Monitoring global volcanic unrest using InSAR data and machine learning

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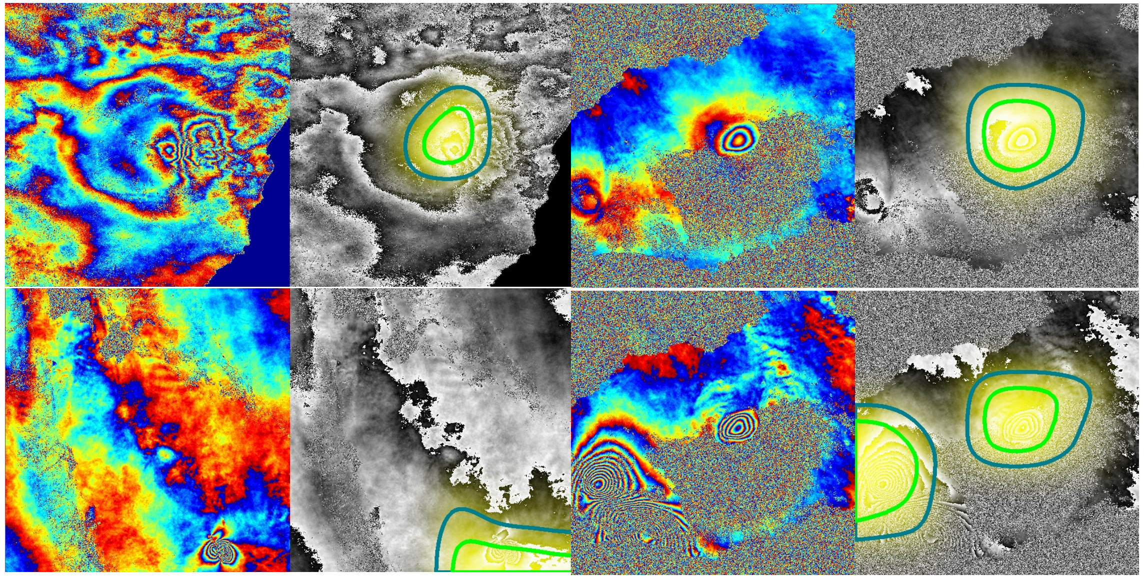
Abstract: Interferometric synthetic aperture radar (InSAR) can be used to measure ground displacement over large geographic areas. However, while detecting deformation using InSAR images is conceptually straightforward, it is difficult to automate, particularly in volcanic regions as atmospheric water vapor is a particular challenge. In this talk, a simple but efficient deep learning framework to detect ground deformation will be present. The model can be applied to individual interferograms for rapid deformations and can be tested on time-series for slow and sustained ones. The image processing techniques employed in the framework will also be discussed, particularly for the areas, where the signals are sparse. Finally, the current detection results on global Sentinel data processed via LiCSAR system will be shown.



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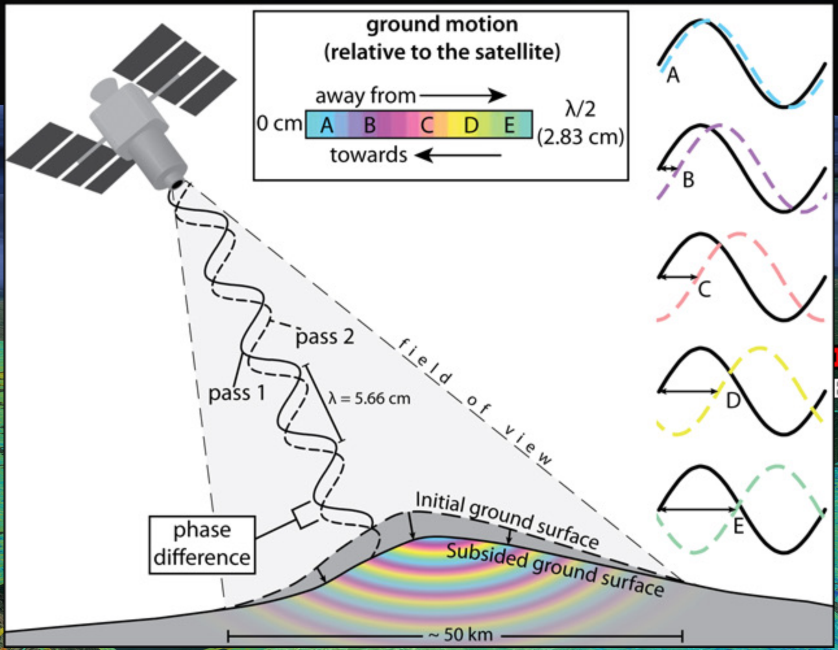
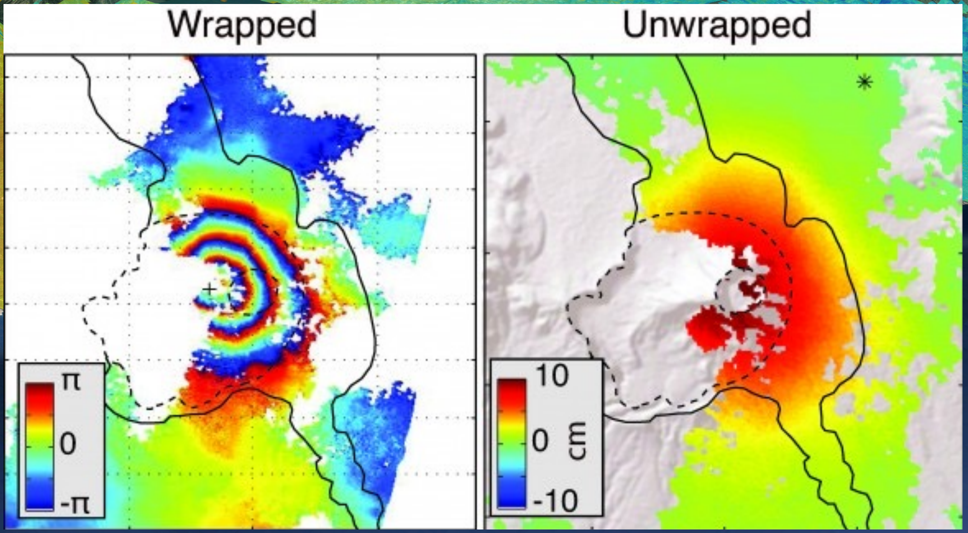
Interferometric Synthetic Aperture Radar (InSAR)

A satellite remote sensing technique used to measure ground displacement at the cm-scale over large geographic areas.

Ground deformation

- The phase difference reveals variations in the distance between the ground and the satellite.
- Interferograms, presented ‘wrapped’, shows coloured ‘fringe’ – seen as a contour line. Each fringe represents a set amount of displacement, roughly equal to half the radar wavelength.
- Interferograms, presented “unwrapped”, show the total amount of ground displacement across a single colour scale.





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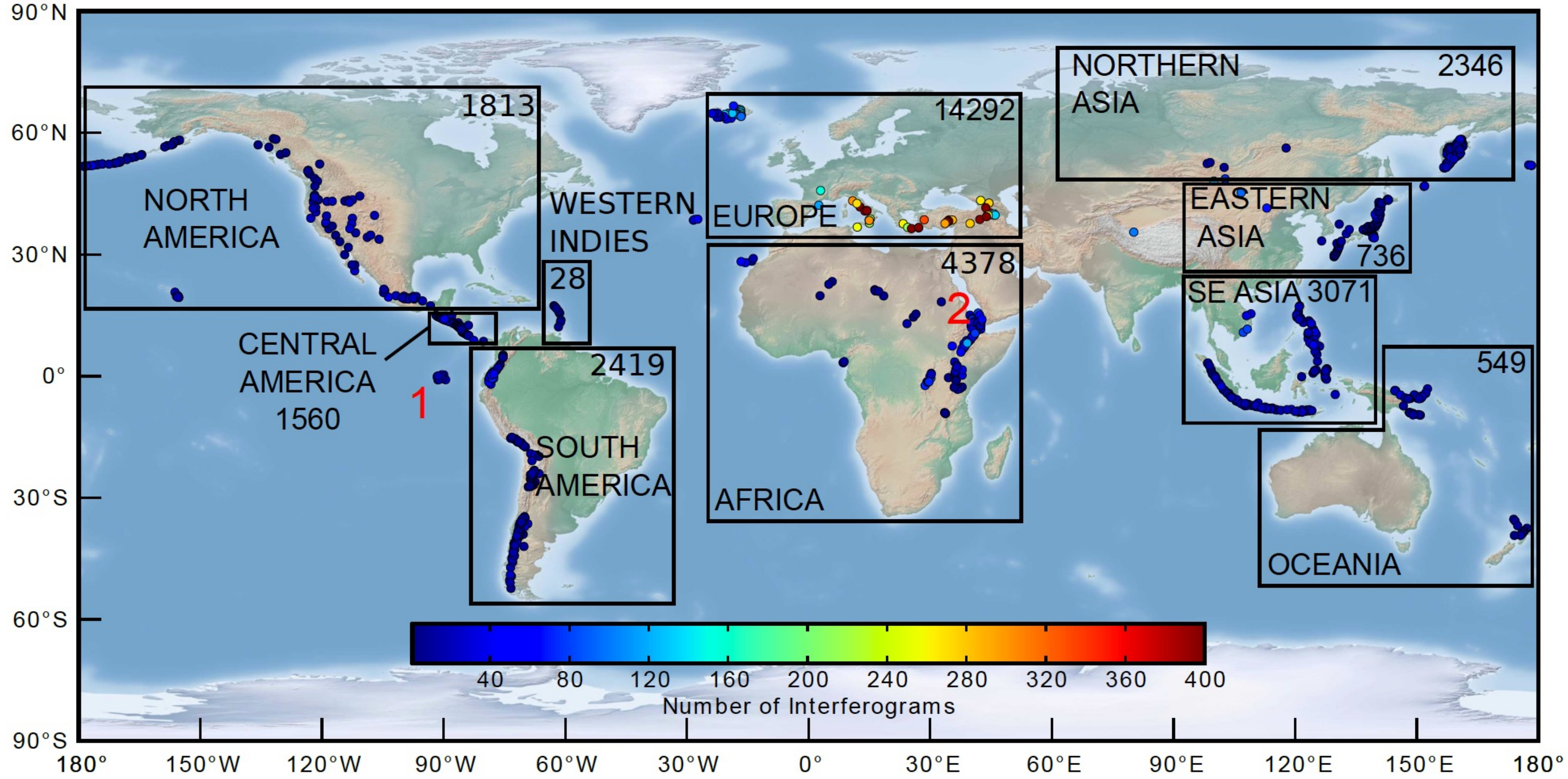
Global Volcano Monitoring: The LïCSAR-volcano database



- Sentinel-1 generates >10-TB data per day
- Now up to >600,000 (May 2021), >1,000 volcanoes.
- Anticipate 1 million images per year when fully operational.

- The explosion in data has brought major challenges associated with timely dissemination of information.

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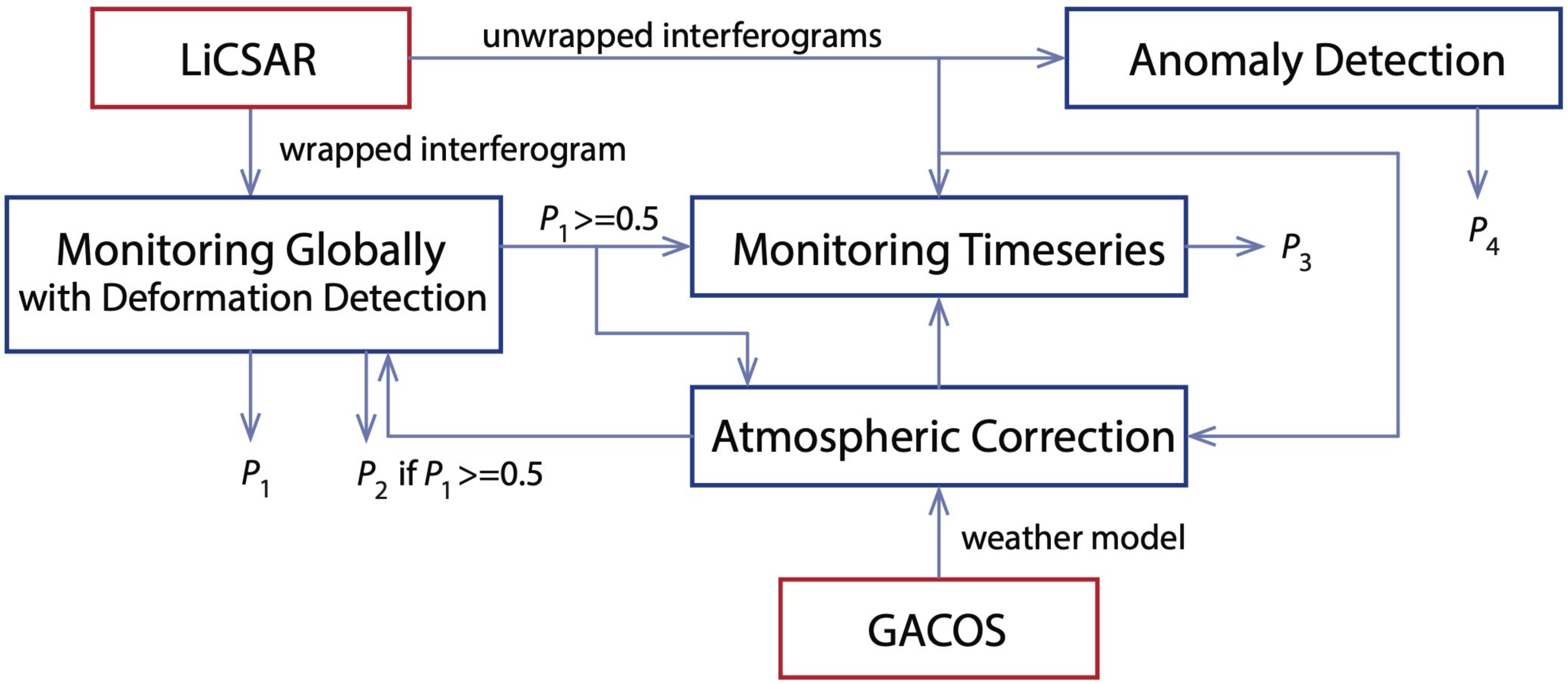
http://comet.nerc.ac.uk/ COMET-LiCS-portal/.

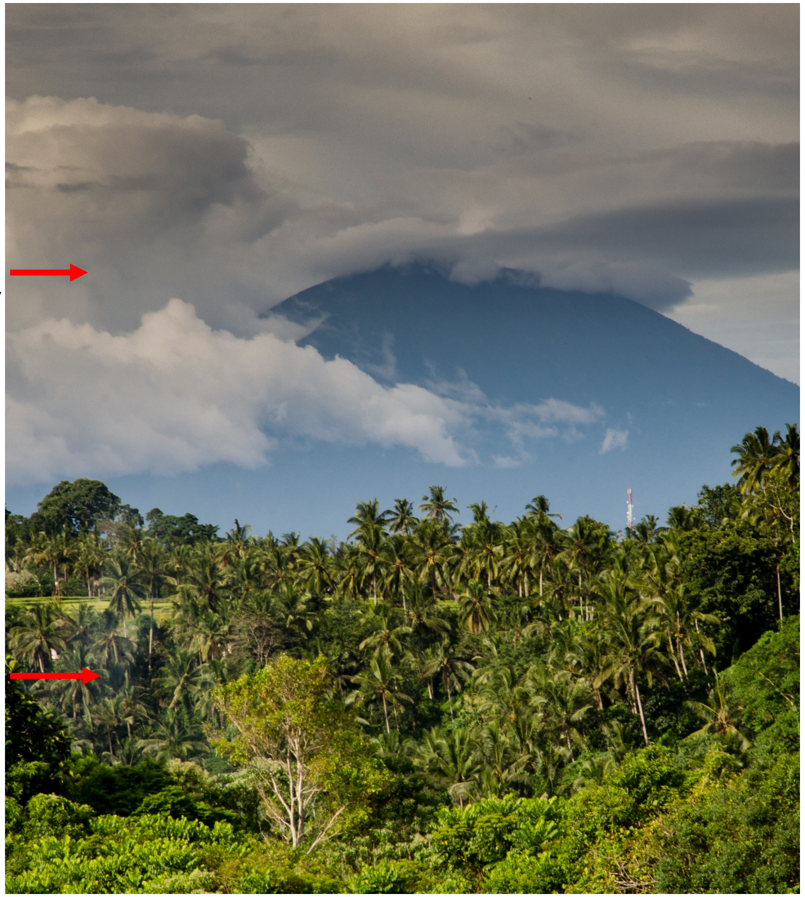
Monitoring framework

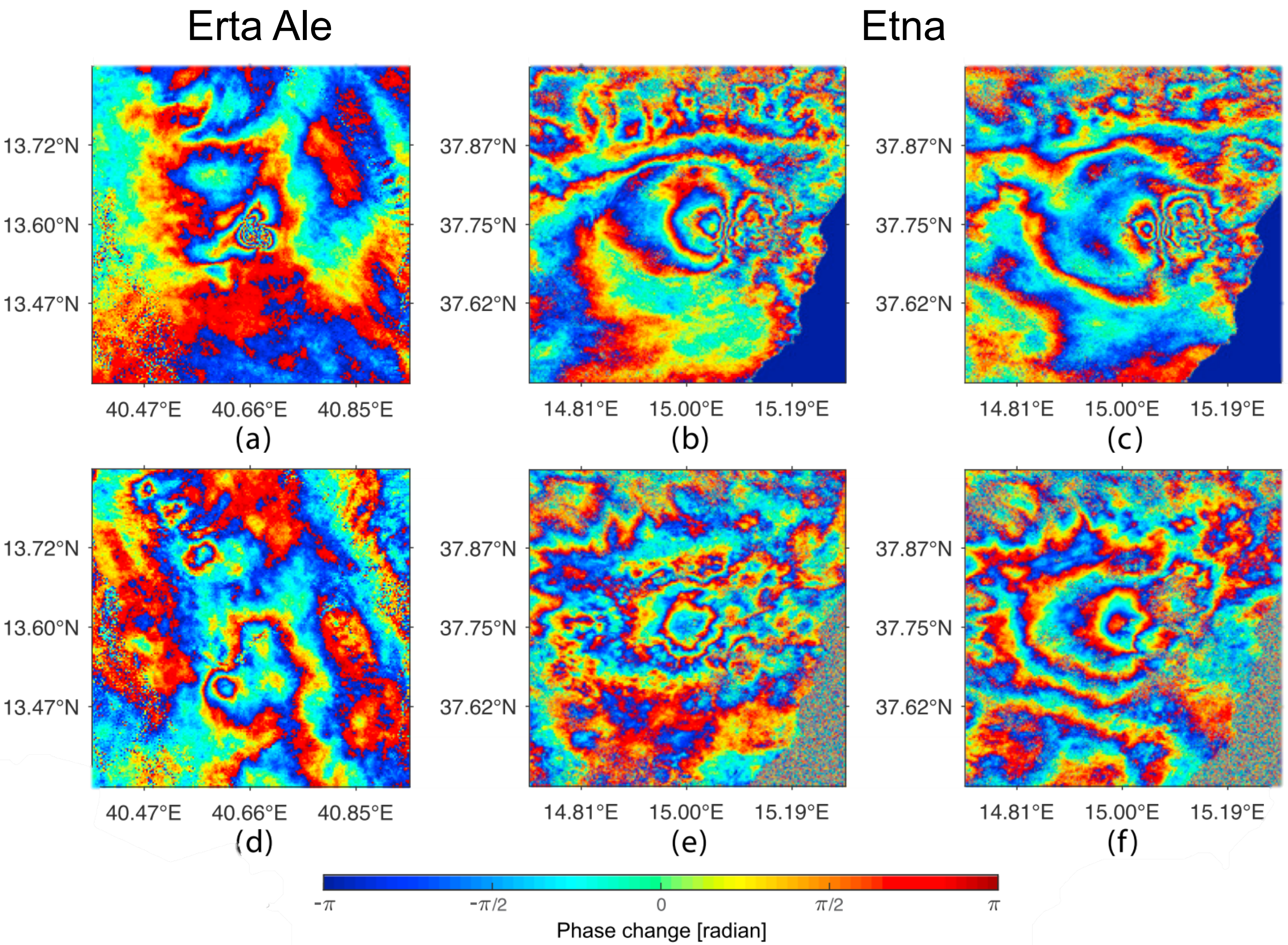


Ground deformation, background, noise or atmosphere?

Variation of water vapor

Dense vegetation





Object Detection

Face detection

Ground deformation in InSAR image: Detect=1 when Prob>0.5

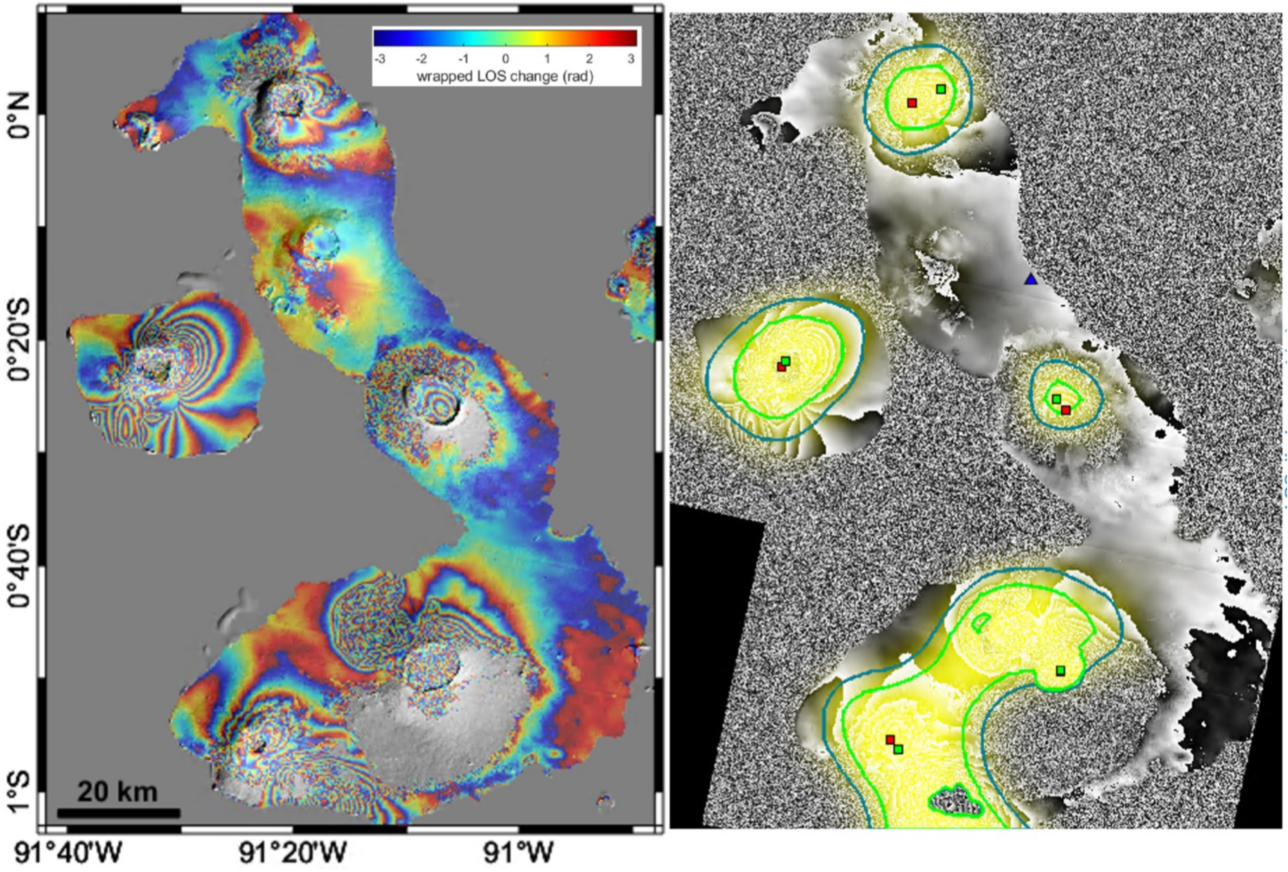
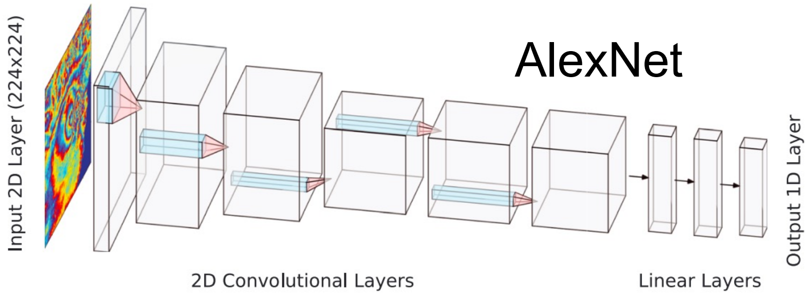


