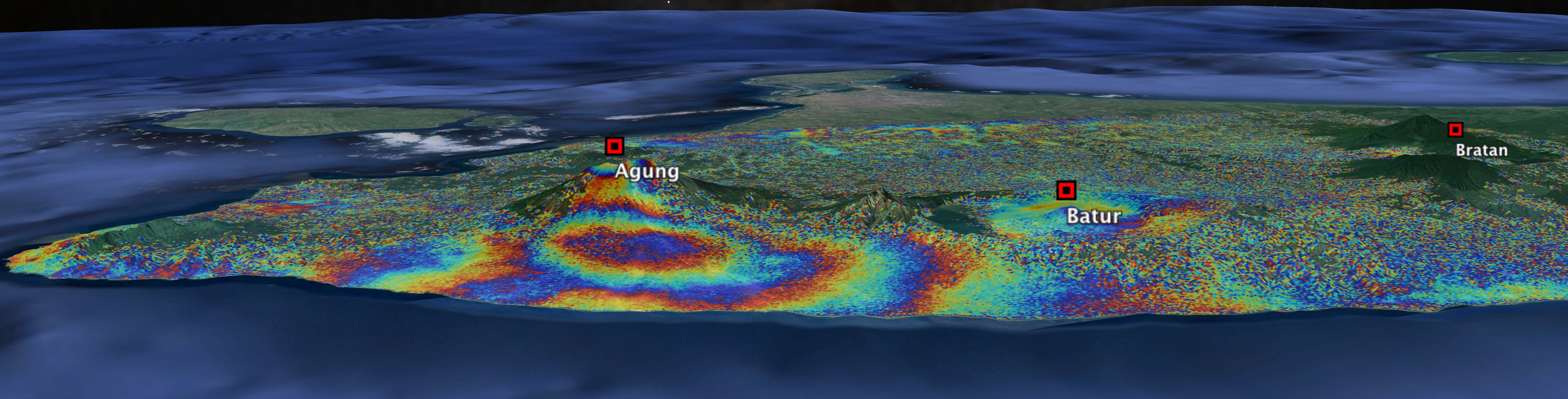
Application of Deep Learning to Detect Ground Deformation in InSAR Data



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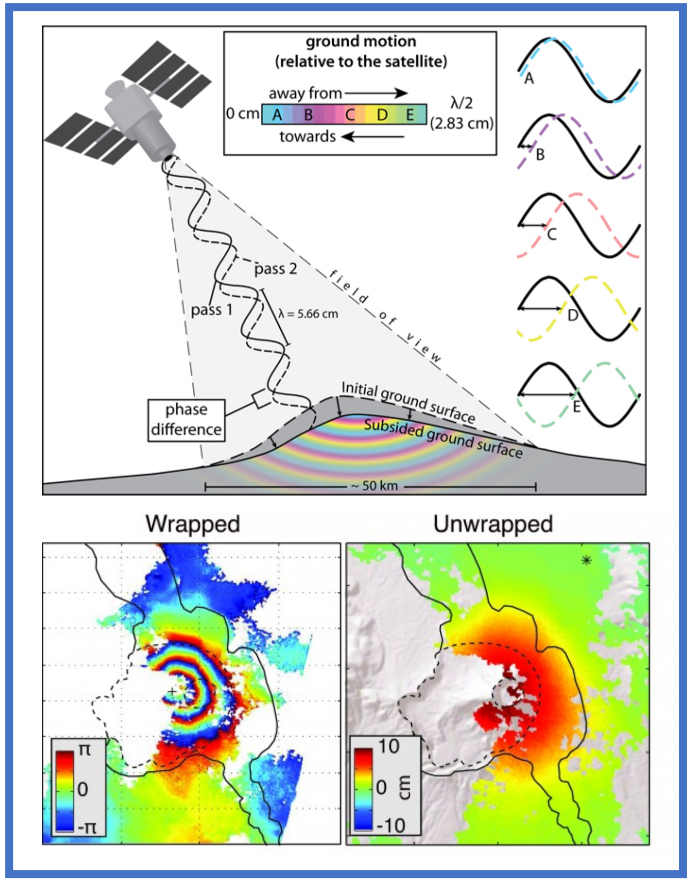
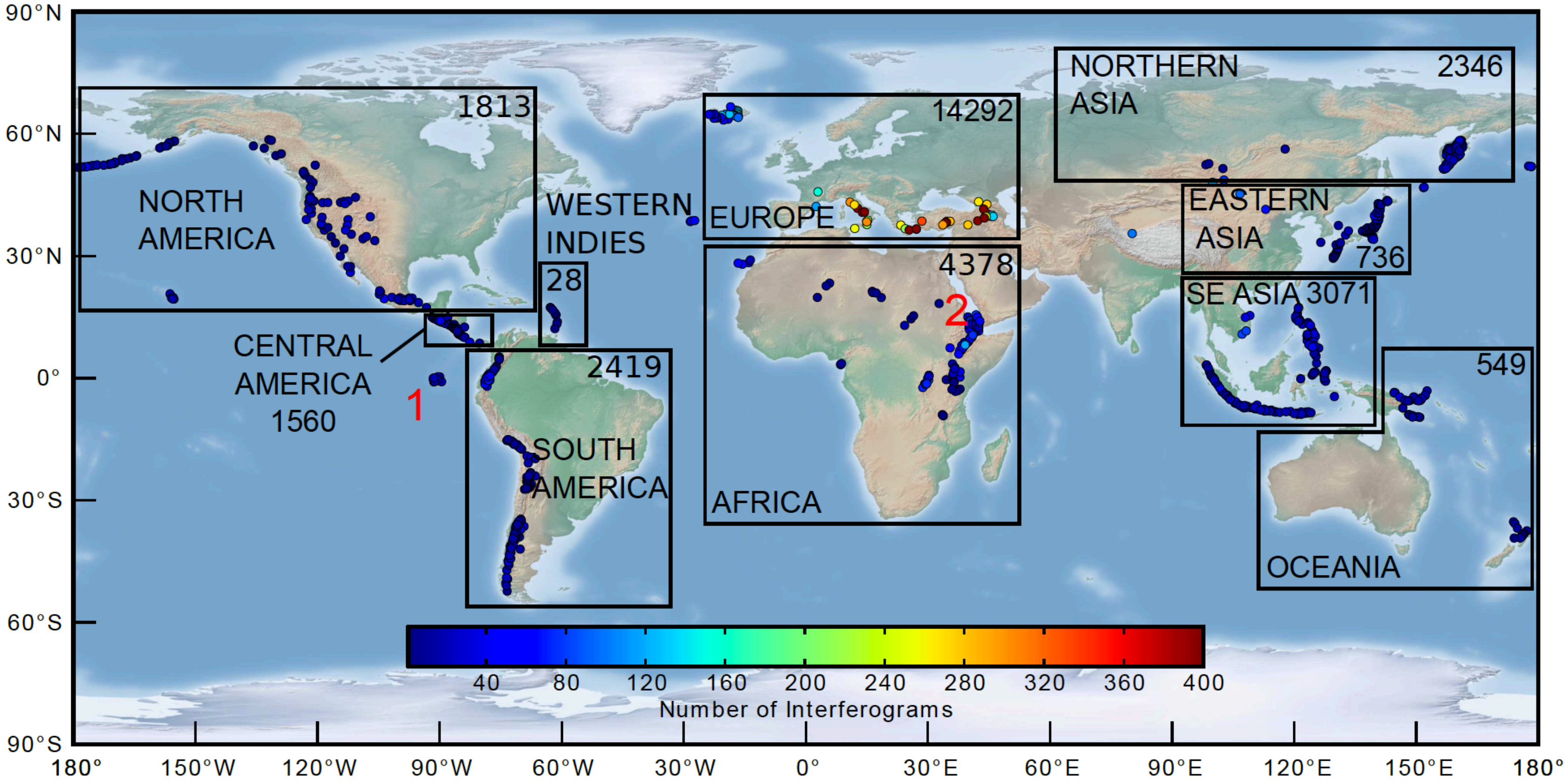
University of BRISTOL
COMET
VILab
Visual Information Laboratory

