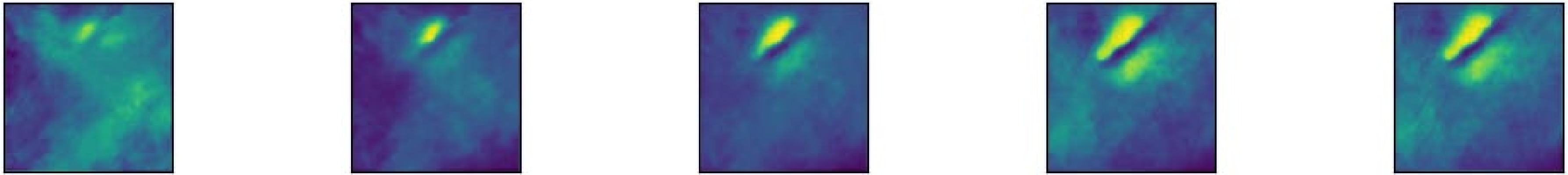
Machine learning for volcano deformation: moving beyond detection and classification to forecasting



Andy Hooper, Matt Gaddes, Camila Novoa Lizama, Lin Shen, Rachel Bilsland, Eilish O'Grady, Josefa Sepulveda Araya, Milan Lazecky, Yasser Maghsoudi, Richard Rigby, Juliet Biggs, Susanna Ebmeier, David Hogg

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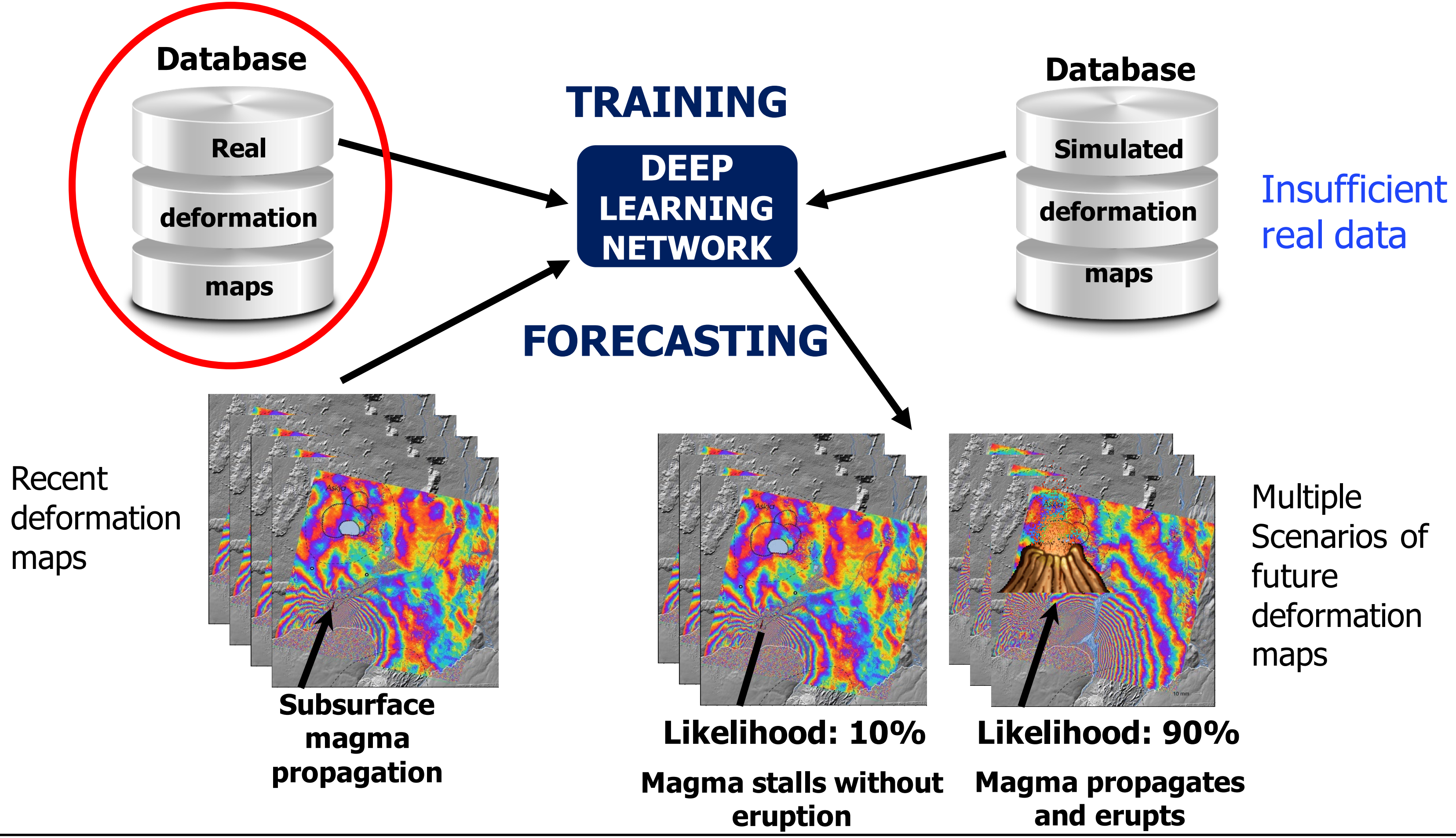
Motivated by video prediction

https://video-prediction.github.io/video_prediction/



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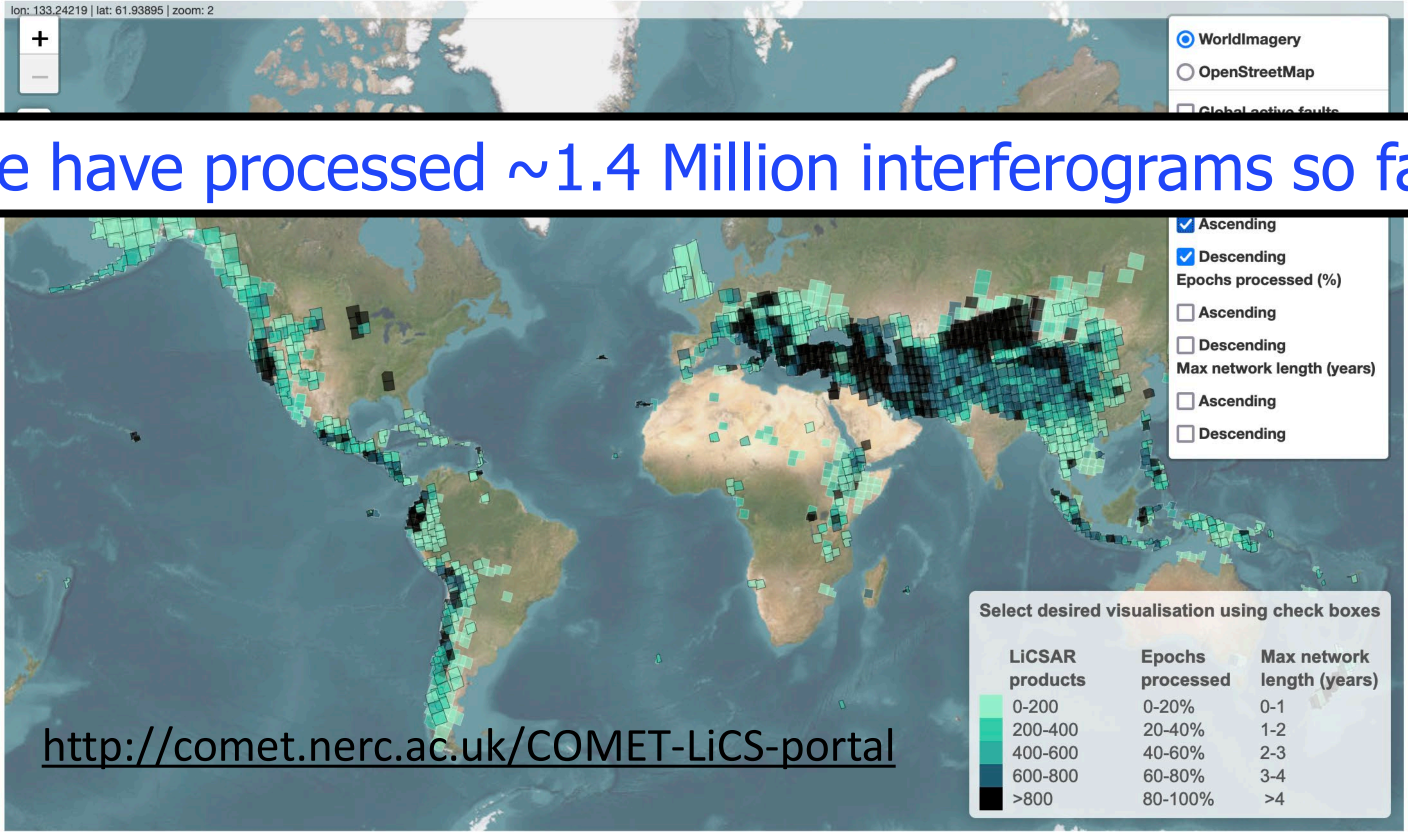
COMET is processing Sentinel-1 data over all volcanoes and straining regions



