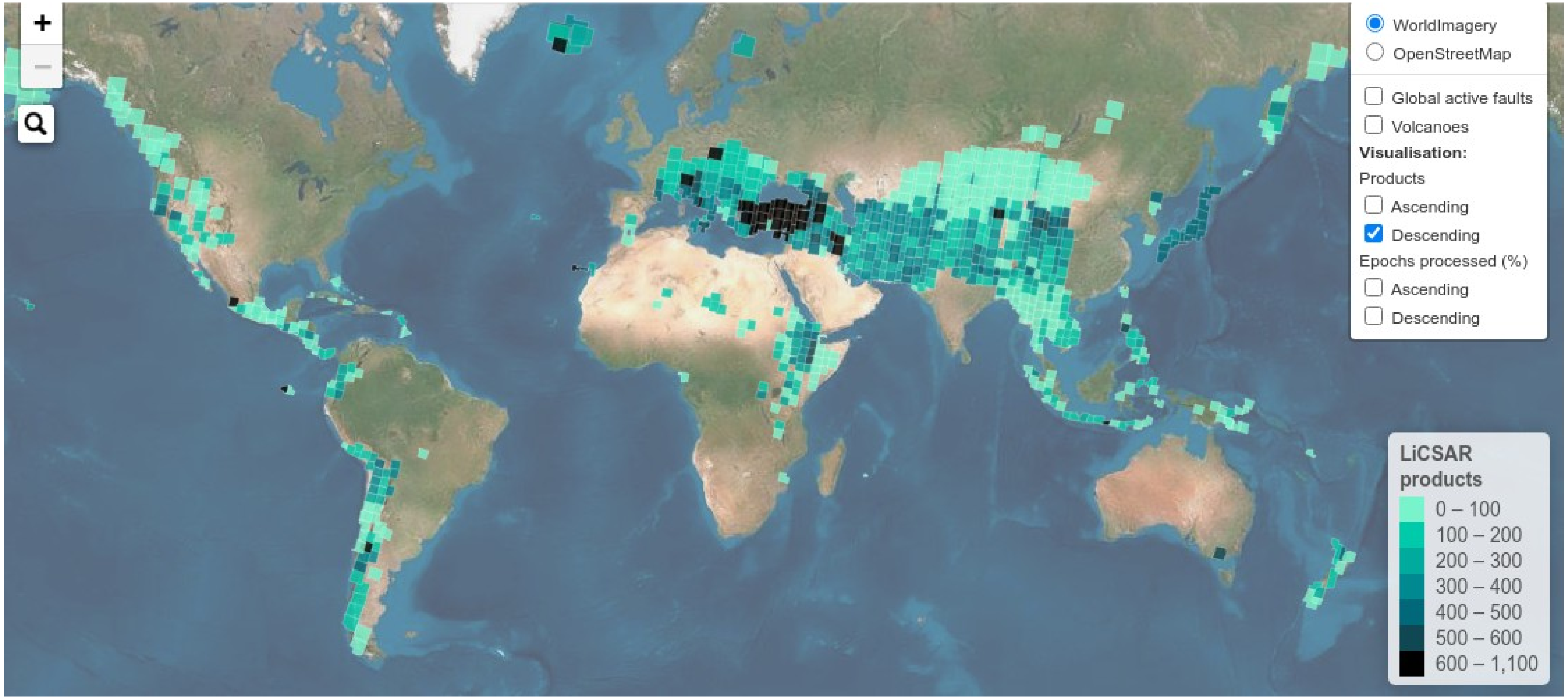


Figure: COMET LiCS portal

InSAR for volcano monitoring: examples (1/2)

- Deformation / no deformation flag on wrapped interferograms (localisation is just nested classification + Gaussian smoothing).

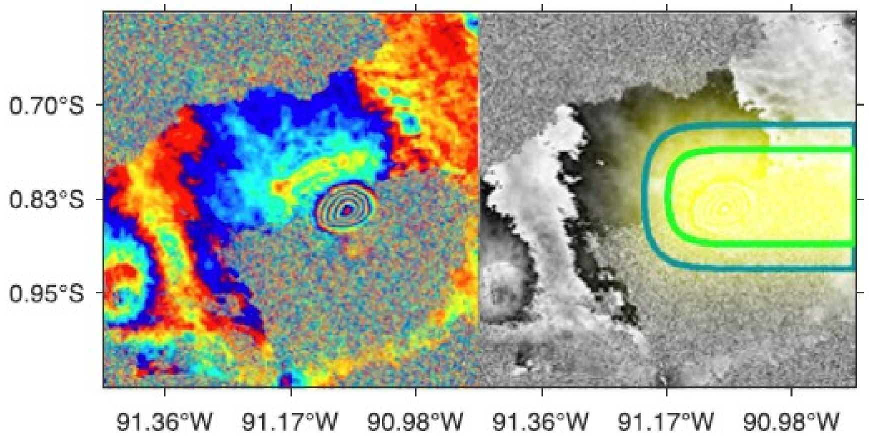
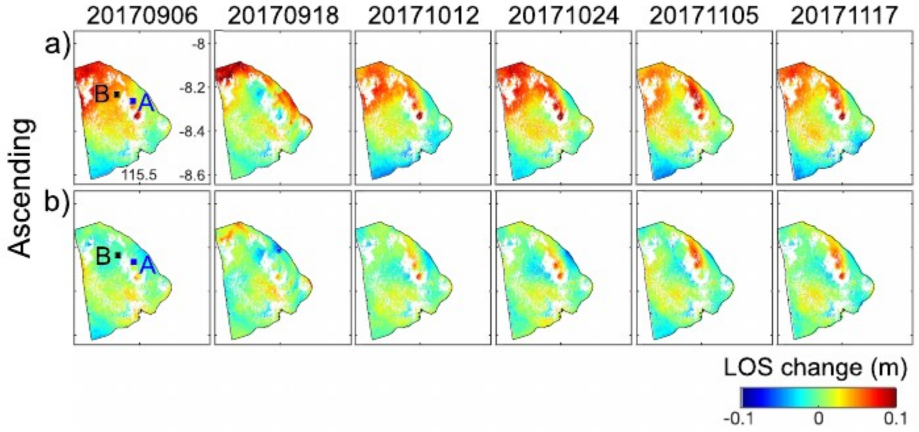


