Towards Systematic Classification of Volcano Deformation Signals

Ben Ireland[1], Juliet Biggs[1], and Nantheera Anantrasirichai[2]
[1]School of Earth Sciences, University of Bristol
[2]Visual Information Laboratory, University of Bristol

1. Research aims and motivations

Global catalogues of volcano deformation signals are very useful for large-scale comparison and classification of deformation characteristics, which can be useful in monitoring contexts by helping to identify analogue volcanoes or systems. This exploratory research investigates methods for more systematic and objective analysis of deformation signals through using clustering approaches and overcoming limitations of current datasets using new techniques.

This research is motivated by:
1.) The parrallel growth of available InSAR data (particularly Sentinel 1) and systematic tools that could analyse and catalogue volcano deformation signals
2.) The potential of deformation signals for identifying analogue volcanic behaviours and their lack of inclusion in previous analogue volcano studies [1]

2. Clustering of existing deformation catalogues:

i. Aims

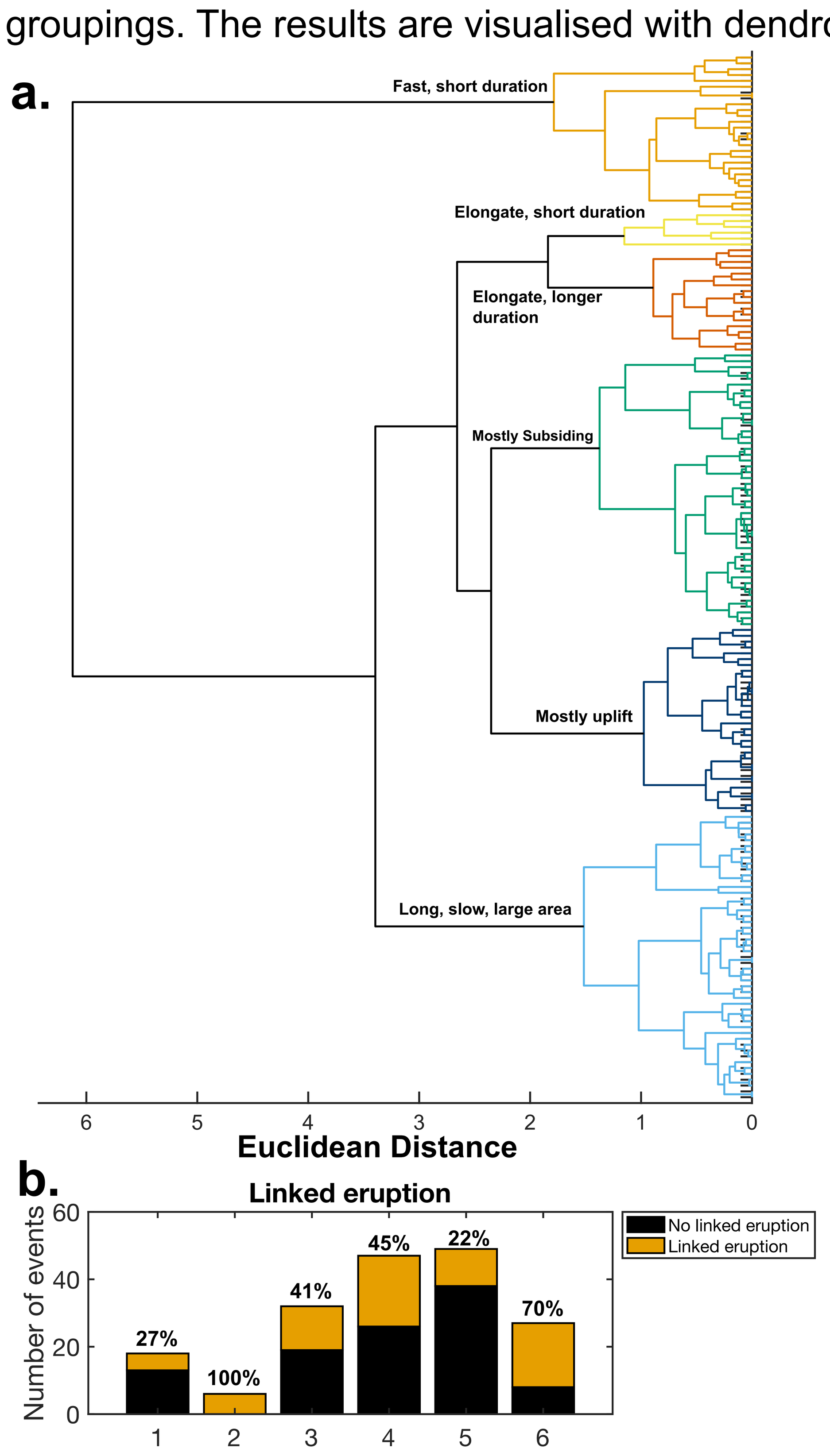
Volcano deformation signals show a wide range of spatial and temporal patterns, influenced by both local and regional processes [2]. We aim to classify deformation signals based on these patterns using clustering methods to:

- **Assess the ability of clustering algorithms to classify volcano deformation signals**
- **Understand the relative importance of different parameters for producing distinct clusters**
- **Interpret clusters in the context of known volcanological phenomena**

ii. Methods and initial results

We apply hierarcichal clustering to a new global dataset of parameters for 179 volcano deformation events merged from two previous metadata catalogues [2,3]. The clustering was based on 4 parameters: deformation rate, duration, signal area, and aspect ratio.

Before clustering, the data were logged and normalised. Numbers of clusters between 2 and 10 were tested, with 4-6 clusters showing the most distinct groupings. The results are visualised with dendrograms and tradeoff plots (Fig. 1).



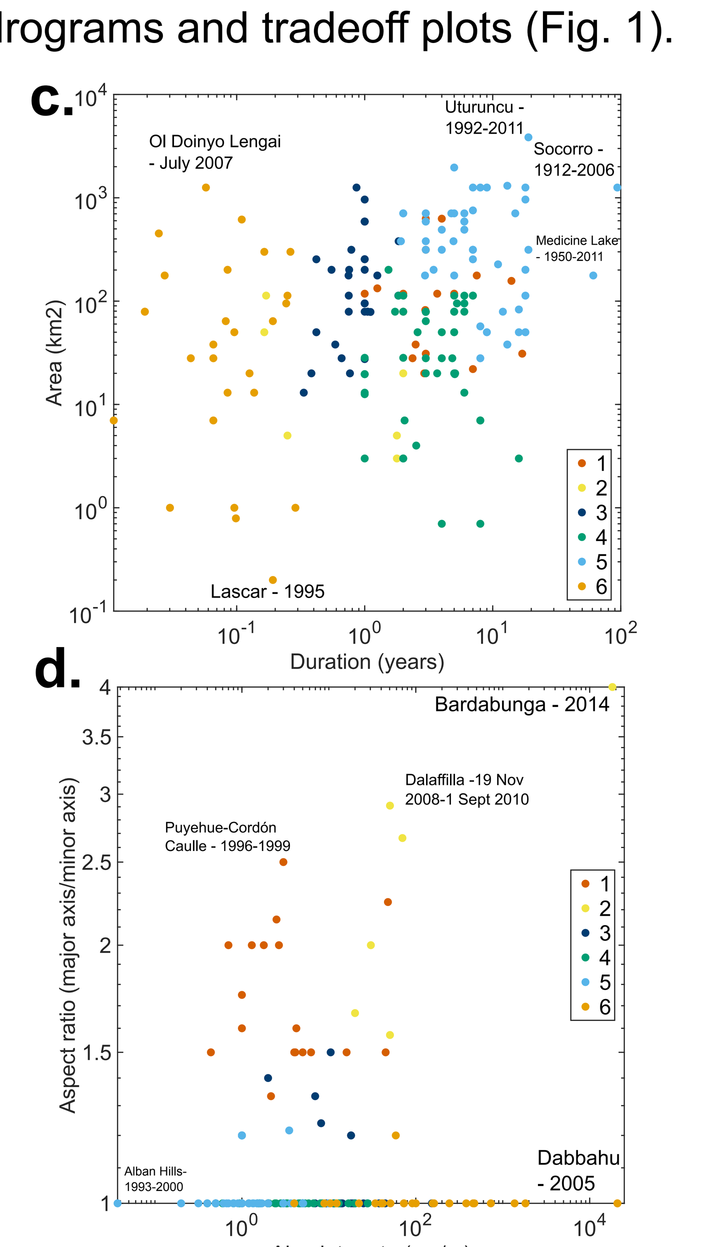
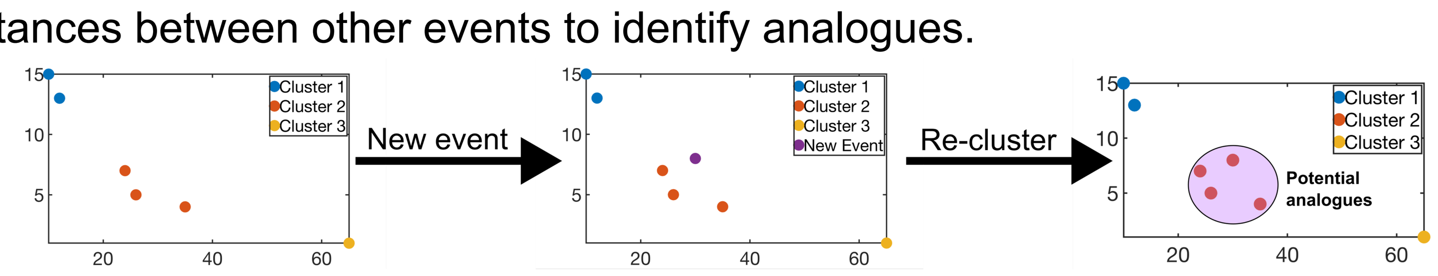


Fig.1. Clustering results a.) visualised as a dendrogram. The horizontal axis shows distance i.e dissimilarity, between different points and groups. b.) shows the proportion of events in each cluster that were linked with an eruption. c.) and d.) show how the results relate to some of the input parameters.

iii. Challenges and next steps

We will demonstrate the use of these clusters for analogue volcano identification, by adding new recent deformation signals and using their clusters and the distances between other events to identify analogues.



We also want to move beyond current catalogues, as they:
- Do not capture the richness of signals seen in interferograms
- Can struggle to be systematic and suffer from incompleteness
- Are not readily updatable

3. Systematic source parameter extraction:

i. Aims

To produce new, more systematic deformation catalogues from Sentinel 1 InSAR data, we need methods to extract information relating to the **deformation source**, the **surface expression**, and the **temporal evolution** (Fig. 2).