Global Volcano Monitoring: The LïCSAR-volcano database

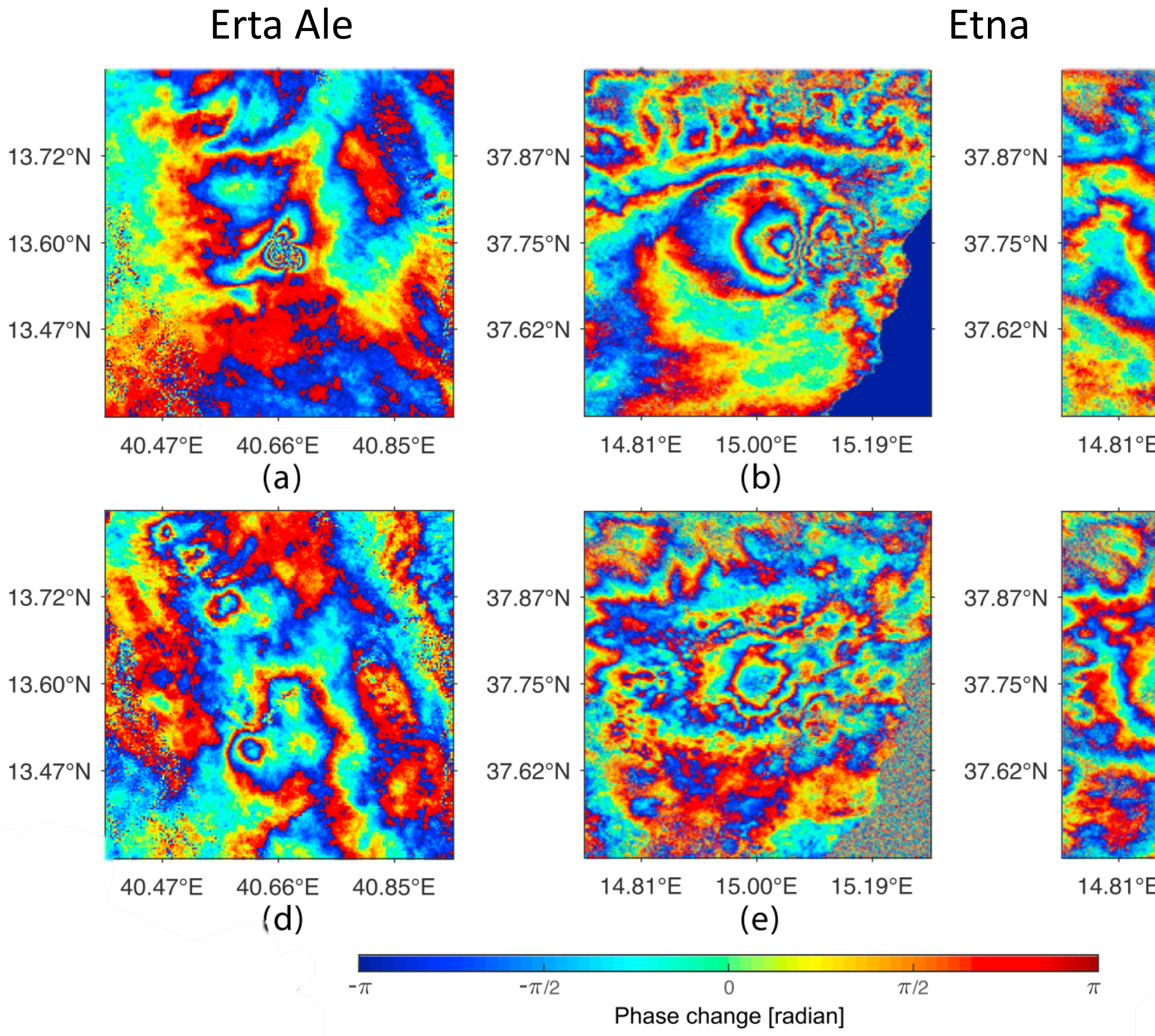


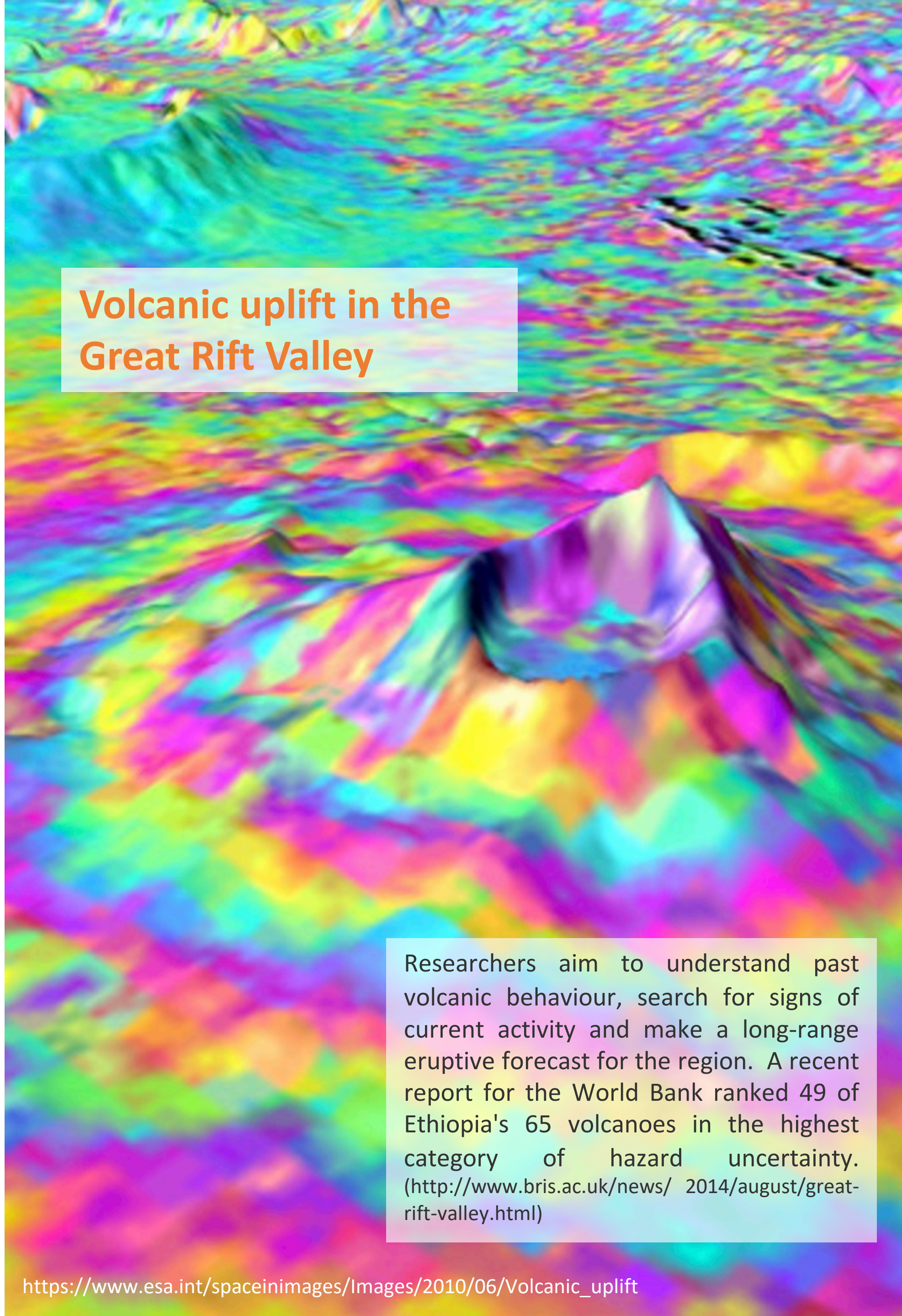


http://comet.nerc.ac.uk/ COMET-LiCS-portal/

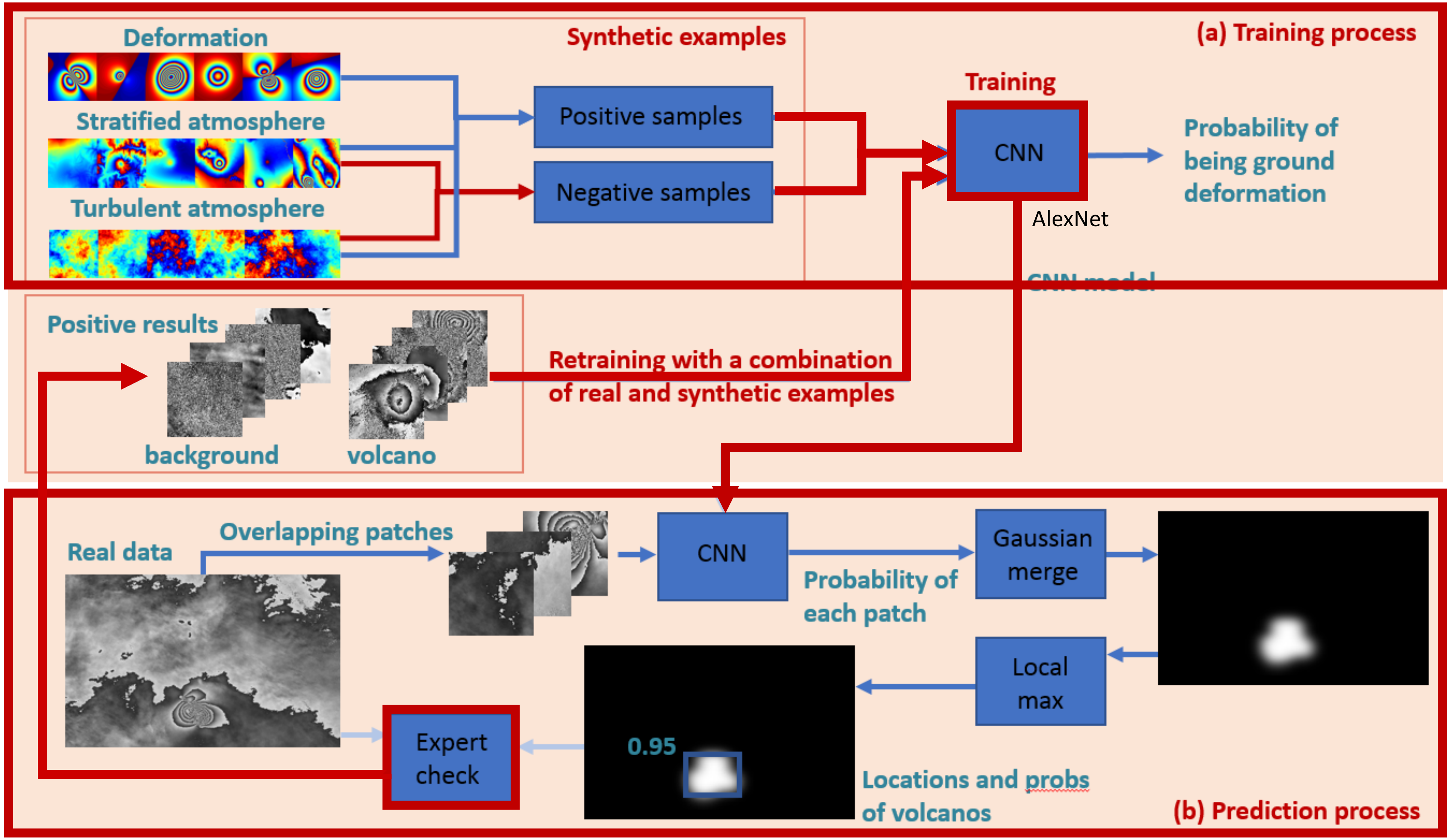
- Sentinel-1 has generated >10-TB data per day
- Test dataset of ~30,000 interferograms at >900 active volcanoes produced by LiCSAR
- Now up to >400,000 (Mar 2019), 80% of volcanoes.
- Anticipate 1 million images per year when fully operational.

Ground deformation, background, noise or atmosphere?