We have processed ~1.4 Million interferograms so far

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

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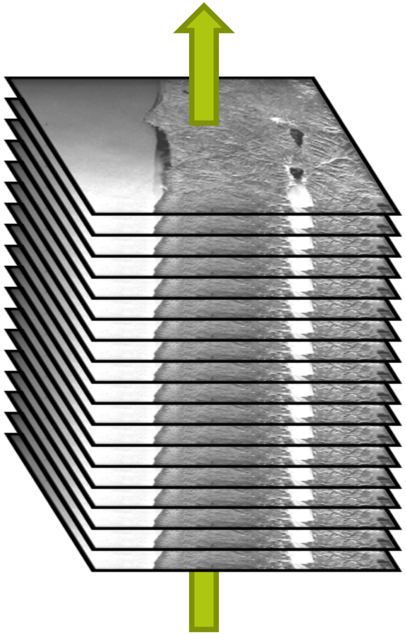
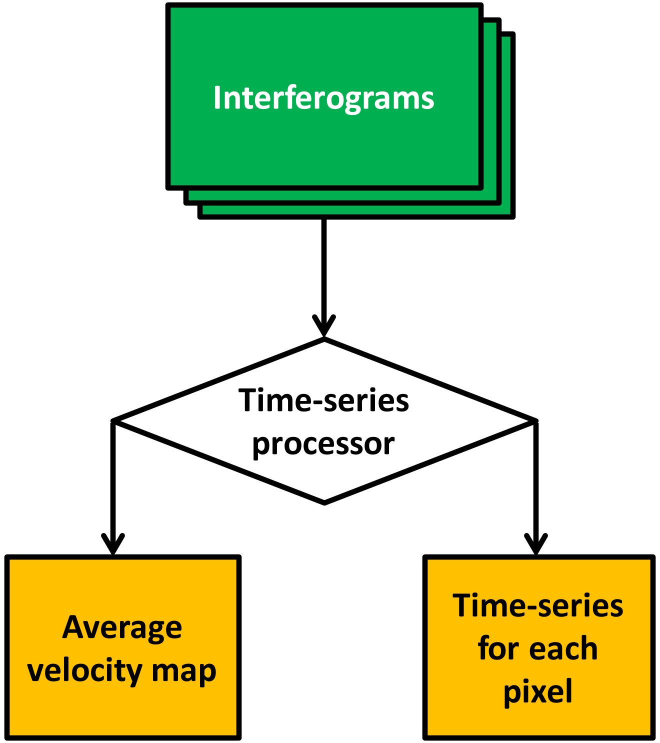
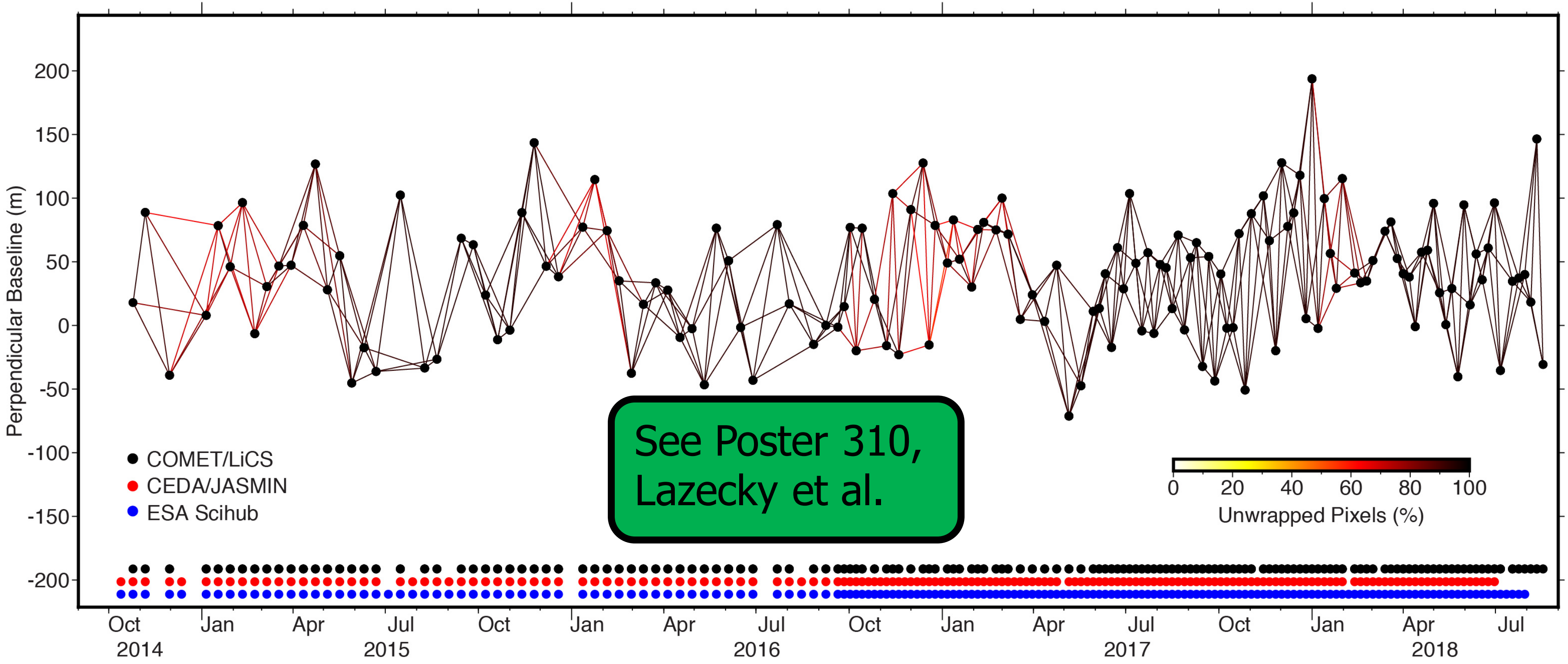
We then carry out time series analysis of interferograms





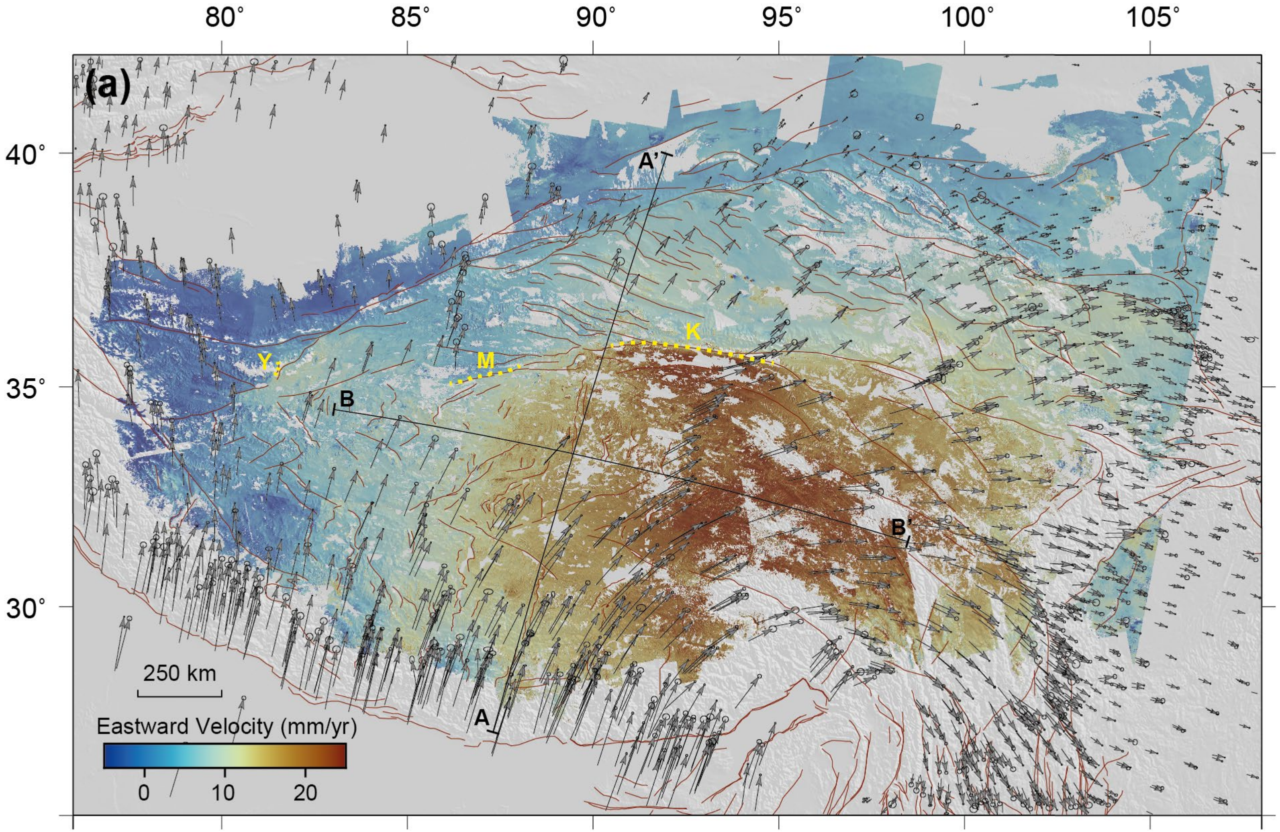
Can be tricky…

Corrupt data files; critical missing bursts; low-coherency timespans (i.e. winter), …



See Poster 310, Lazecky et al.

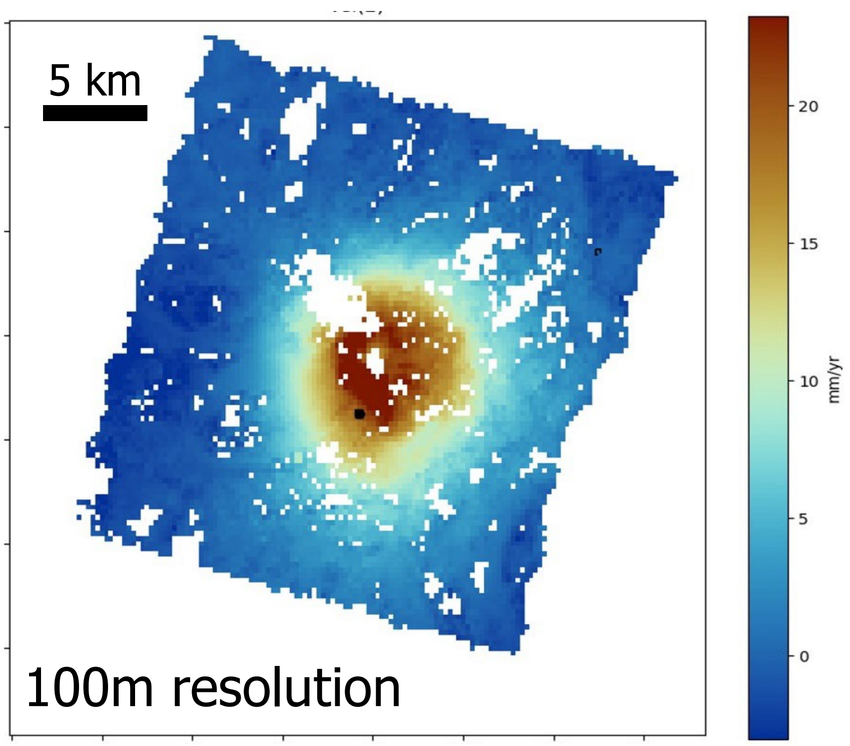
Inverting network gives average velocity and time series