Image classification (binary) + Sliding Window Detector



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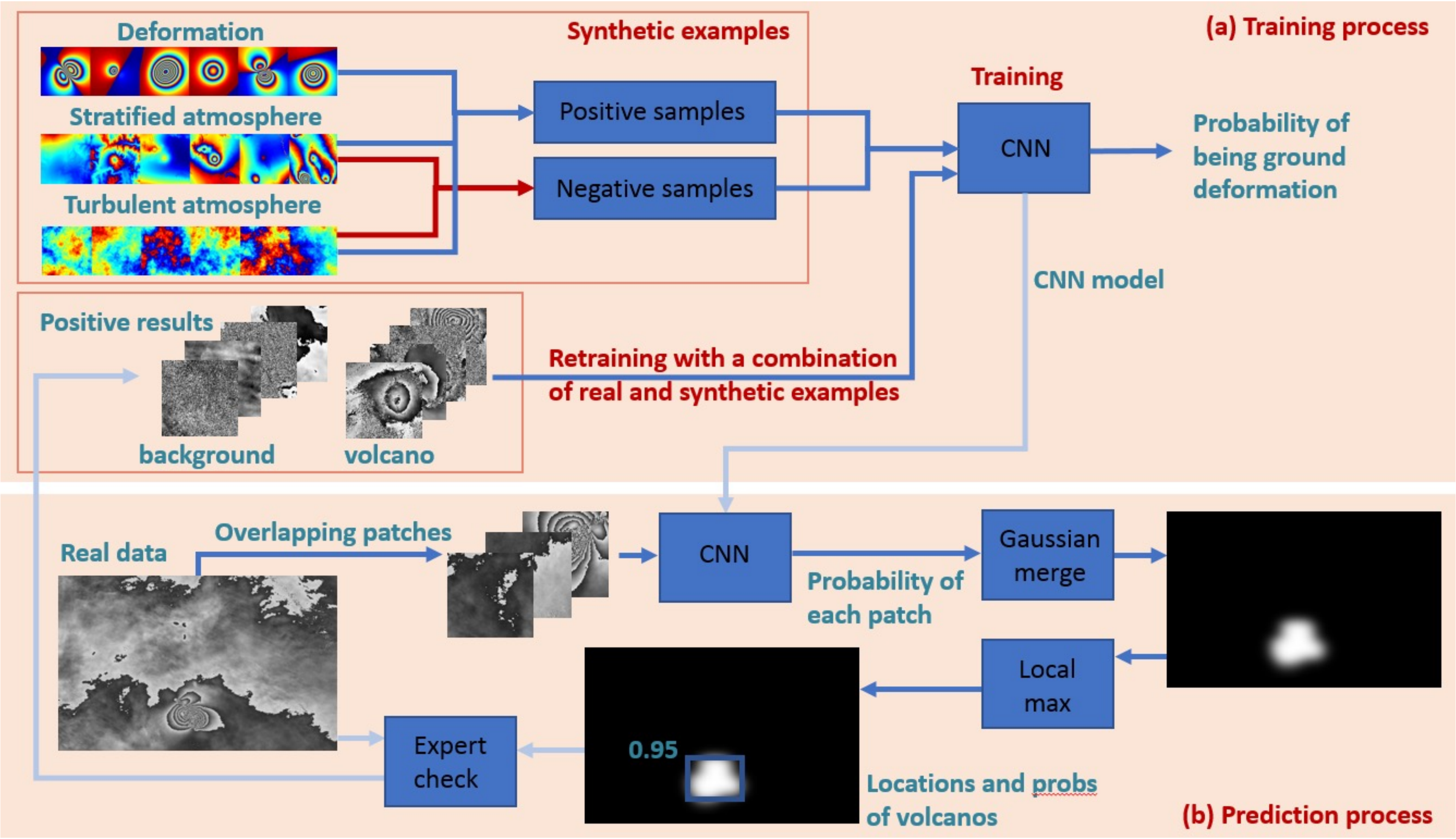
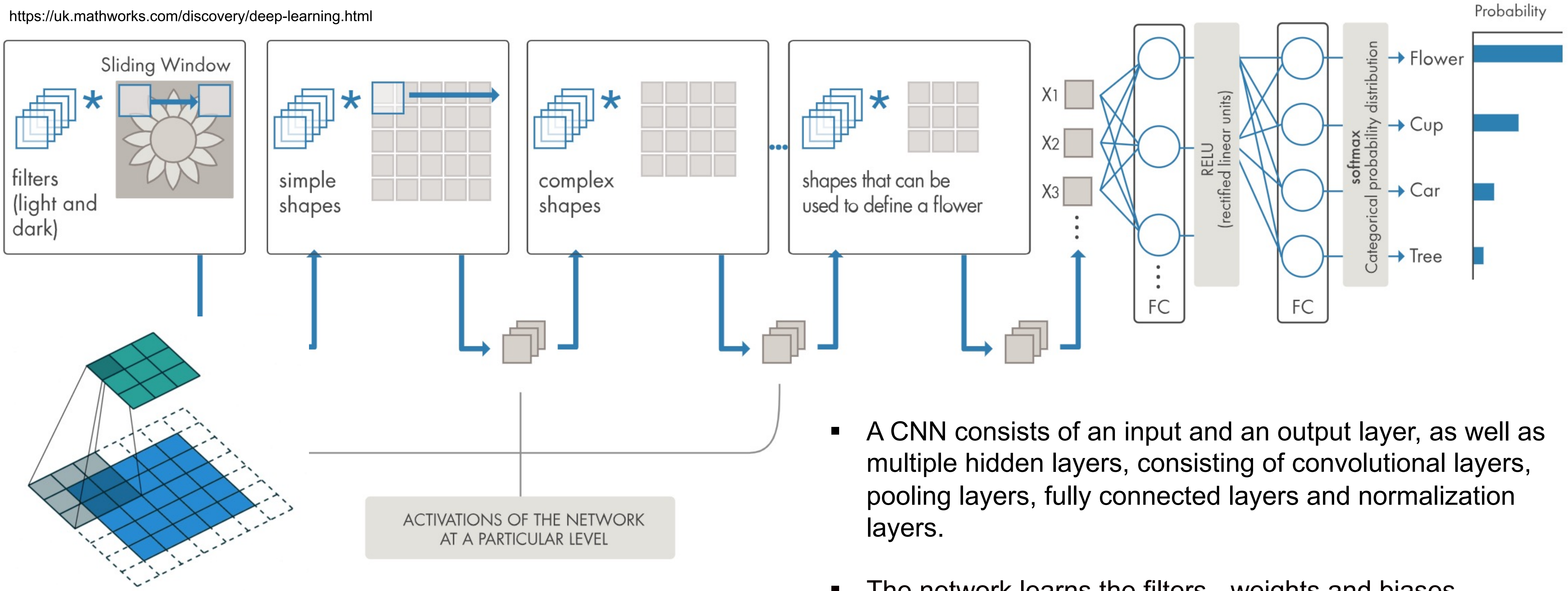
N Anantrasirichai, J Biggs, F Albino, P Hill, D Bull , Application of Machine Learning to Classification of Volcanic Deformation in Routinely Generated InSAR Data Journal of Geophysical Research: Solid Earth, 2018

Learning-based detection framework



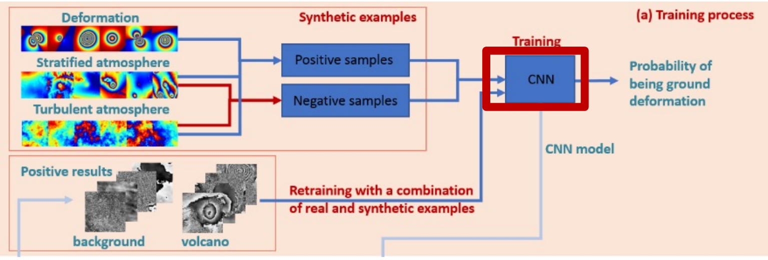
Convolutional Neural Network (CNN)

https://uk.mathworks.com/discovery/deep-learning.html

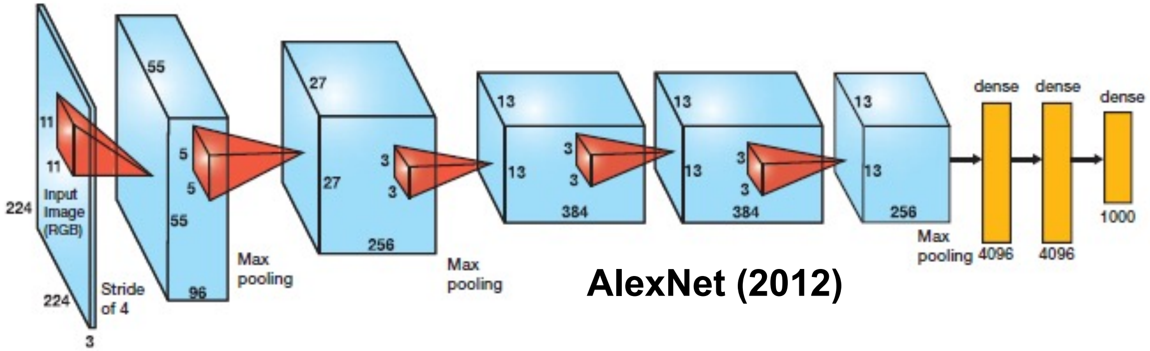


- A CNN consists of an input and an output layer, as well as multiple hidden layers, consisting of convolutional layers, pooling layers, fully connected layers and normalization layers.
- The network learns the filters - weights and biases.

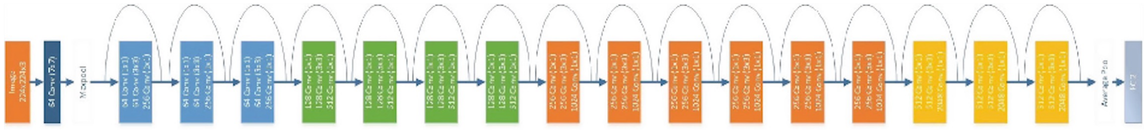
CNN – Pretrained networks



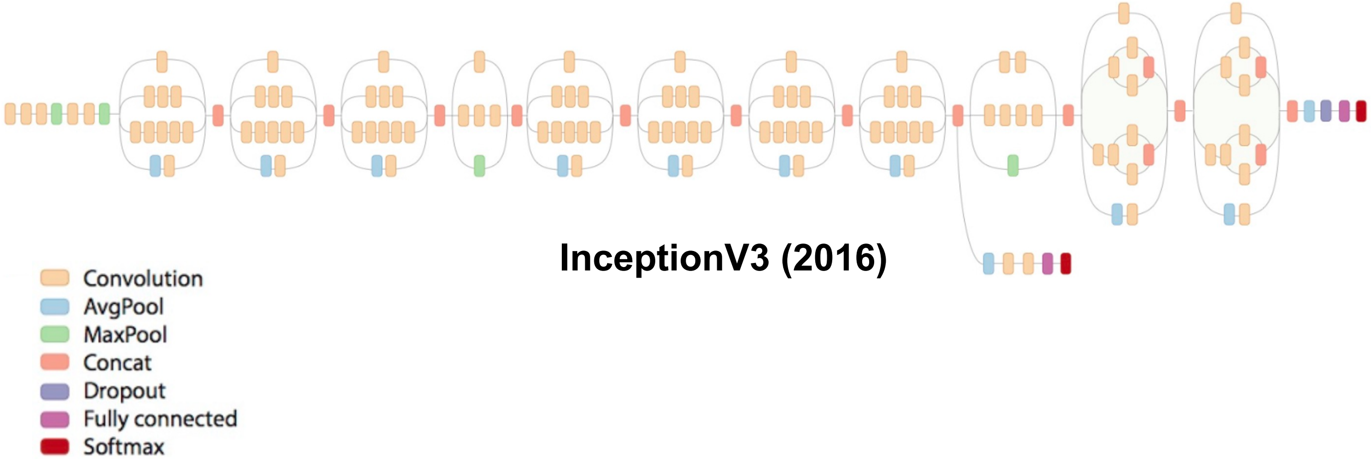
- Transfer learning strategy by fine-tuning a pretrained network
- Parameters and features of these networks have been learned from a very large dataset of natural images.



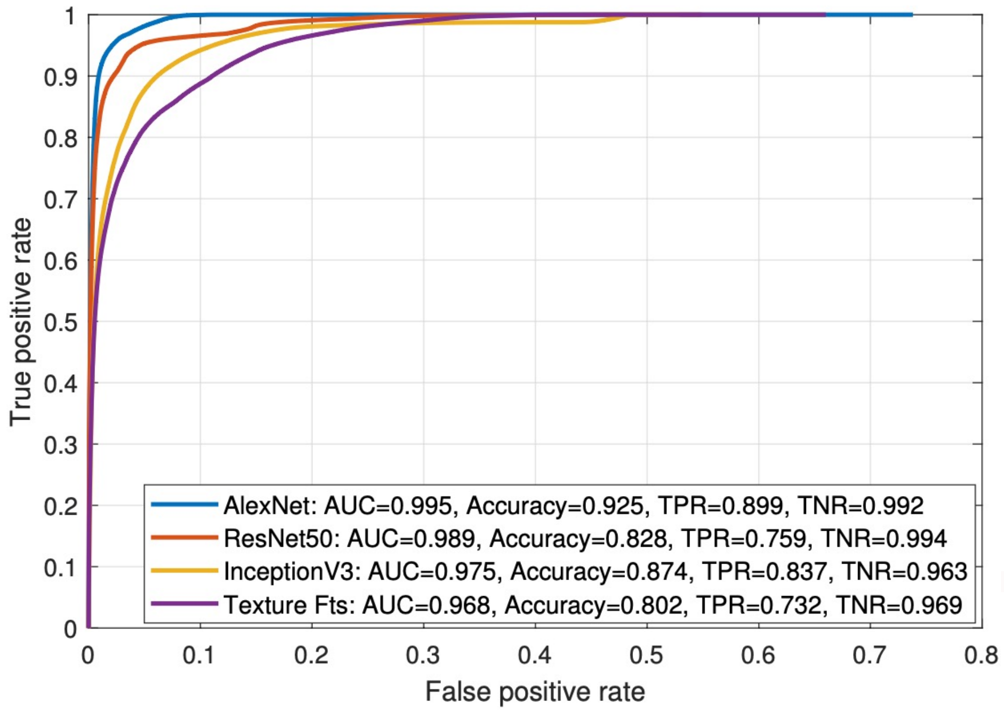
AlexNet (2012)



ResNet50 (2016)



InceptionV3 (2016)



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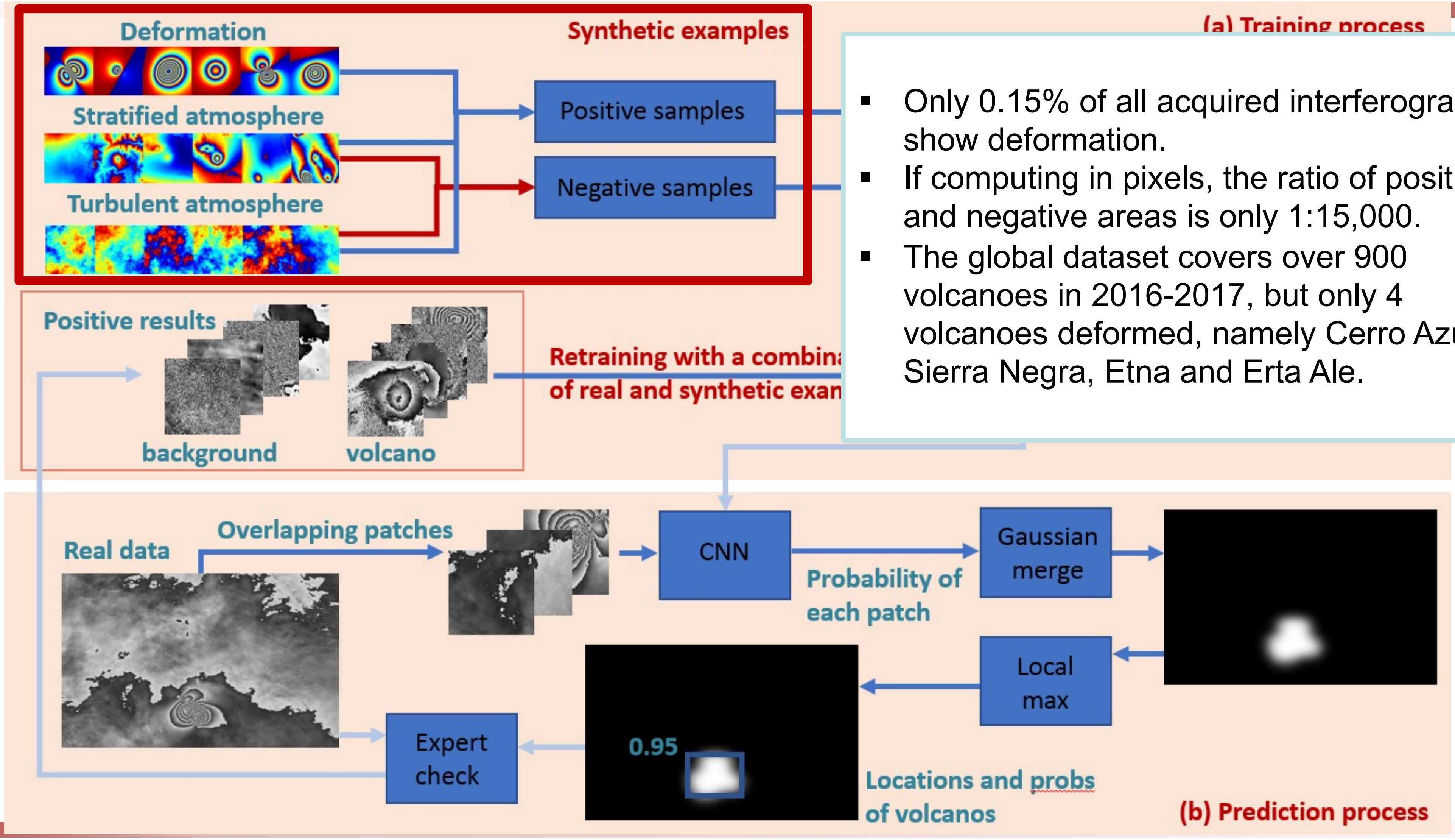
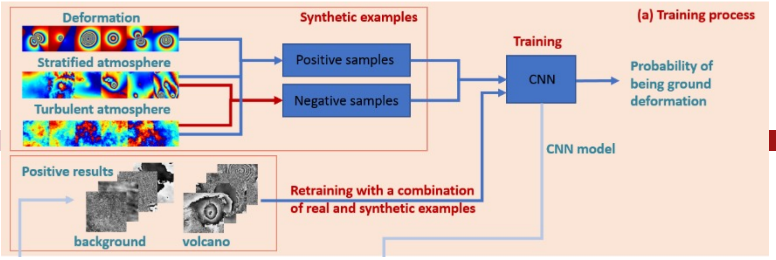
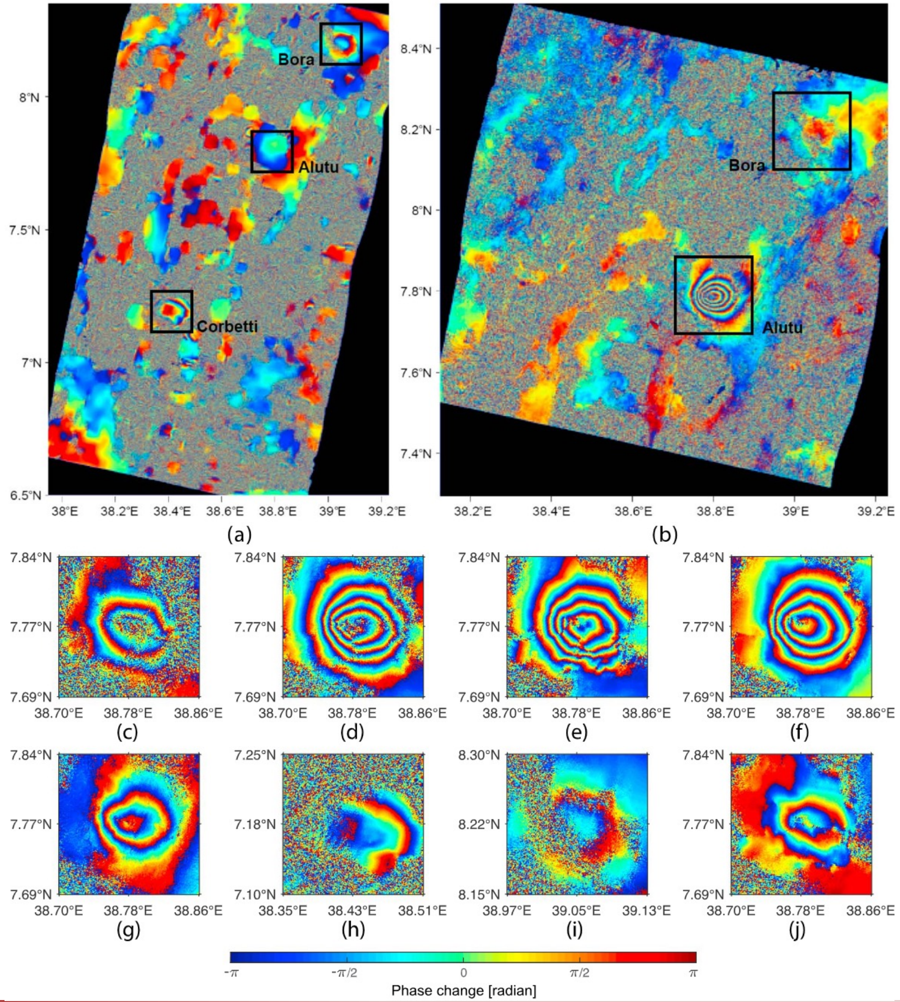
Learning-based detection framework



- Only 0.15% of all acquired interferograms show deformation.
- If computing in pixels, the ratio of positive and negative areas is only 1:15,000.
- The global dataset covers over 900 volcanoes in 2016-2017, but only 4 volcanoes deformed, namely Cerro Azul, Sierra Negra, Etna and Erta Ale.

Imbalanced training dataset

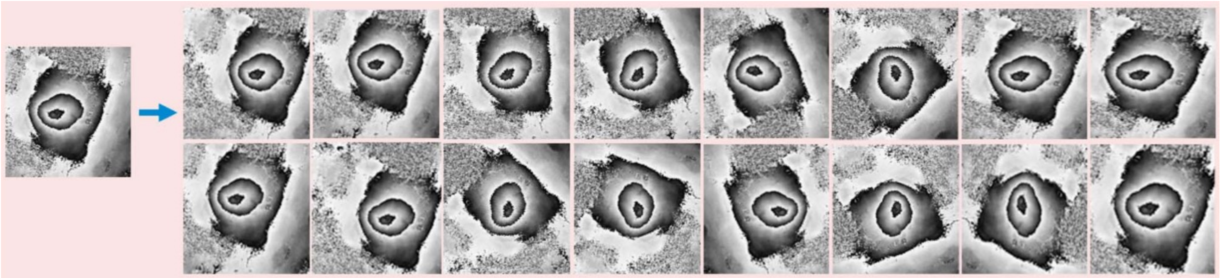




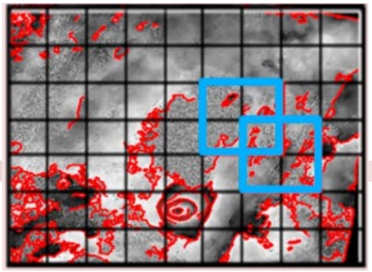
Envisat Dataset

Volcano name	Type	Period	# of interferograms
Alutu	Stratovolcano	2003–2010	158
Bora	Pyroclastic cone	2003–2010	52
Corbetti	Caldera	2003–2010	44
Haledebi	Fissure vent	2003–2010	46

Data augmentation: rotations, flips, distortions, and pixel shifts.



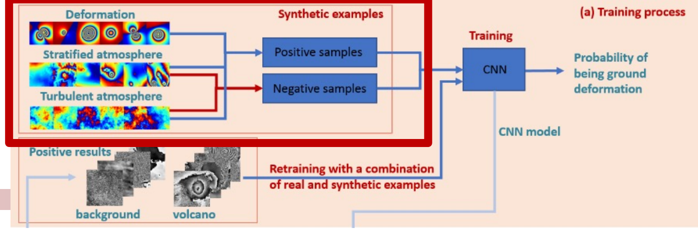
300 positive samples → 10,000 positive samples



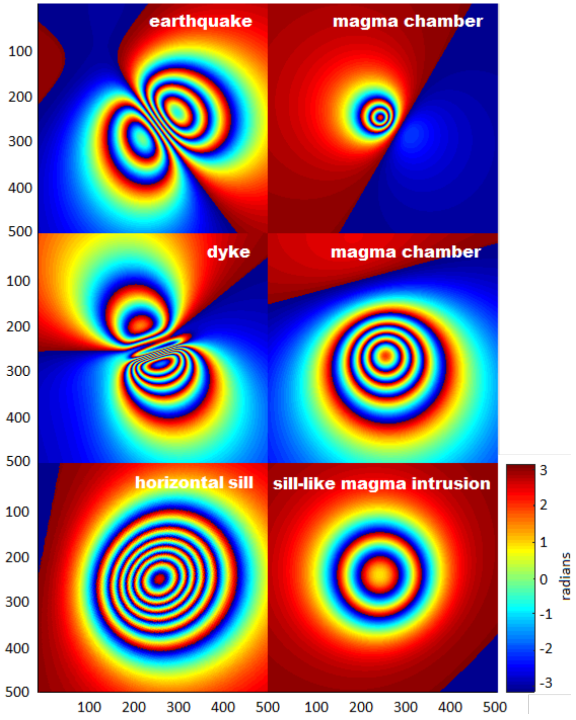
Data down-sampling:

Edge detection to **reduce negative samples**, then randomly select 10,000 of them.

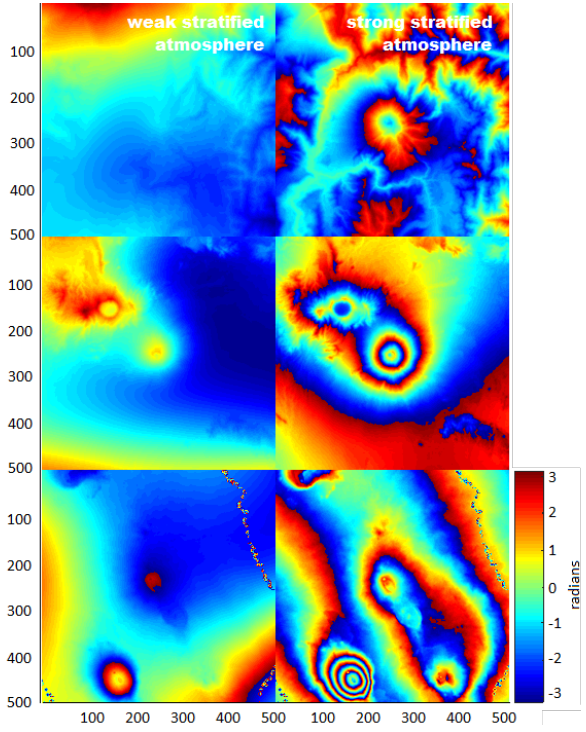
Training Dataset: Synthetic components



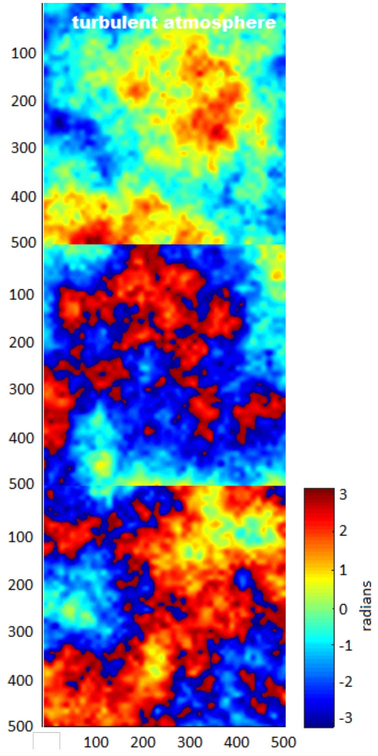
Deformation (D)

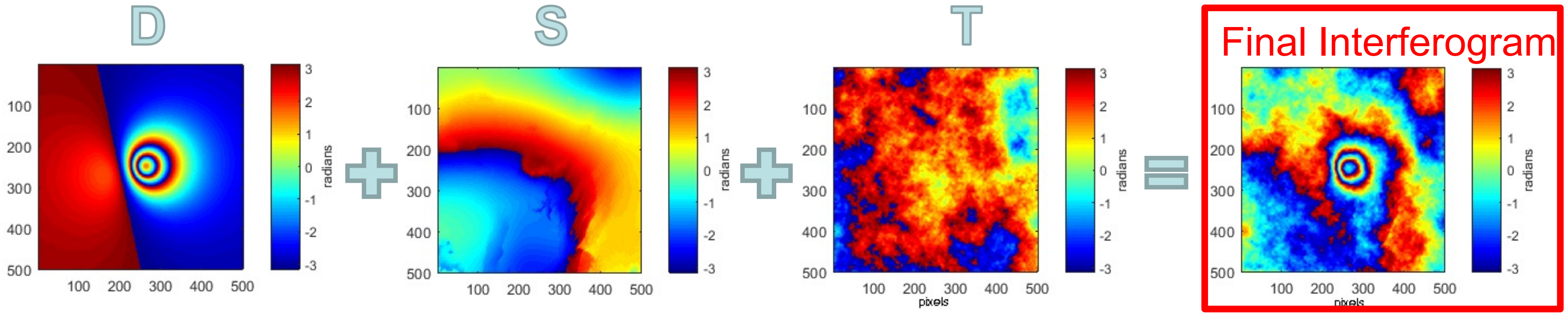


Stratified atmosphere (S)