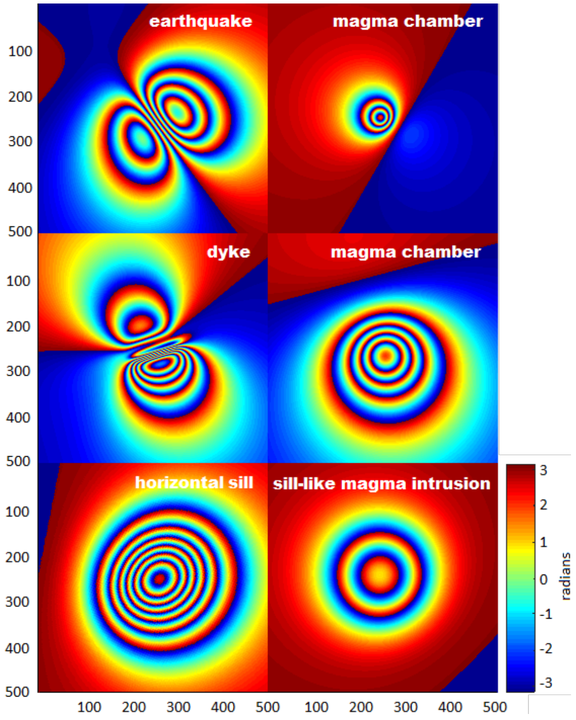


Proposed framework

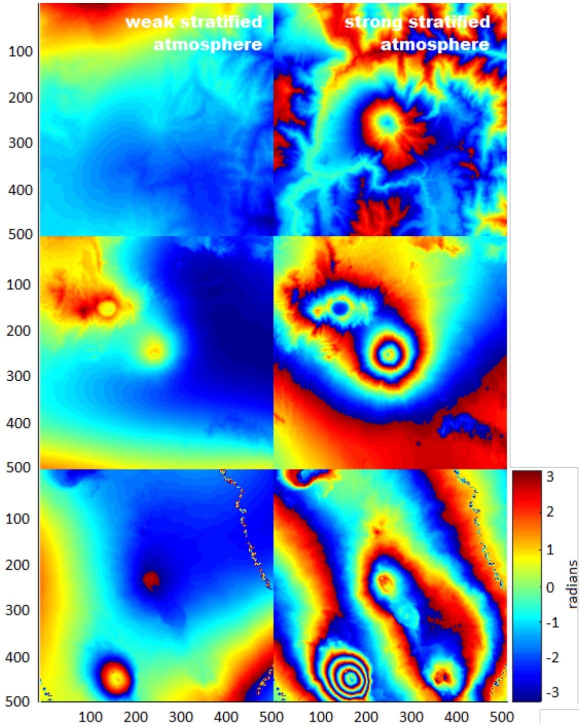


Training Dataset: Synthetic components

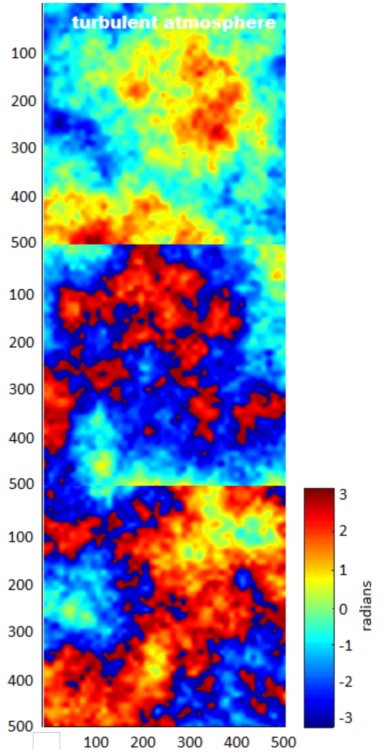
Deformation (D)



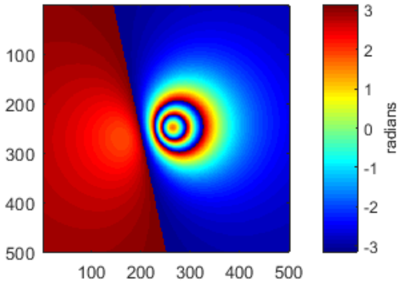
Stratified atmosphere (S)



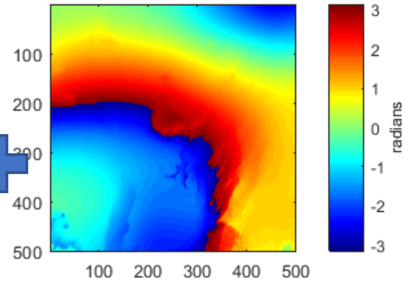
Turbulent atmosphere (T)



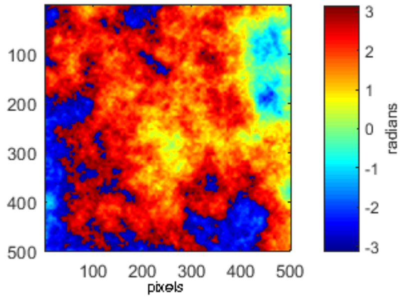
D



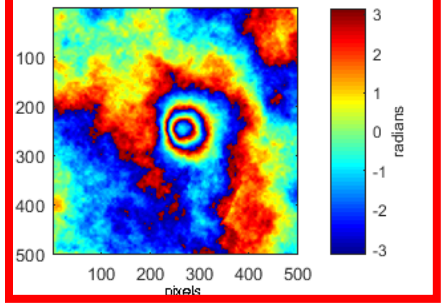
S



T



Final Interferogram

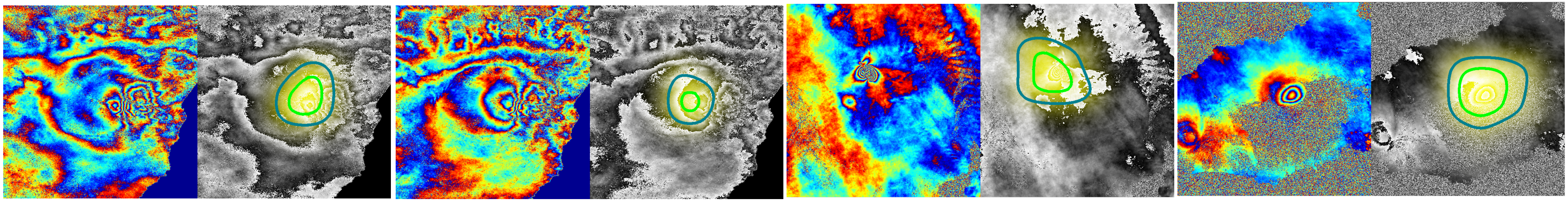


Anantrasirichai et al, 2019, RSE

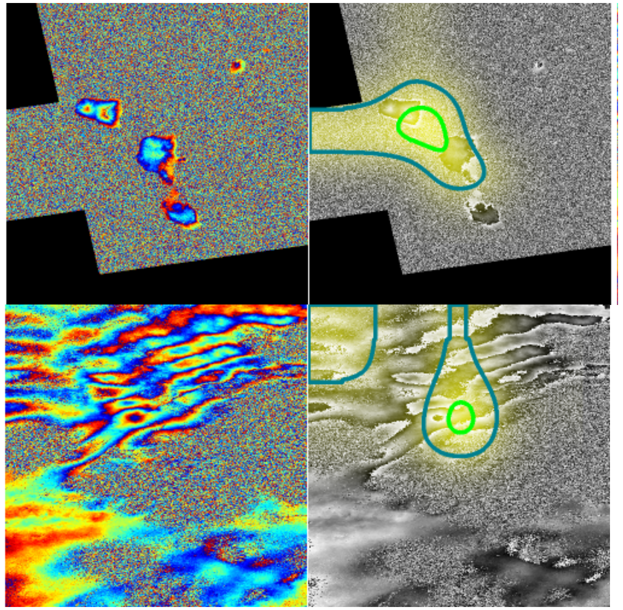
Results

Areas inside dark and bright green contours are where P>0.5 and P>0.8, respectively.

- **True positive results**



- **False positive results**



30,249 interferograms of the Sentinel-1 dataset

Trained by	#P	#TP	#FP	#FN
Synthetic	334	41	293	1
+ Sentinel	**50**	**41**	**9**	**1**

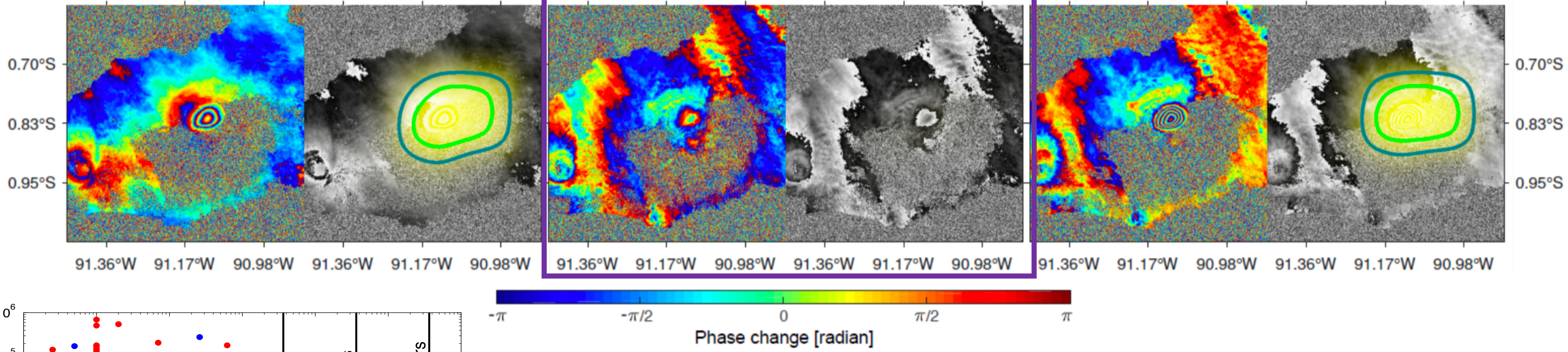
False Negatives

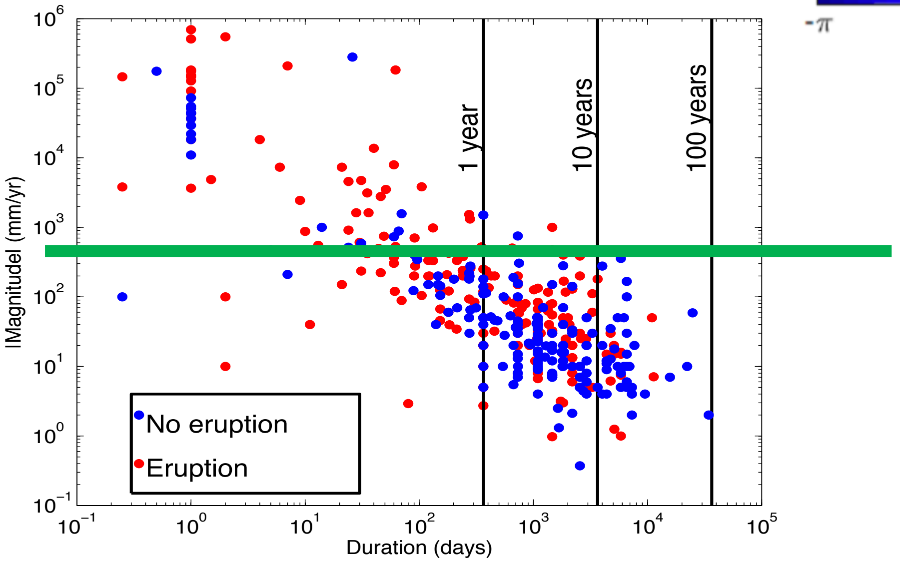
- Current CNN trained to detect rapid deformation signals that produce multiple fringes in a single interferogram

(20170425-20170531)

False negative result Sierra Negra
(20170519-20170531)

(20170519-20170718)