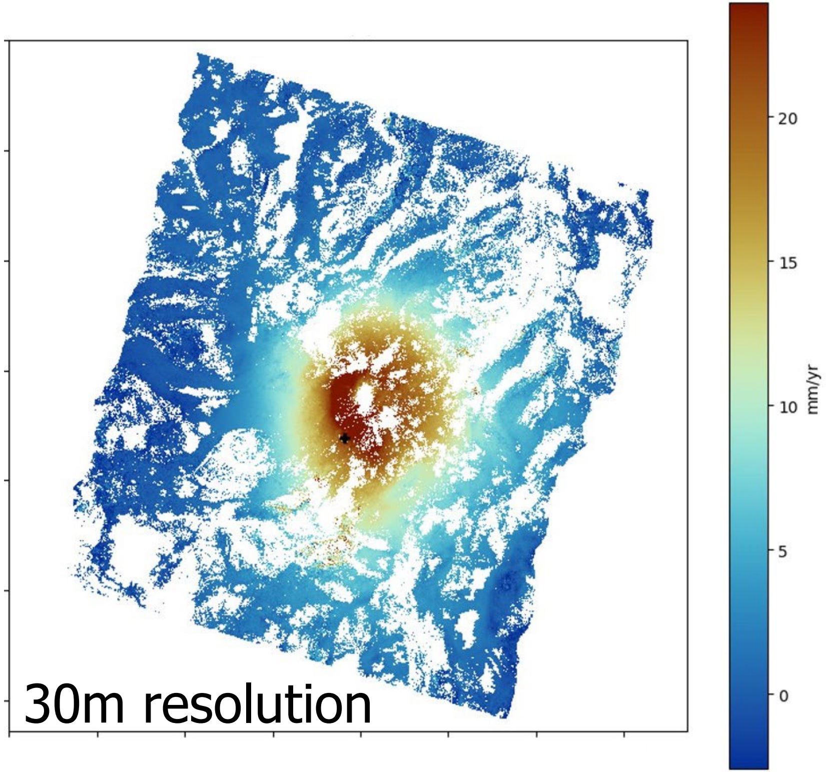


See Talk 4.03a, 15.20, Wright et al.

Tibet east-west velocities

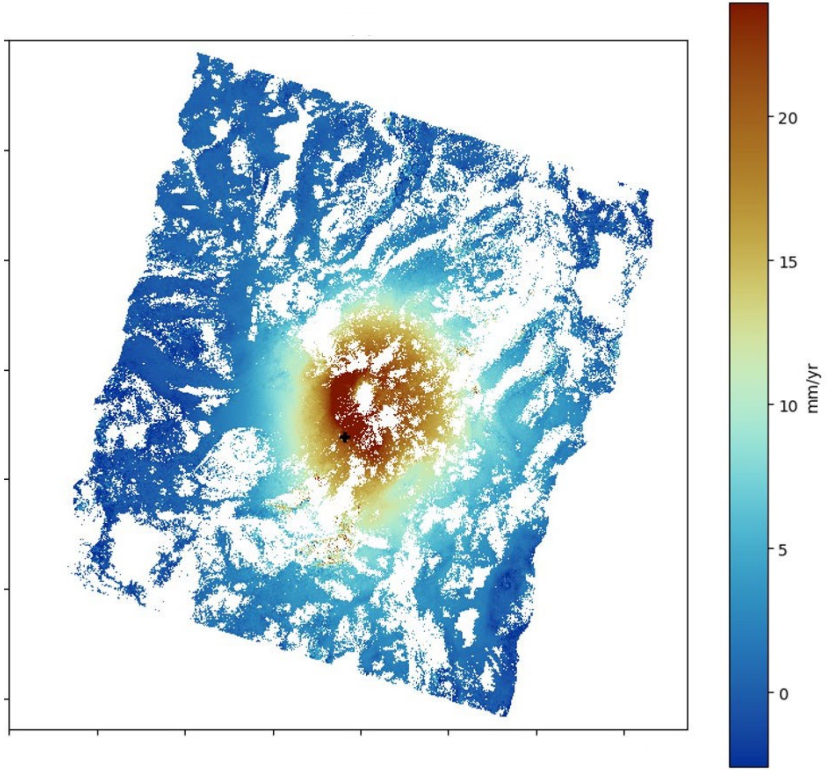
We have a modified higher-res processing for volcanoes

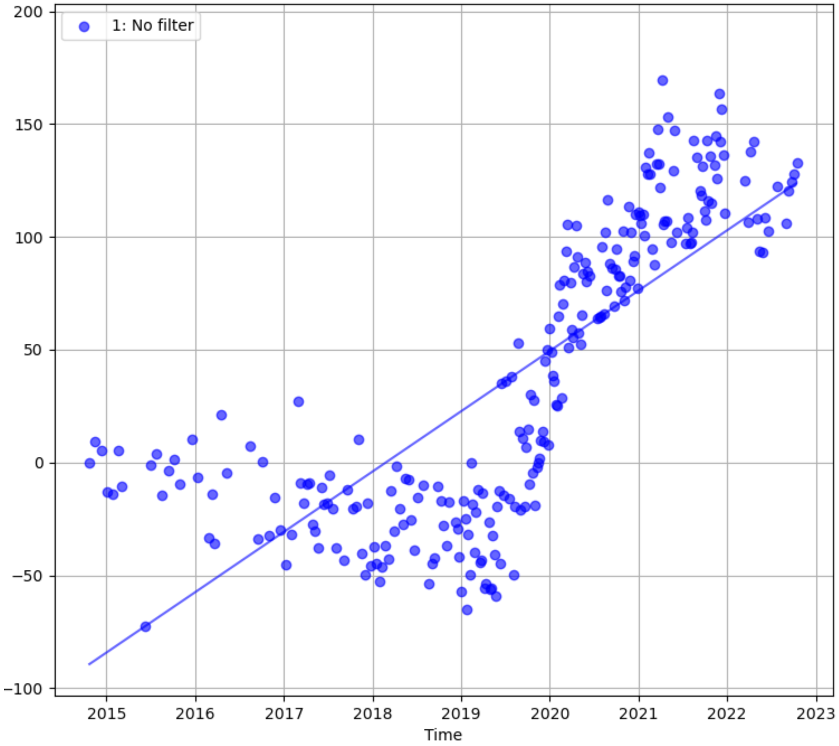




Nevados de Chillán Volcano

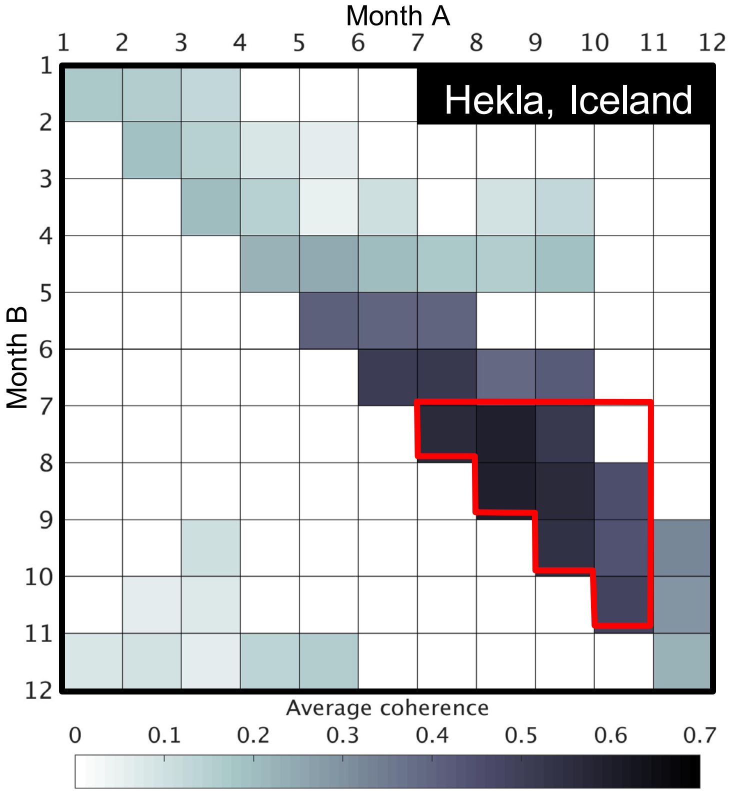
Time evolution is typically not linear



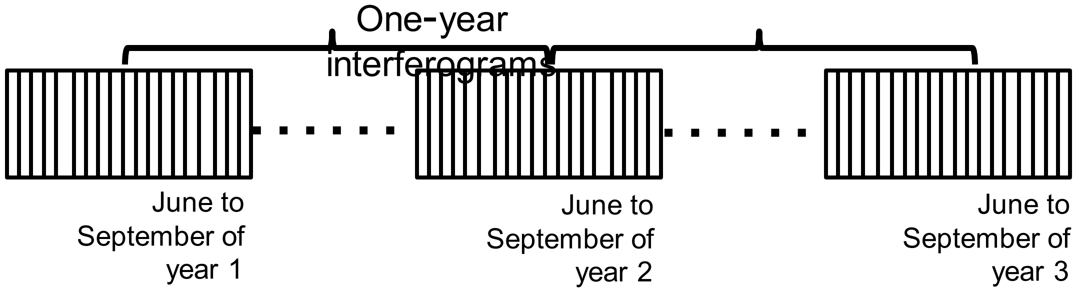


Nevados de Chillán Volcano

Use coherence analysis for each volcano to optimise interferogram network



- To deal with snow/high vegetation



- ❑ Short-temporal baseline interferograms
- ❑ One-year interferograms

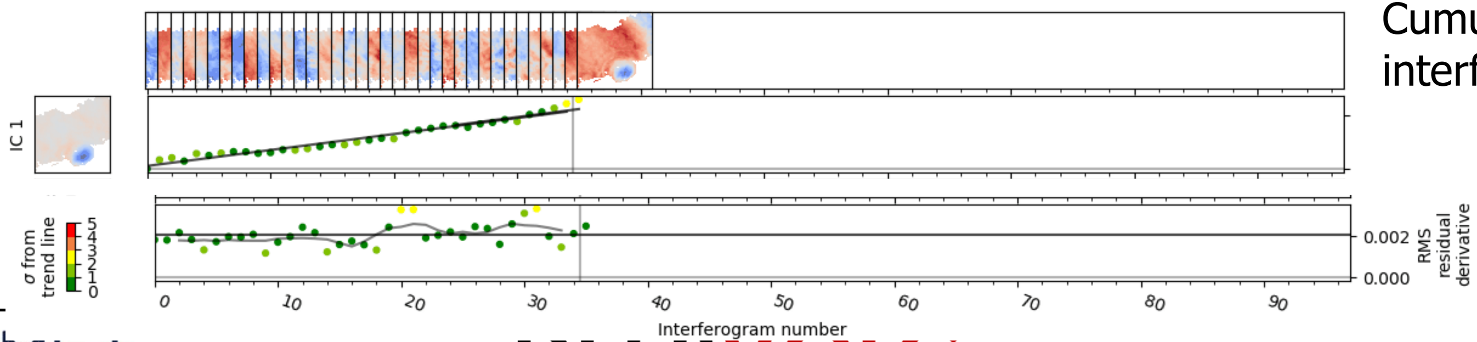
See Talk 1.04a 17:30, Shen et al.