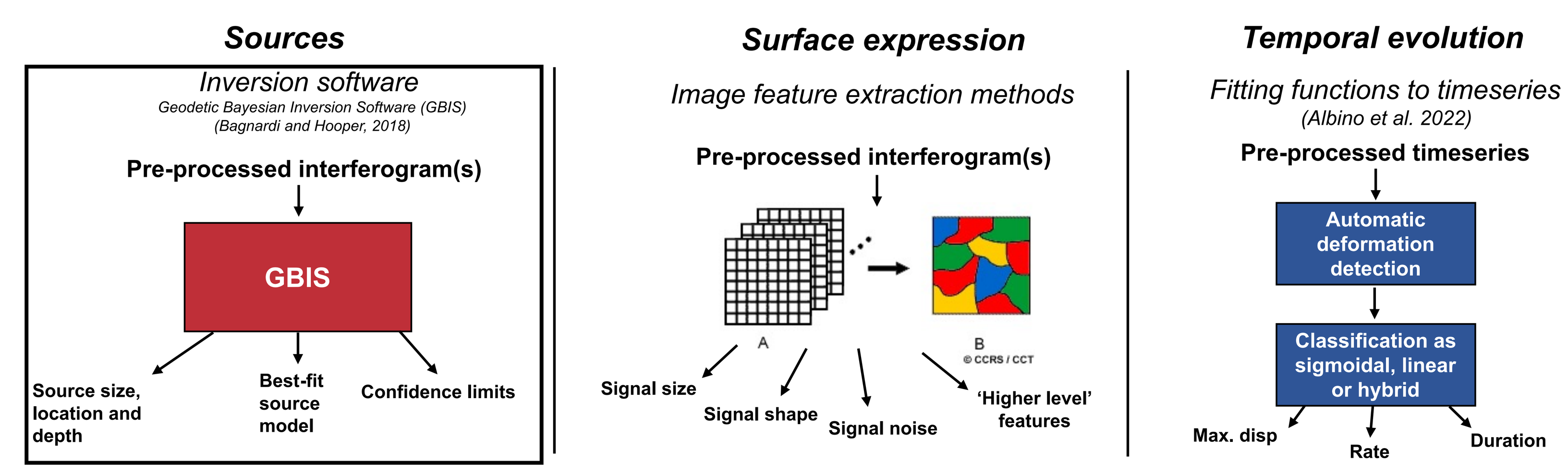
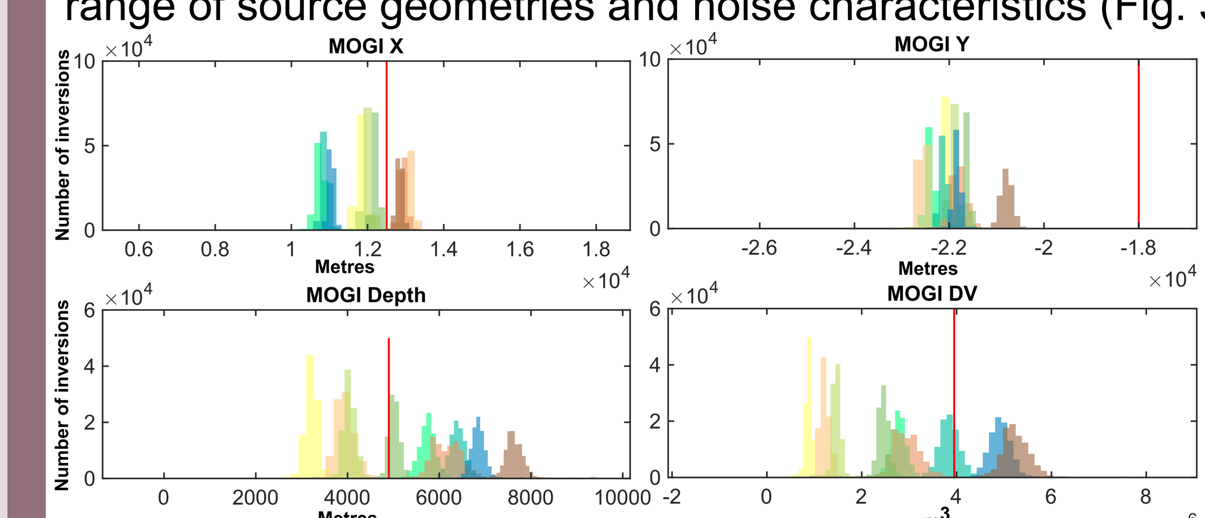


Fig.2. Potential approaches for systematically extracting comparable deformation parameters

Firstly, we are aiming to develop a method to systematically extract deformation source parameters from interferograms using GBIS [4]. Our method should produce reasonable, comparable outputs in most cases, rather than absolute true values.

ii. Methods and initial results

GBIS is usually optimised on a case-by-case basis. To adapt it for systematic use, we removed the noise-sensitive quadtree threshold parameter, and are using synthetic tests to find a range of input parameters (downsampling method/level, model input bounds etc...) that produce good estimates for source parameters for a range of source geometries and noise characteristics (Fig. 3).