Figure: Anantrasirichai et. al., 2018

- Considering pixels in time series with atmospheric corrections applied:



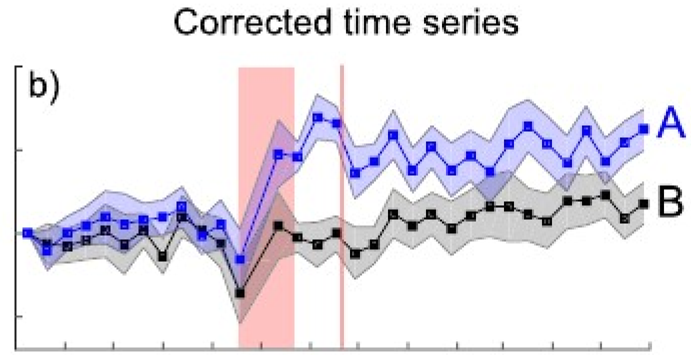
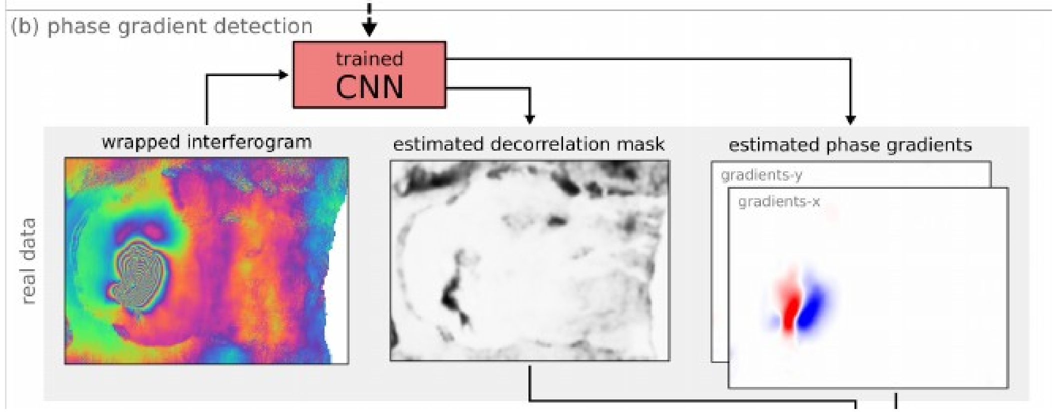


Figure: Albino et. al., 2020

InSAR for volcano monitoring: examples (2/2)

- “Monitoring Unrest from Space” (MOUNTS),
  Sentinel-1 (InSAR), Sentinel-2 (InfaRed), Sentinel-5 (SO_2), and seismic data.



- LiCSAlert,
  Time series method that detects deviations from baseline behaviour.

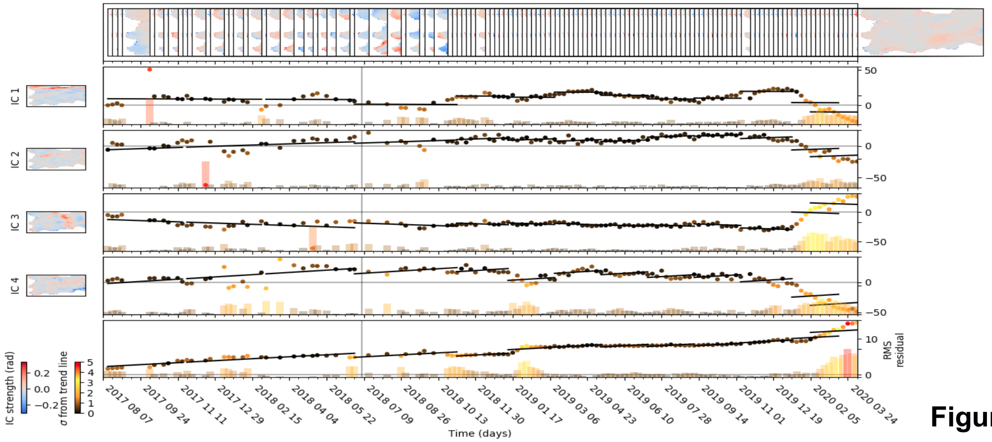


Figure: Gaddes et al., in prep.

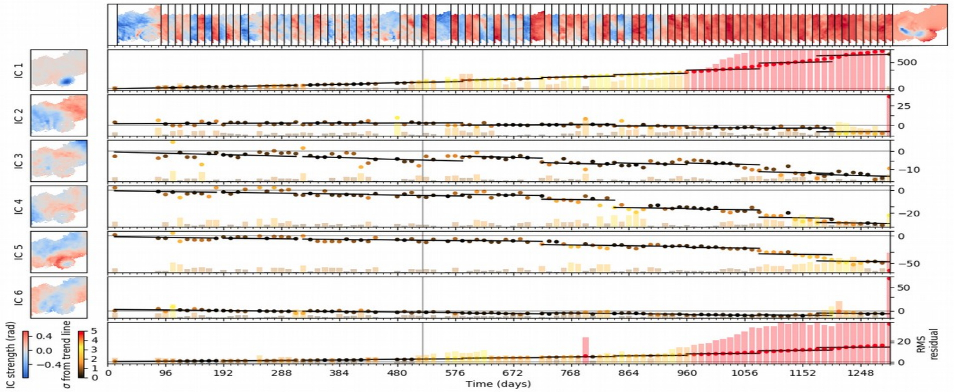


Figure: Gaddes et al., 2019

Objective 1: deep learning with single interferograms

- Advancing the state of the art up the hierarchy of computer vision:
- Convolutional neural networks (CNNs) have revolutionised the field and are ideal for this task.