Unsupervised ML can be applied to the InSAR time series directly

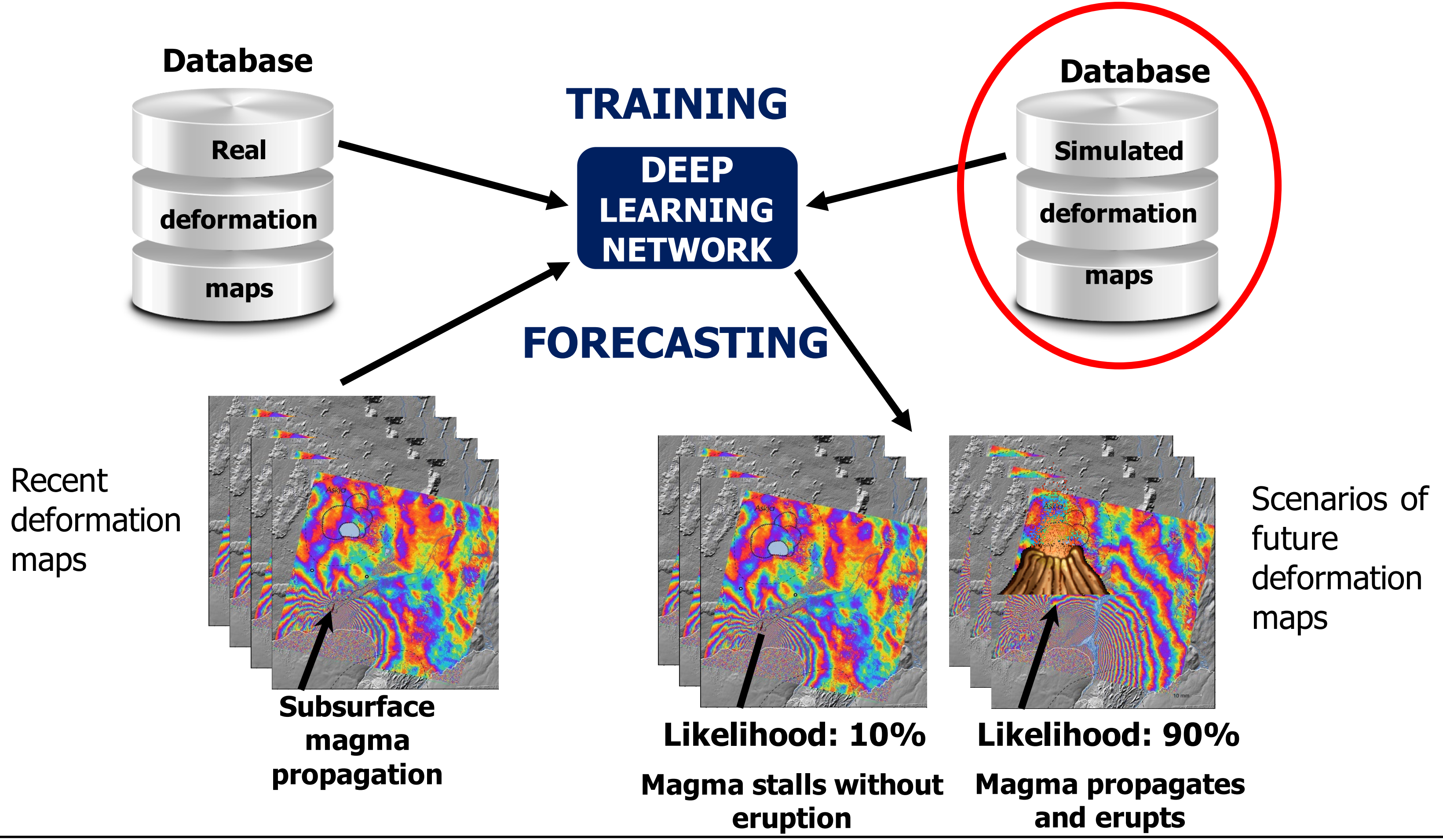
We developed algorithm based on independent component analysis to :

- Flag deformation that departs from background (rate or pattern)
- Detect changes with slow onset
- Work automatically

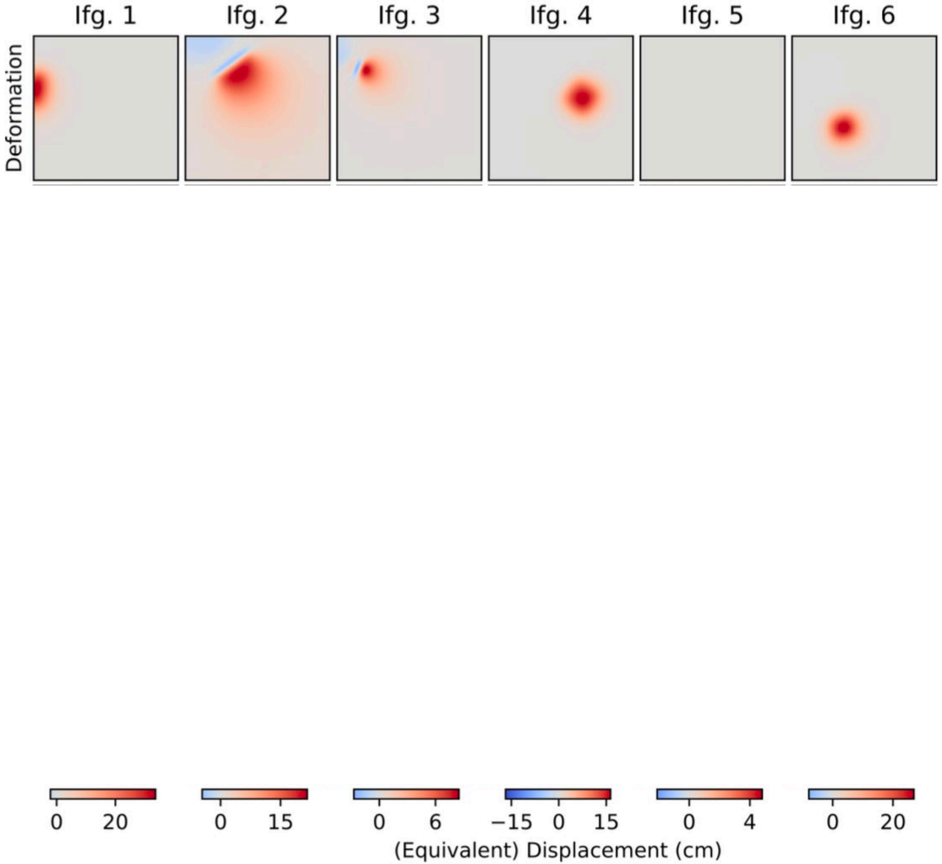
See Next Talk, Gaddes et al.