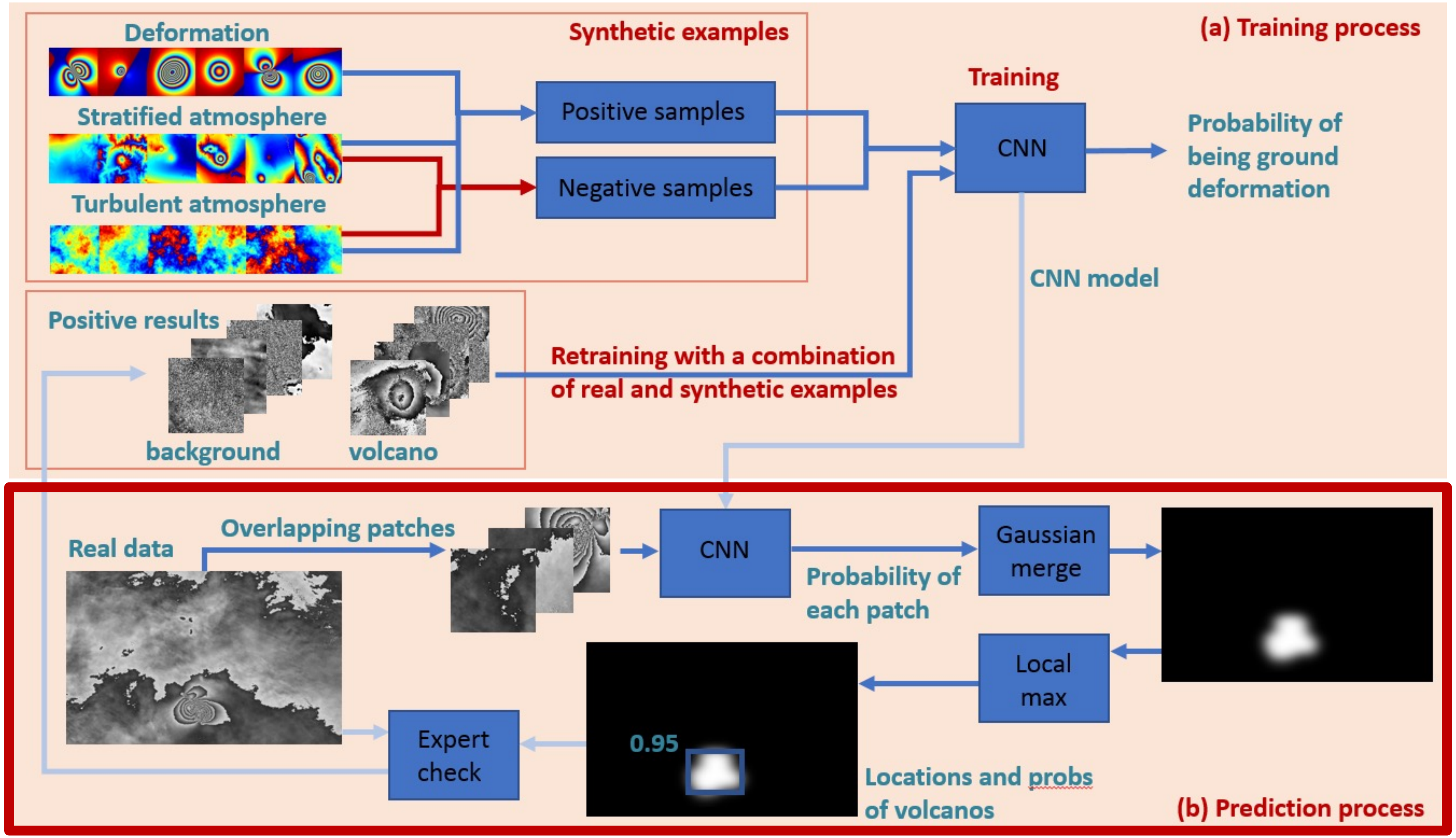


Turbulent atmosphere (T)





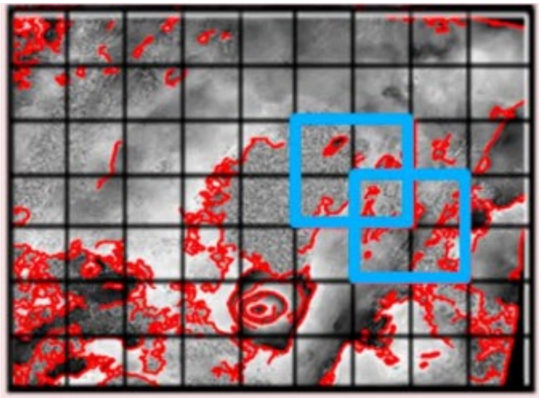
Learning-based detection framework



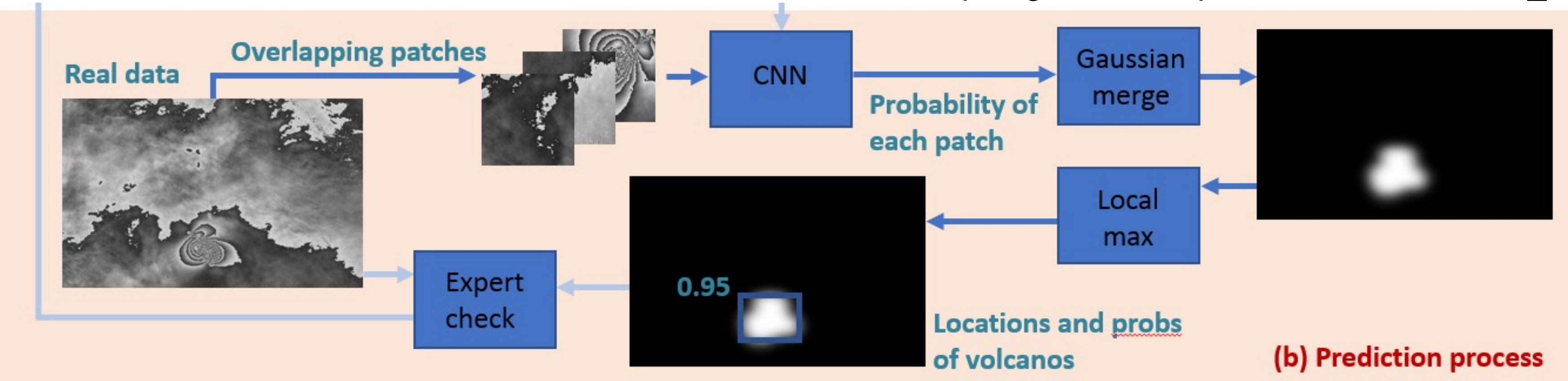
Learning-based detection framework

Edge detection and overlapping patches

- Canny operator
- Each image is divided into patches equal to the size of input of the CNN.
- They are overlapped by half of their size.
- If the patch doesn't have edge, it is 'background'.



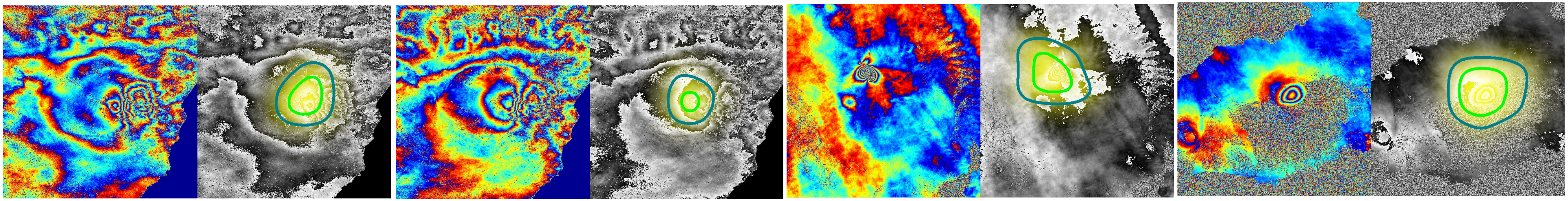
https://github.com/pui-nantheera/volcano_deform_detection



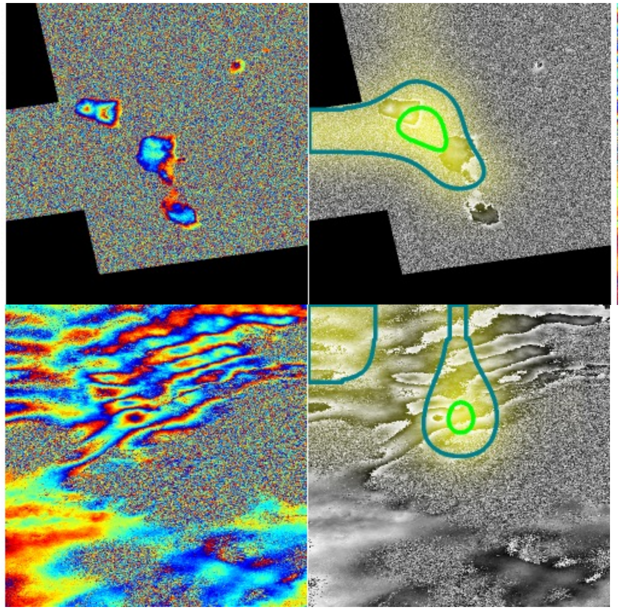
Results

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

- **True positive results**



- **False positive results**



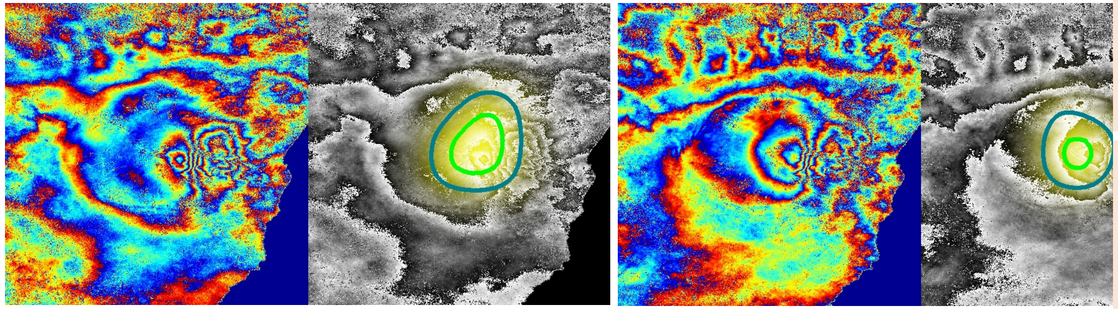
30,249 interferograms of the Sentinel-1 dataset

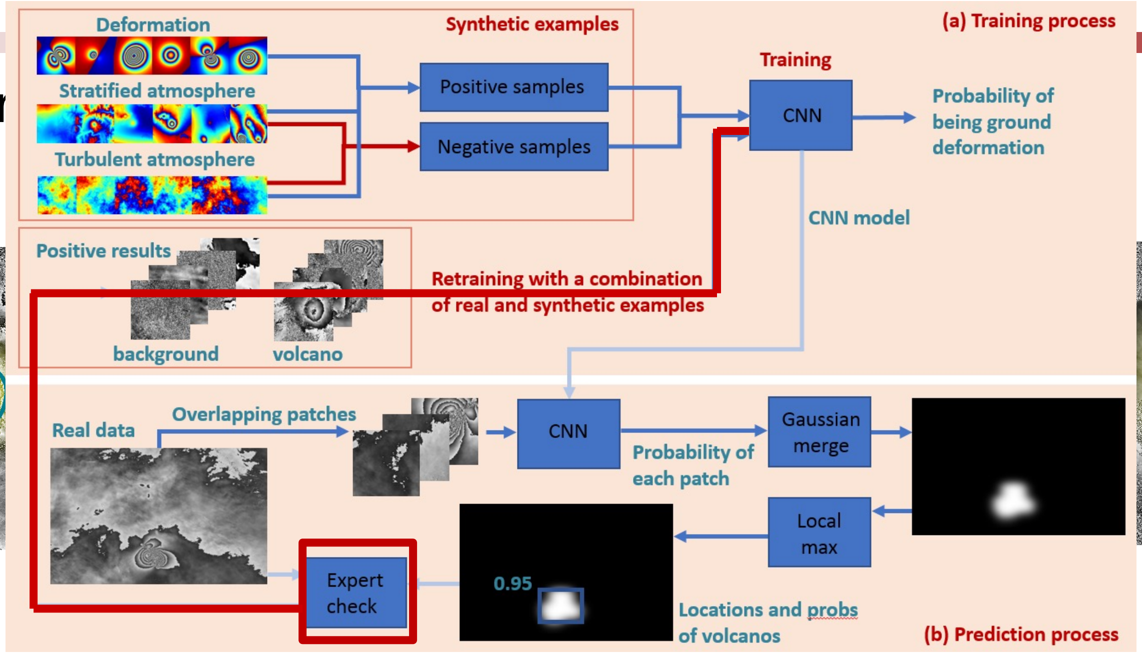
Trained by	#P	#TP	#FP	#FN
Synthetic	334	41	293	1

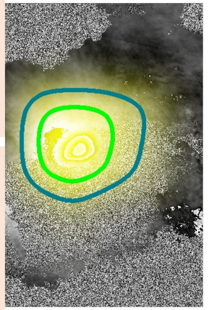
Results

Areas inside dark and bright green contours ar

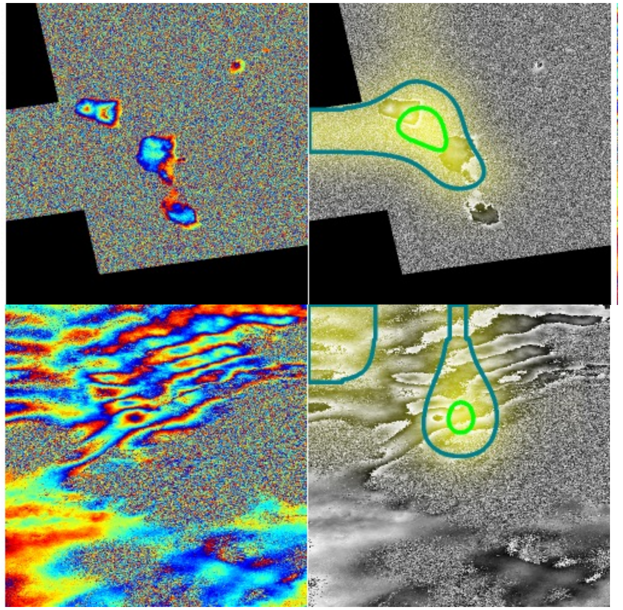
- **True positive results**







- **False positive results**



30,249 interferograms of the Sentinel-1 dataset

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

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Volcanic and Magmatic Deformation Portal

Worldwide Database of Volcanic Ground Deformation

Select Language

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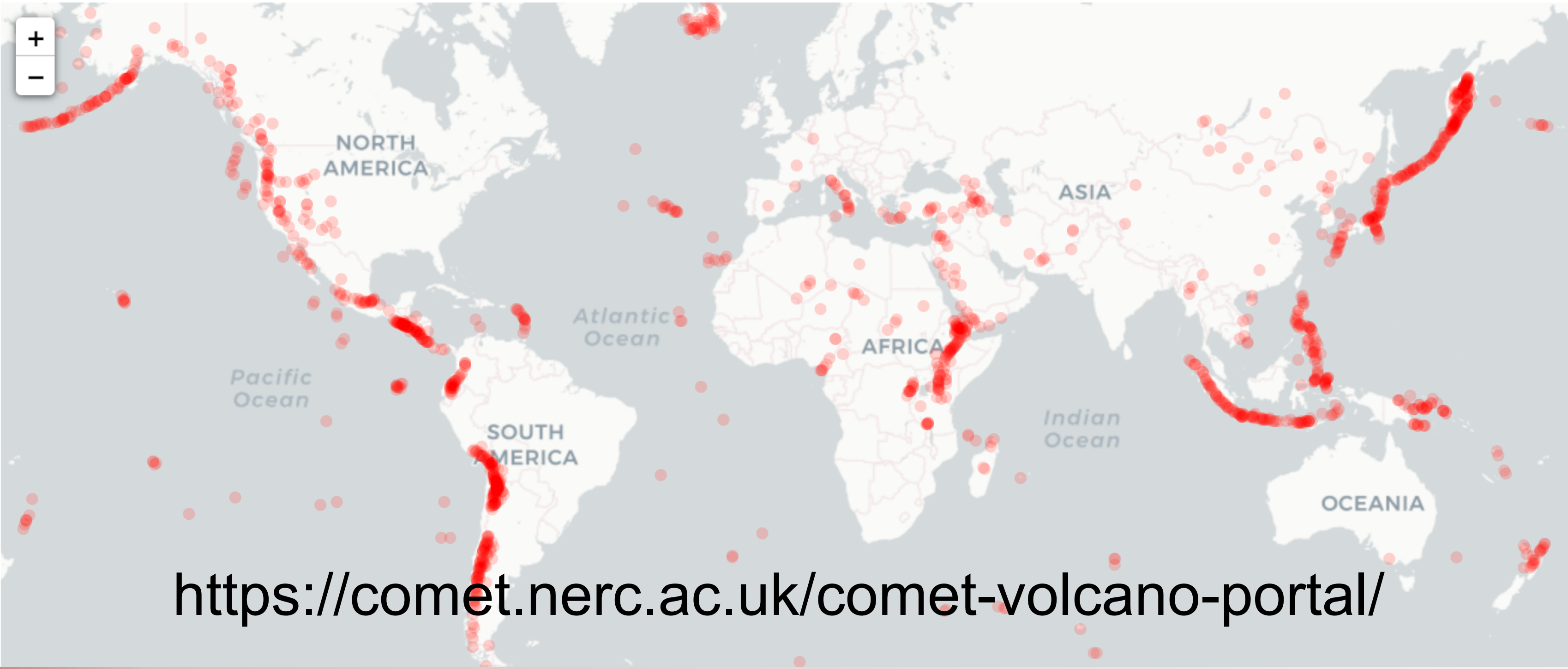
Home | About deformation catalogue | About online analysis tools | Volcano Index | Glossary | Contact/Give Feedback | Login

This data portal is in a testing phase. Data are not yet analysis-ready

Welcome to the COMET portal for volcanic and magmatic deformation. This site has two functions: (1) to document published and unpublished historical instances of deformation at volcanoes around the world and (2) to provide online tools for the analysis of Sentinel-1 interferograms produced by LiCSAR at active volcanoes. You can read a summary of the COMET historical deformation catalogue and instructions here About the COMET Volcano deformation catalogue. Online tools for interrogating Sentinel-1 imagery are available through the individual volcano pages linked to the map below or through our index and are described here About our online analysis tools.

Interactive map of volcanoes on this database

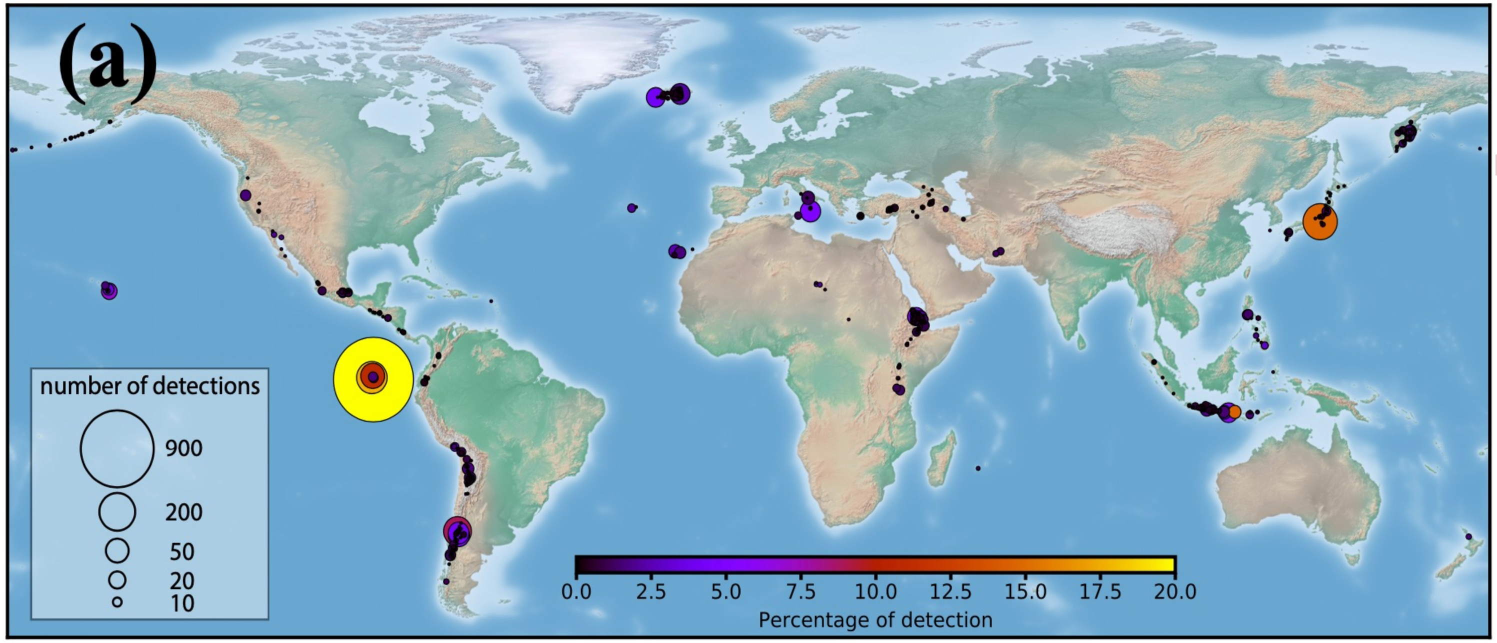


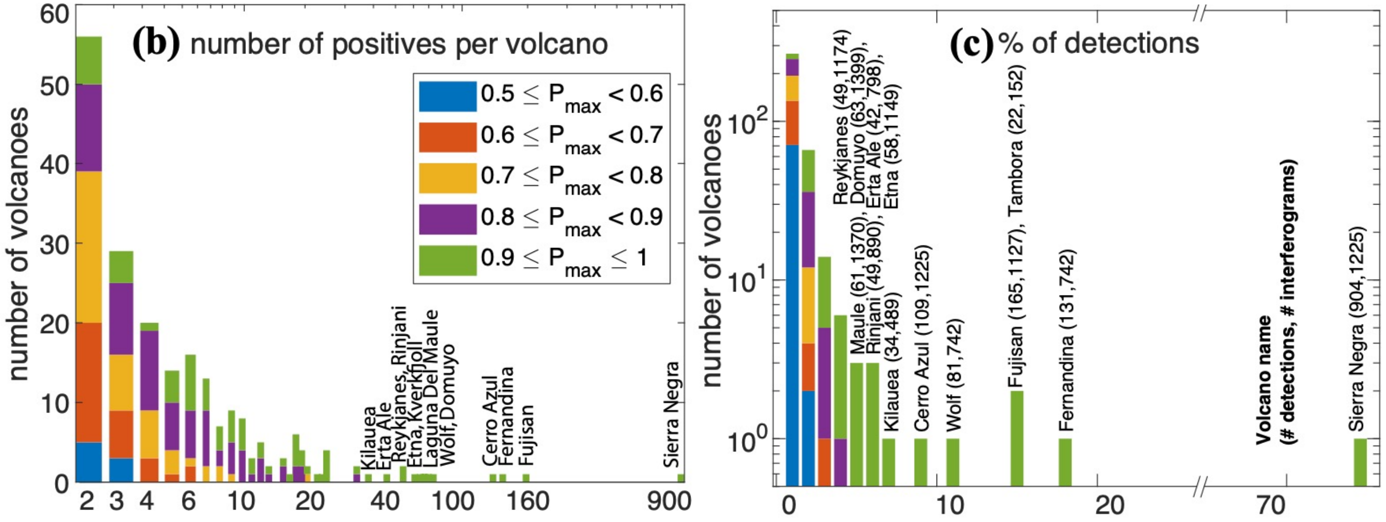
https://comet.nerc.ac.uk/comet-volcano-portal/

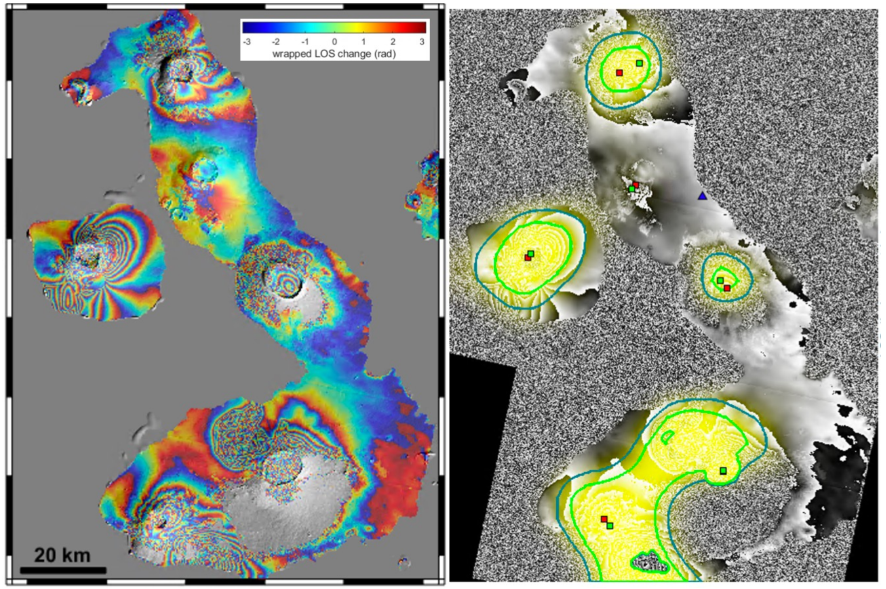
Global Results

15 Feb 2021

- >640,000 interferograms
- 1,098 volcanoes
- 3,953 interferograms detected positives
- 1,800 interferograms with probability >0.9
- >35% from Galapagos Islands

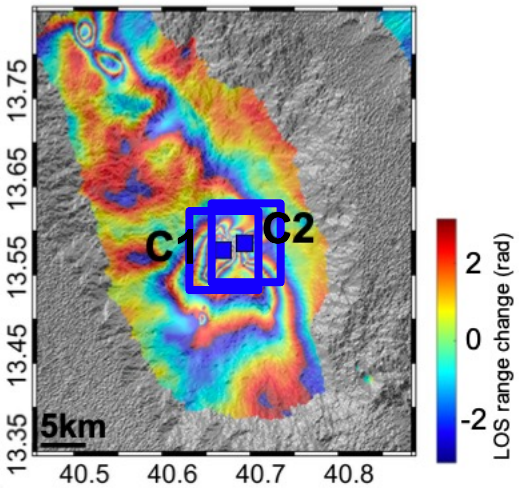




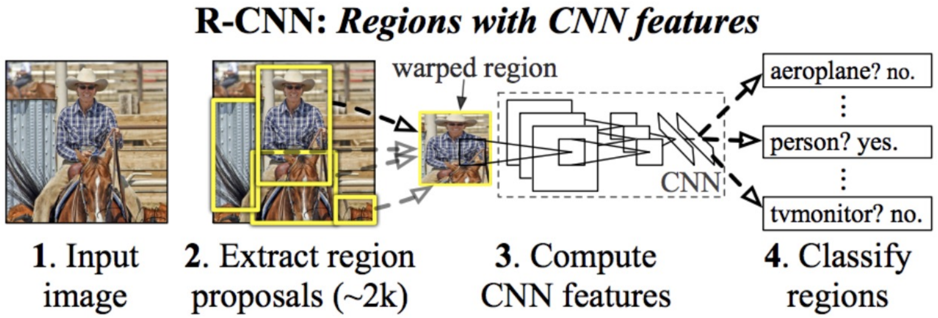


Other Object Detection Techniques

Draw a bounding box around the object of interest

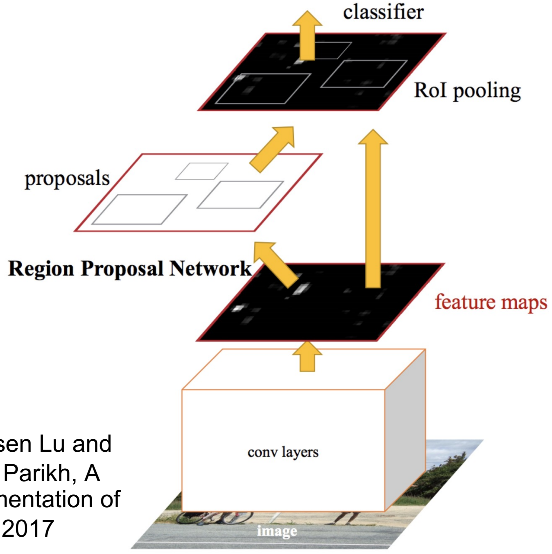


Erta Ale



R. Girshick, J. Donahue, T. Darrell and J. Malik, "Rich Feature Hierarchies for Accurate Object Detection and Semantic Segmentation," IEEE CVPR, 2014