E.g. Anantrasirichai et. al., 2018, 2019 → This work

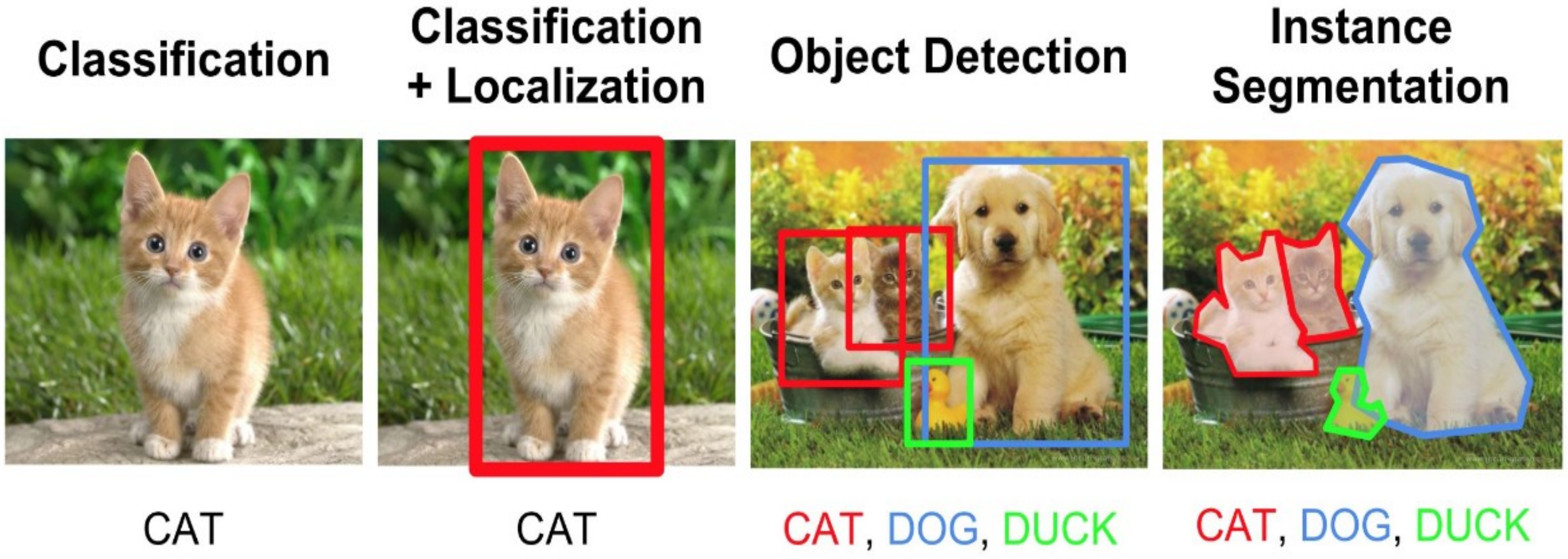
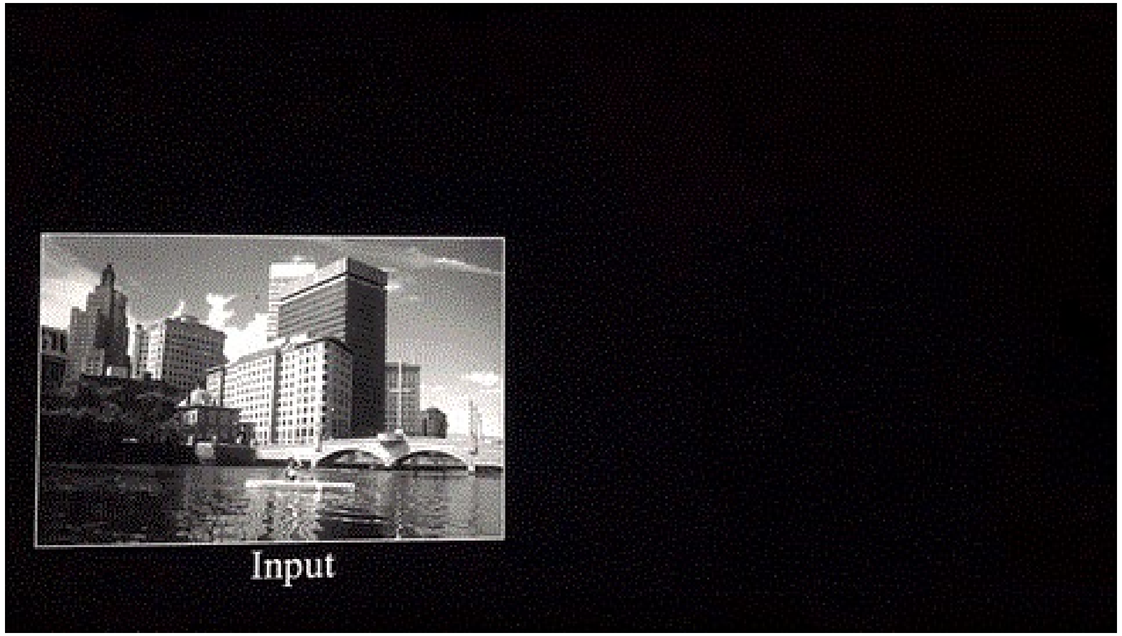
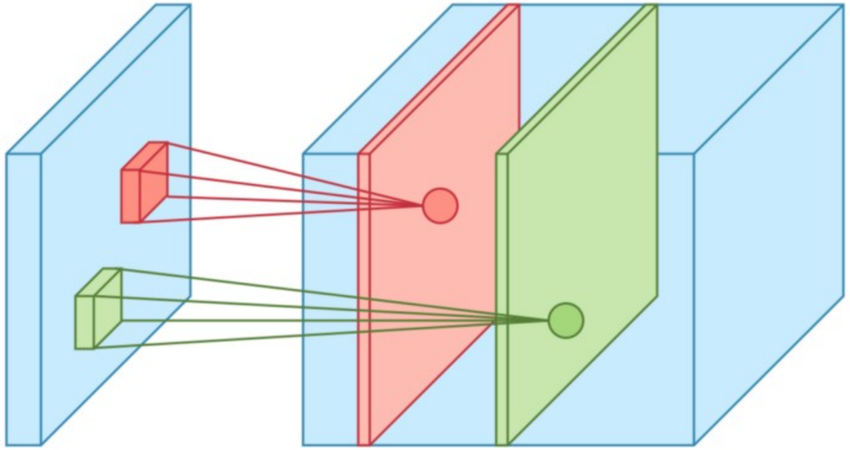


Figure: Stanford CS231 notes

Convolutional neural networks (very briefly)

- Working with images so can slide (convolve) filters over an image.
- We don't design the filters, the network learns them.
- An example of two filters (right):
- And how to record their output as layers of a tensor (below):