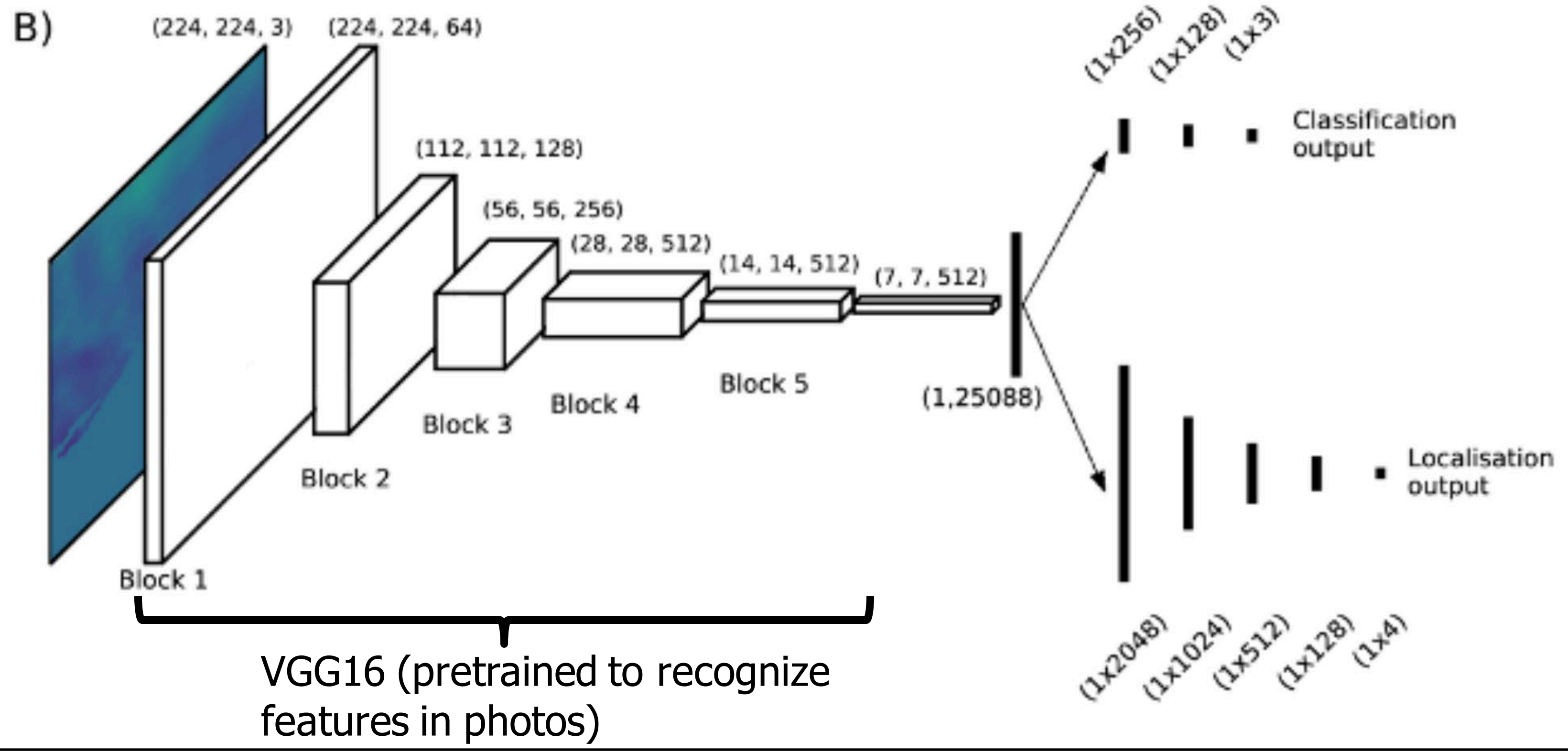
Cumulative interferograms


Database
Real
deformation
maps
TRAINING
DEEP
LEARNING
NETWORK
Database
Simulated
deformation
maps
FORECASTING
Recent
deformation
maps
Subsurface
magma
propagation
Likelihood: 10%
Magma stalls without
eruption
Likelihood: 90%
Magma propagates
and erupts
Scenarios of
future
deformation
maps

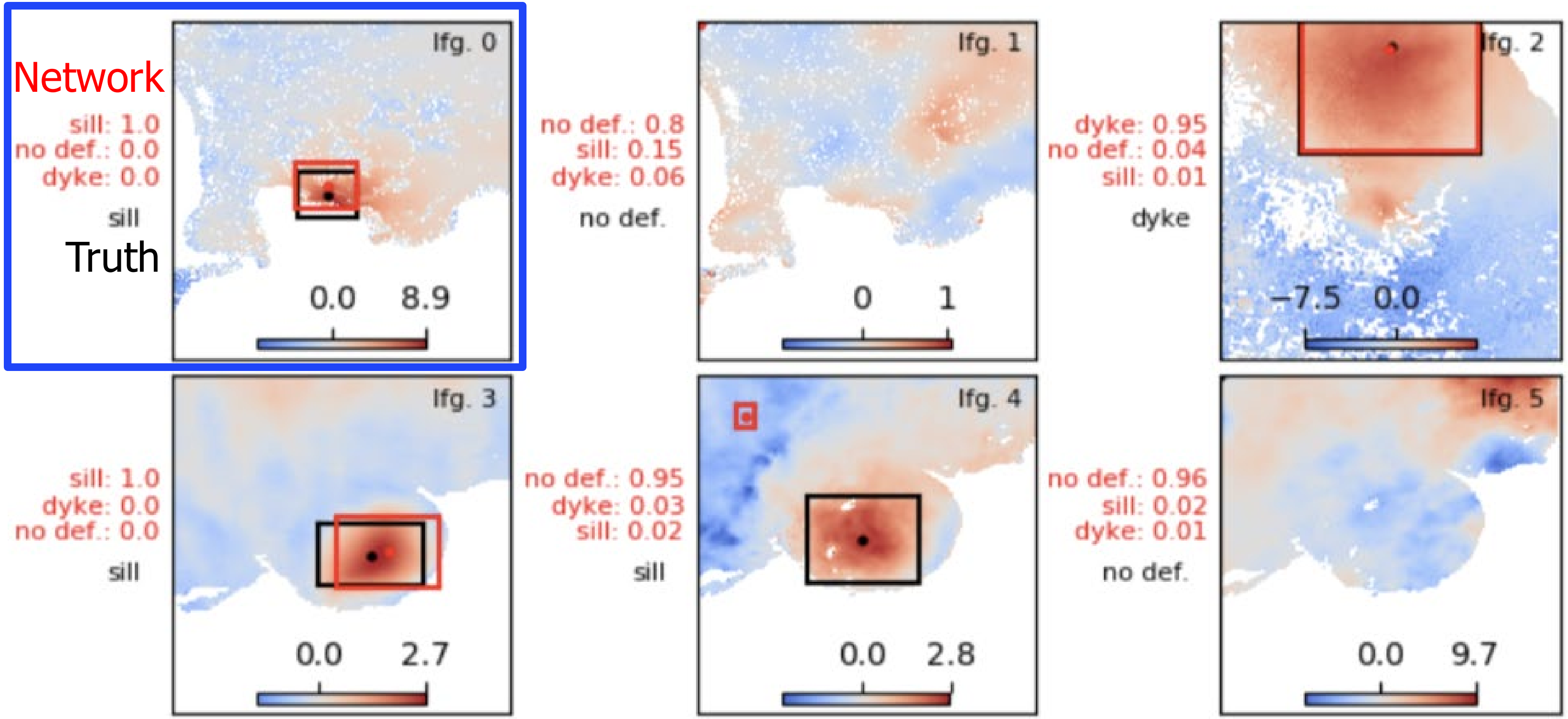
Our initial simulations used simple sources



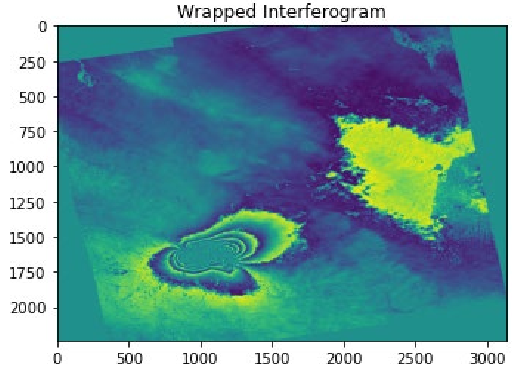
We use a two-headed CNN for simultaneous location and classification of deformation

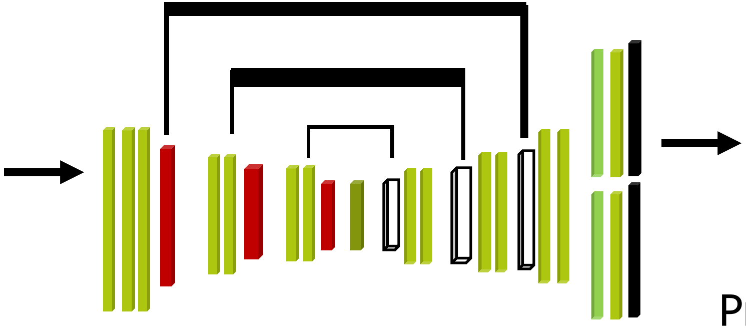


Our CNN trained on simulated data can classify and localize deformation in real images

