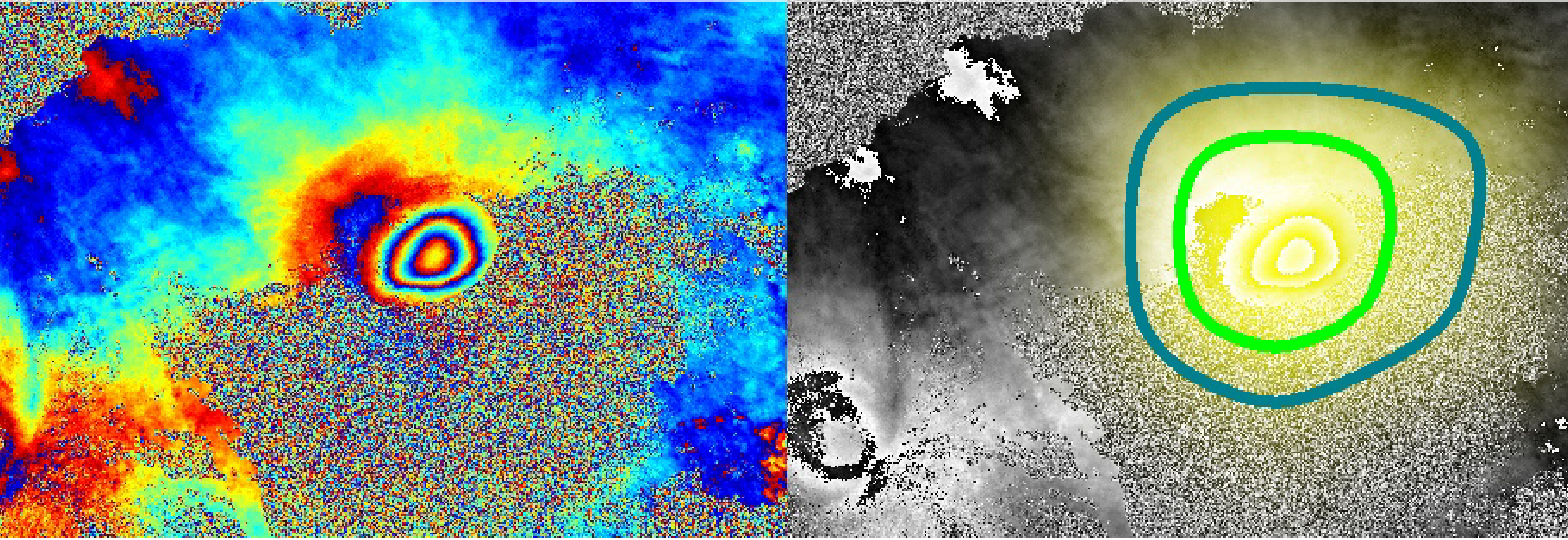
Towards global volcano deformation monitoring using satellite InSAR