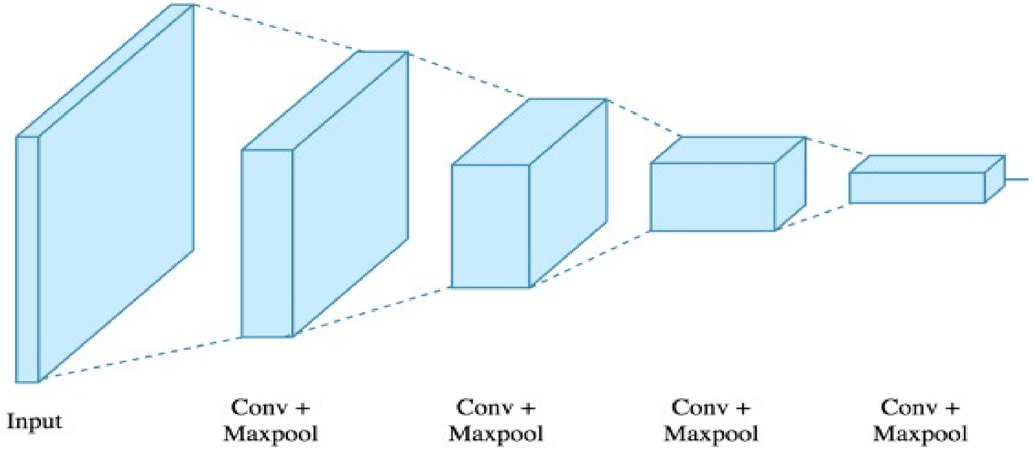




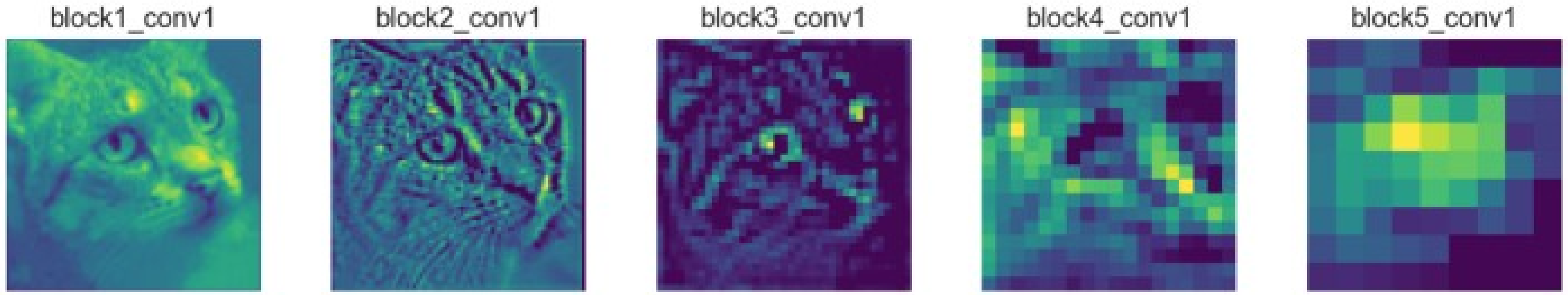
Animation: Deep learning methods for vision, CVPR 2012 Tutorial. **Diagram**: towardsdatascience.com

Convolutional neural networks (very briefly)

- We can then apply filters to the results of the previous filters (and spatially downsample to allow our representations to get deeper without becoming too large):



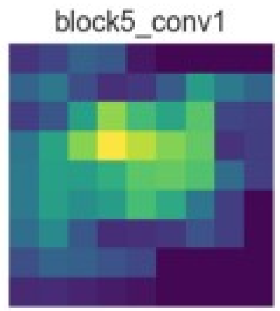
- The first filters are usually edge detectors.
- The second filters only see edges, and perhaps detect shapes.
- The third filters only see shapes, and perhaps detect objects.
- Some randomly chosen filter results from a trained model (below):



Diagrams: towardsdatascience.com

Convolutional neural networks (very briefly)

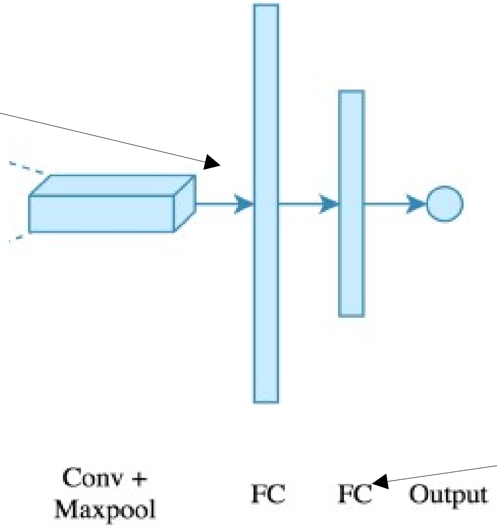
- What to do with the spatially downsampled (but deep) representations?
- Pixels probably represent things like “has a nose”, “has whiskers” etc.
  Visualising one of these layers in our model’s deep representation (right):



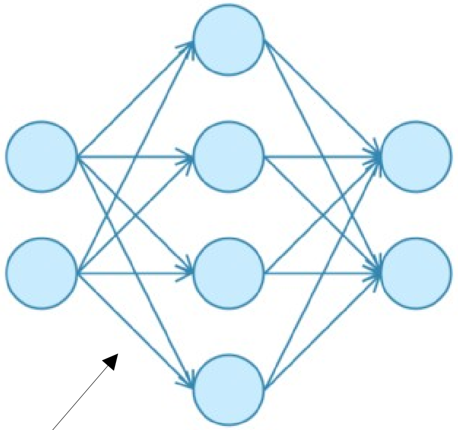
(one slice of the 3D representation)

- How to use this?
  A common approach is to just connect a simple neural network to each pixel of the final deep representation:

3D → 1D



FC = fully connected



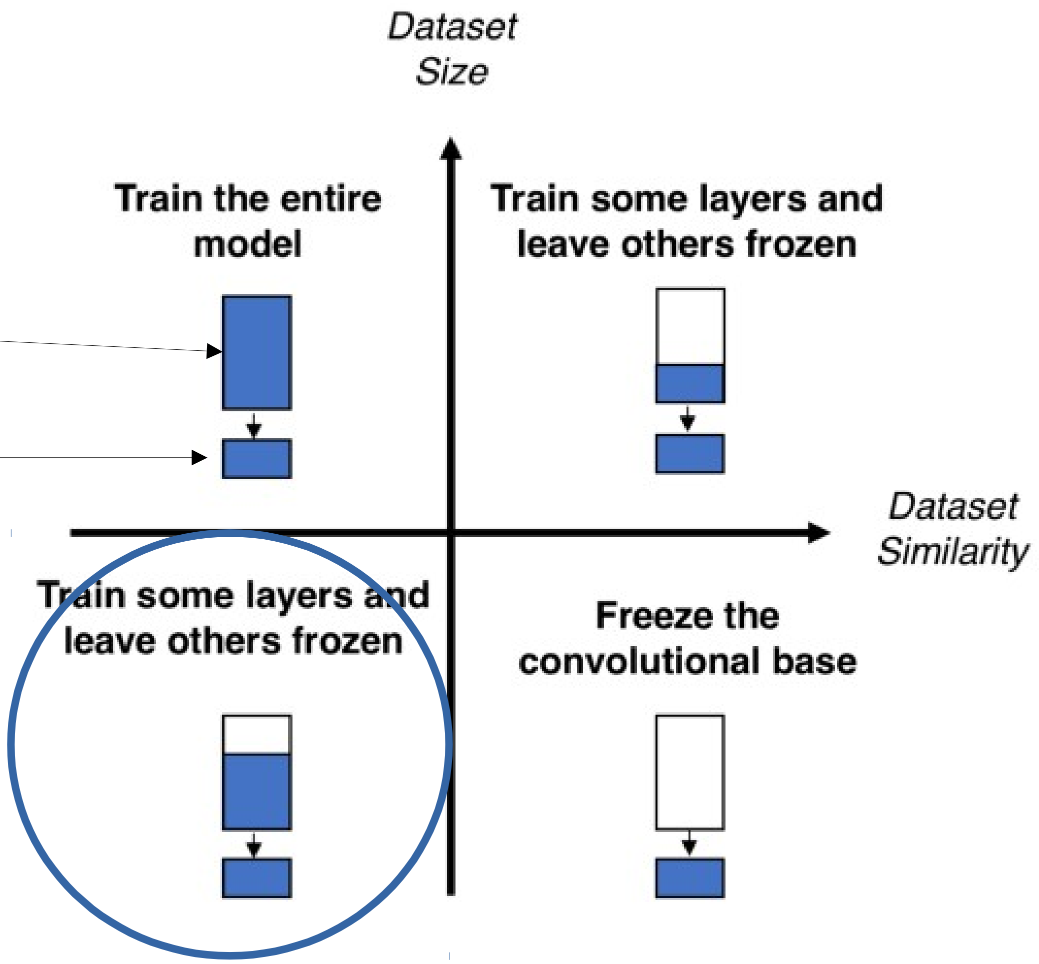
Diagrams: towardsdatascience.com

Using CNNs with interferograms

- Design a new model?
- Train an existing one?

convolving filters to make a deep representation

deep representation used by fully connected part



- "Lots of data" = $10^6 – 10^8$, in deep learning, so InSAR is low in that dimension.

- Similarity is harder to gauge. It could be worse!

VGG16 for classification and localisation

- VGG16 was a state of the art model several years ago and weights (filters) are freely available.

- We modify it to have two fully connected heads:
  - **Classification**, to determine the type/class of deformation (e.g. sill, dyke).
  - **Localisation**, to determine the position of size of the deformation signal.