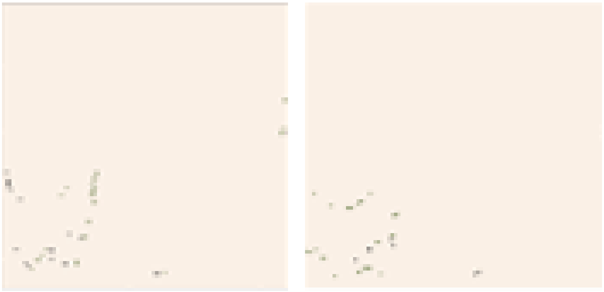


Phase unwrapping CNN also be trained on these "simple" synthetic data

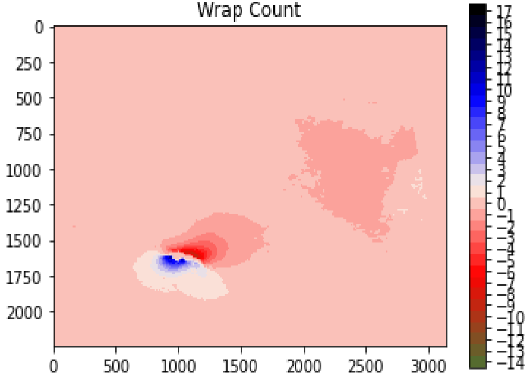




Integer ambiguity gradients



Probability-based integration



Conv 3x3, ReLU, Batch Normalization

MaxPool

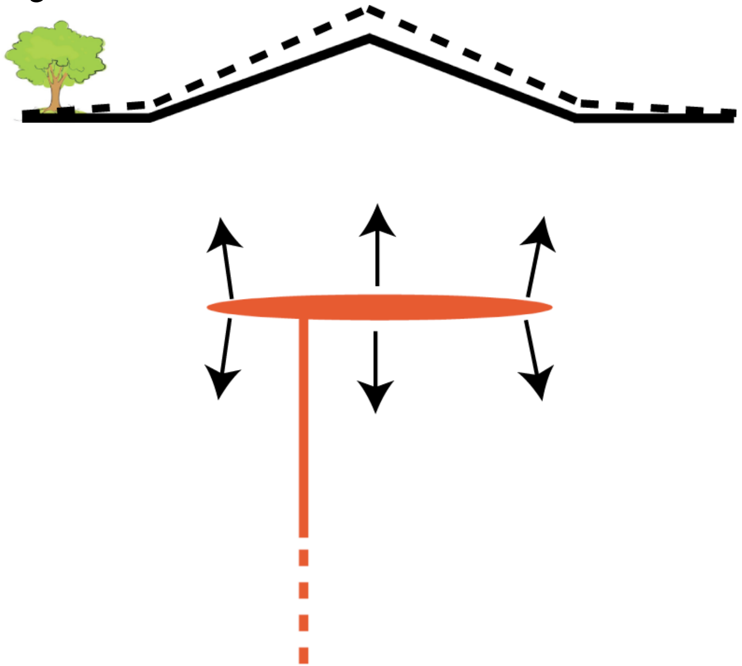
Dropout

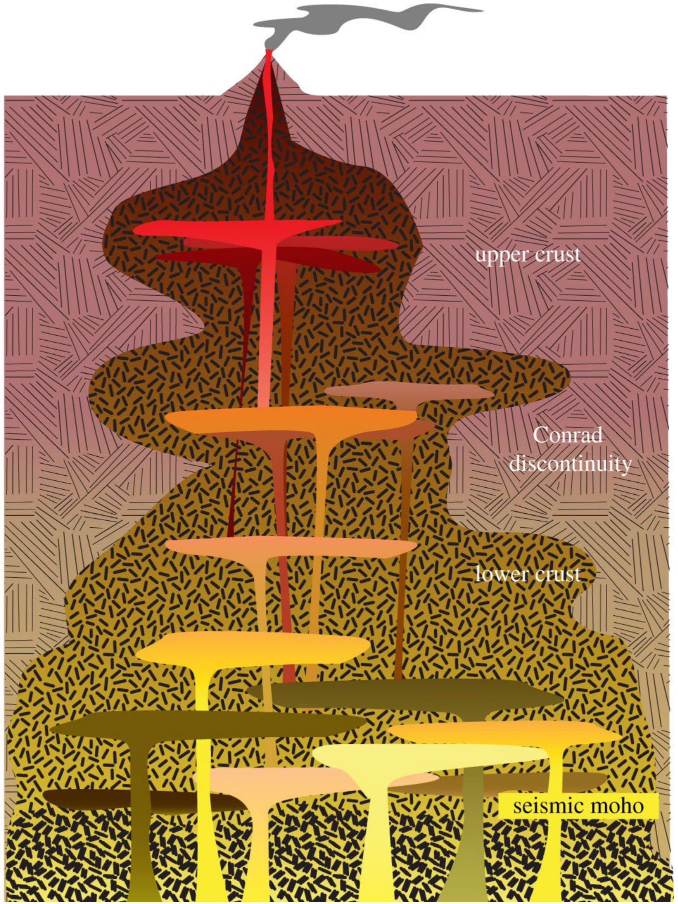
Conv 1 Output

Upsampling

See Poster 308, O'Grady et al.

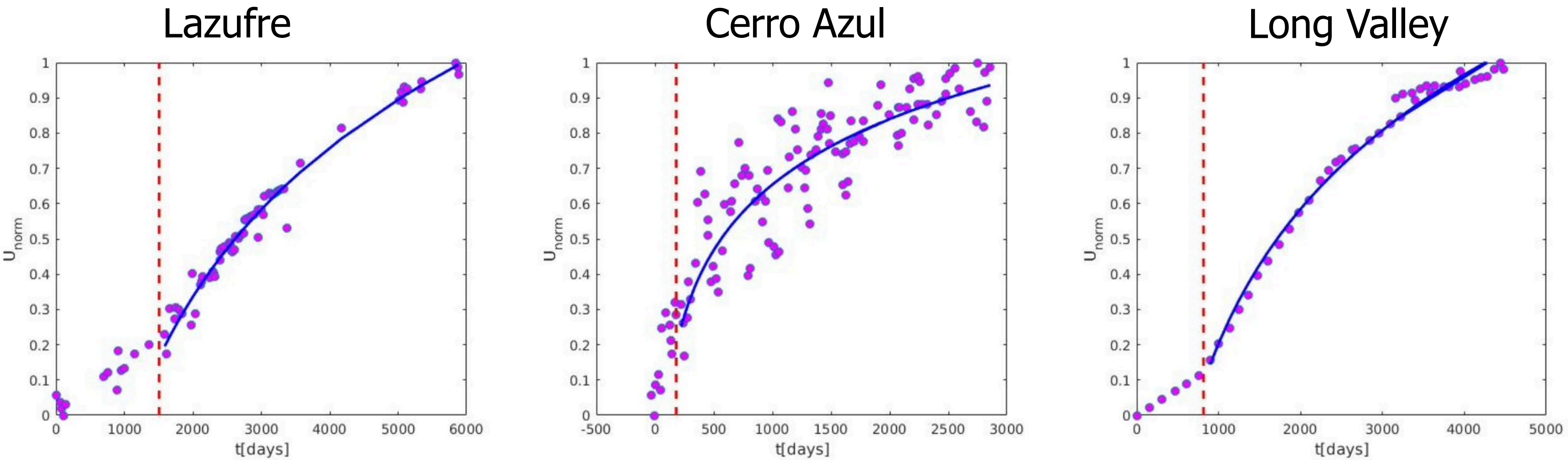
To simulate time series of deformation we need to consider complexity of real plumbing systems





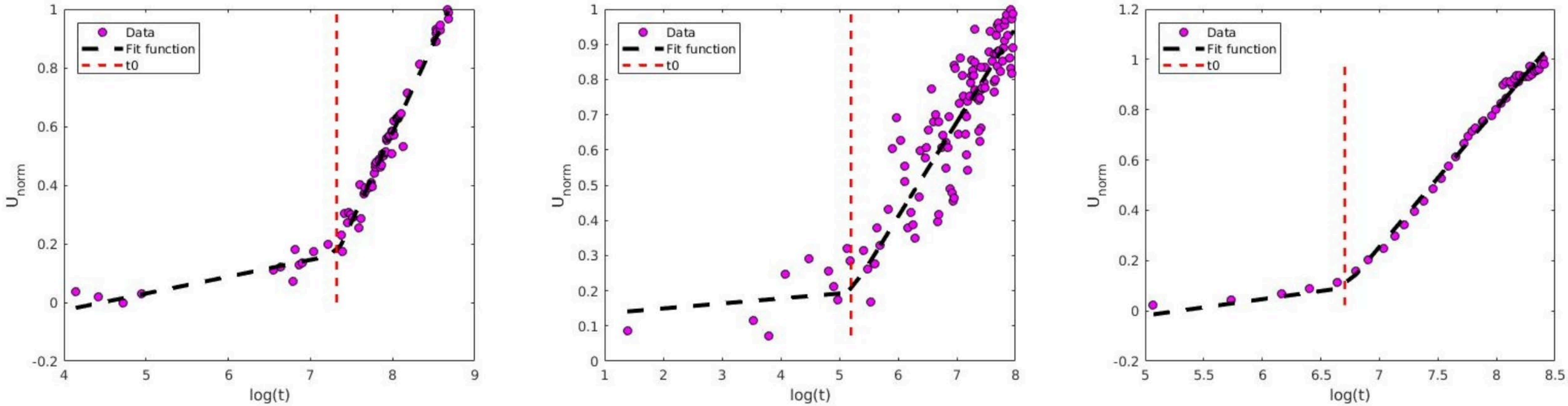
Cashman et al. (2017)