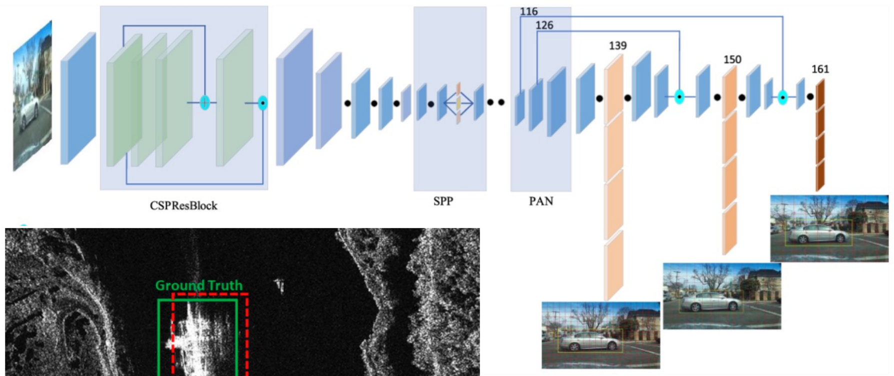
Faster R-CNN

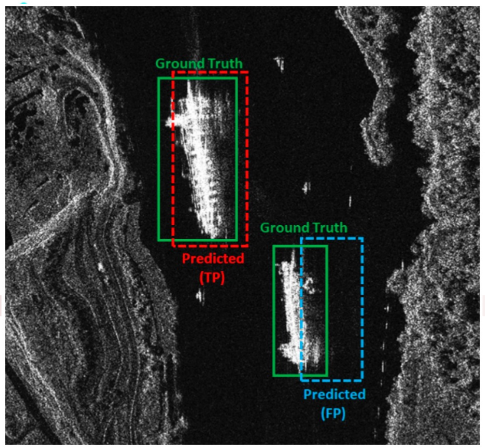


Jianwei Yang and Jiasen Lu and Dhruv Batra and Devi Parikh, A Faster Pytorch Implementation of Faster R-CNN, NIPS, 2017

YOLO — You Only Look Once (real-time detection)

Bochkovskiy et al. YOLOv4 https://arxiv.org/pdf/2004.10934.pdf





Tang, G.; Zhuge, Y.; Claramunt, C.; Men, S. N-YOLO: A SAR Ship Detection Using Noise-Classifying and Complete-Target Extraction. Remote Sens. 2021

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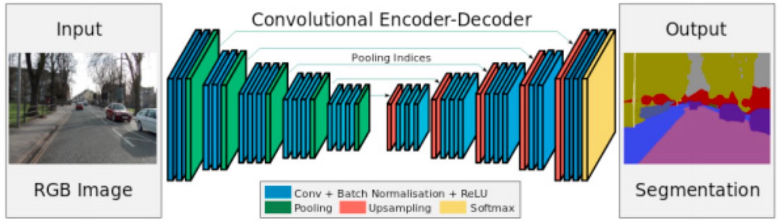
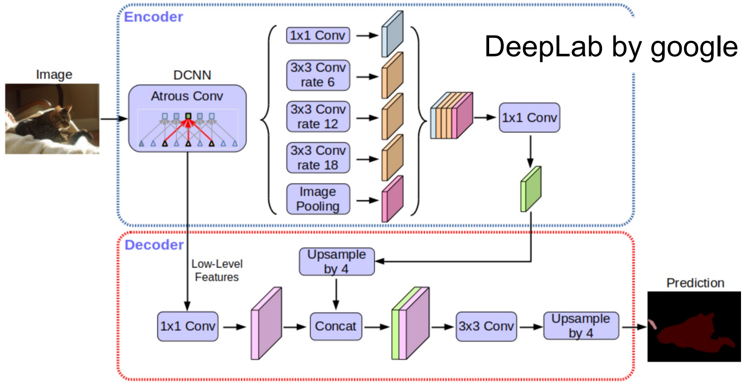
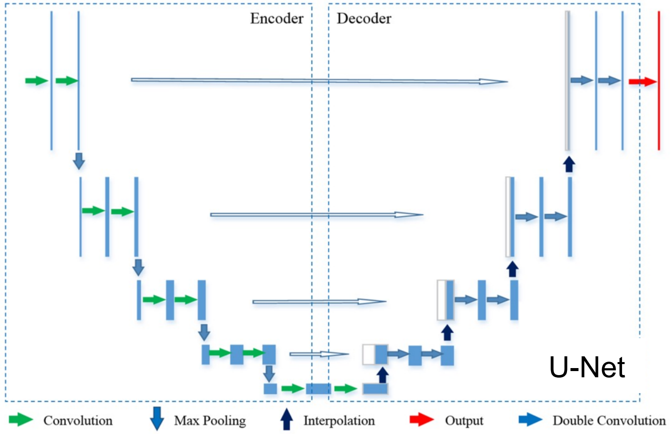
Other Object Detection Techniques

Semantic segmentation = segmentation + classification

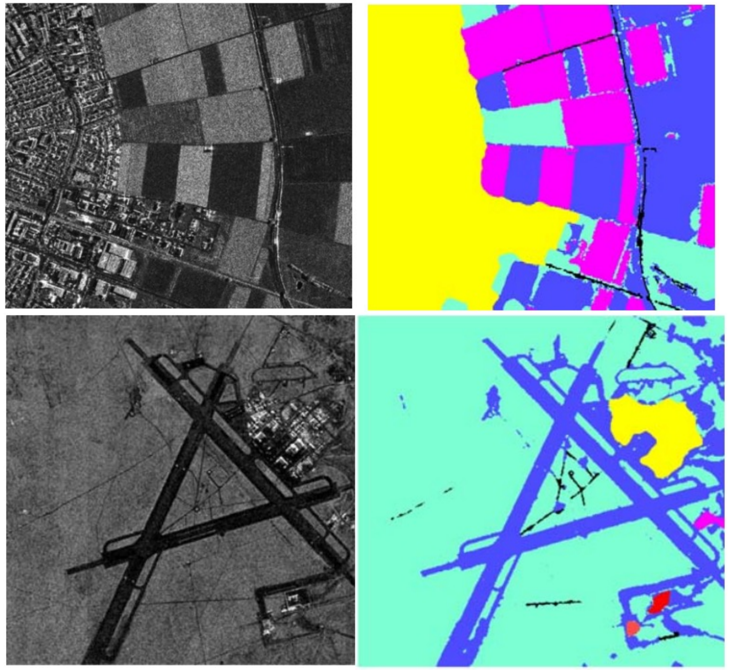


DeepLab by google





F. Liu et al., "SAR Image Segmentation Based on Hierarchical Visual Semantic and Adaptive Neighborhood Multinomial Latent Model," IEEE TGRS, 2016.



Other Object Detection Techniques

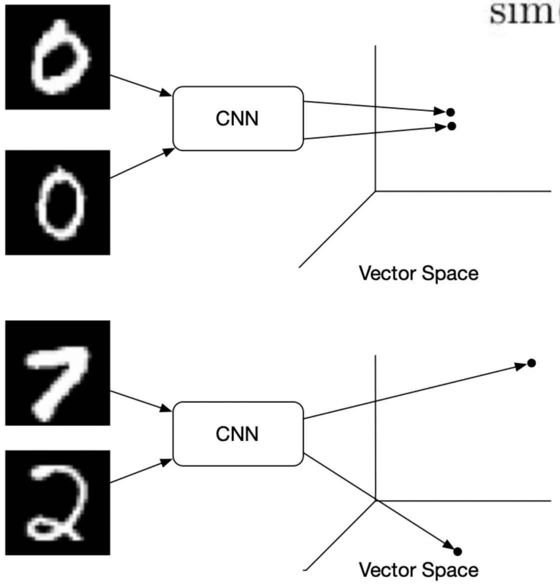
Self-supervised learning with contrastive learning

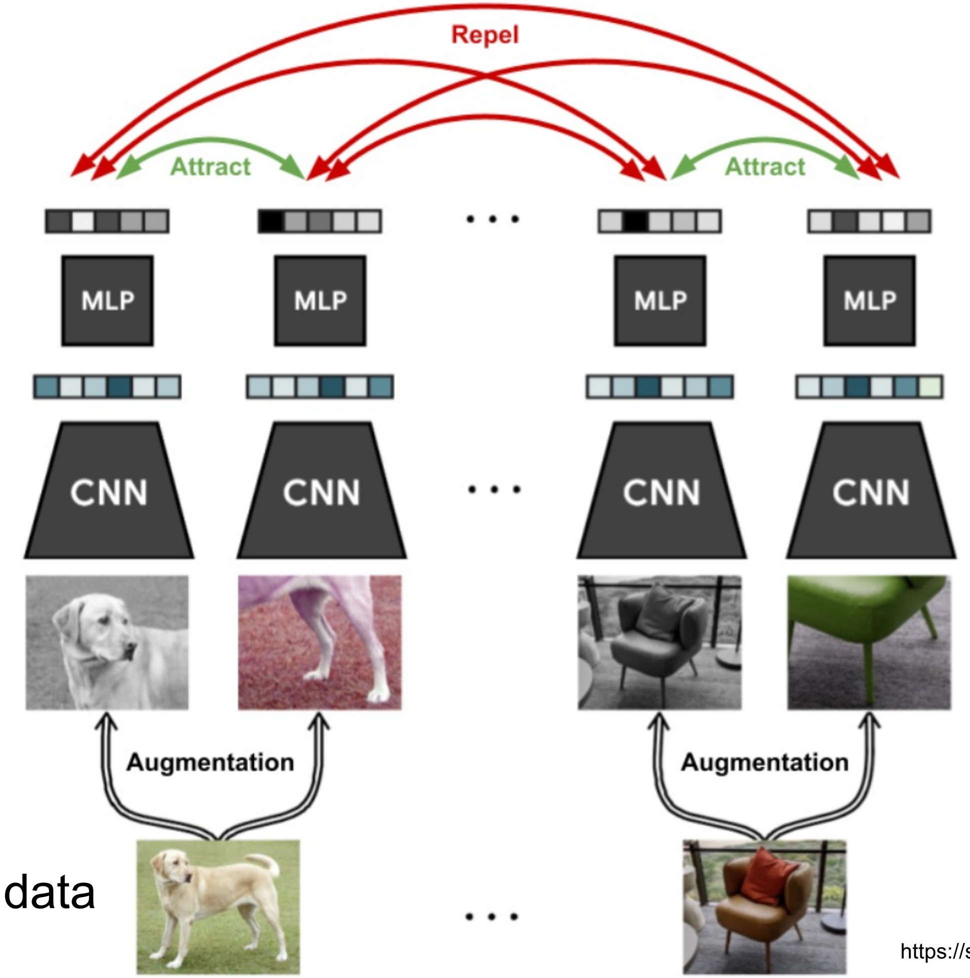
simCLR by Google

Contrastive Loss:

$$\ell_{i,j} = -\log \frac{\exp(\mathrm{sim}(\boldsymbol{z}_i, \boldsymbol{z}_j)/\tau)}{\sum_{k=1}^{2N} \mathbb{1}_{[k \neq i]} \exp(\mathrm{sim}(\boldsymbol{z}_i, \boldsymbol{z}_k)/\tau)}$$

$$\mathrm{sim}(\boldsymbol{u}, \boldsymbol{v}) = \boldsymbol{u}^\top \boldsymbol{v} / \|\boldsymbol{u}\| \|\boldsymbol{v}\|$$





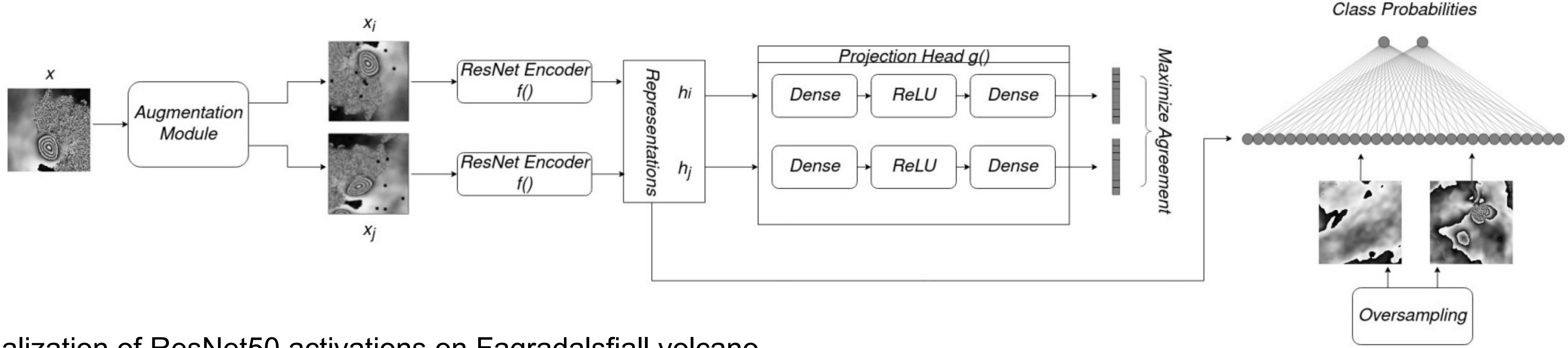
Unlabeled data

https://simclr.github.io/

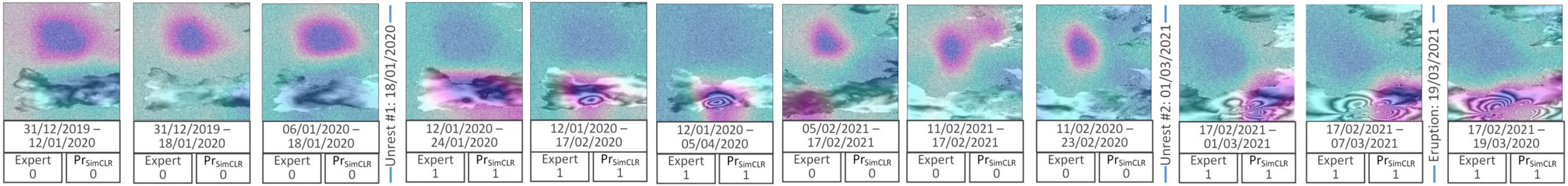
Other Object Detection Techniques

DEEP CUBE

Self-supervised learning with contrastive learning



Visualization of ResNet50 activations on Fagradalsfjall volcano.
Pink represents the area that affected the network's decision the most



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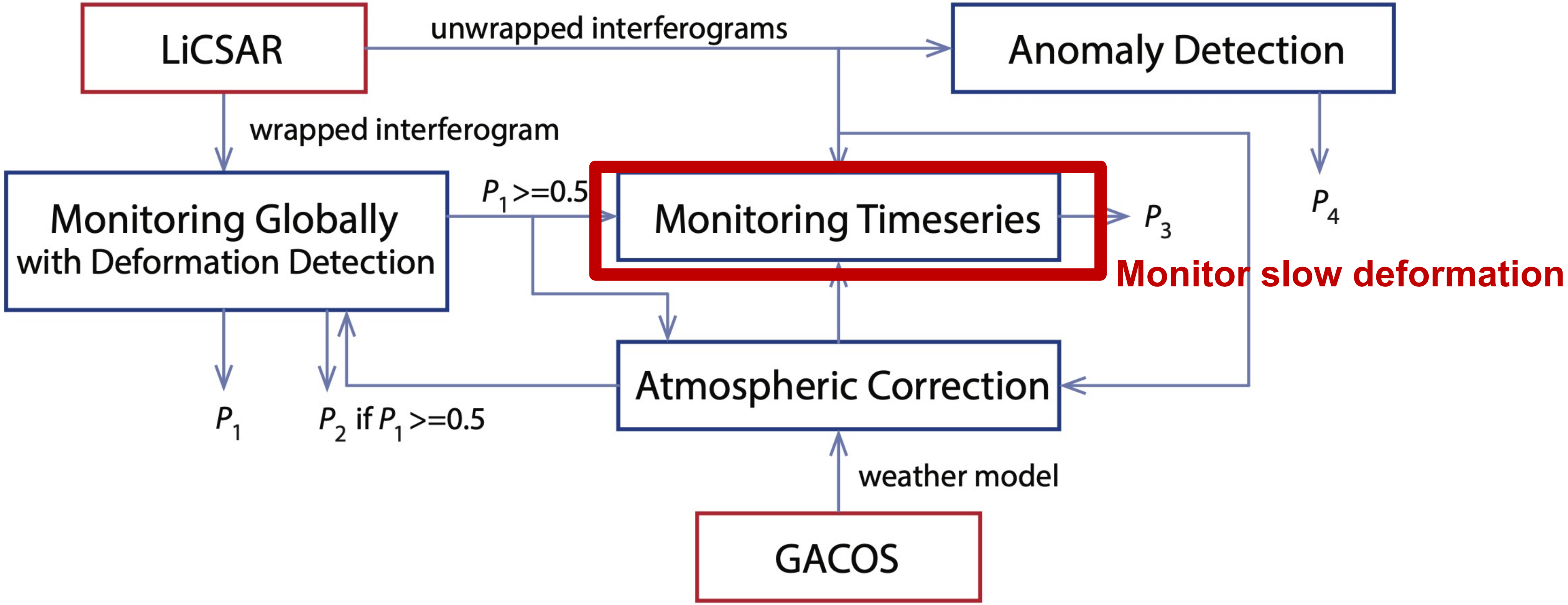
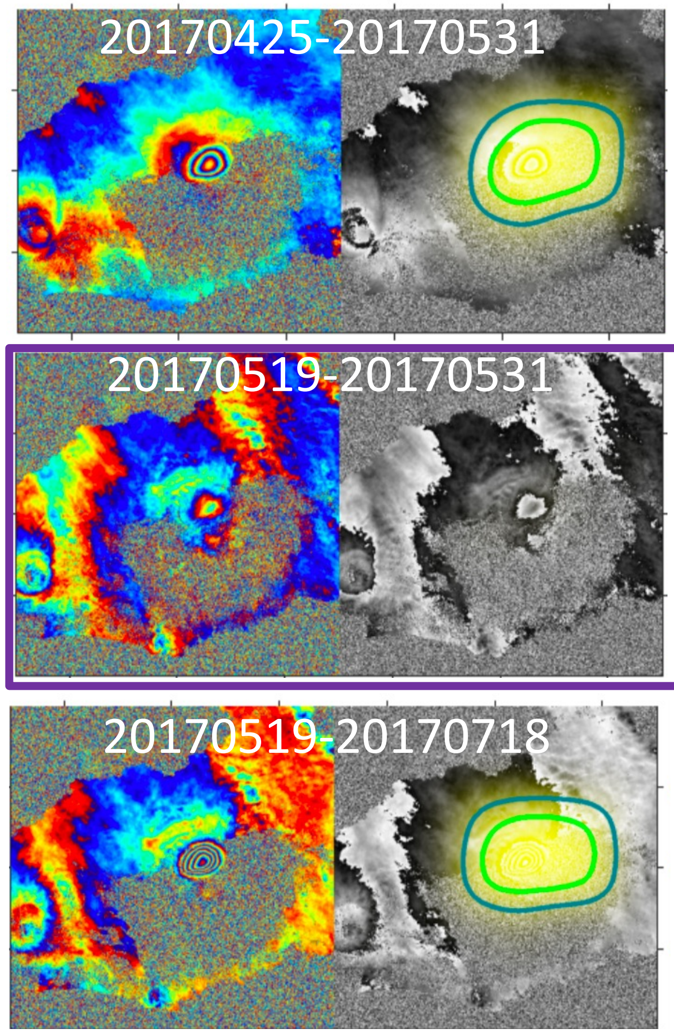
N. I. Bountos, I. Papoutsis, D. Michail and N. Anantrasirichai, "Self-Supervised Contrastive Learning for Volcanic Unrest Detection," in IEEE Geoscience and Remote Sensing Letters, 2021

Monitoring framework

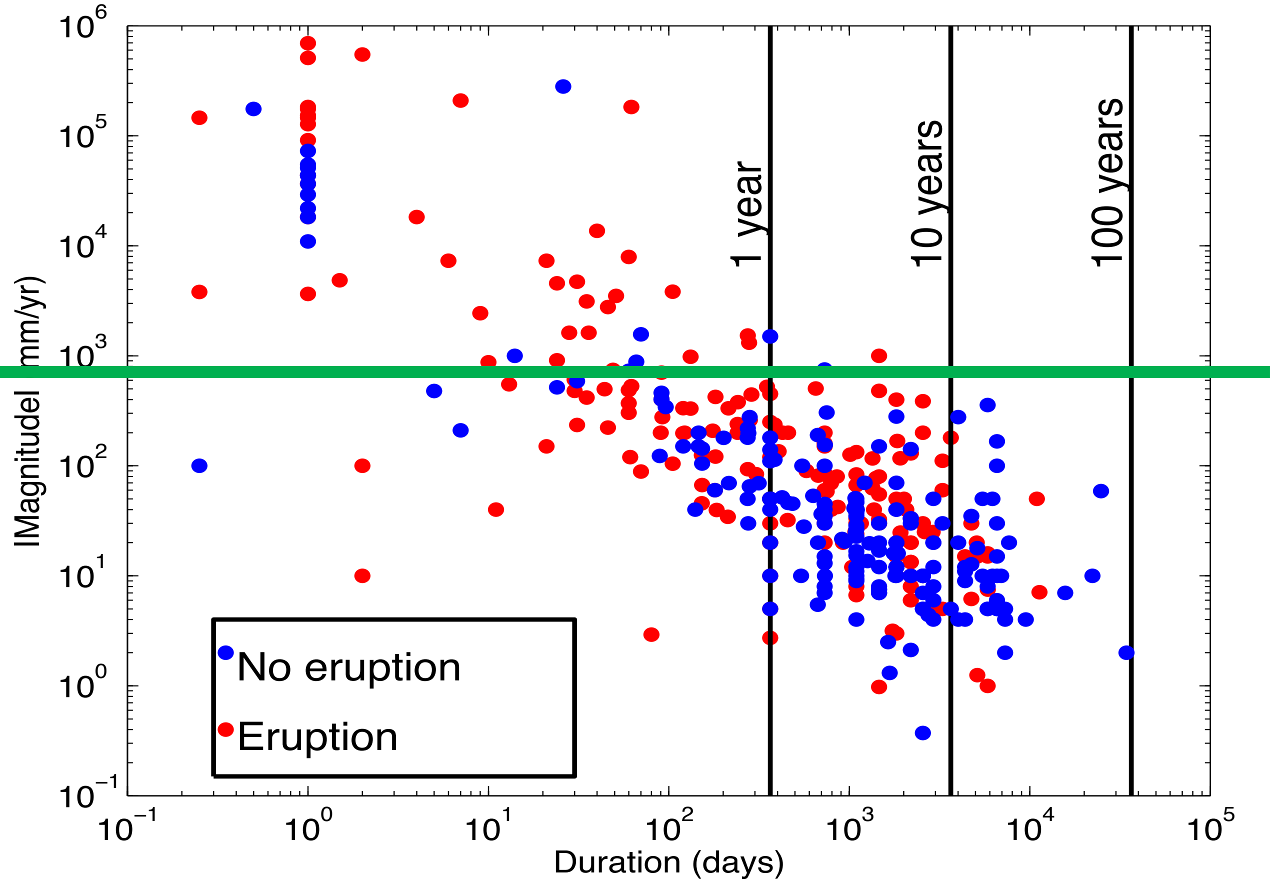


Detecting Slow Deformation



False negative result:
Sierra Negra

1 fringe in a 12 day interferogram = 85 cmyr



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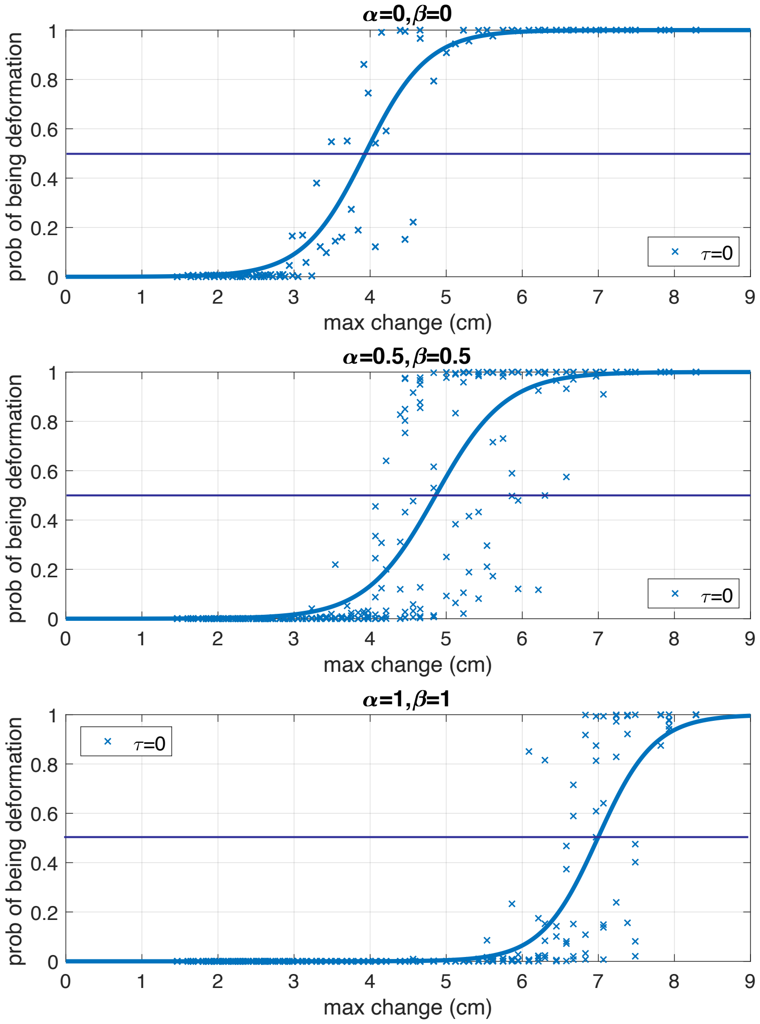
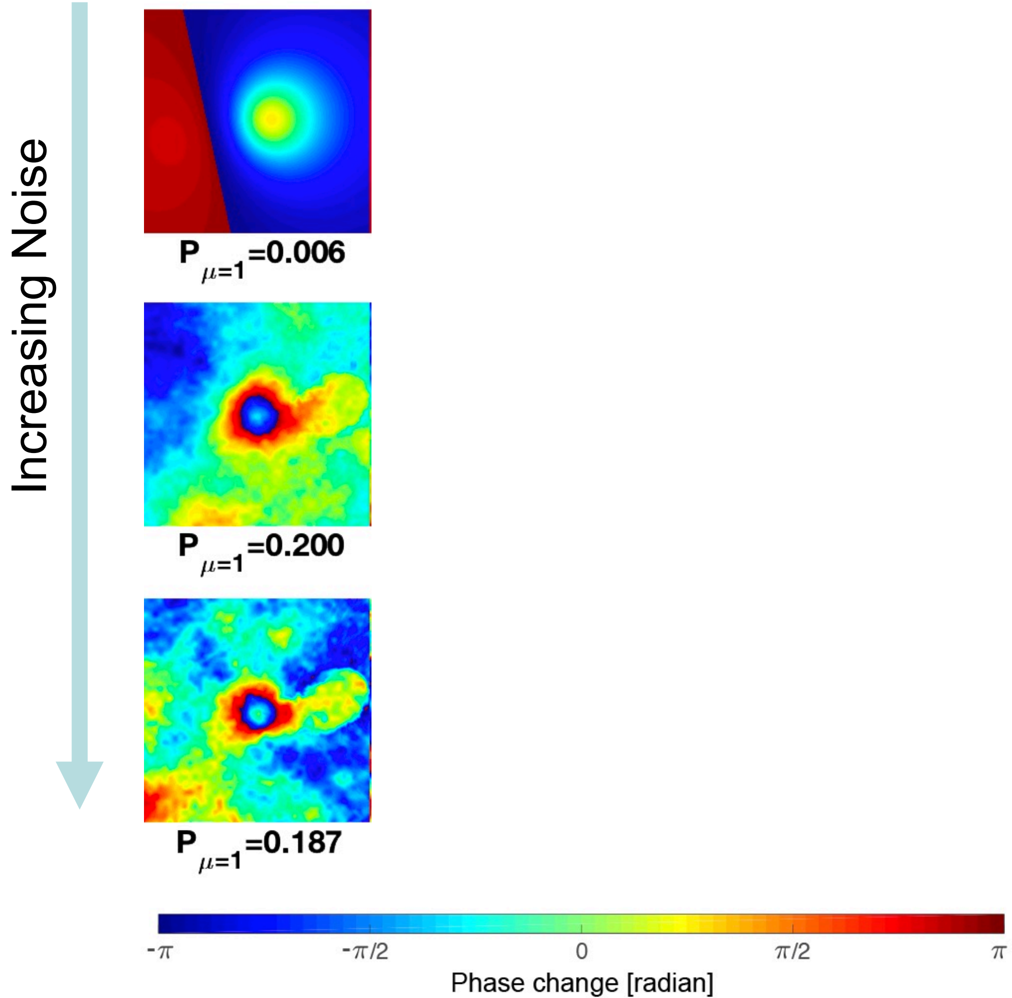
Biggs & Pritchard, 2017