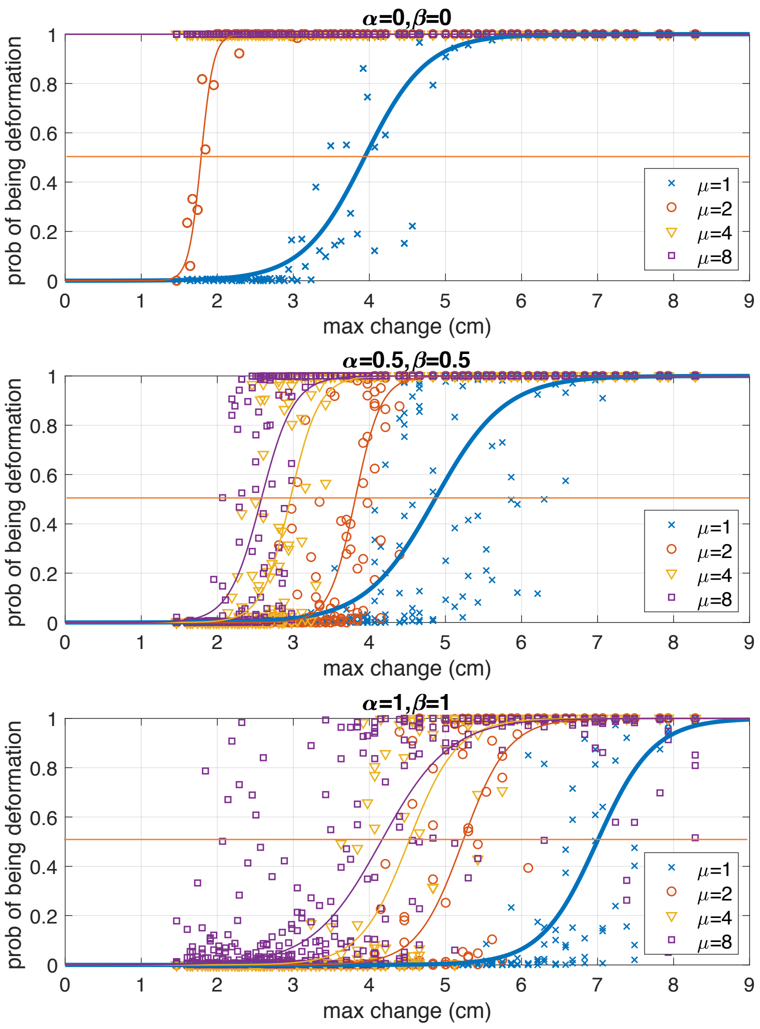


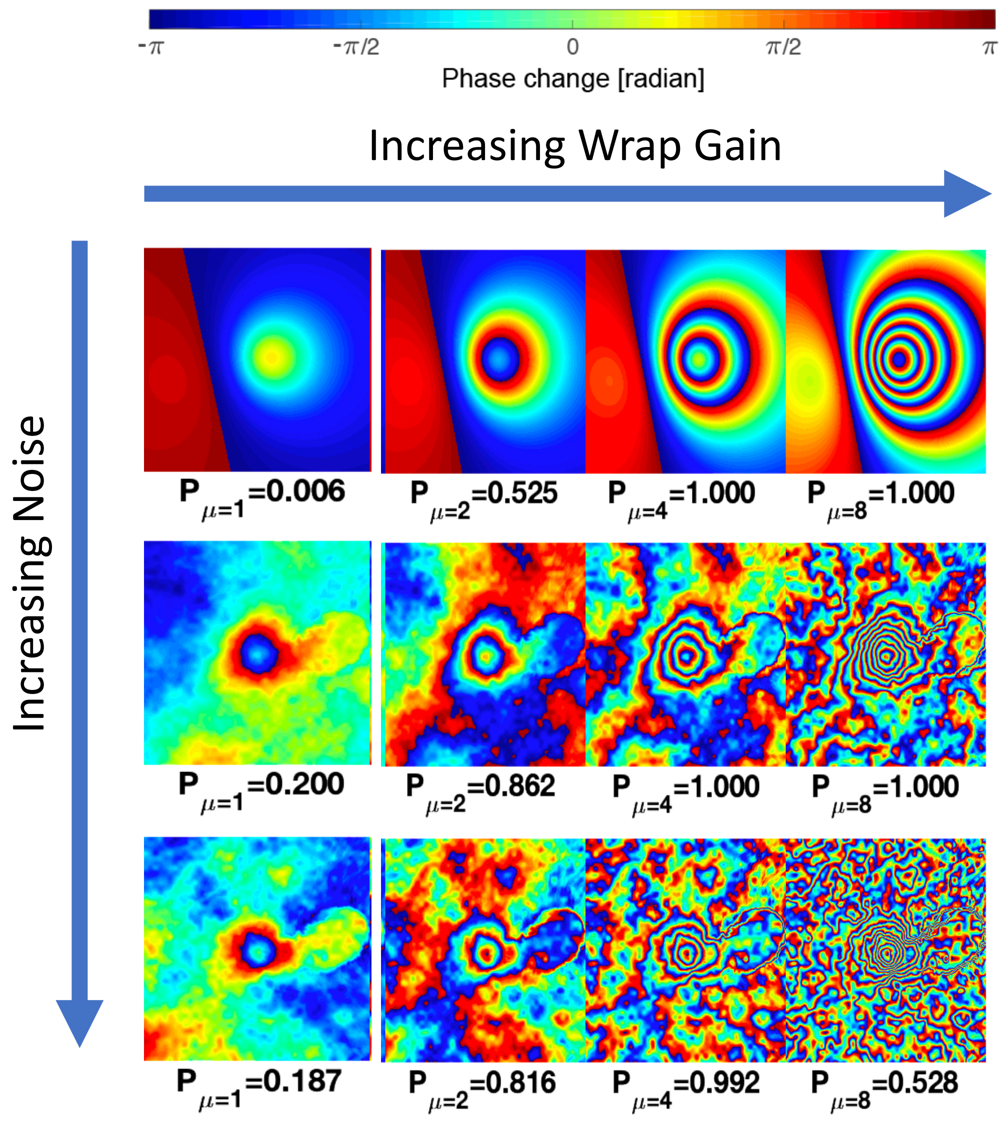
1 fringe in a 12 day interferogram = 85 cm/yr

- Slow, steady deformation is common.
- Can we improve detection thresholds?

Overwrapping technique

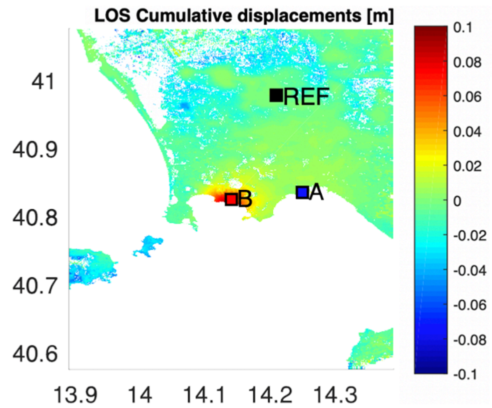
- Method: $\psi'_\mu \equiv \mu\psi'_\tau \mod 2\pi \quad \mu \in \{1, 2, 4, 8\}$