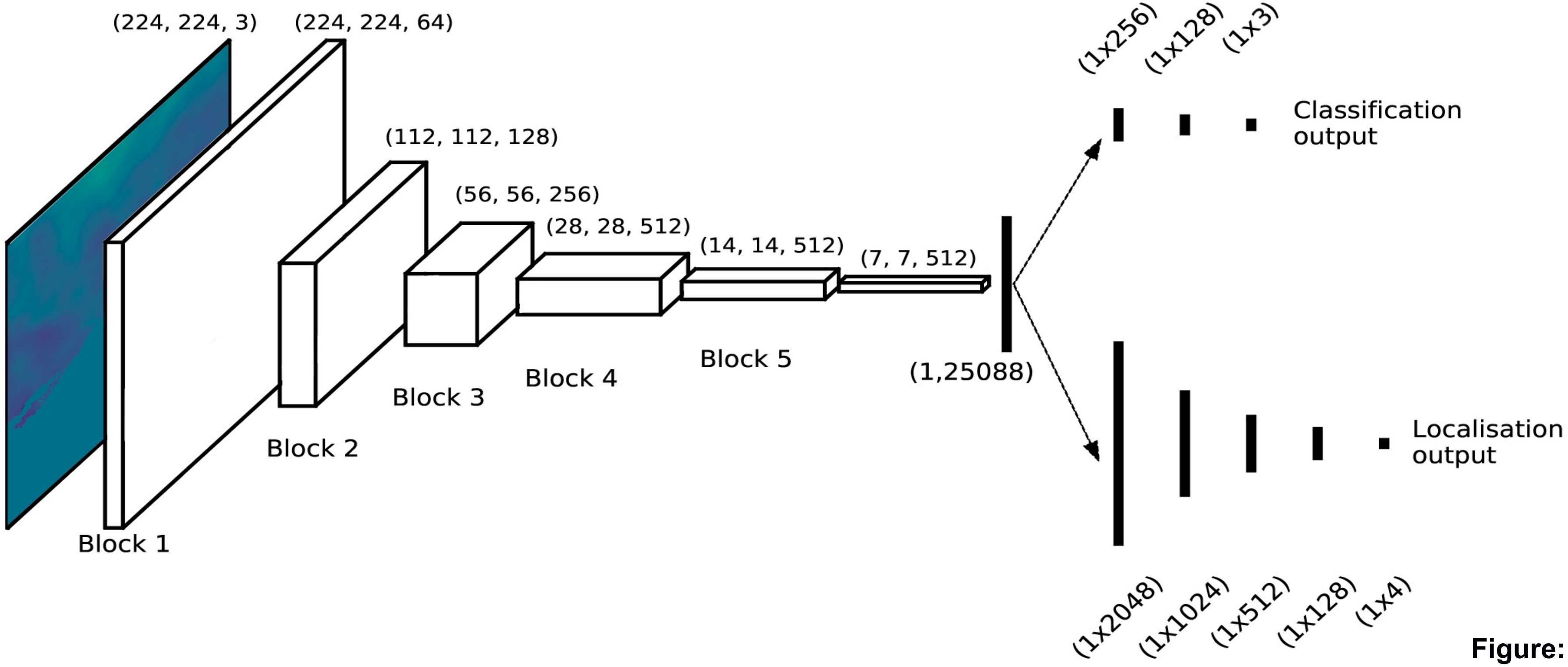
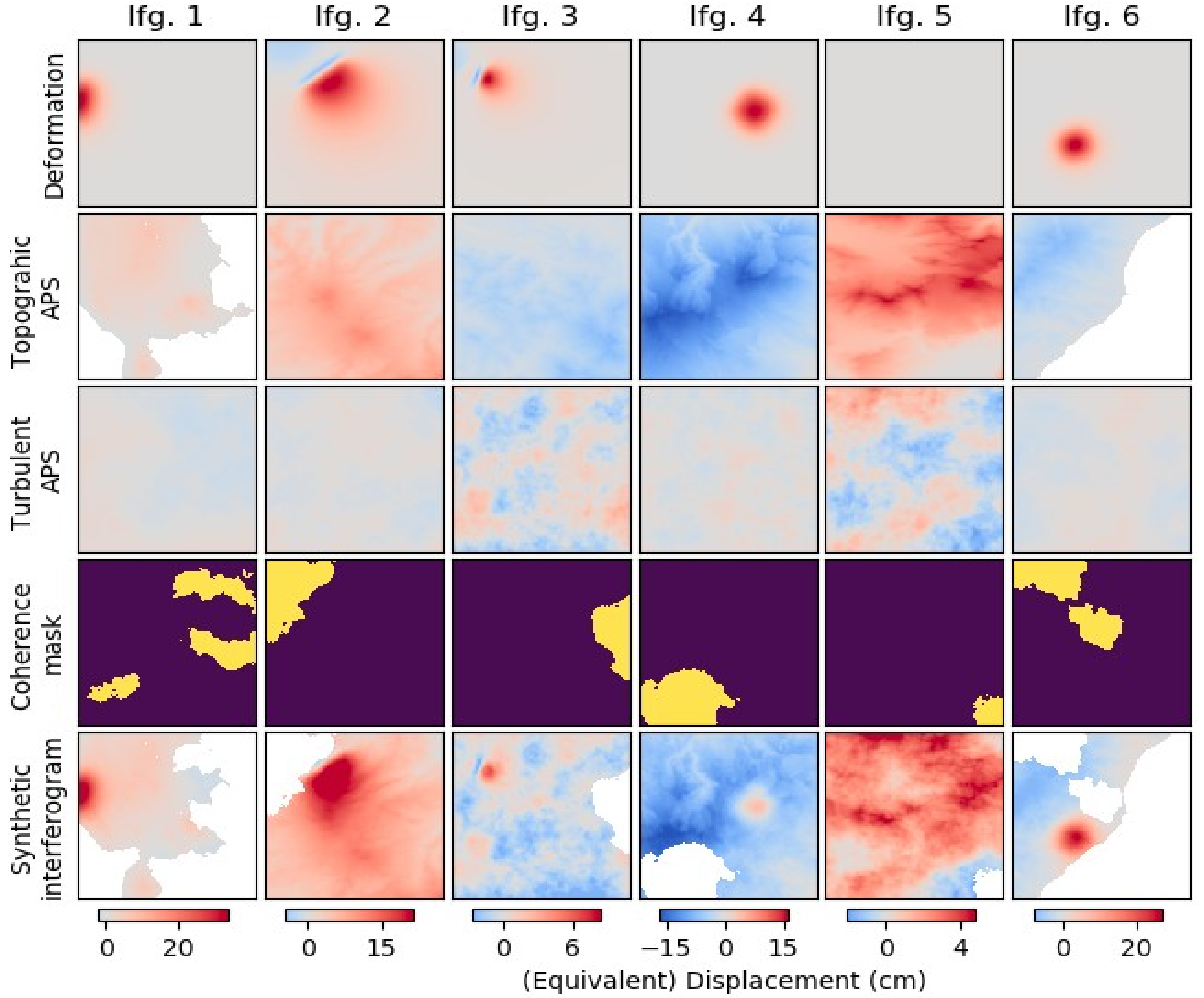


Figure: Gaddes et al., (in prep.)