Overwrapping technique

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





Overwrapping technique

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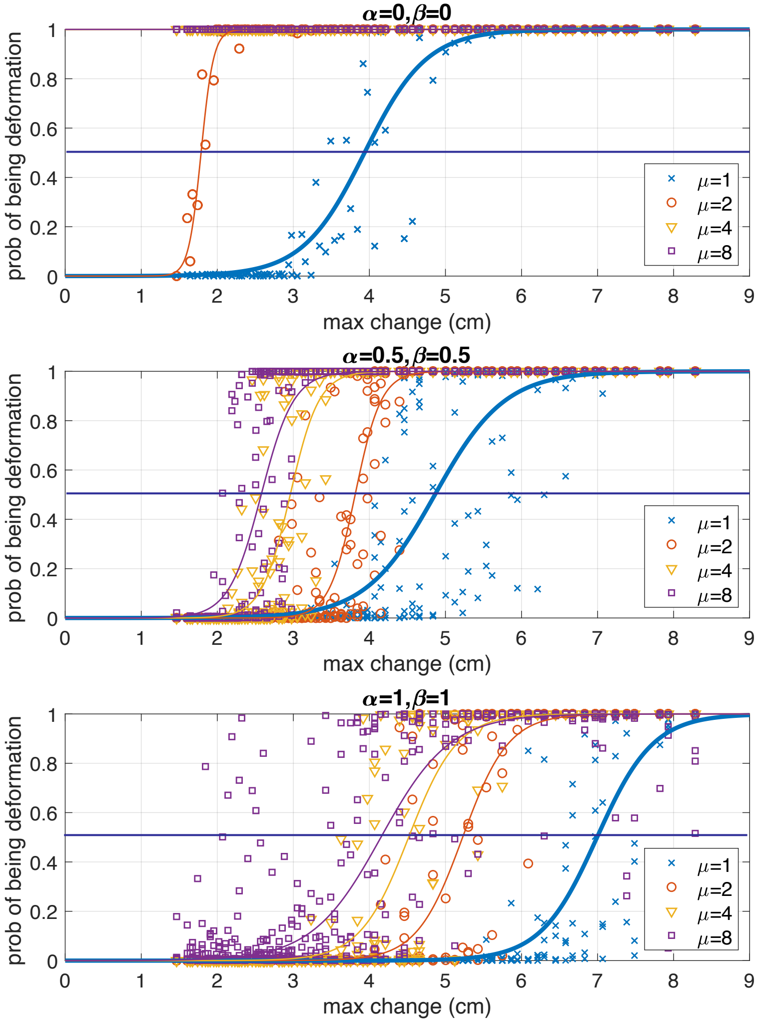
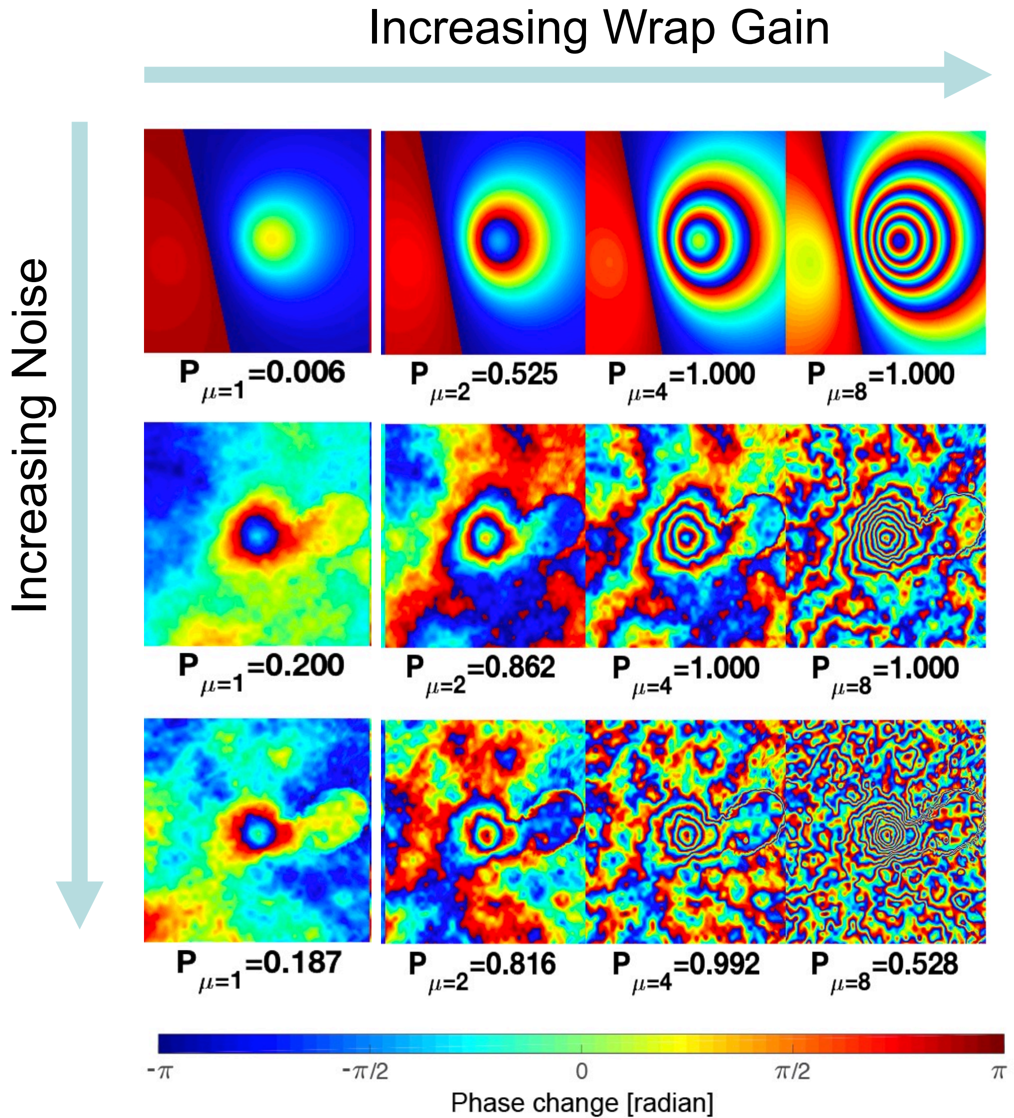
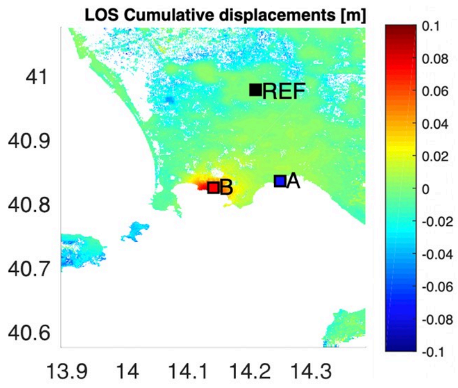
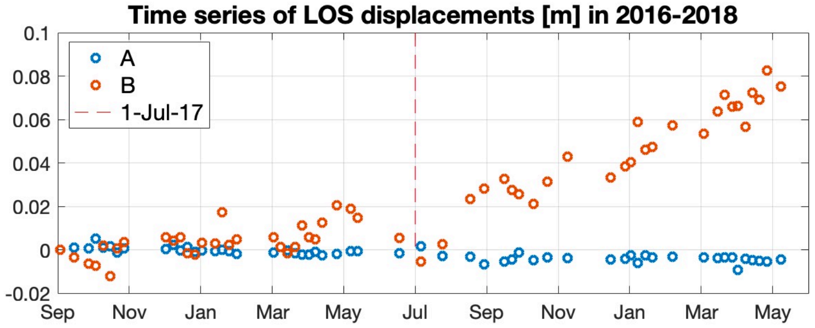




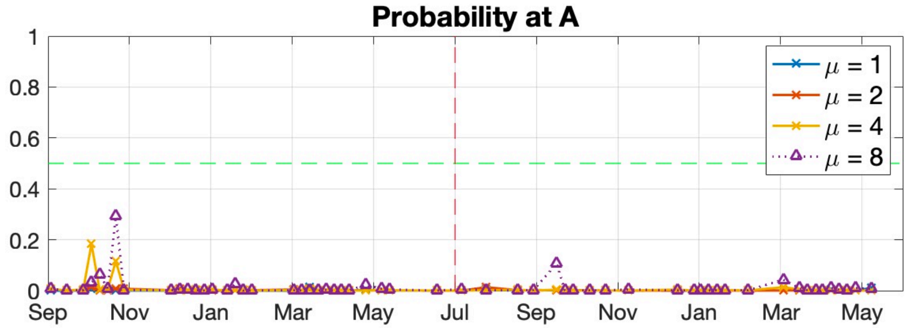
Example: Campi Flegrei, Italy

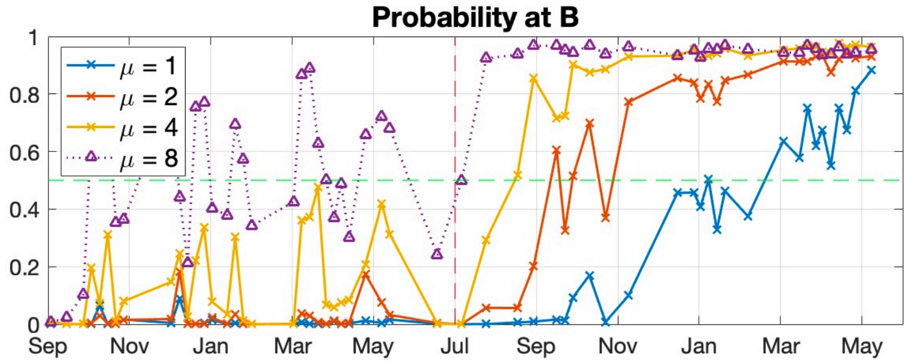
Campi Flegrei

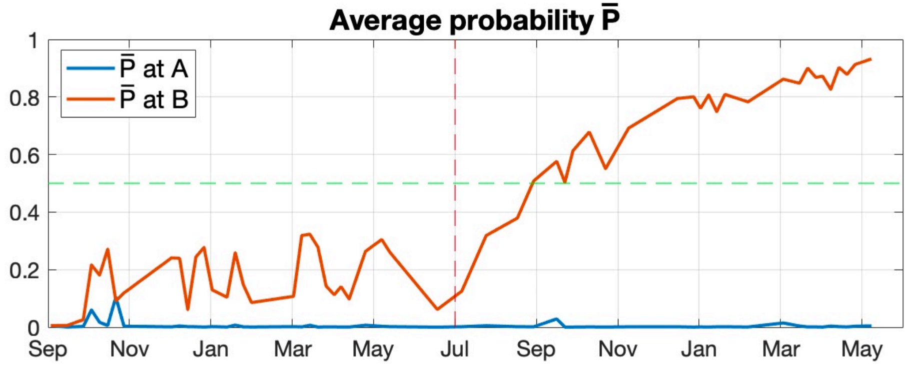




New pulse of uplift started in July 2017, rate of 8.5 cm/yr.







μ=1: detect deformation 7 months after onset (~ 5 cm)

μ=8: 15 false positives before onset of deformation

Combined Probability

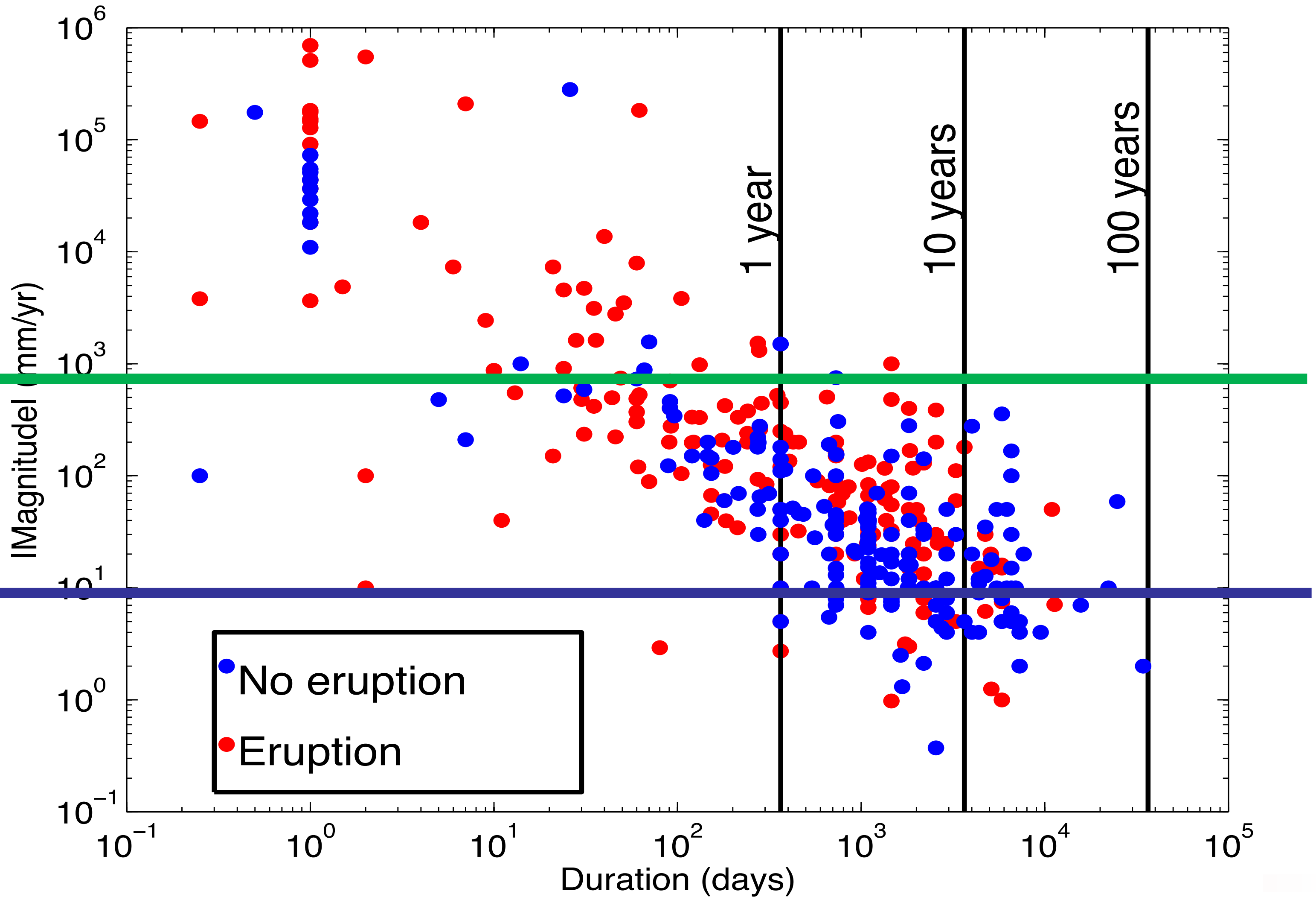
$$\overline{P} = \frac{1}{N}\sum_{i=0}^{N-1} P_{\mu=2^i}.$$

Detection 2 months after onset

Detecting Slow Deformation

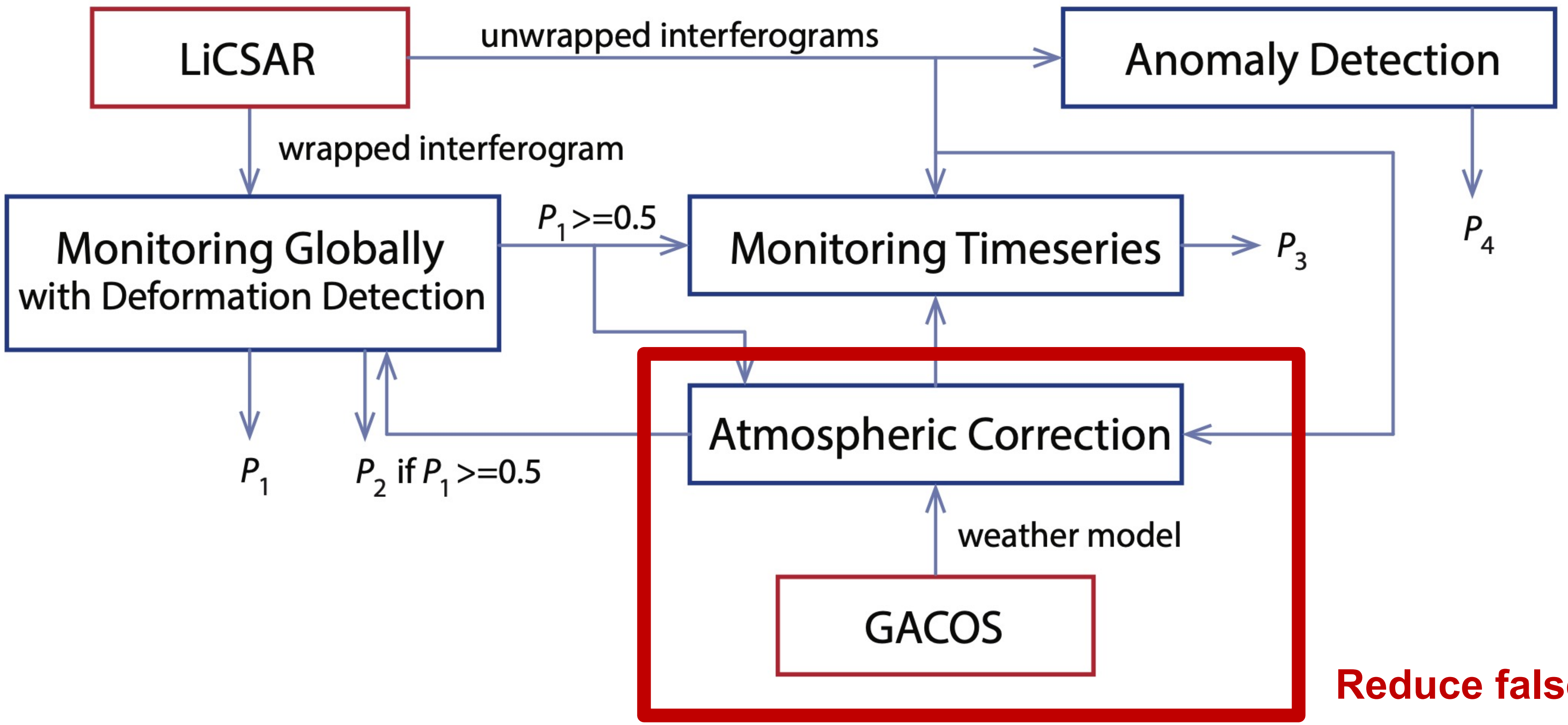
1 fringe in a 12 day interferogram
= 85 cm/yr

4 cm in 4 years of Sentinel-1 data
= 1 cm/yr



Biggs & Pritchard, 2017

Monitoring framework



Reduce false positives

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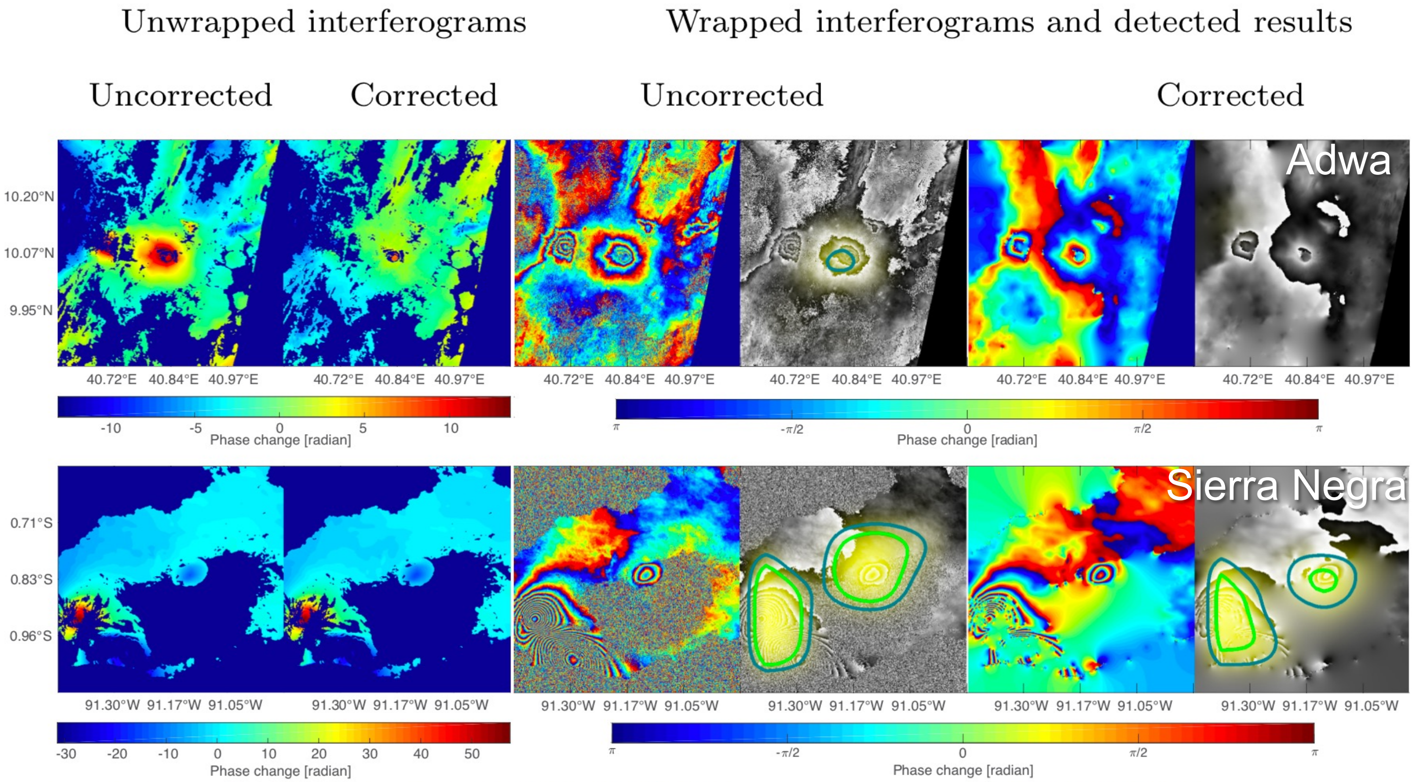
Atmospheric correction to reduce false positives

- GACOS zenithal tropospheric delays for the corresponding locations and acquisition dates
- Calculate the ZTD difference (slave-master) for each interferogram
- Reproject it in the corresponding line-of-sight

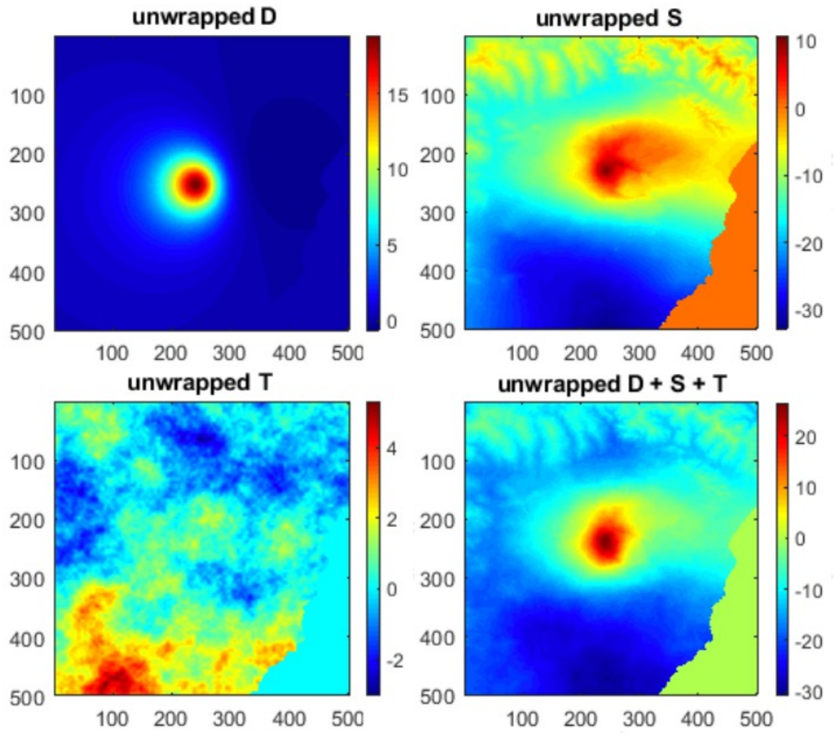
Name	location	type	dates	P_{max} uncorrected	P_{max} corrected
Adwa	Ethiopia	stratovolcano	20170410-20170609	0.521	0.104
Adwa	Ethiopia	stratovolcano	20170516-20170609	0.528	0.001
Alayta	Ethiopia	shield volcano	20170104-20170305	0.512	0.000
Alayta	Ethiopia	shield volcano	20170516-20170609	0.851	0.010
Ale Bagu	Ethiopia	stratovolcano	20170516-20170609	0.691	0.004
Etna	Italy	stratovolcano	20161027-20161202	0.689	0.001
Etna	Italy	stratovolcano	20161202-20161208	0.516	0.004
Etna	Italy	stratovolcano	20161214-20170302	0.547	0.045
Etna	Italy	stratovolcano	20170425-20170507	0.543	0.291
Gran Canaria	Canary Islands	fissure vent	20170417-20170423	0.626	0.465
Gran Canaria	Canary Islands	fissure vent	20170417-20170505	0.519	0.450
Pico	Pico Island	stratovolcano	20170621-20170727	0.507	0.475