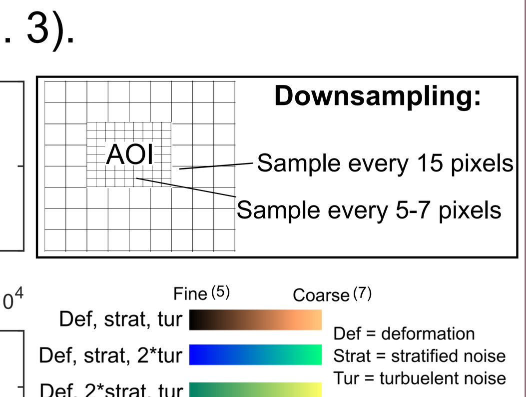


Fig.3. Inversion results for synthetic Mogi sources with different noise (colormap) and downsampling (shade) levels compared to the true result (red line).

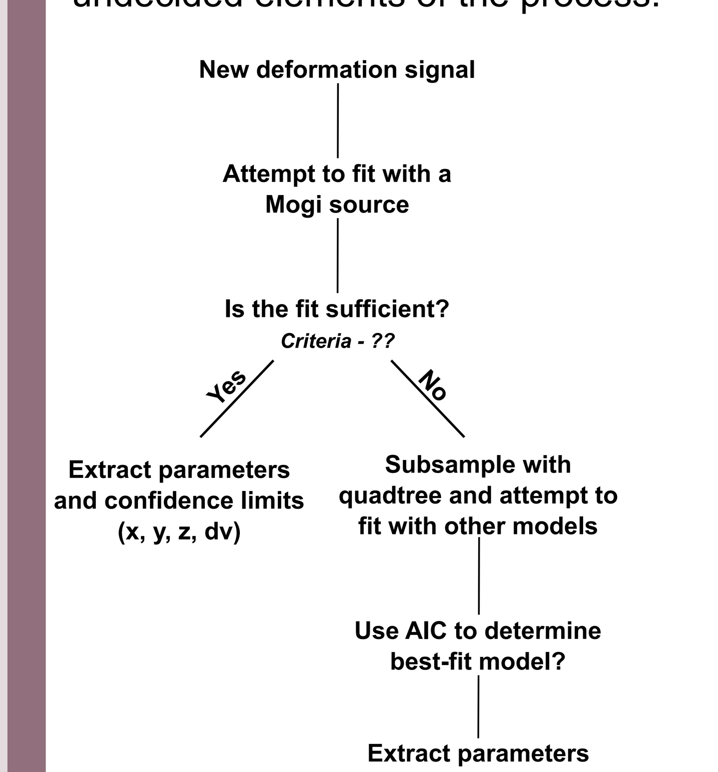


Fig.4. Flowchart for the source parameter extraction framework. "?" refer to currently undecided elements of the process.

Currently, we are getting better results for Mogi sources (Fig. 3) although we are having difficulties with more complex geometries e.g. Okada Dykes, especially without using Quadtree downsampling.

Our most-likely approach (Fig. 4) will attempt to fit all signals with a Mogi source, suitable for ~85% of signals, and will try alternative approaches if Mogi model fit is poor. We hope to test the method on the East African Rift dataset [5,6].

iii. Challenges and next steps

- Decide how to quantify sufficient Mogi fit
- More synthetic tests to determine the range of workable input parameters
- Apply the approach to interferograms from the East African Rift
- Explore methods of extracting other spatial and temporal parameters from interferograms (Fig. 2)

References:

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Find out more:

jl20461@bristol.ac.uk
@BensVolcanology