Analysis of temporal evolution of uplift episodes

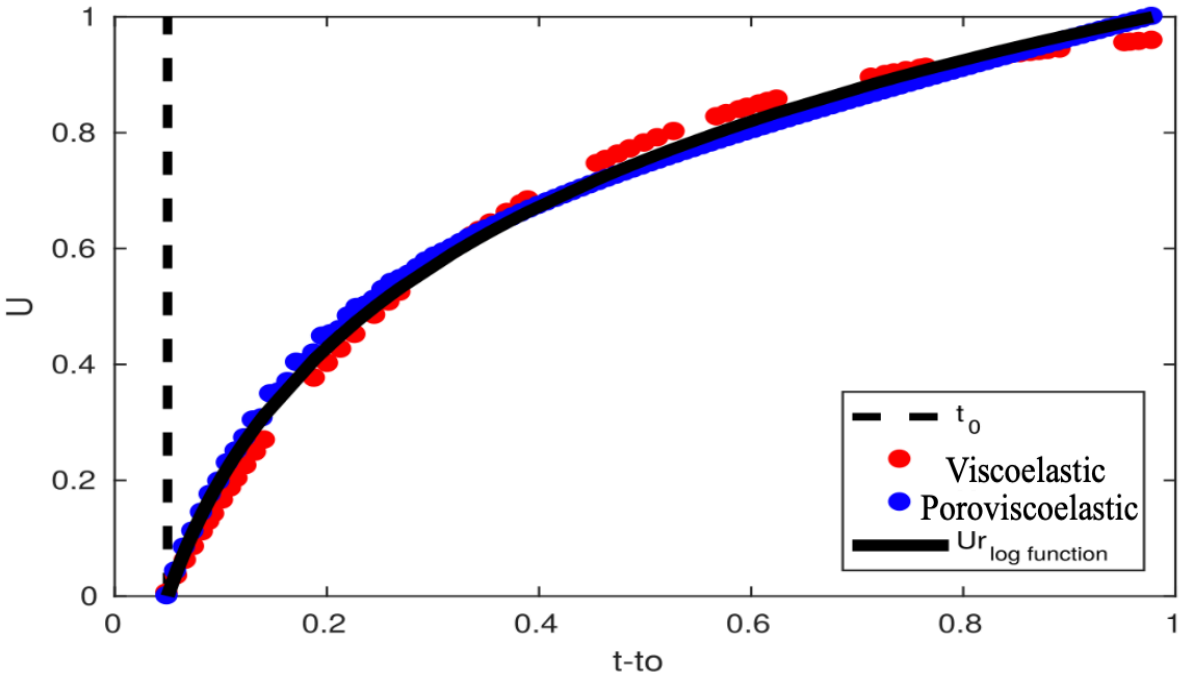


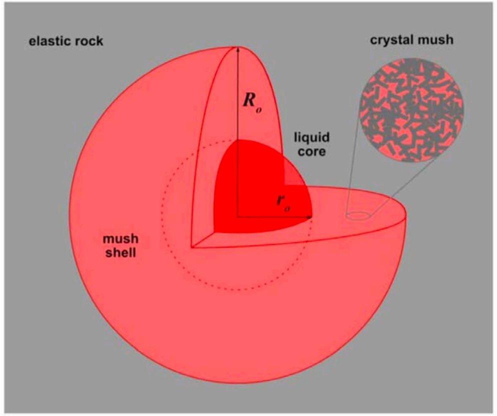
- 3 examples of many

All uplift episodes evolve logarithmically after a certain point in time



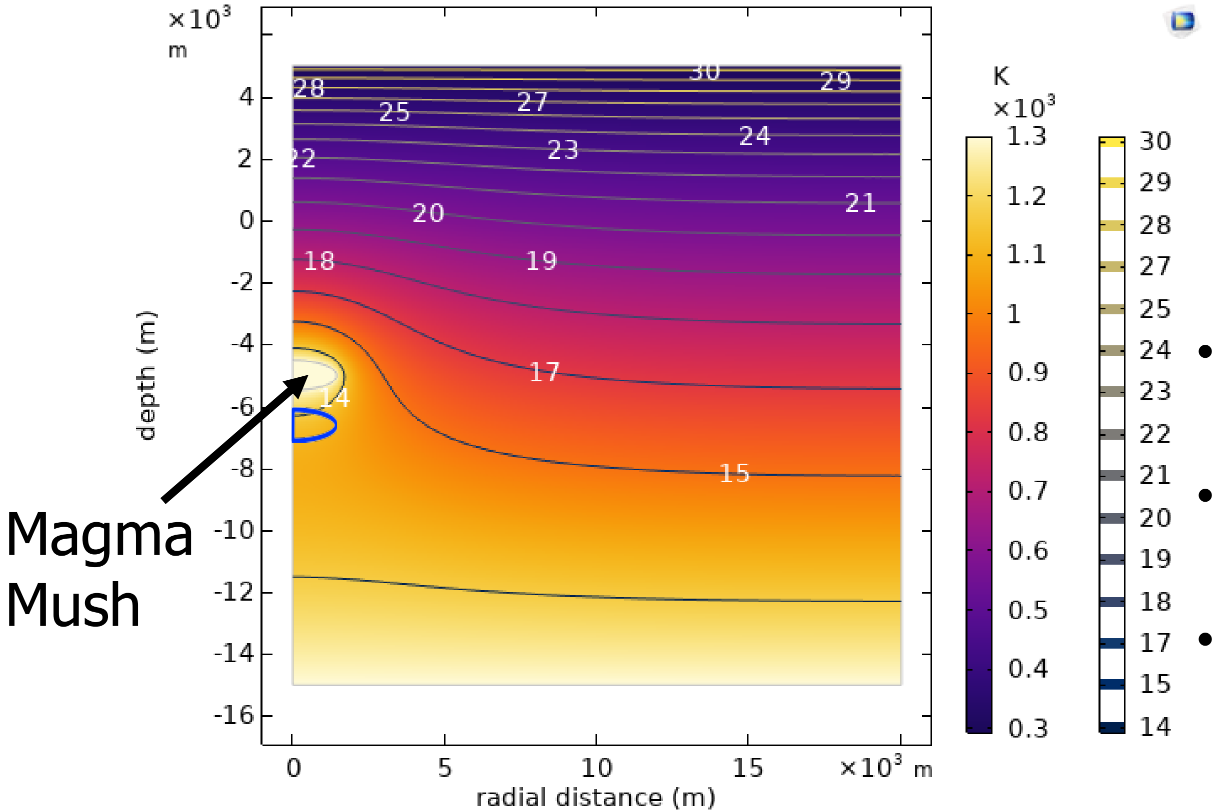
Can be explained with flow through and relaxation of poro-visco-elastic medium





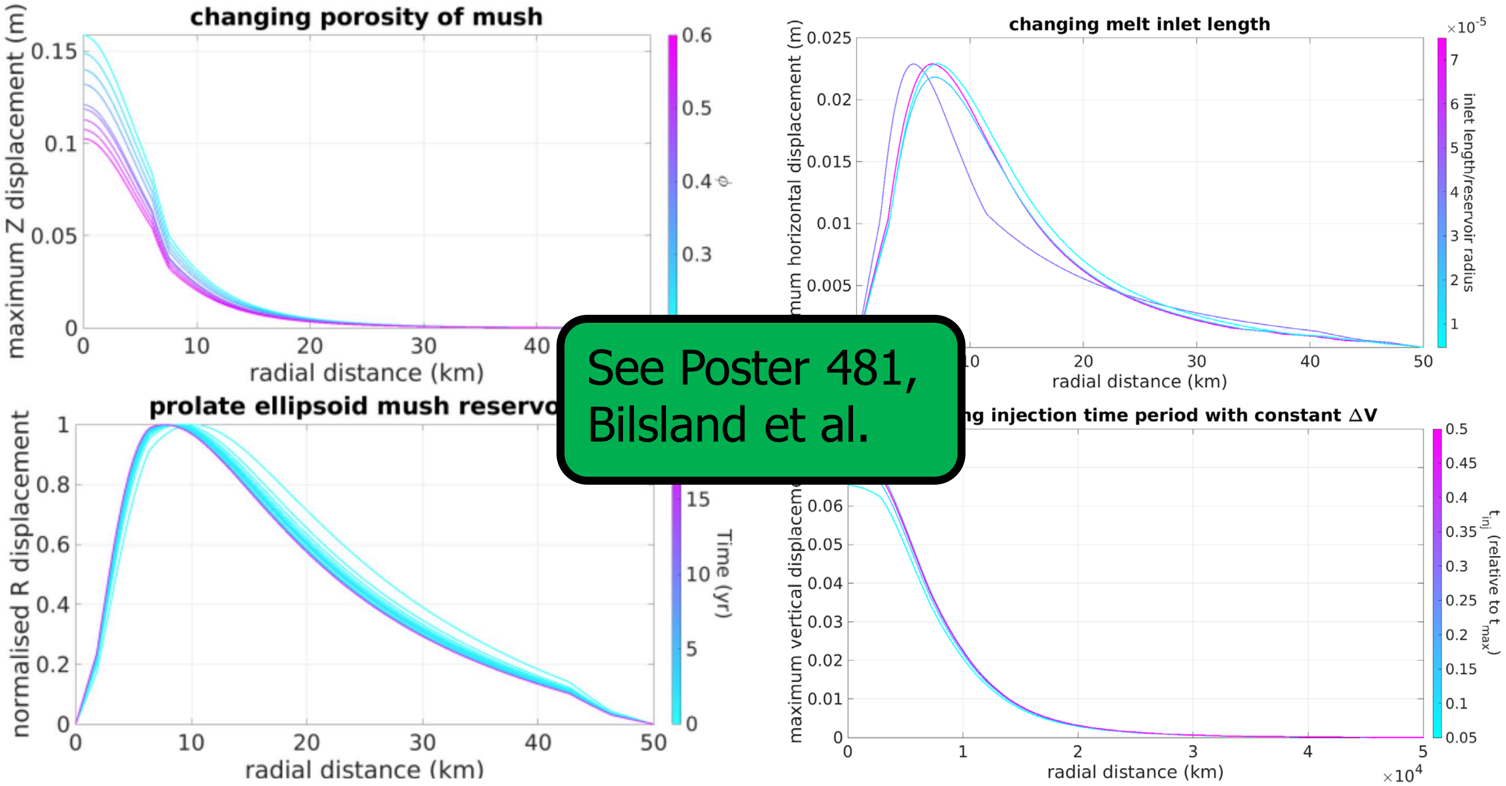
See Poster 474, Novoa et al.

More general poro-visco-elastic finite element models



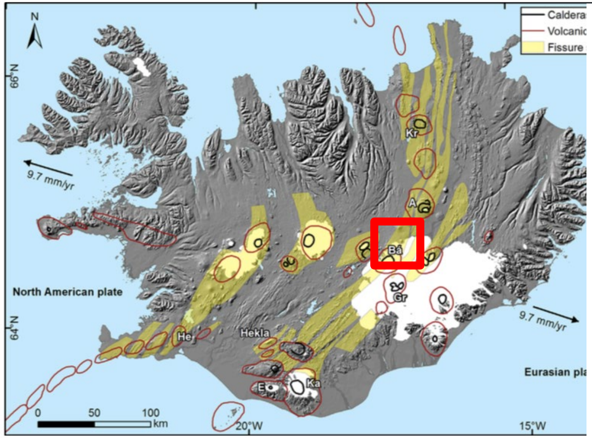
- Thermally-dependent viscosity structure
- Poro-elastic magma mush zone
- Injection of magma from below

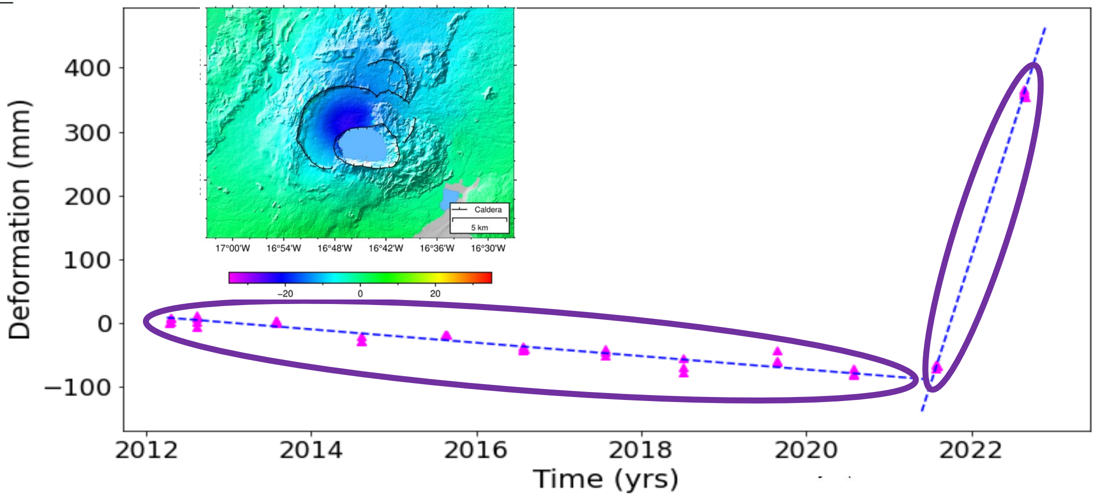
Vary model parameters within ranges constrained by petrology, geophysics, geochemistry, numerical models

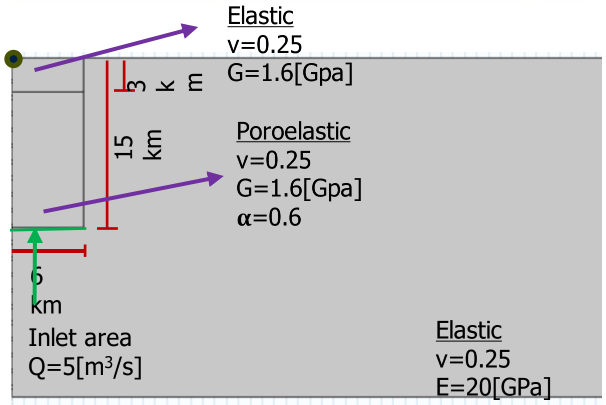


See Poster 481, Bilsland et al.