N Anantrasirichai, J Biggs, F Albino, D Bull, A deep learning approach to detecting volcano deformation from satellite imagery using synthetic datasets, Remote Sensing of Environment, 2019

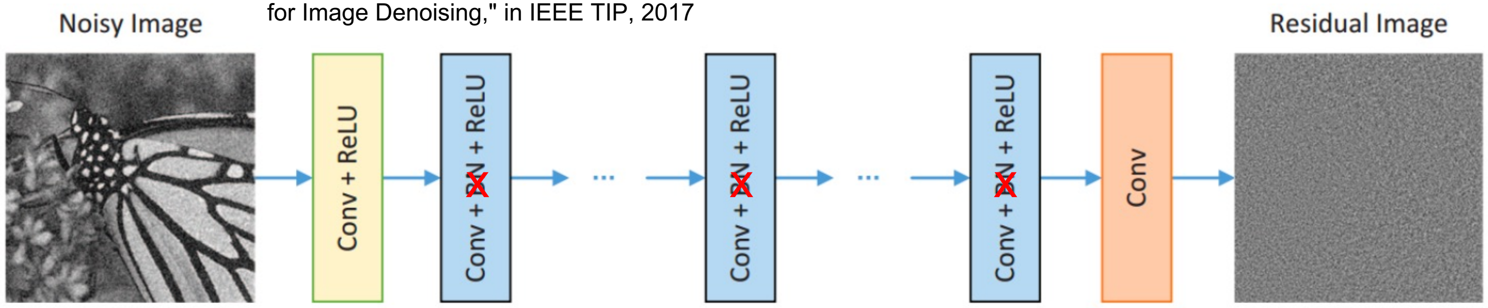
Denoising

Removing atmospheric signals with DnCNN



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*

K. Zhang, W. Zuo, Y. Chen, D. Meng and L. Zhang, "Beyond a Gaussian Denoiser: Residual Learning of Deep CNN for Image Denoising," in IEEE TIP, 2017



Unwraped D+S+T

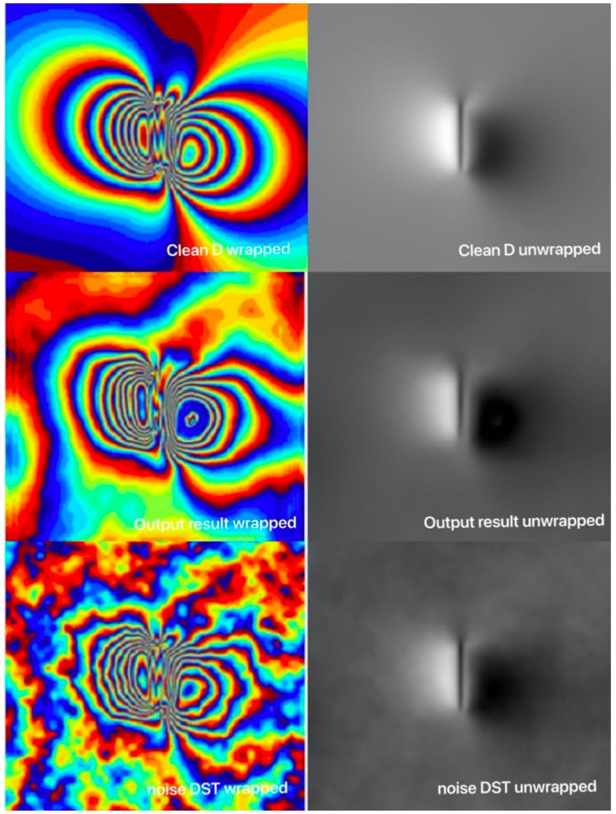
unwrapped S+T

Denoised image

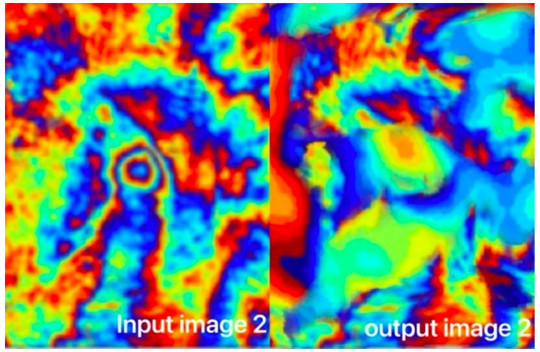
Xiao Tian, Automatic Atmosphere Removal in InSAR, MSc Thesis, University of Bristol, 2021

Denoising

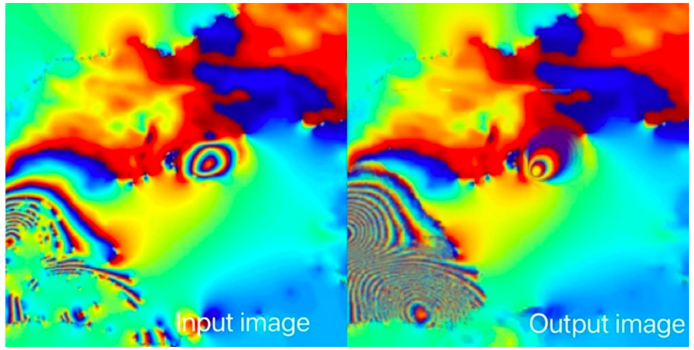
Removing atmospheric signals with DnCNN



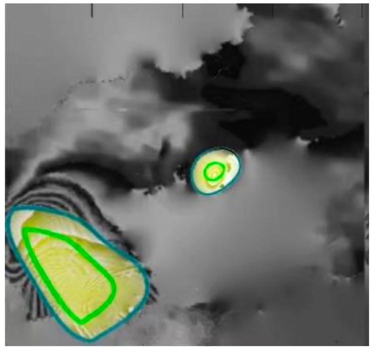
Synthetic sample



Real atmosphere sample



Real deformation sample



Detection result

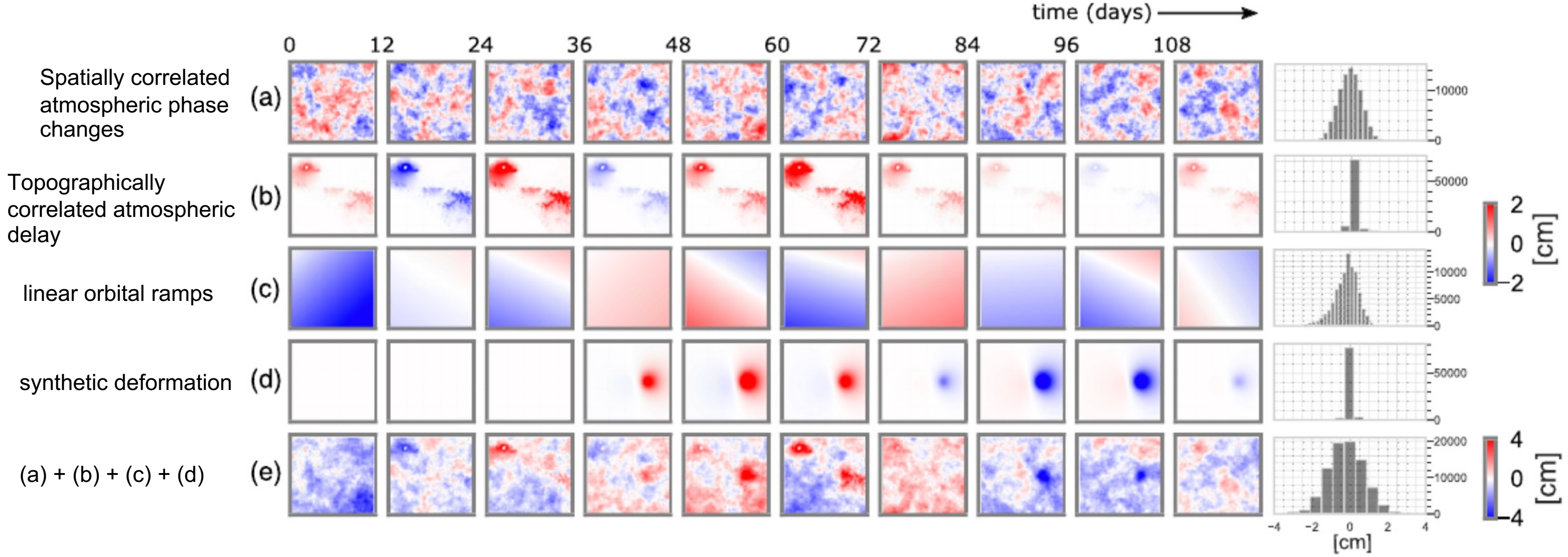
Test on 378 positive samples before denoising

model	data	positive	True positive	False positive
2-Class	Initial real images	378	153	225
	Real images after denoising	260	163	97

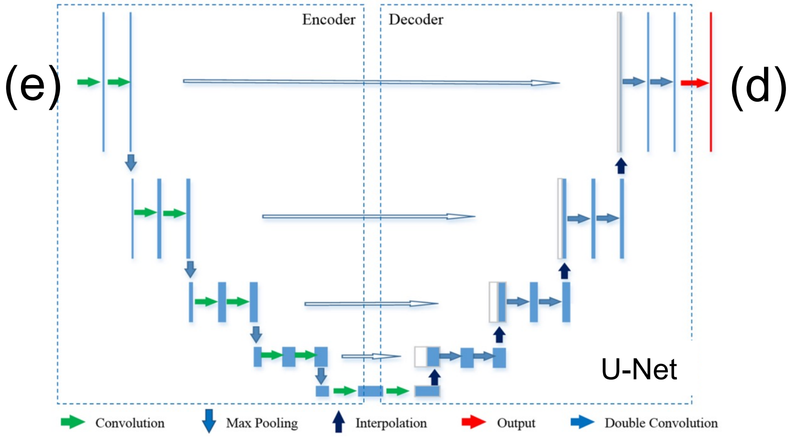
Xiao Tian, Automatic Atmosphere Removal in InSAR, MSc Thesis, University of Bristol, 2021

Denoising

Removing atmospheric signals with U-Net



Sun, J., Wauthier, C., Stephens, K., Gervais, M., Cervone, G., La Femina, P., & Higgins, M. (2020). Automatic detection of volcanic surface deformation using deep learning. *Journal of Geophysical Research: Solid Earth*, 125



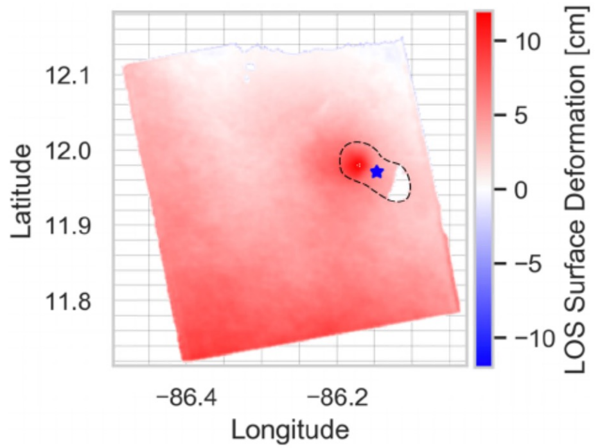
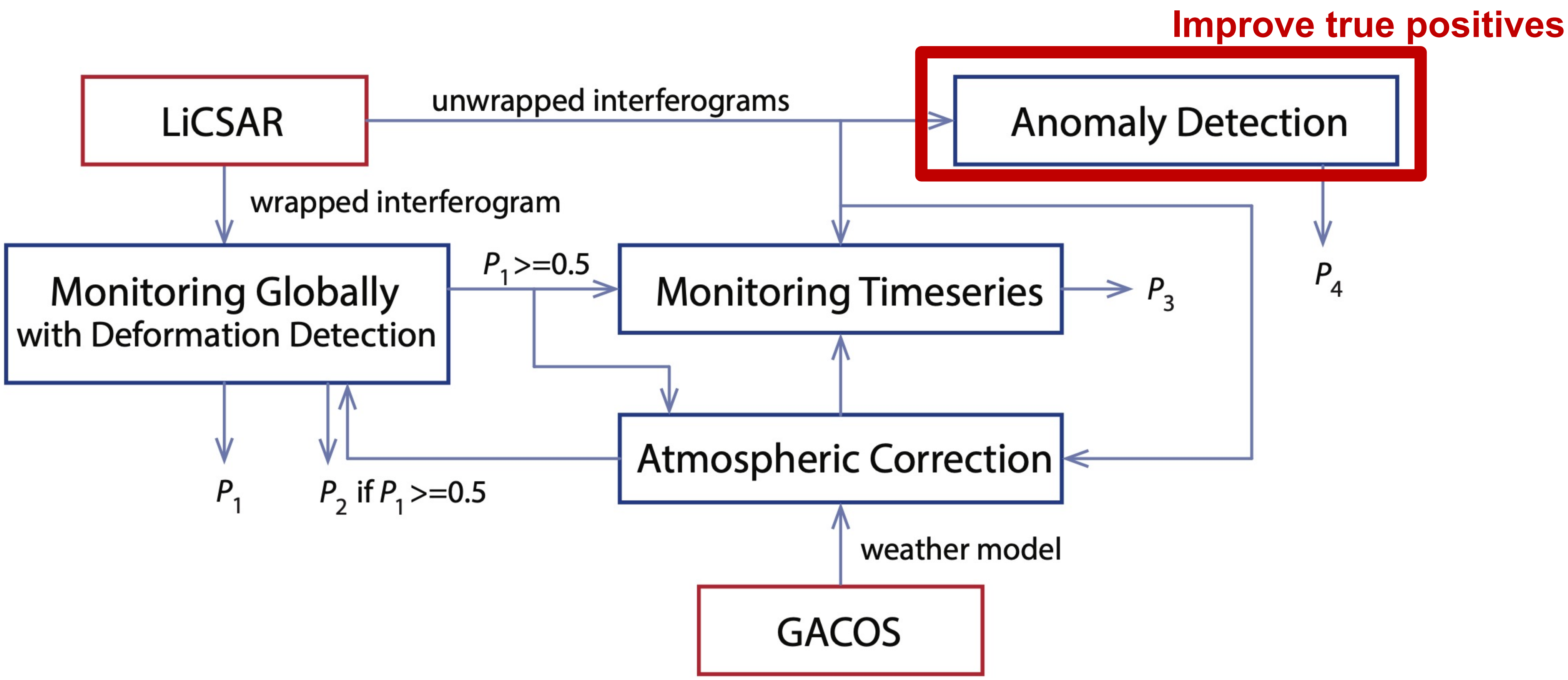
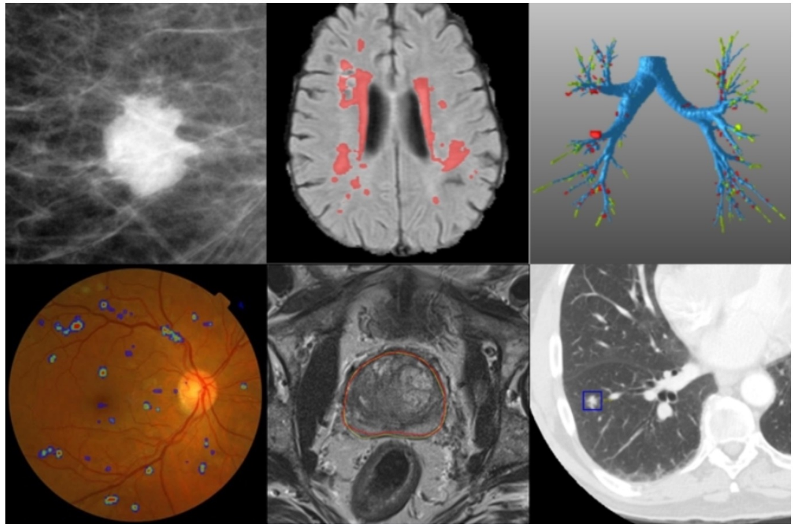


Figure 12. The average prediction of LOS surface deformation on 15 October 2016, extracted from the last time segment in Figure 11. The blue star represents the location of MAVC GPS station within Masaya caldera indicated in the dashed line.

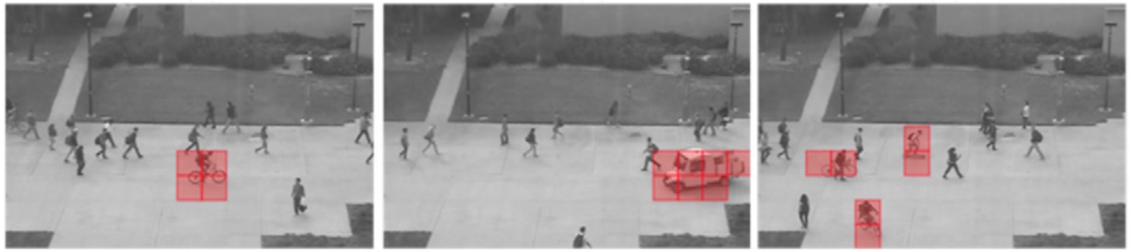
Monitoring framework



Anomaly Detection

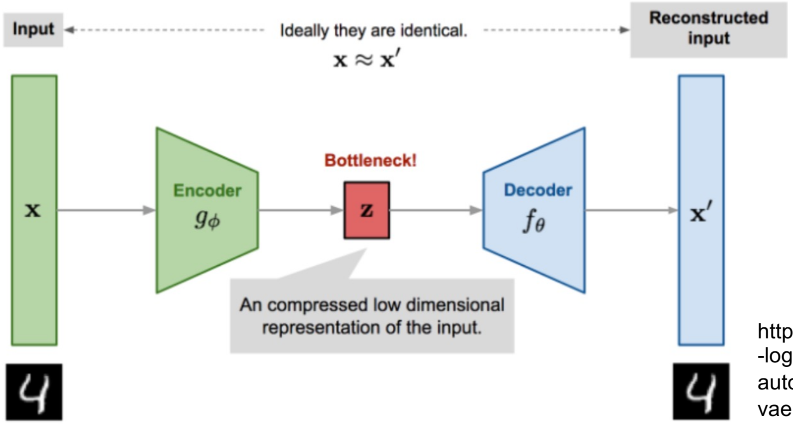


https://abacus.ai/blog/2020/04/27/real-time-anomaly-detection-a-deep-learning-approach/



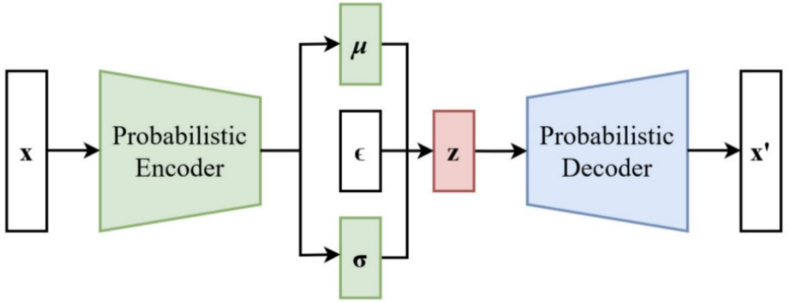
Fan et al, 2020, Video anomaly detection and localization via Gaussian Mixture FullyConvolutional Variational Autoencoder, Computer Vision and Image Understanding

Autoencoder



https://lilianweng.github.io/lil-log/2018/08/12/from-autoencoder-to-beta-vae.html

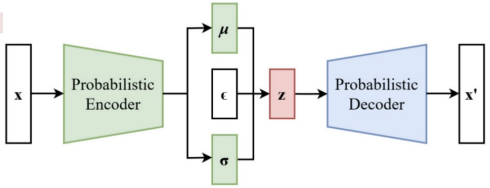
Variational autoencoder (VAE)

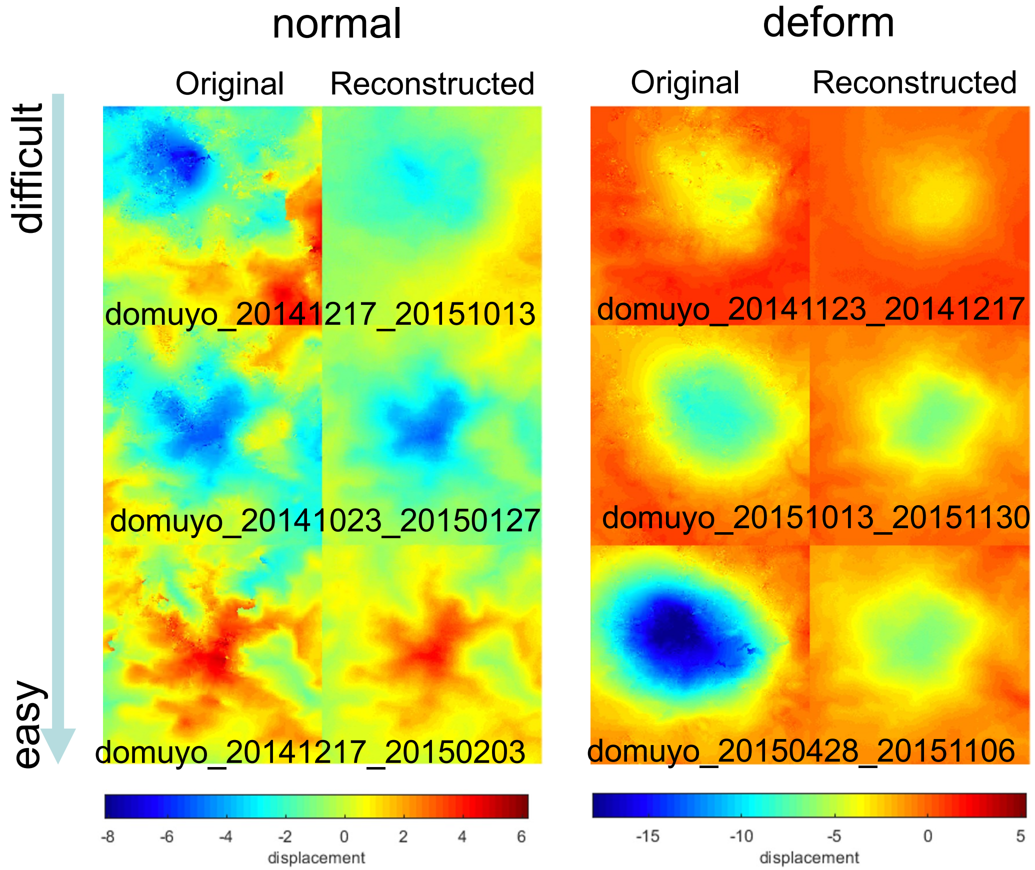


https://en.m.wikipedia.org/wiki/File:Reparameterized_Variational_Autoencoder.png

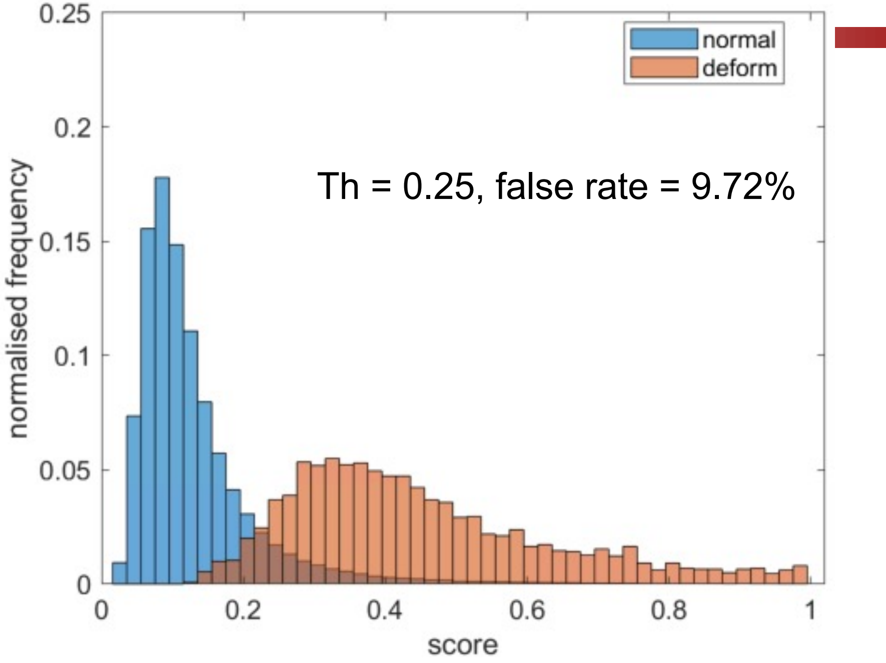
Anomaly Detection

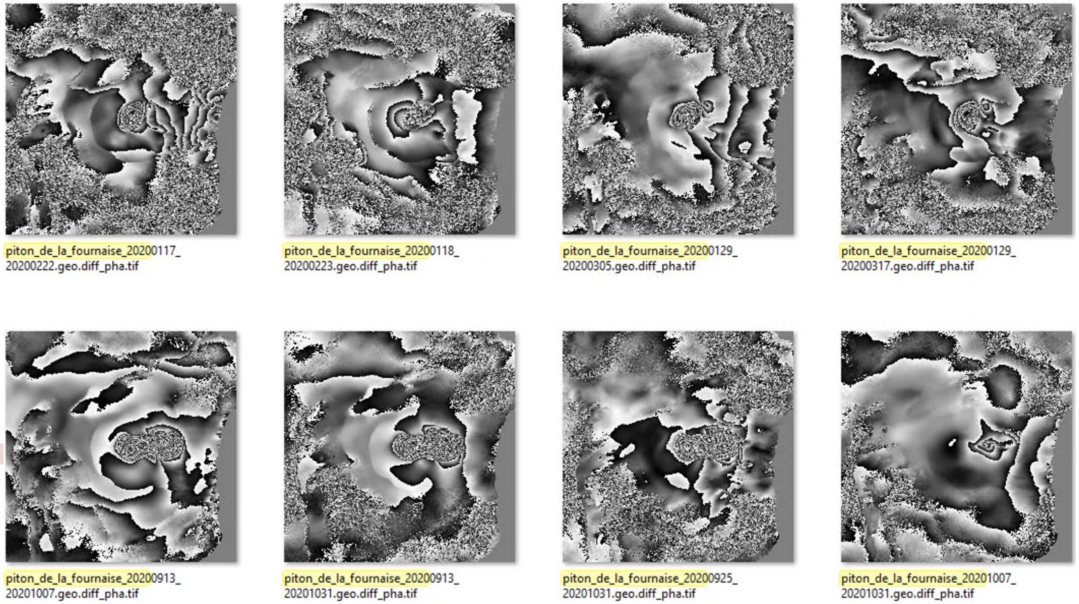
Variational autoencoder (VAE)





LiCSAR dataset (400k interferograms)





Detecting Ground Deformation in the Built Environment

Pui Anantrasirichai, Juliet Biggs, Alin Achim, David Bull
University of Bristol

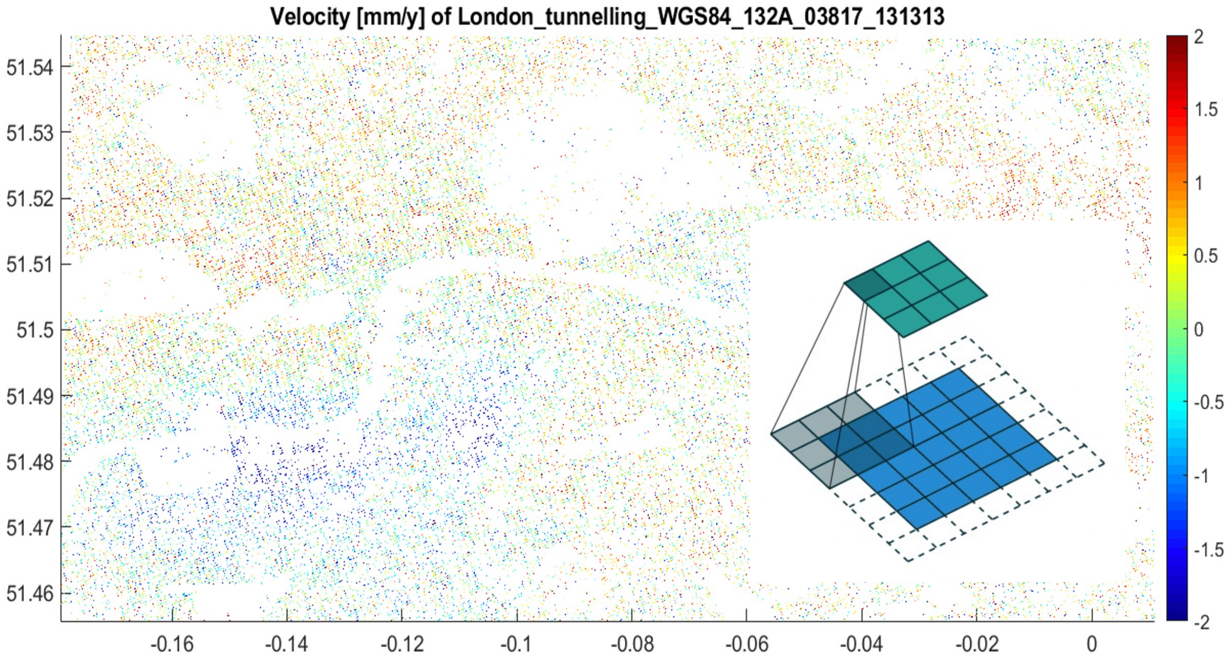
Krisztina Kelevitz, Zahra Sadeghi, Tim Wright
University of Leeds, UK

Anantrasirichai, N., Biggs, J., Kelevitz K., Sadeghi Z., Wright T., Thompson J., Achim A. and Bull, D., 2020. Detecting Ground Deformation in the Built Environment using Sparse Satellite InSAR data with a Convolutional Neural Network. IEEE Transactions on Geoscience and Remote Sensing.