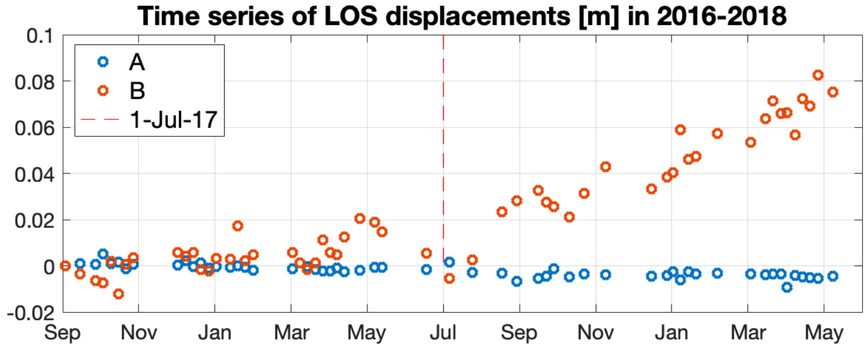




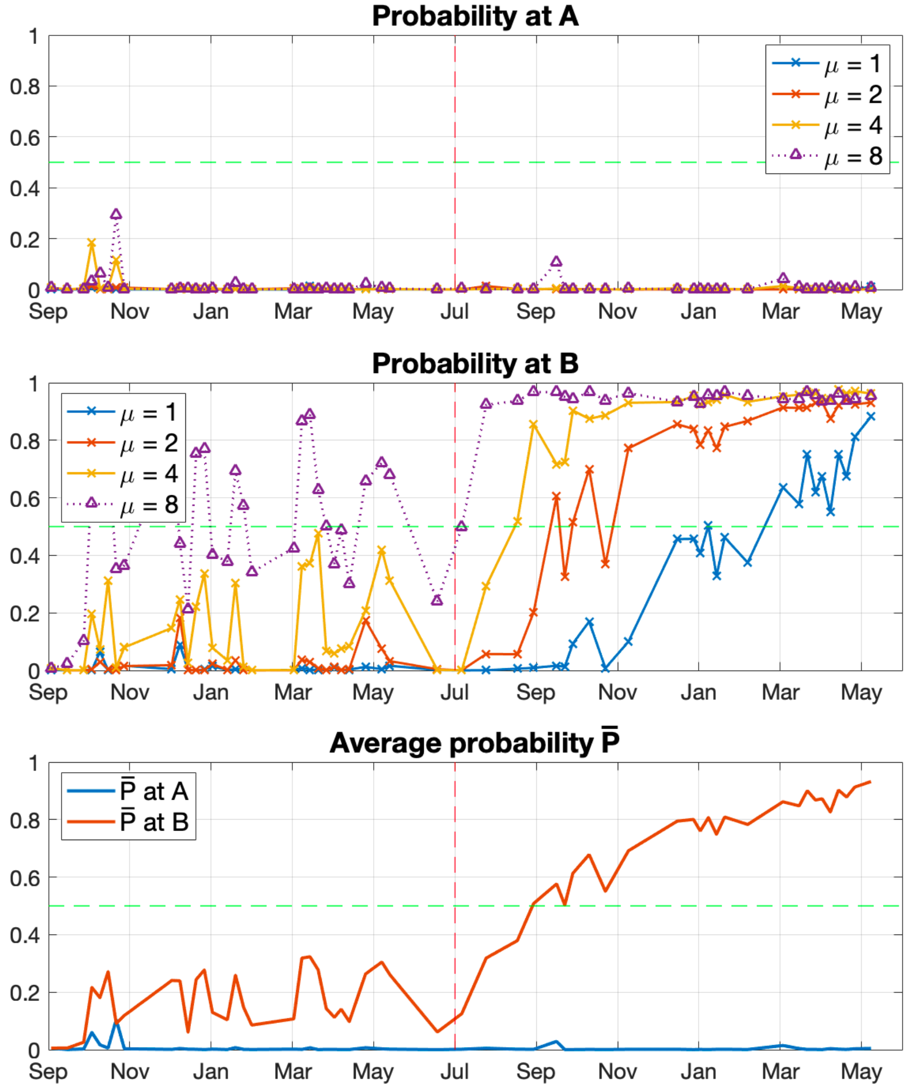
Example: Campi Flegrei, Italy

Campi Flegrei



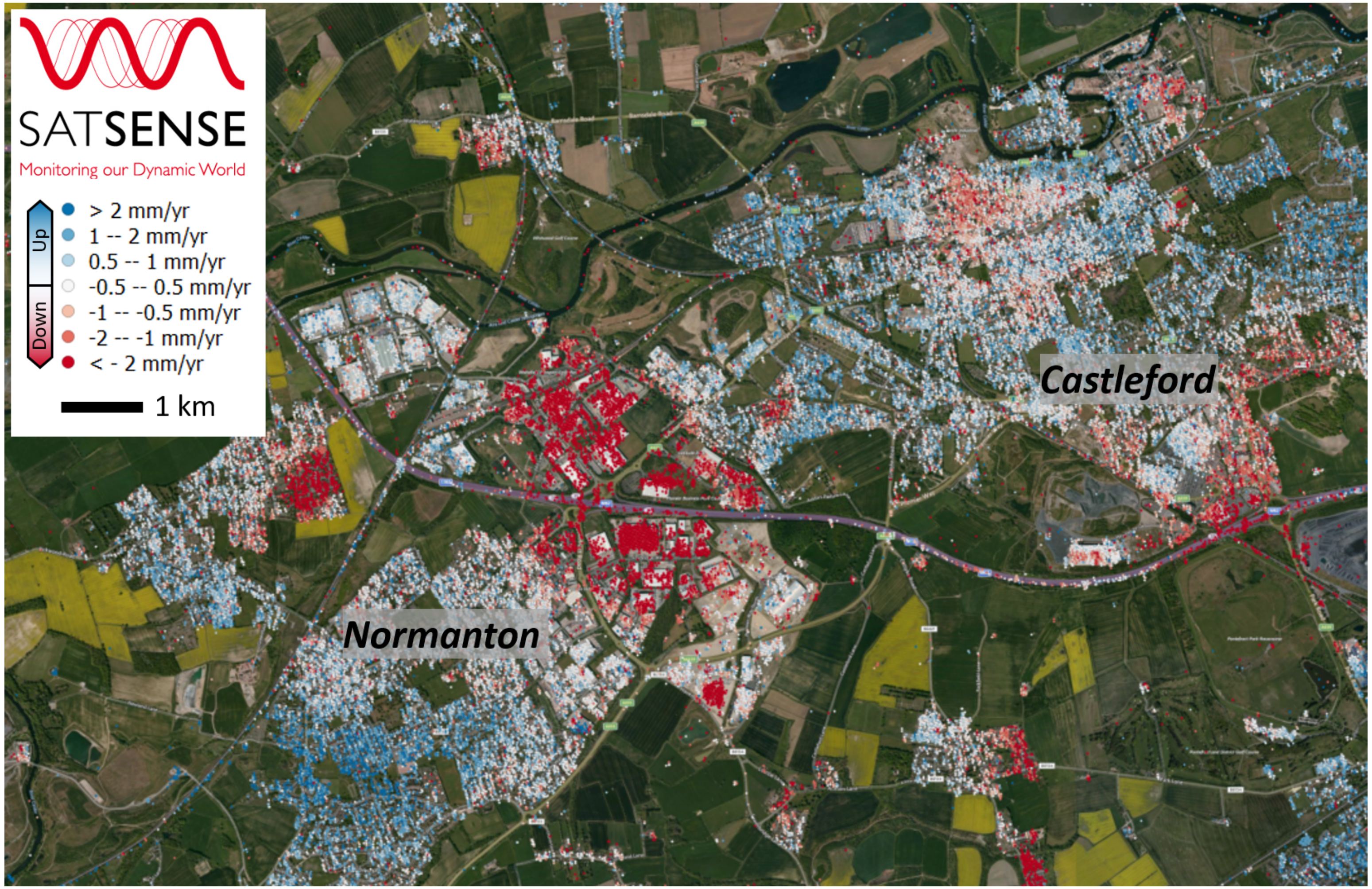


- Three short-duration interferograms for each time acquisition
- No atmospheric correction
- A linear least-square inversion is performed on the network of unwrapped interferograms



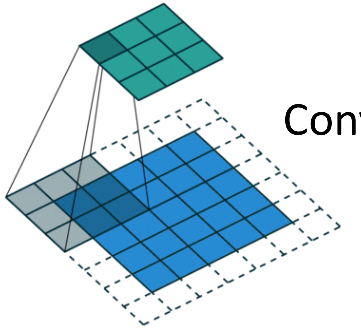
- A new pulse of uplift began in July 2017

Urban Sources – UK Digital Environment



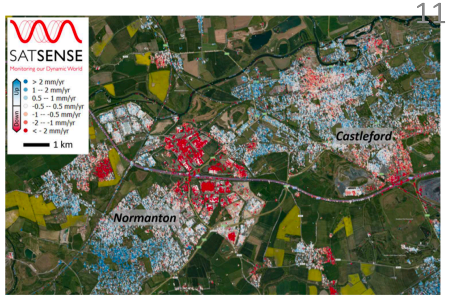
Problems:
- Sparsity and noise
- Lack of real data (deformation types: sinkholes, coal mining subsidence, landside, fracking site, etc.)

Adapted Methods:
- Synthetic data (D + T)
  - point source – ground subsidence
- Spatial interpolation
  - Matrix completion with soft thresholding