Training the modified model

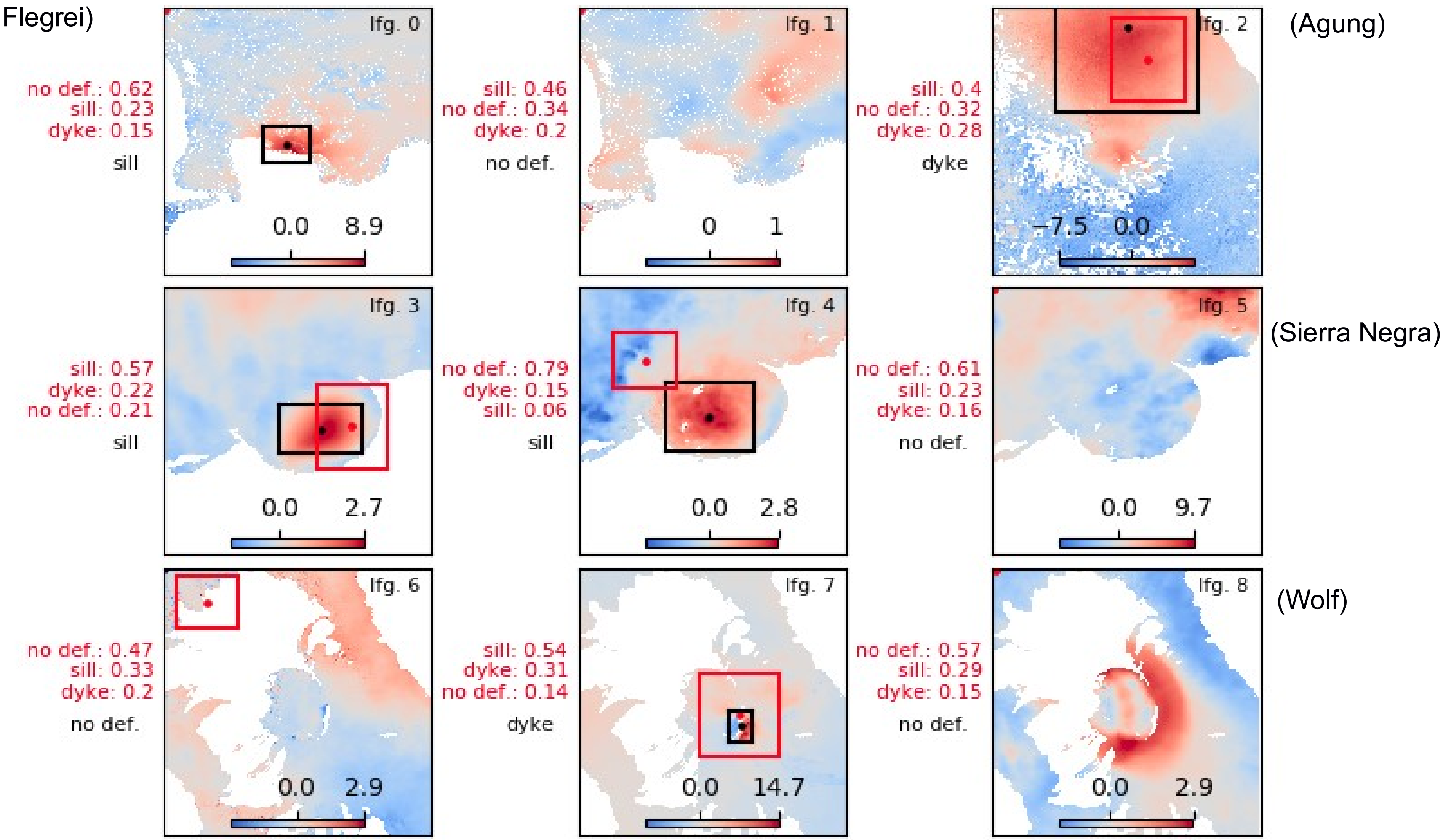
- 10^2 real data is challenging, so we try to use synthetic data to train the new fully connected classification and localisation heads.
- **Deformation** from dykes, sills, and point (Mogi) sources.
- **Topographically correlated APS** (atmospheric phase screen) for all subaerial volcanoes.
- **Turbulent APS**. (spatially correlated noise).



Gaddes et al., (in prep.)

Results

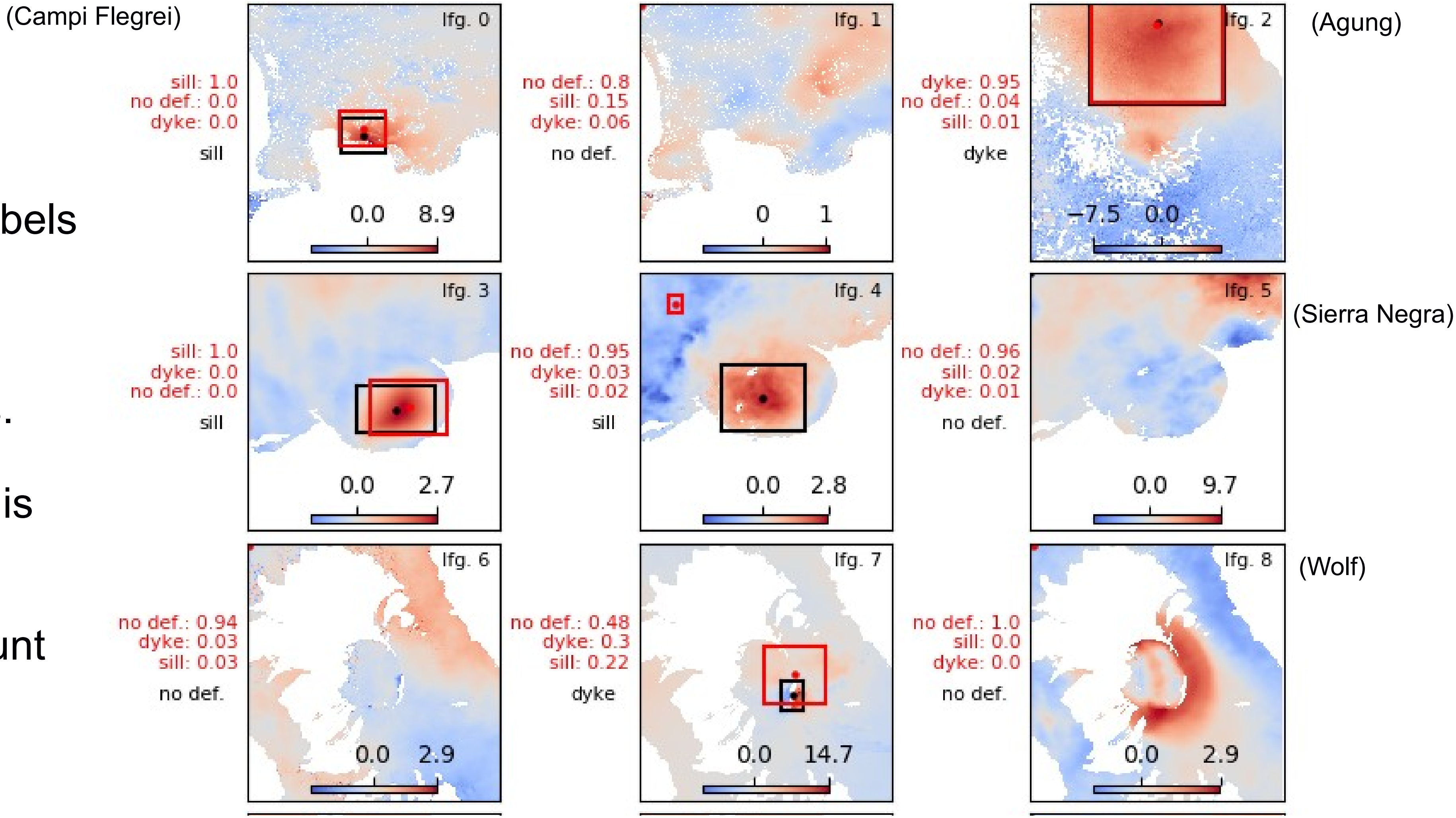
- Results with real data:
  - units = cm
  - Black = human added labels (for classification and localisation).
  - Red = model predictions. Classification has a probabilistic output, and is expressed as a decimal.