Detecting ground deformation in the UK

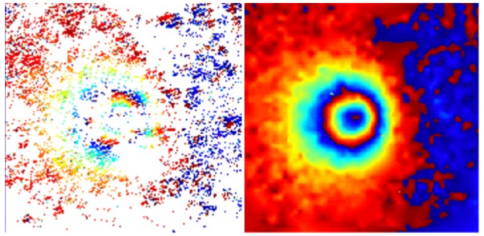
Statement of problems

- Data sparsity with spiky noise
- Lack of real data samples
- Slow, localised motion

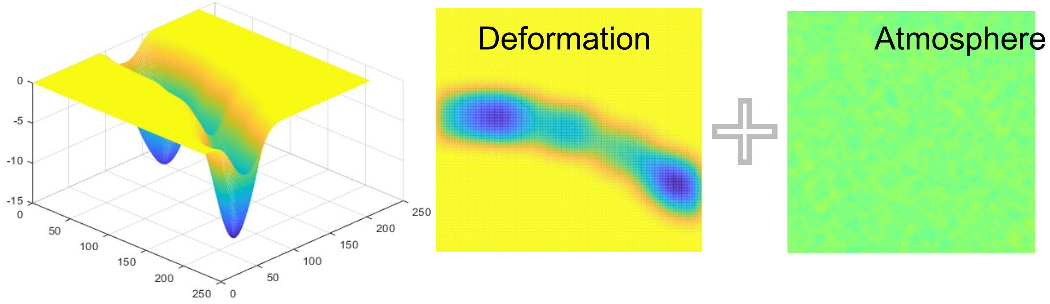


Solutions

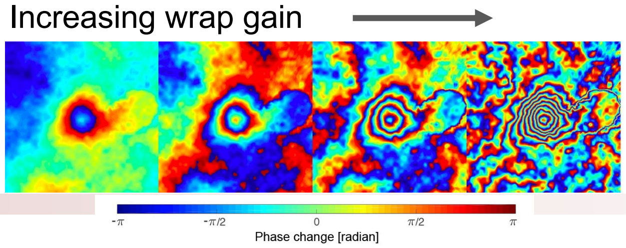
- 1. Spatial interpolation – matrix completion



- 2. Synthetic examples



- 3. Overwrapping technique



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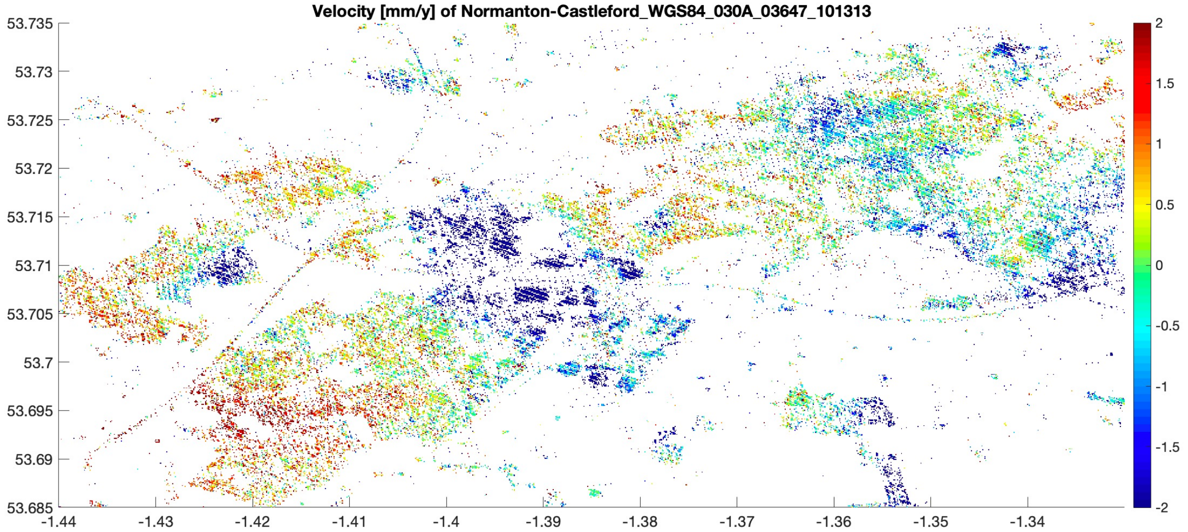
Spatial interpolation and denoising

- Matrix completion



Normanton and Castleford - coal mining area uplift

- Inverse problem: $y = \mathcal{S}x + n$
  - y is an observed signal of an ideal dense signal, $\mathcal{S}$ is randomly sub-sampling matrix
- Solving: $\hat{x} = \arg\min_{x}\{||y - \mathcal{S}x||_2^2 + \alpha||x||_p^p\},\ p > 0, \alpha = 1$
  - Matrix completion via iterated soft thresholding and singular value decomposition (SVD)
  - Initial iteration with Delaunay triangulation

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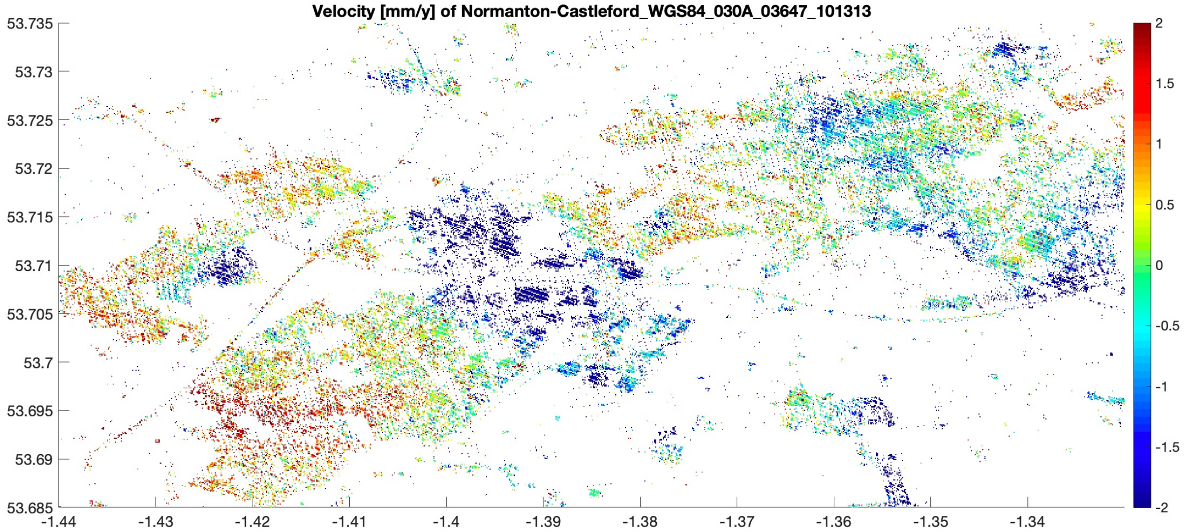
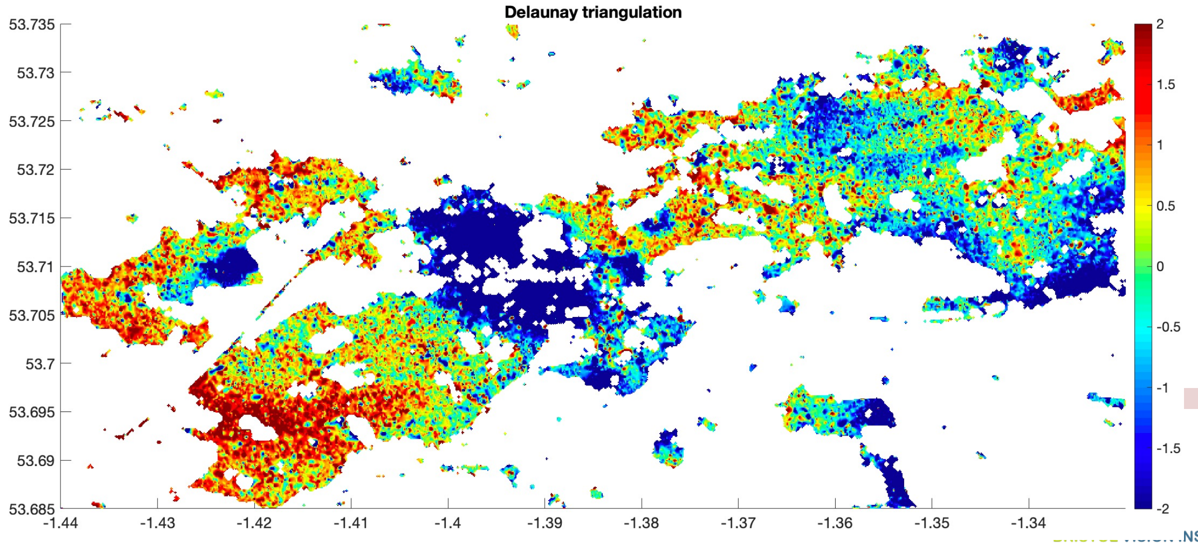
Anantrasirichai, N., Biggs, J., Kelevitz K., Sadeghi Z., Wright T., Thompson J., Achim A. and Bull, D., 2020. Detecting Ground Deformation in the Built Environment using Sparse Satellite InSAR data with a Convolutional Neural Network. IEEE Transactions on Geoscience and Remote Sensing.

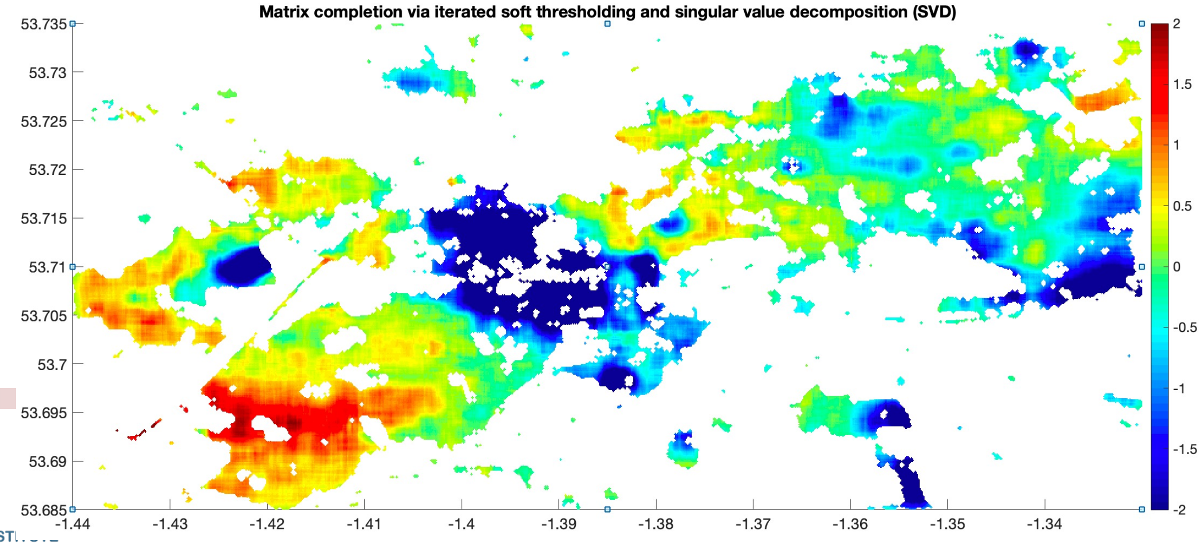
Spatial interpolation and denoising

- Matrix completion



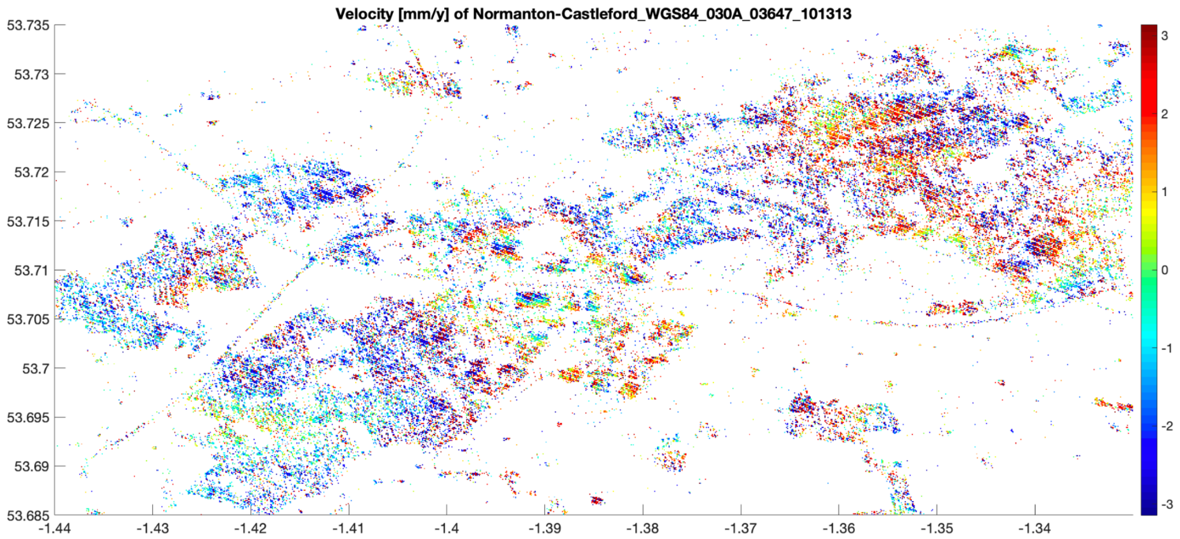
Normanton and Castleford - coal mining area uplift

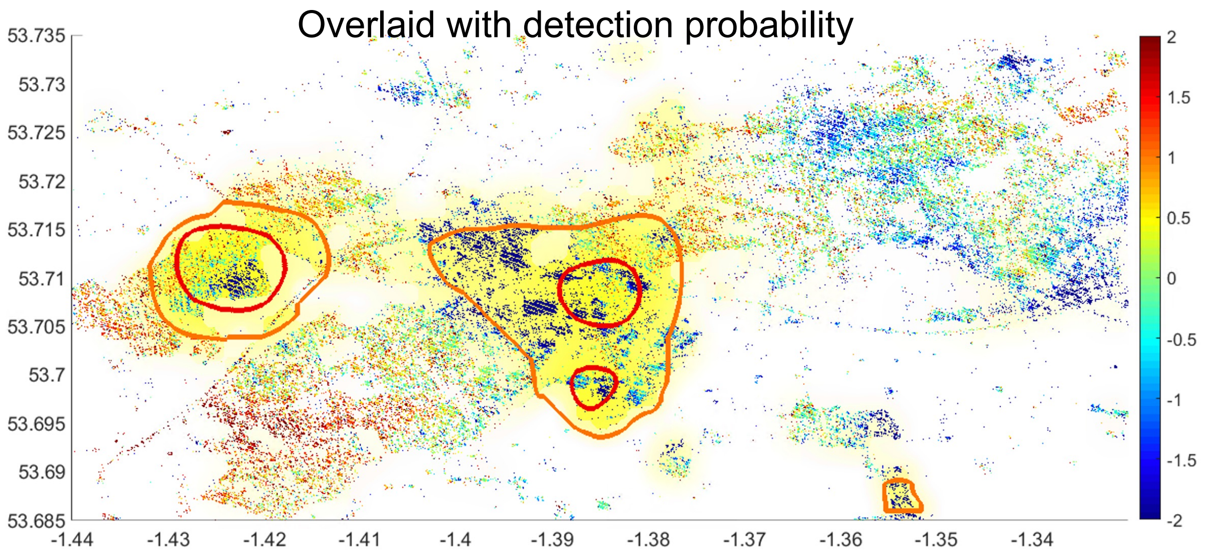


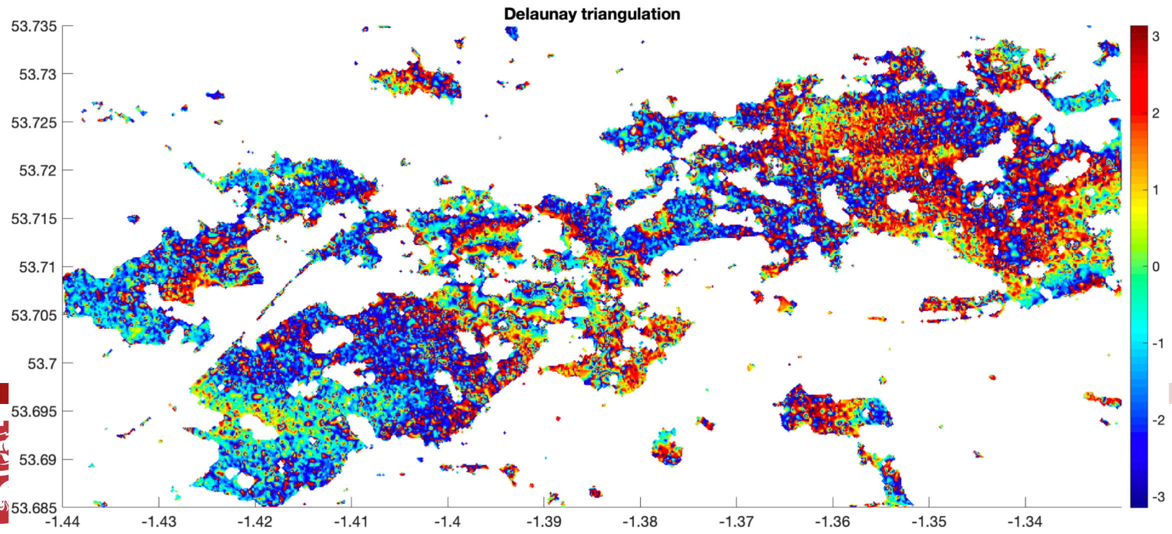


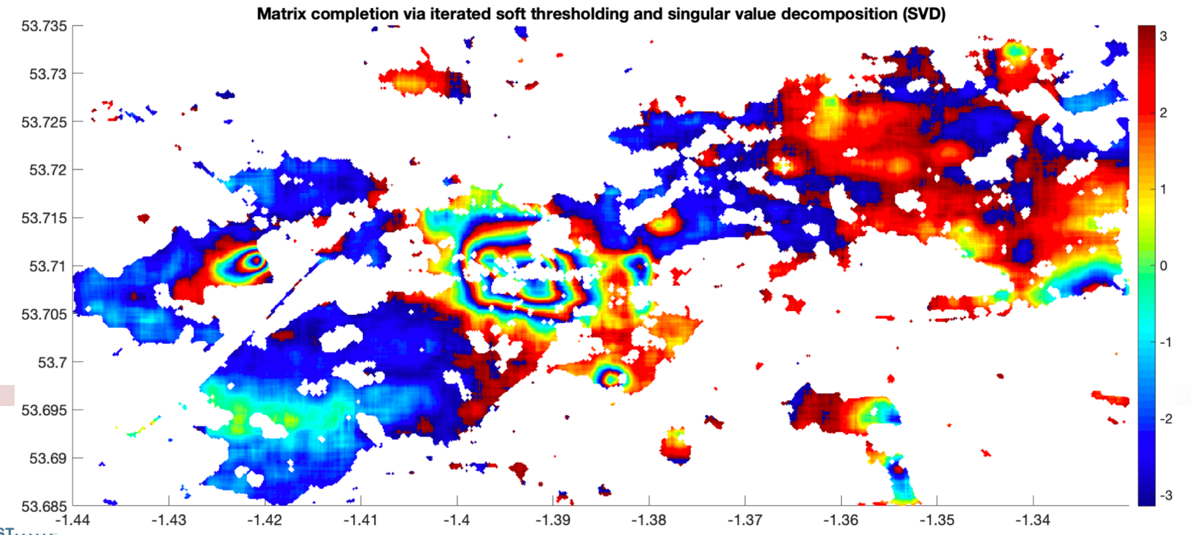
Spatial interpolation and denoising

- Wrapping and applying deforming detection



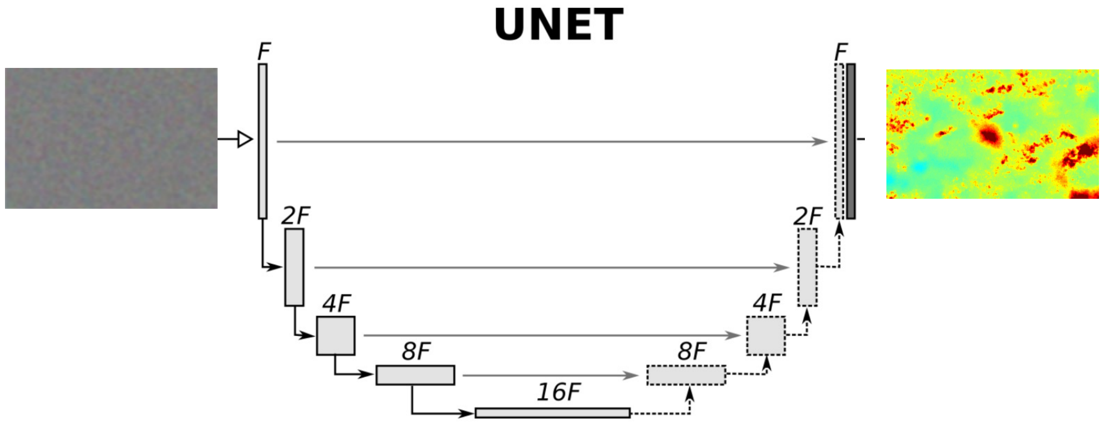


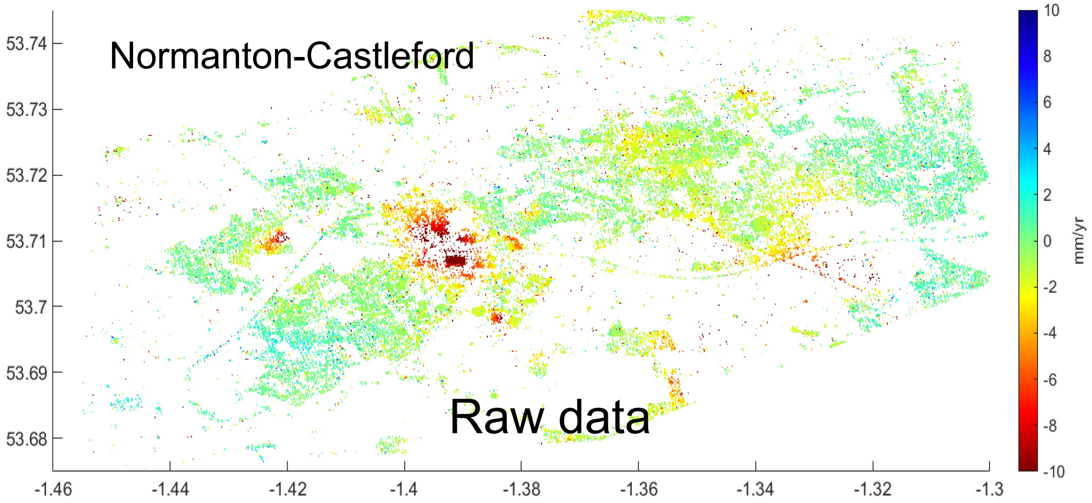


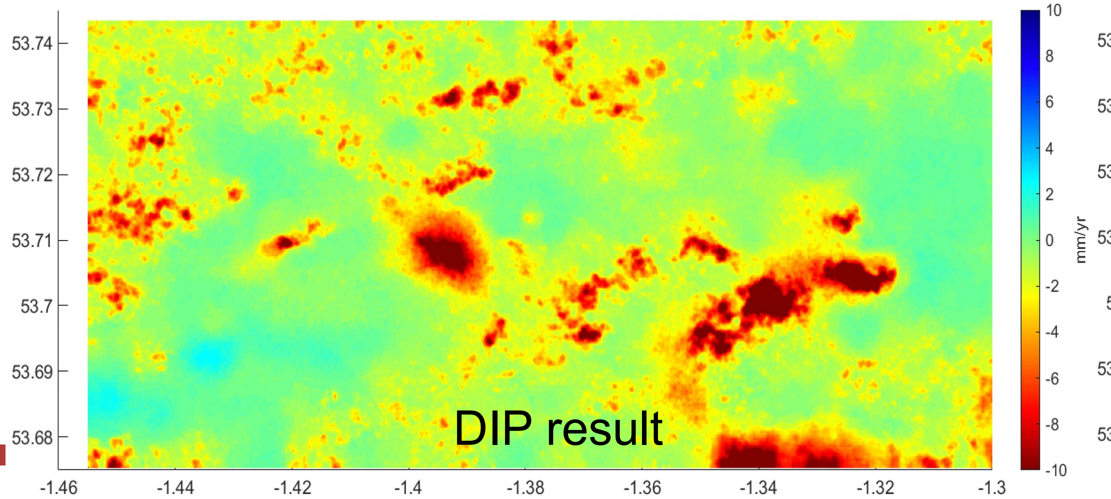


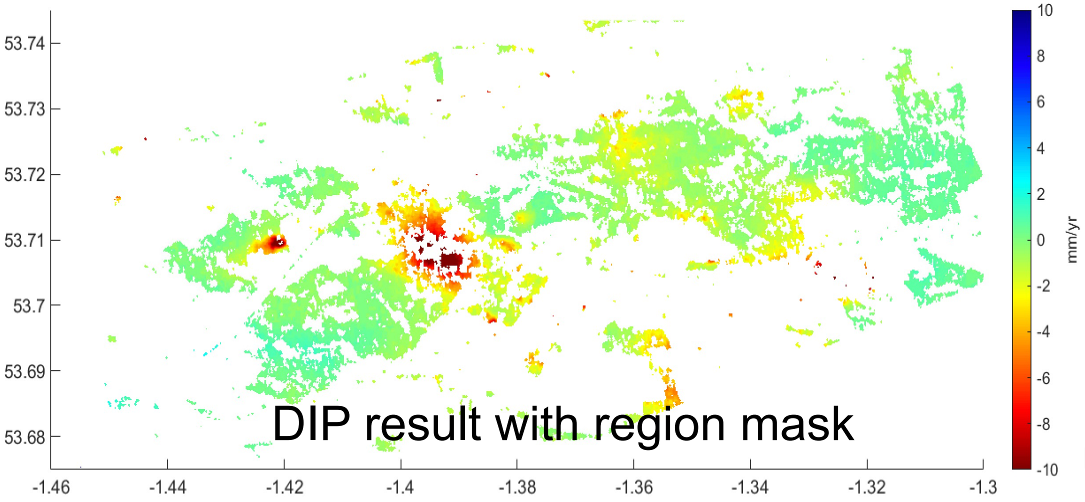
Spatial interpolation and denoising

- **Deep image prior** (DIP): Self-supervised learning to remove spiky noise and interpolation simultaneously