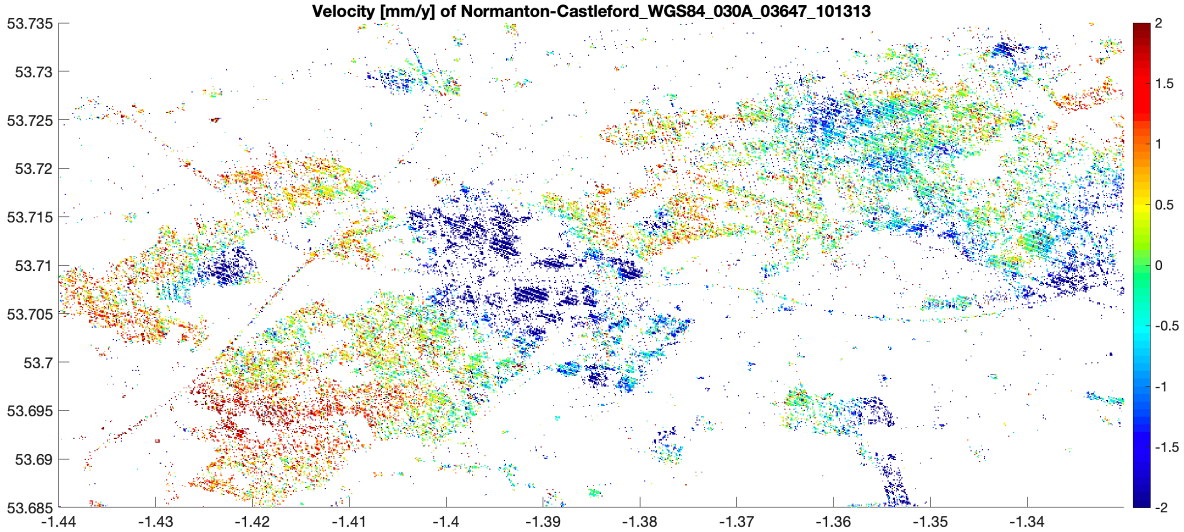


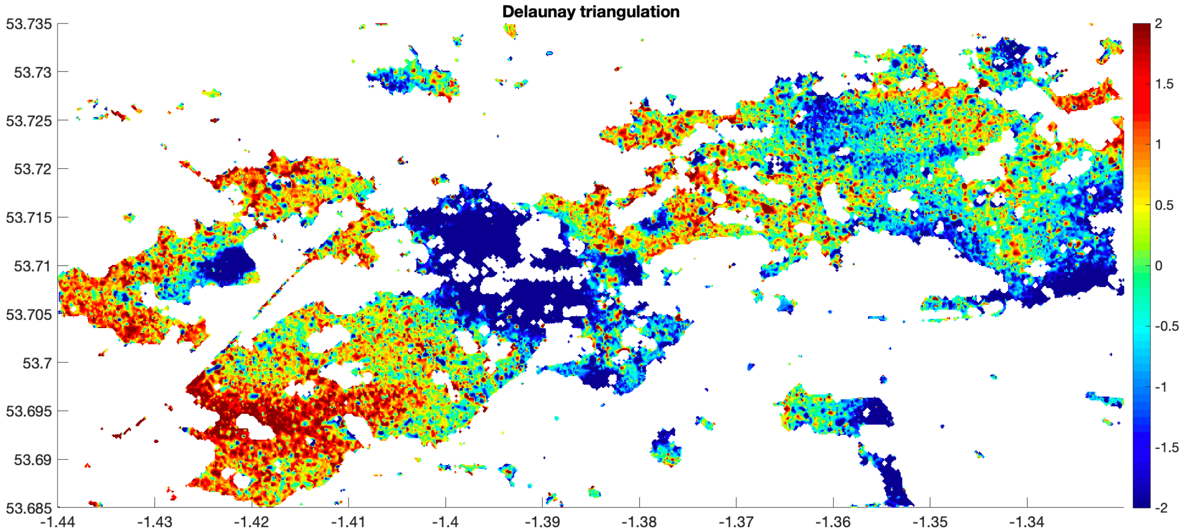
Convolution

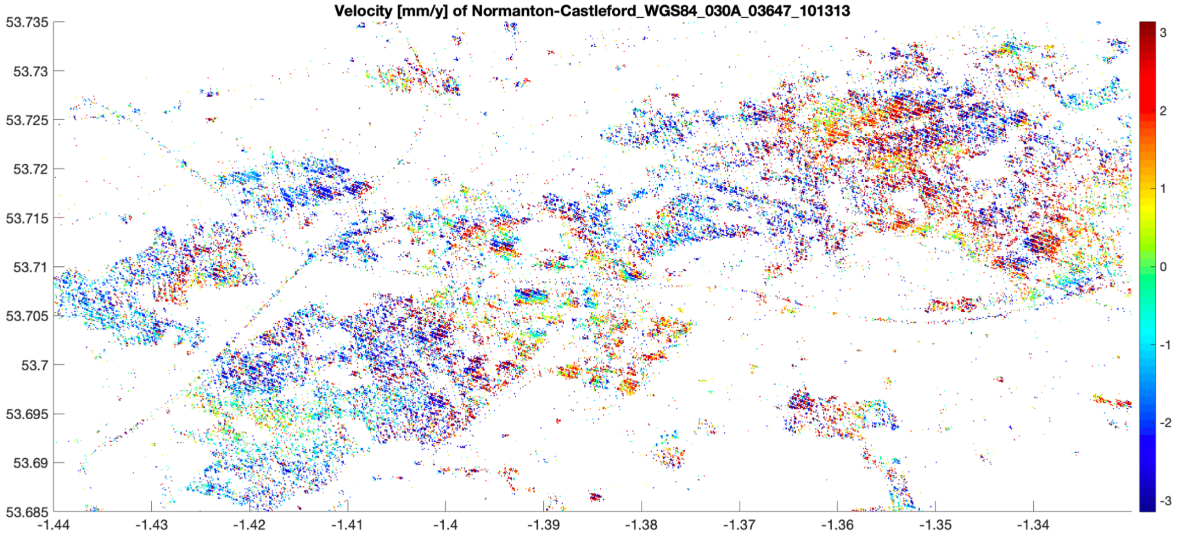
Sparsity and spatial interpolation

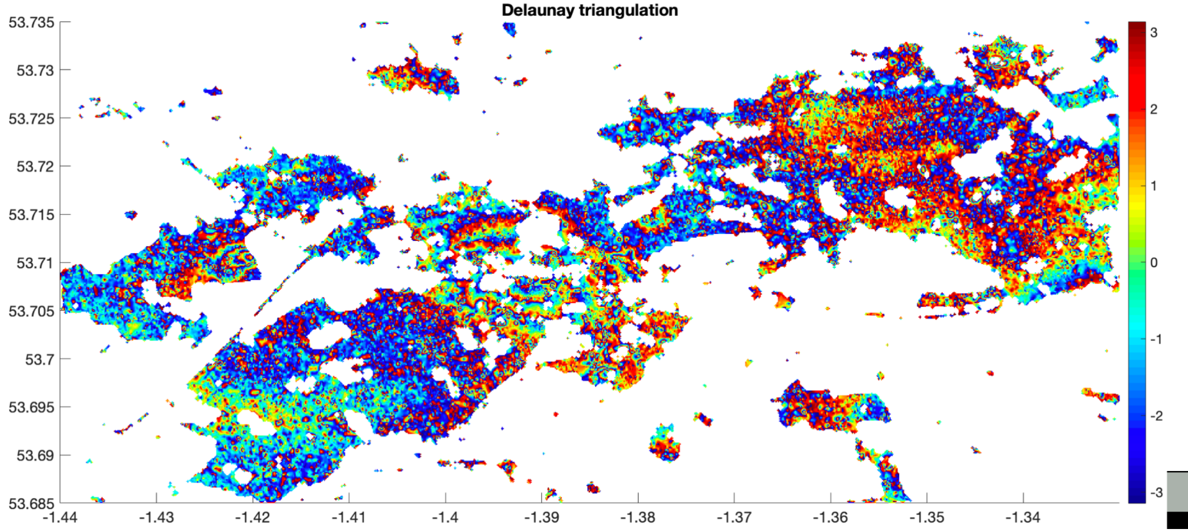


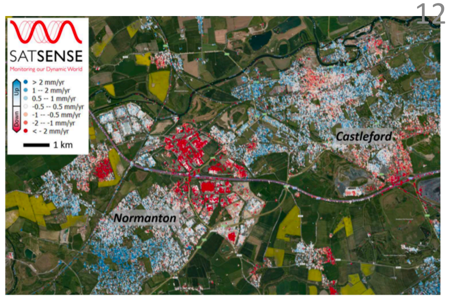
Normanton and Castleford - coal mining area uplift