Gaddes et al., (in prep.)

Results

- Results with real data:
  - units = cm
  - Black = human added labels (for classification and localisation).
  - Red = model predictions. Classification has a probabilistic output, and is expressed as a decimal.
- Training with a small amount of real data improves performance.



Gaddes et al., (in prep.)

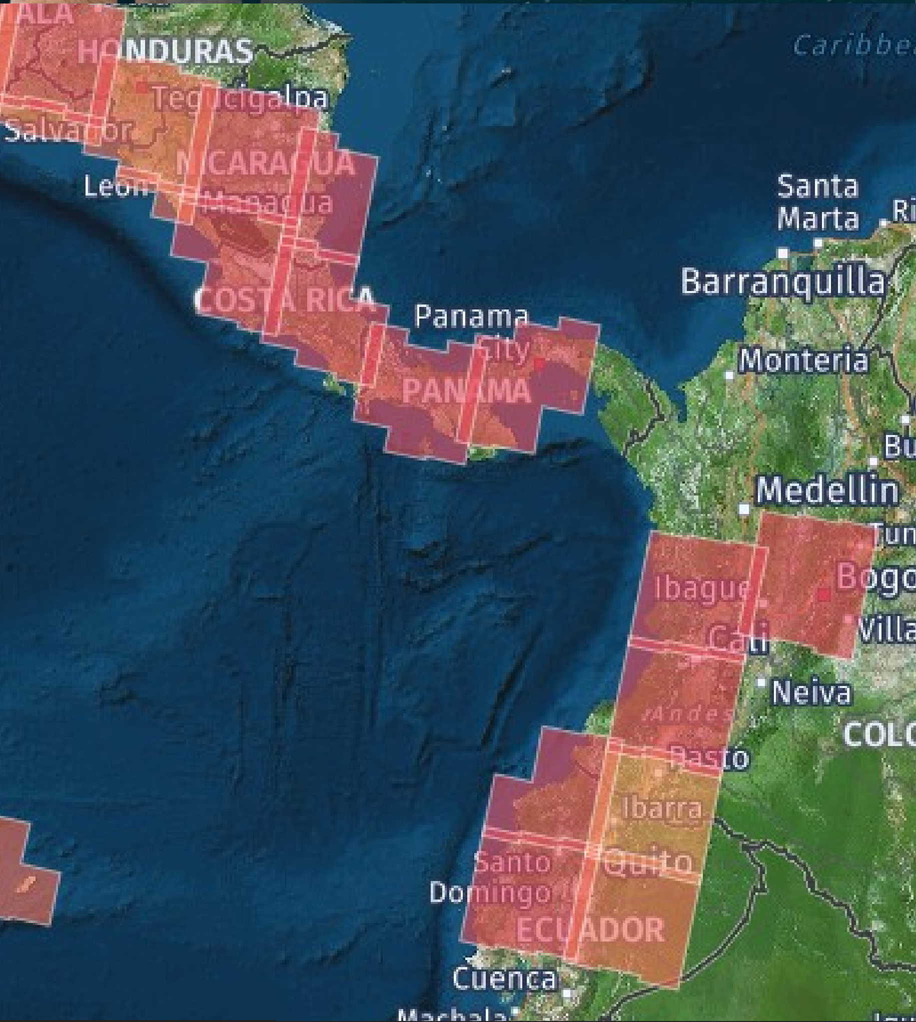
Conclusions

- The filters contained within convolutional neural networks that were trained on natural images can be used as starting points for models used with unwrapped interferograms.

- Our model can determine the location (and size) of a deformation pattern, and classify it (within three classes).

- Want to try the code?

  Synthetic interferograms:
  https://github.com/matthew-gaddes/SyInterferoPy
  Train CNNs:
  https://github.com/matthew-gaddes/Detect-Locate-CNN



References

- Albino F, Biggs J, Yu C, Li Z. Automated Methods for Detecting Volcanic Deformation Using Sentinel-1 InSAR Time Series Illustrated by the 2017–2018 Unrest at Agung, Indonesia. Journal of Geophysical Research: Solid Earth. 2020 Feb;125(2):e2019JB017908.
- Anantrasirichai, N., Biggs, J., Albino, F., Hill, P. and Bull, D., 2018. Application of Machine Learning to Classification of Volcanic Deformation in Routinely Generated InSAR Data. *Journal of Geophysical Research: Solid Earth*, *123*(8), pp.6592-6606.
- Anantrasirichai N, Biggs J, Albino F, Bull D. A deep learning approach to detecting volcano deformation from satellite imagery using synthetic datasets. Remote Sensing of Environment. 2019 Sep 1;230:111179.
- Biggs J, Ebmeier SK, Aspinall WP, Lu Z, Pritchard ME, Sparks RS, Mather TA. Global link between deformation and volcanic eruption quantified by satellite imagery. Nature communications. 2014 Apr 3;5(1):1-7.
- Gaddes, M.E., Hooper, A., Bagnardi, M., Inman, H. and Albino, F., 2018. Blind signal separation methods for InSAR: The potential to automatically detect and monitor signals of volcanic deformation. *Journal of Geophysical Research: Solid Earth*, *123*(11), pp.10-226.
- Gaddes ME. Automatic Detection of Volcanic Unrest Using Interferometric Synthetic Aperture Radar (Doctoral dissertation, University of Leeds).
- Valade S, Ley A, Massimetti F, D'Hondt O, Laiolo M, Coppola D, Loibl D, Hellwich O, Walter TR. Towards global volcano monitoring using multisensor sentinel missions and artificial intelligence: The mounts monitoring system. Remote Sensing. 2019 Jan;11(13):1528.