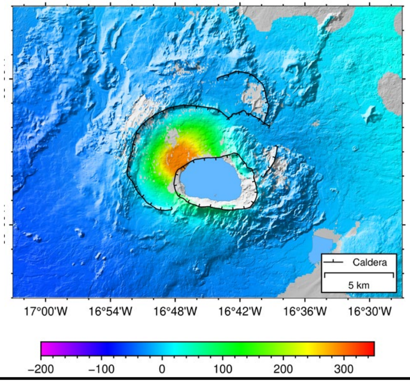
Modify models to explain indiviual volcanoes E.g., Askja



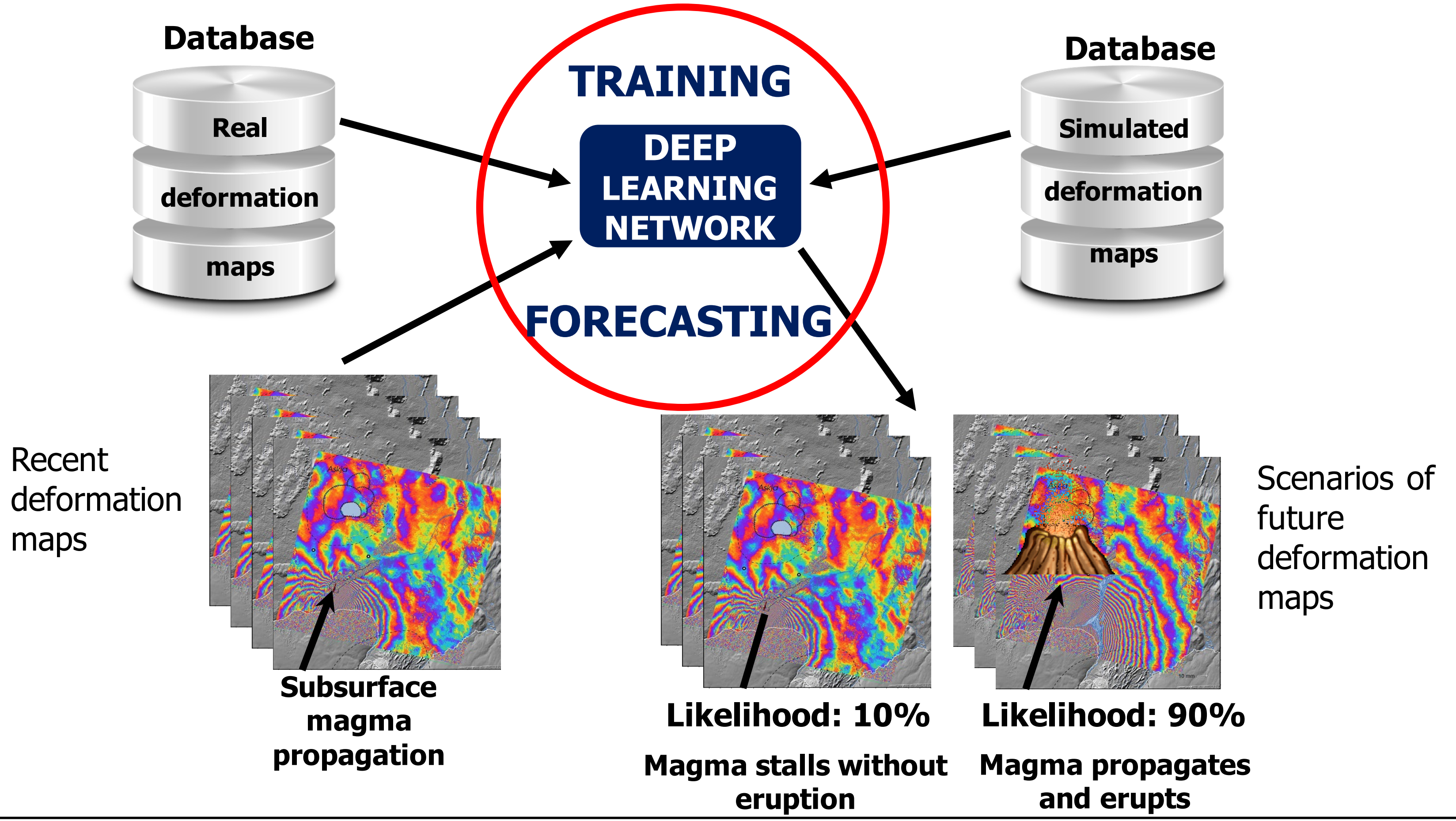




See Poster 464, Sepúlveda et al.



Velocity


Database
Real
deformation
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TRAINING
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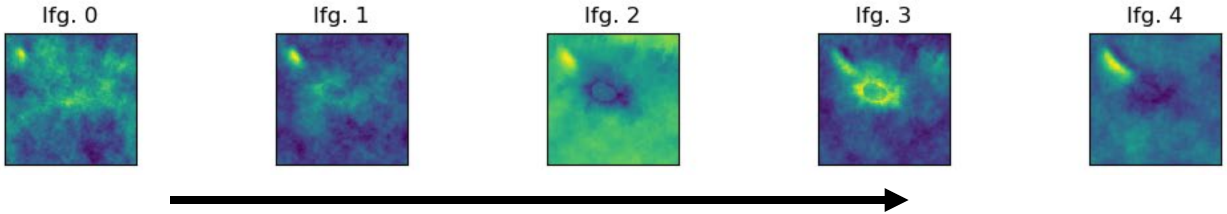
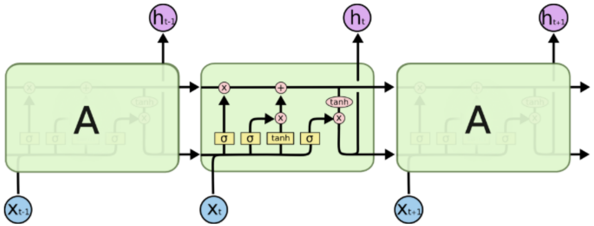
LEARNING
NETWORK
FORECASTING
Database
Simulated
deformation
maps
Recent
deformation
maps
Subsurface
magma
propagation
Likelihood: 10%
Magma stalls without
eruption
Likelihood: 90%
Magma propagates
and erupts
Scenarios of
future
deformation
maps

Training data: propagating dikes

We simulate multiple instances of 5 time steps of a propagating dike and add atmosphere and noise

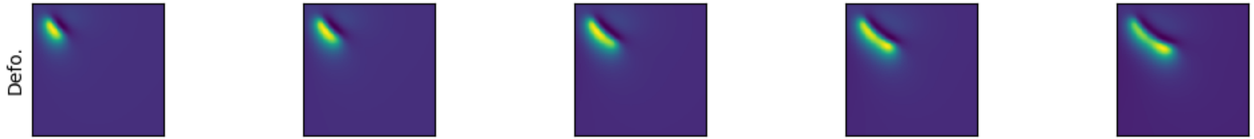


Time

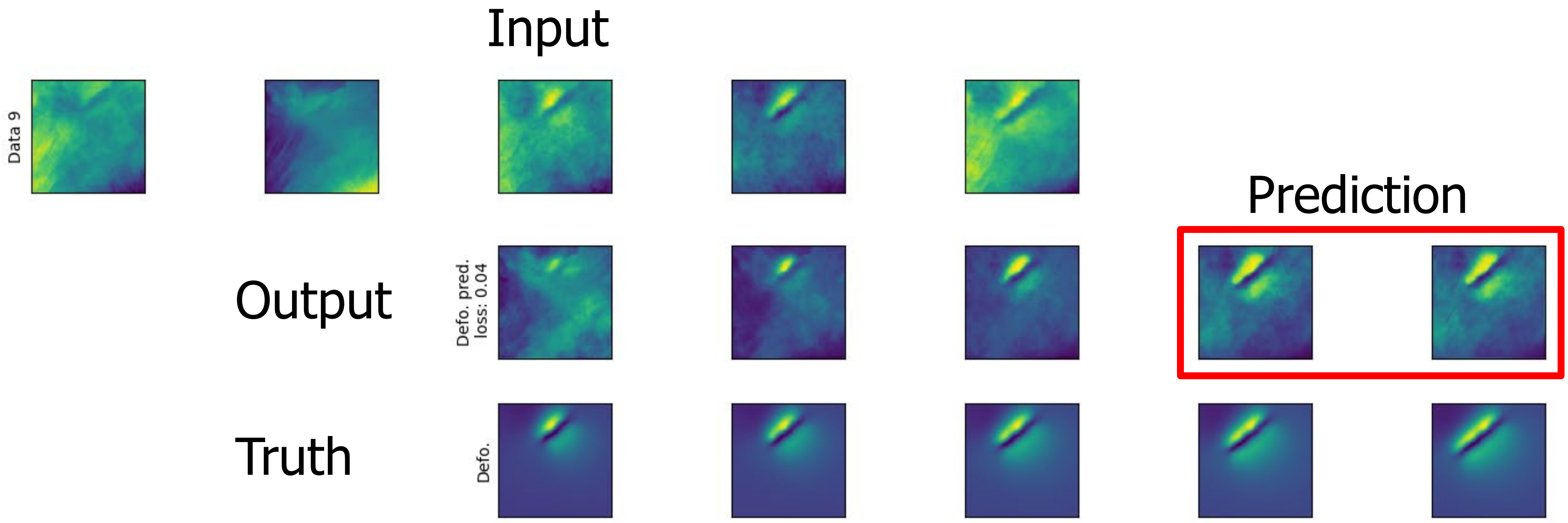


Long short-term memory (LSTM) network

We then train an LSTM network to extract deformation for steps 3 to 5 and predict deformation at steps 6 and 7



Preliminary results from neural network



- Reasonable preliminary results. Transformer approach likely to do better
- Will expand simulated data to include all deformation processes at volcanoes
- Will also explore the addition of physics to network (physics-informed deep learning)

Summary

- We use ICA-based machine learning to automatically detect new deformation and changes in rate at volcanoes
- Using deep learning we can locate and classify simple deformation sources and unwrap interferometric phase
- Realistic simulations are key to forecasting deformation, which we are currently working on. Porous flow through mush seems to be a ubiquitous process.
- Preliminary results for forecasting dike propagation show promise