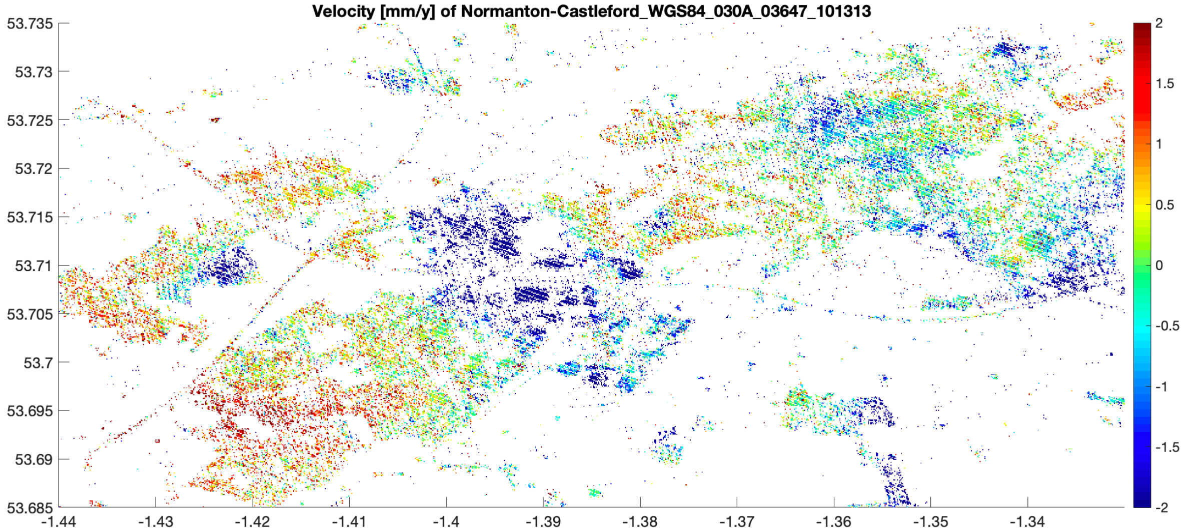


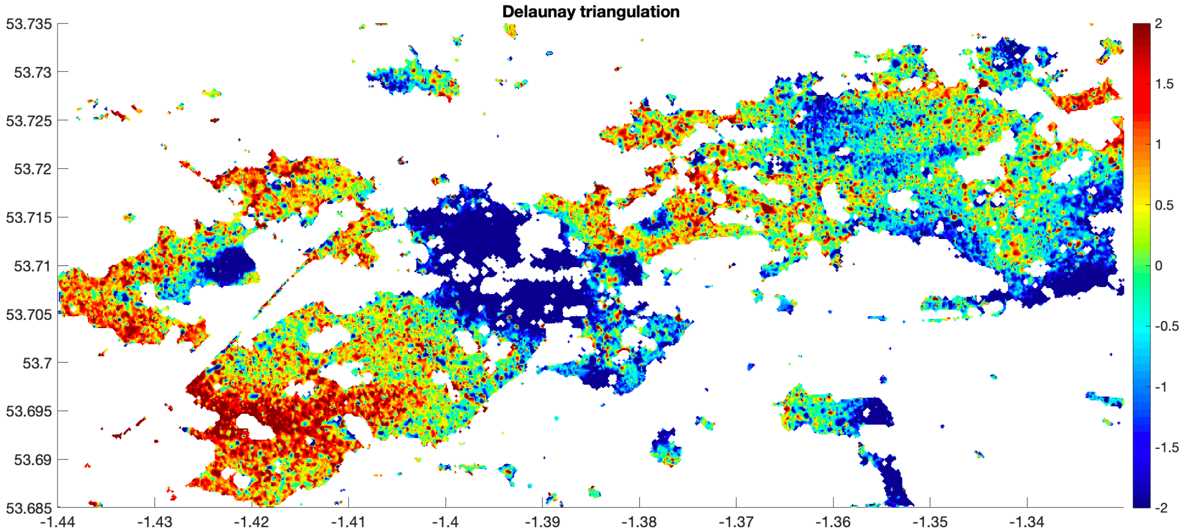


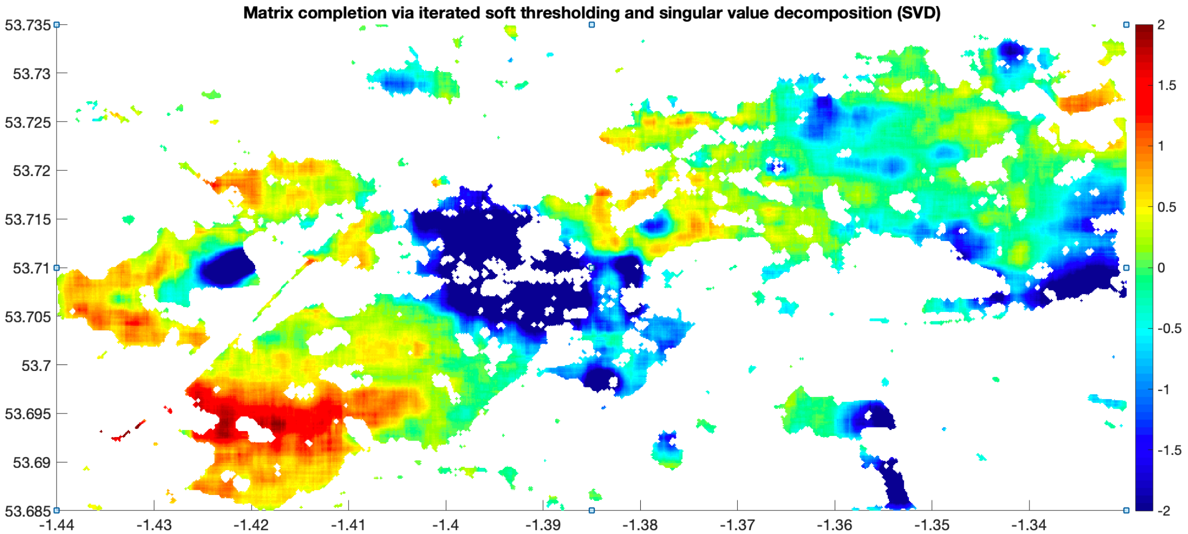


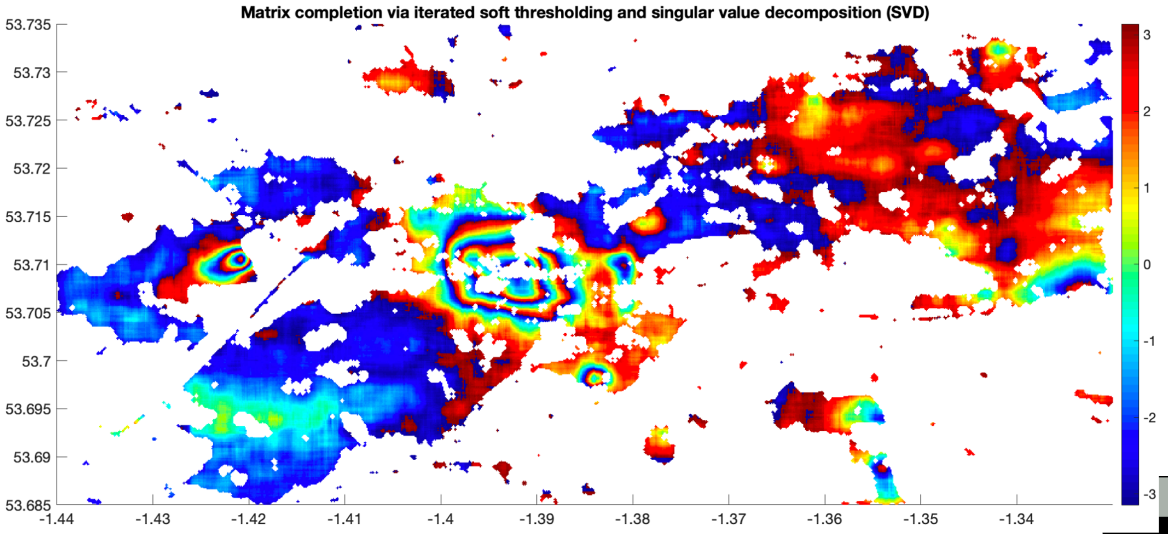
Sparsity and spatial interpolation

- Matrix completion with soft thresholding

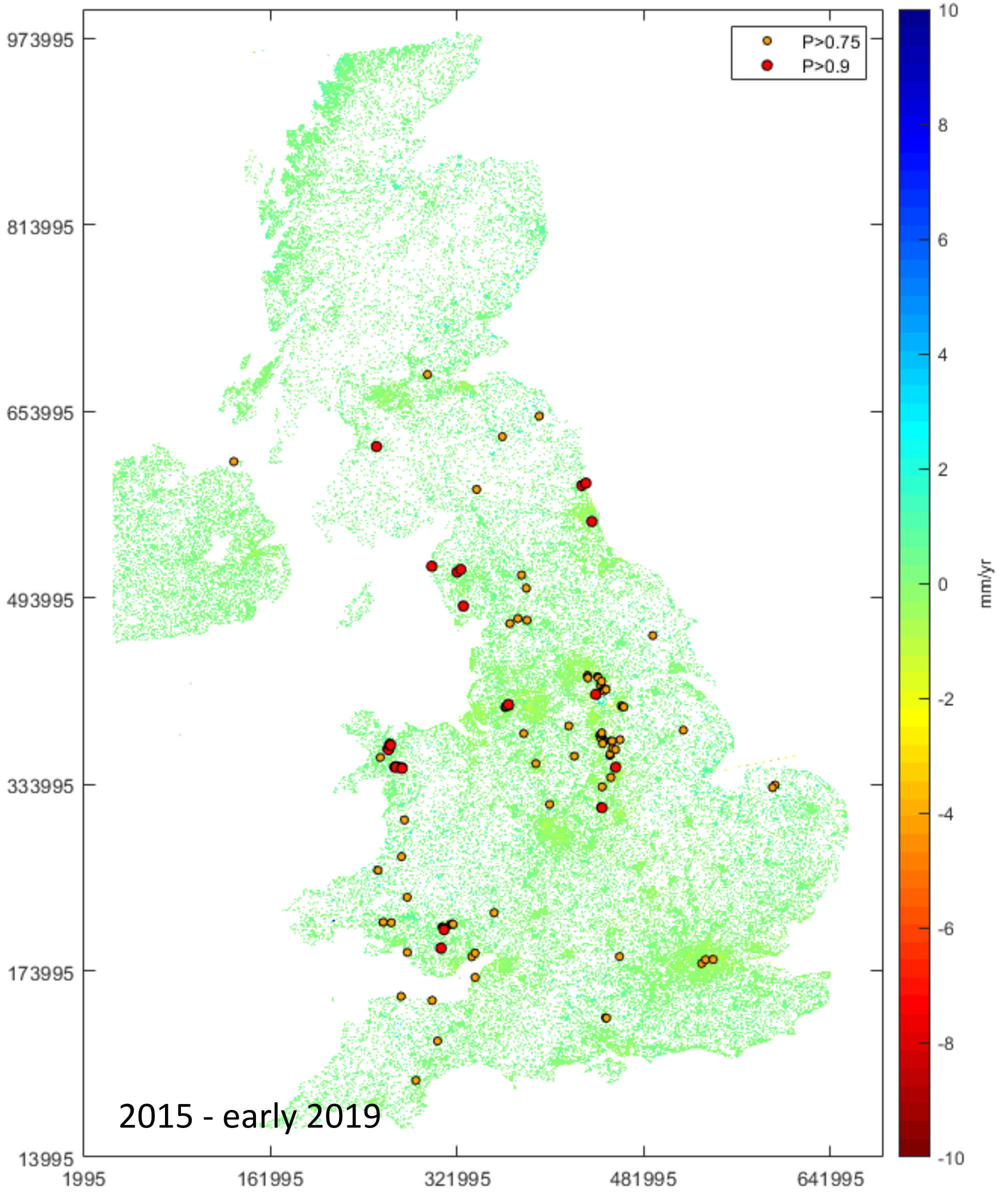








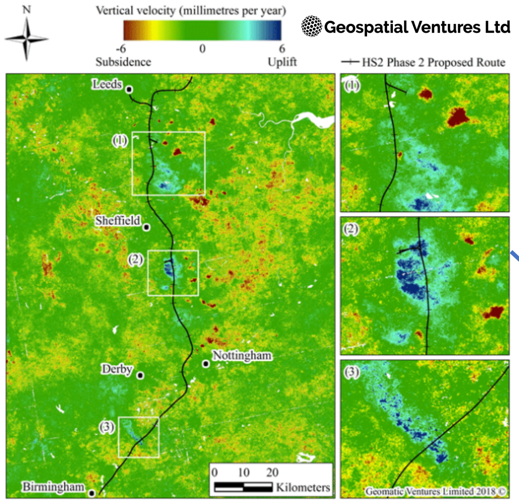
Detection results

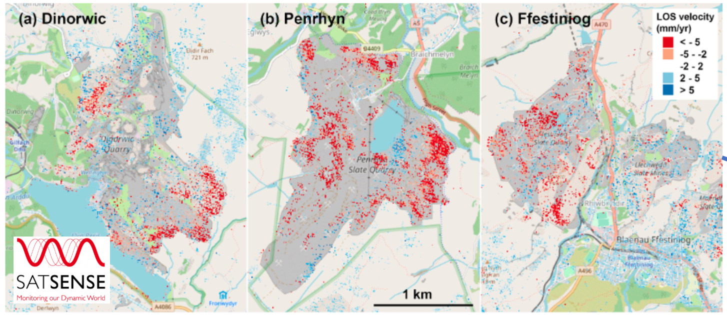


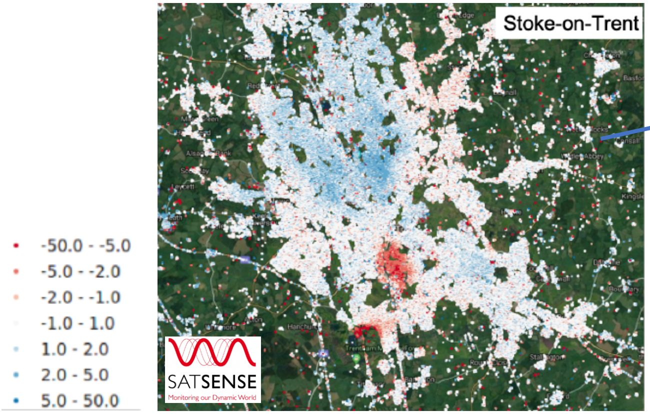
satsense

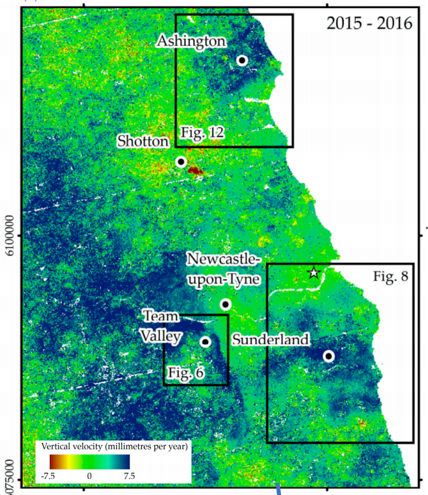
- 66,801x121,501 pixels
- >64 million points (ascending)
- >29 million points (descending)
- Interpolating process at 2500x2500 pixels
- CNN input size is 224x224 pixels