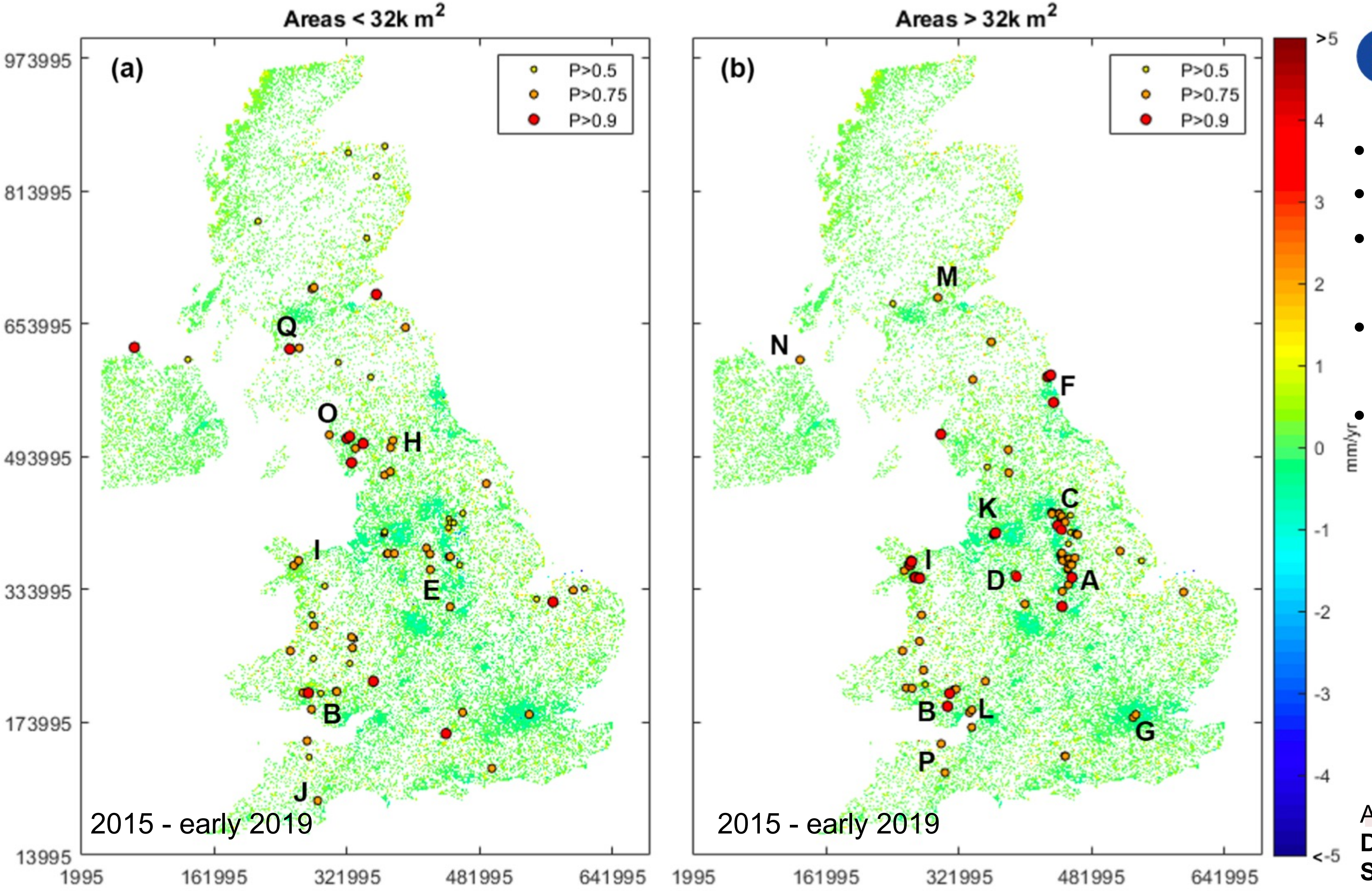








Detection results of CNN

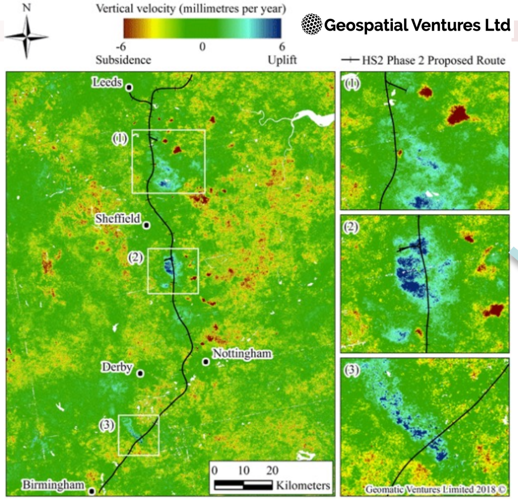


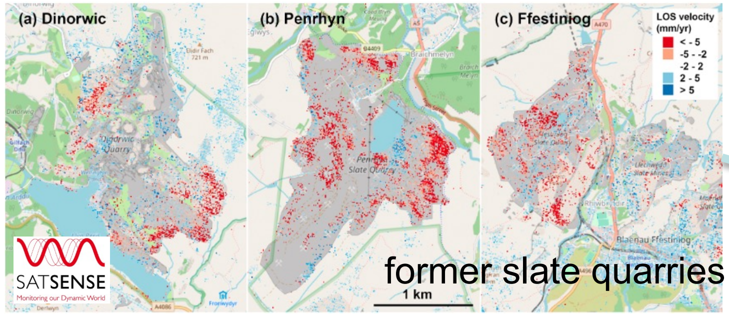
satsense

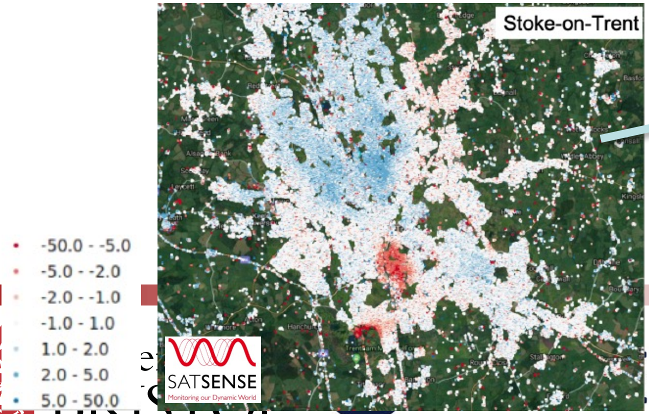
- 68,504x98,504 pixels
- >64 million points (ascending)
- >29 million points (descending)
- Interpolating process at 2500x2500 pixels
- CNN input size is 224x224 pixels

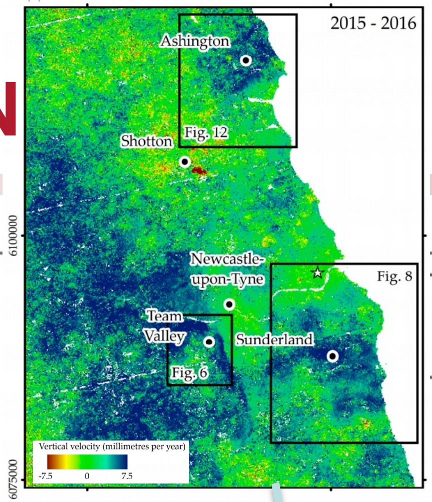
Anantrasirichai et al. 2020. **Detecting Ground Deformation in the Built Environment using Sparse Satellite InSAR data with a Convolutional Neural Network**. IEEE TGRS

Detection results of CNN

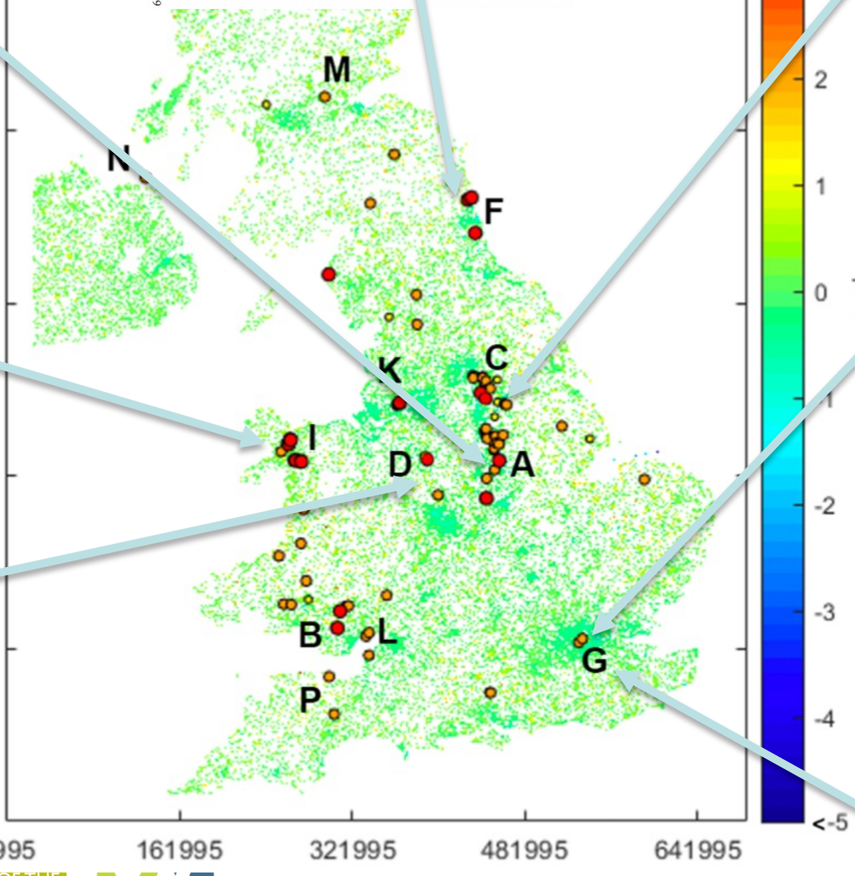






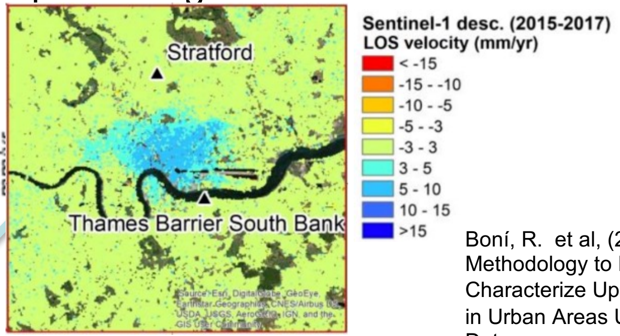


Gee, D., et al. (2017). Ground motion in areas of abandoned mining: Application of the intermittent sbas (isbas) to the northumberland and durham coalfield, uk



Subsidence and uplift from coal mining

Uplift from ground water rebound

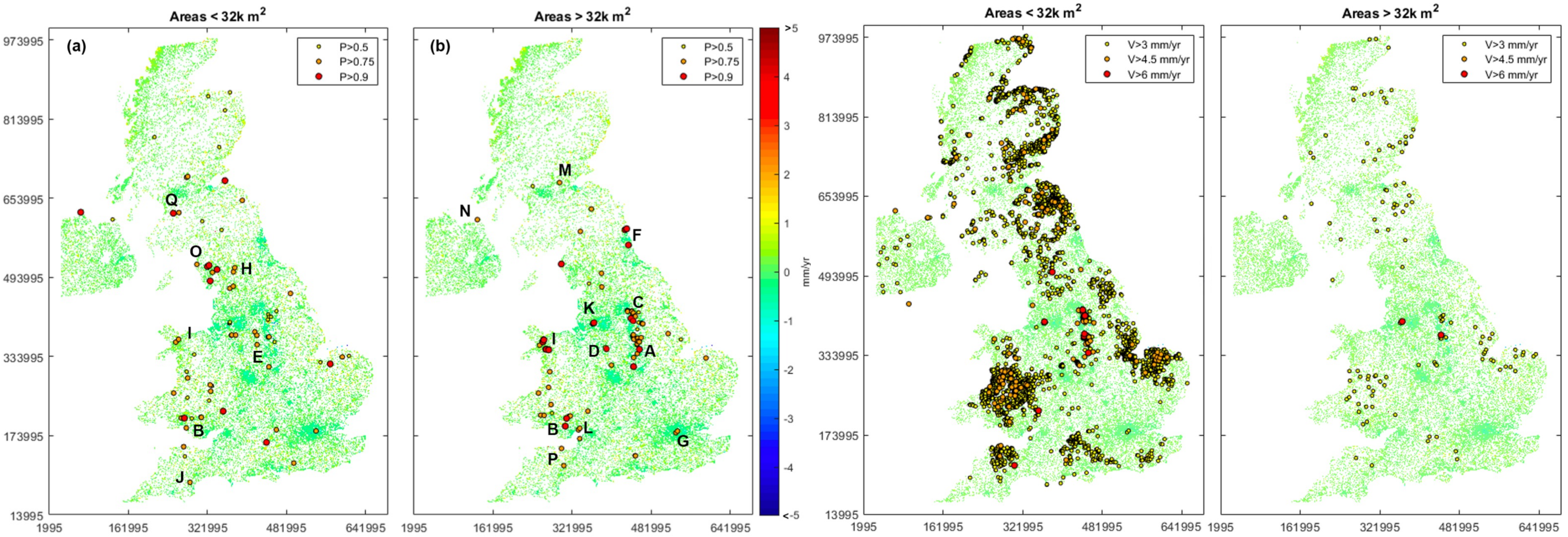


Boní, R. et al, (2018) A Methodology to Detect303and Characterize Uplift Phenomena in Urban Areas Using Sentinel-1 Data

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

Subsidence from engineering work

Comparison with thresholding technique

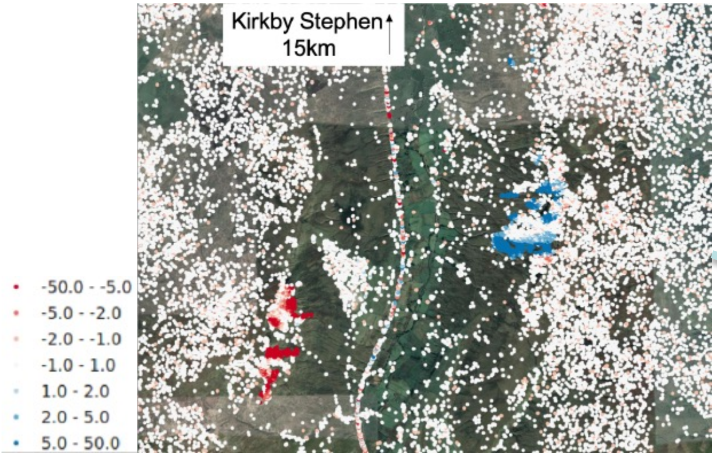


CNN

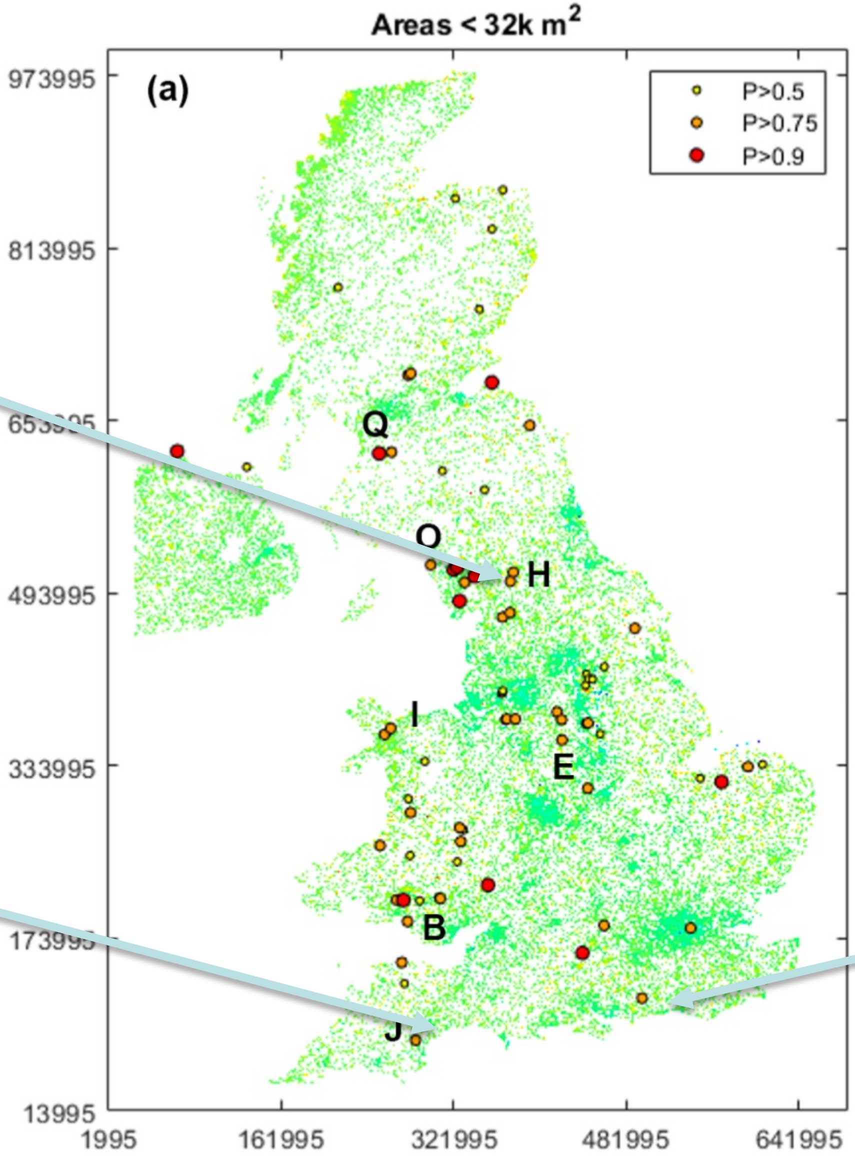
thresholding

Limitations

Landslides

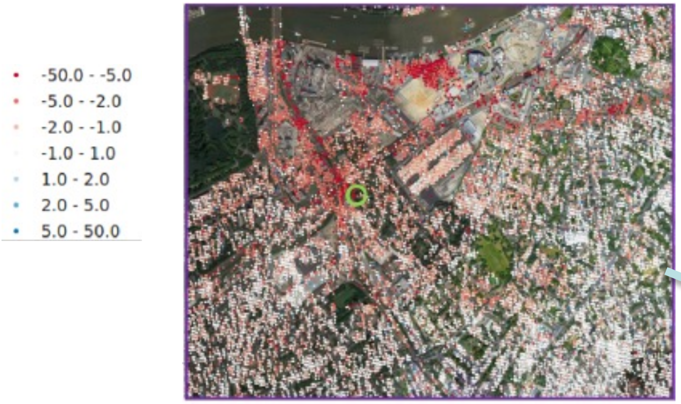


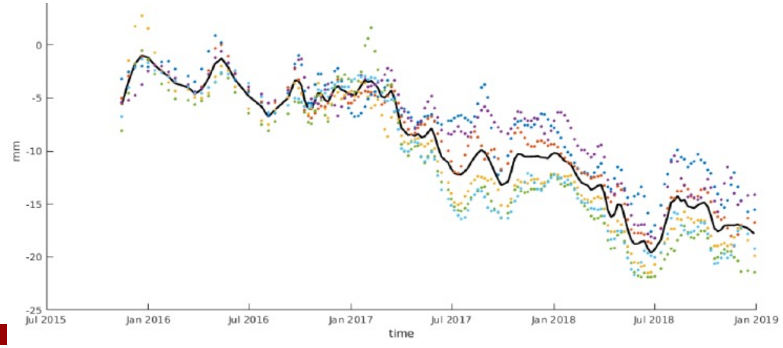
Landslides

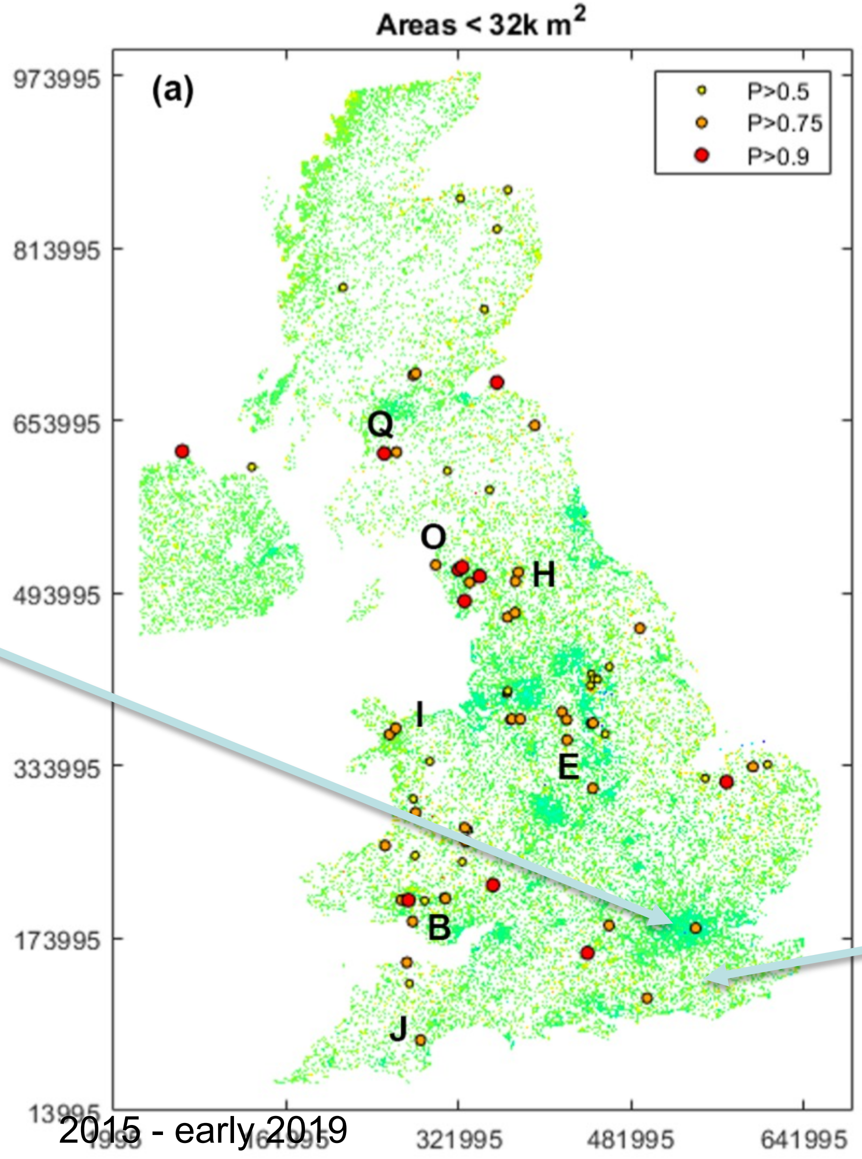


sinkhole

Limitations

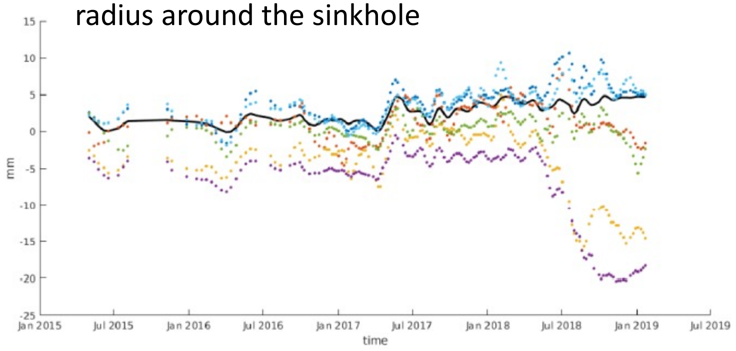






2015 - early 2019

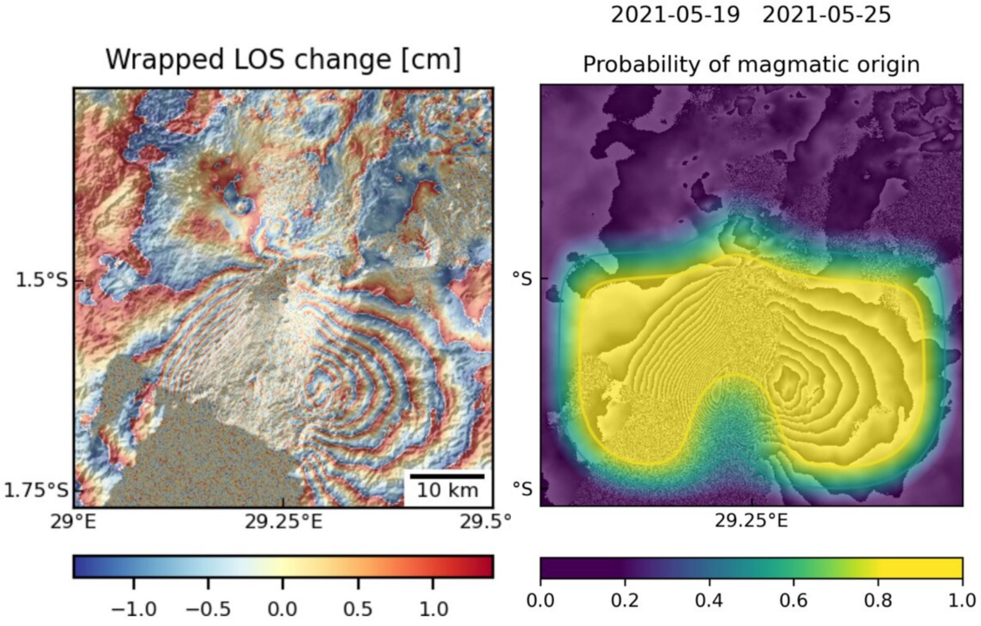
Individual displacement time series from a 15m radius around the sinkhole



sinkhole

Conclusion

- **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.
- Classification models were initialised with these synthetic datasets using the pretrained CNN, **AlexNet**.
- **Slow deformation** can be detected using cumulative signals and over-wrapped data
- Adaptable to **urban sources** of deformation with preprocessing techniques, including spatial interpolation



Q & A

Thank you

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