Detection results

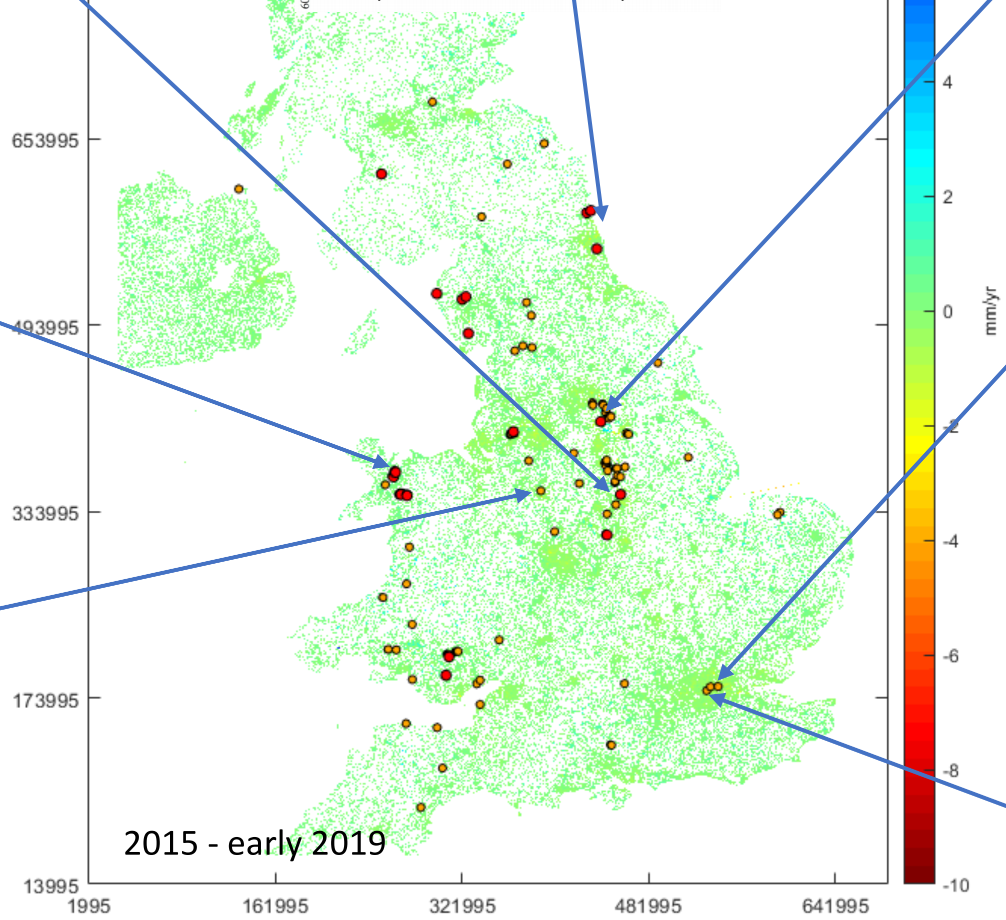




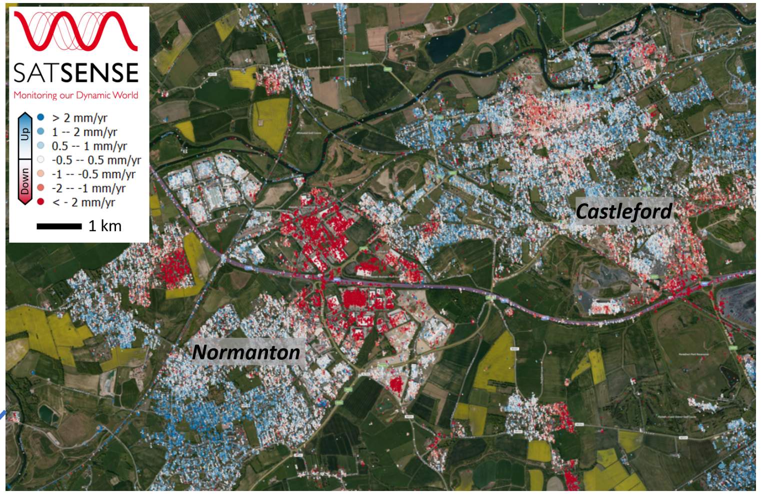




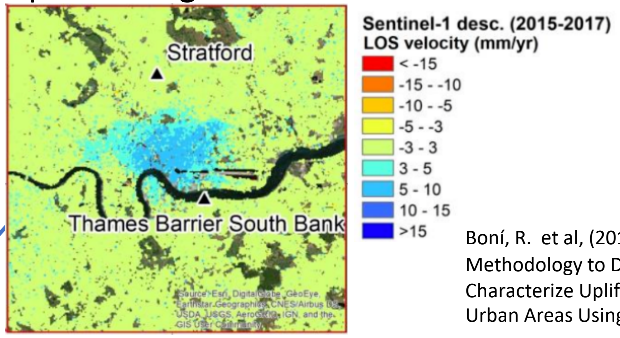
Gee, D., et al. (2017). Ground motion in areas of abandoned mining: Application of the intermittent sbas (isbas) to the northumberland and durham coalfield, uk



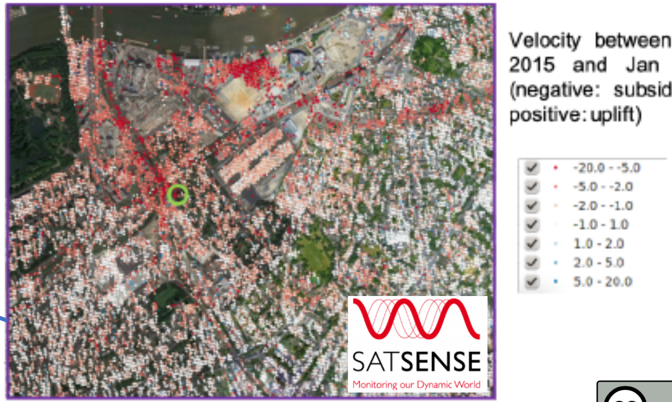
Subsidence and uplift from coal mining



Uplift from ground water rebound



Boní, R. et al, (2018) A Methodology to Detect303and Characterize Uplift Phenomena in Urban Areas Using Sentinel-1 Data

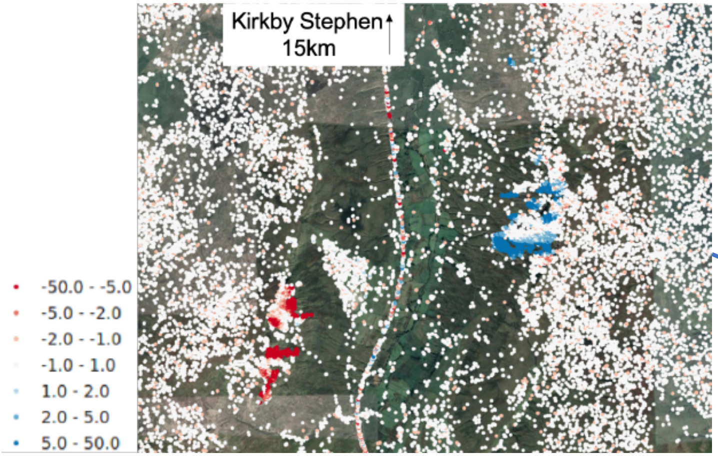


Velocity between May 2015 and Jan 2019 (negative: subsidence, positive: uplift)

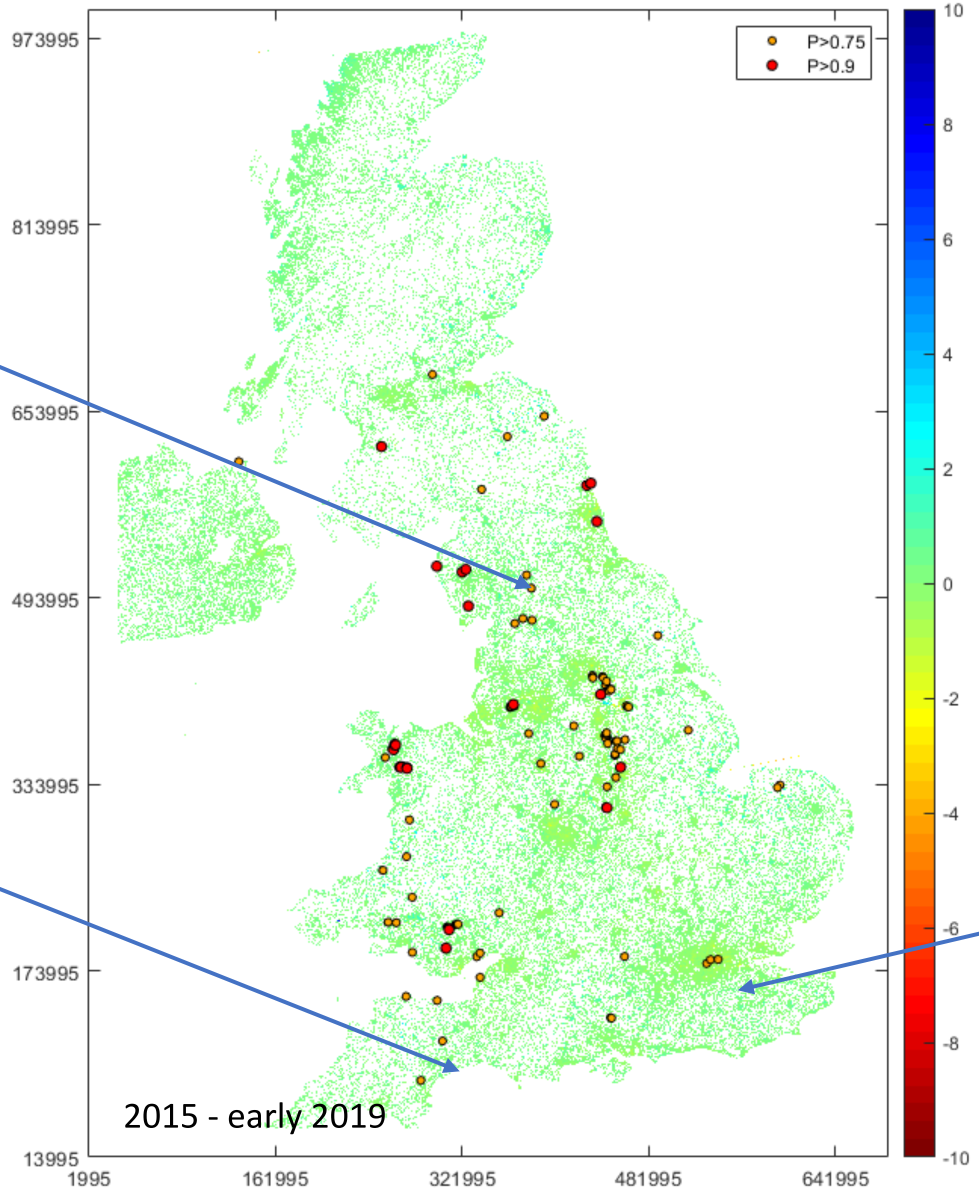
Subsidence from engineering work

Limitations

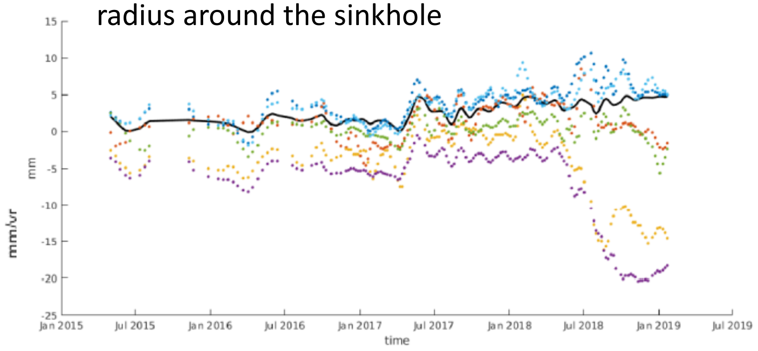
Landslides



Landslides



Individual displacement time series from a 15m radius around the sinkhole



sinkhole

Conclusions

- **Global datasets** have value for monitoring and understanding magmatic processes.
- **LiCSAR routine processing** producing large data volumes (>100,000 volcano images).
- **Deep learning** framework automatically searches through large volumes of wrapped **InSAR** images to detect rapid **ground deformation** that may be related to **volcanic activity**.
- Problem of **imbalanced training data** was solved using **synthetic examples**, where three major components, i.e. deformation, stratified and turbulent atmosphere.
- **Slow deformation** can be detected using cumulative signals and over-wrapped data.
- Adaptable to **urban sources** of deformation with preprocessing techniques, including spatial interpolation.

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), 6592-6606.
Anantrasirichai, N., Biggs, J., Albino, F., and Bull, D., 2019. A deep learning approach to detecting volcano deformation in satellite imagery using synthetic training data. *Remote Sensing of the Environment. 230, 111179*
Anantrasirichai, N., Biggs, J., Albino, F., and Bull, D., 2019. The ability of Convolutional Neural Networks to Detect Slow Ground Deformation in InSAR Timeseries, *Geophysical Research Letters.*