uliet Biggs, Pui Anantrasirichai, Fabien Albino, Milan Lazecky, Yasser Maghsoudi

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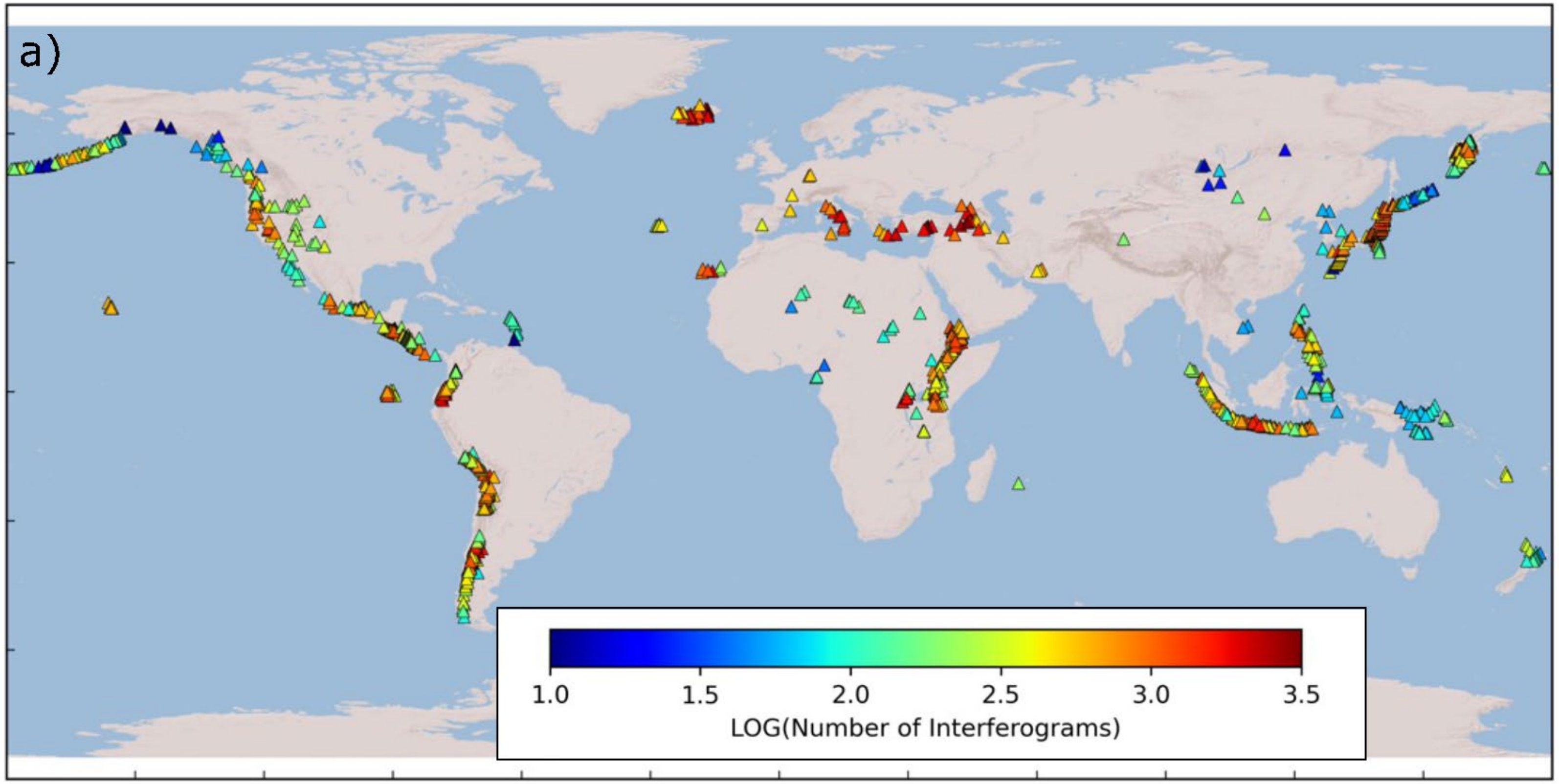
Volcano Deformation: Measurements

The LïCSAR volcano database of Sentinel-1 InSAR data

Dataset: 2,019,621 images of 1150 volcanoes



Biggs et al, Bull Volc, 2022

Opportunities

- Understanding Magmatic Systems
- Monitoring and Forecasting

Challenges:

- Interpretation
- Timely dissemination

Machine Learning Tools

Towards global volcano deformation monitoring using satellite InSAR

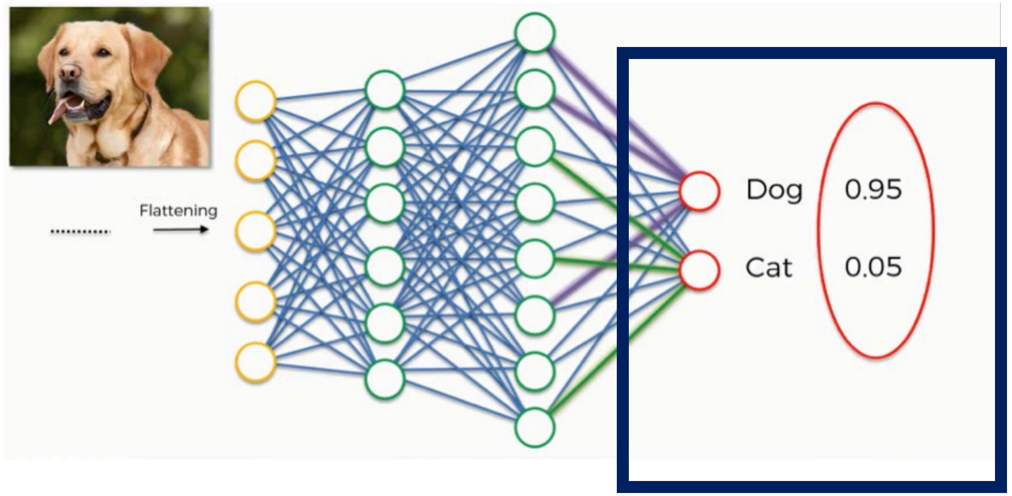
Part 1: CNN

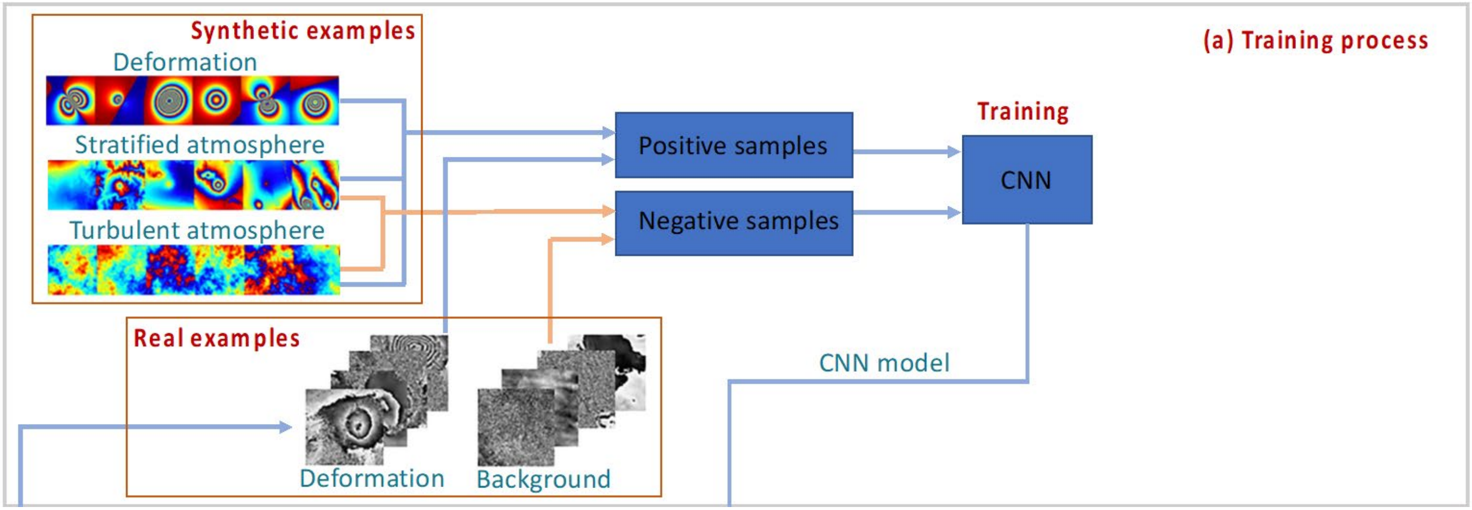
- Large Scale Demonstration of Anantrasirichai et al (2018,2019a,b)

Part 2: Development of New Methods

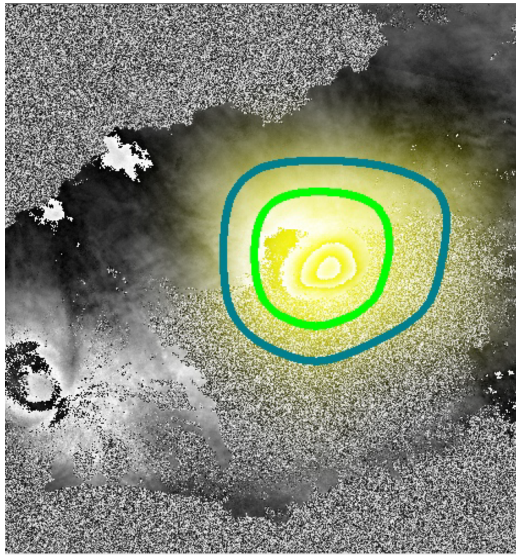
- New Architectures
- New Applications
- New Catalogues

Deep Learning Framework: CNN



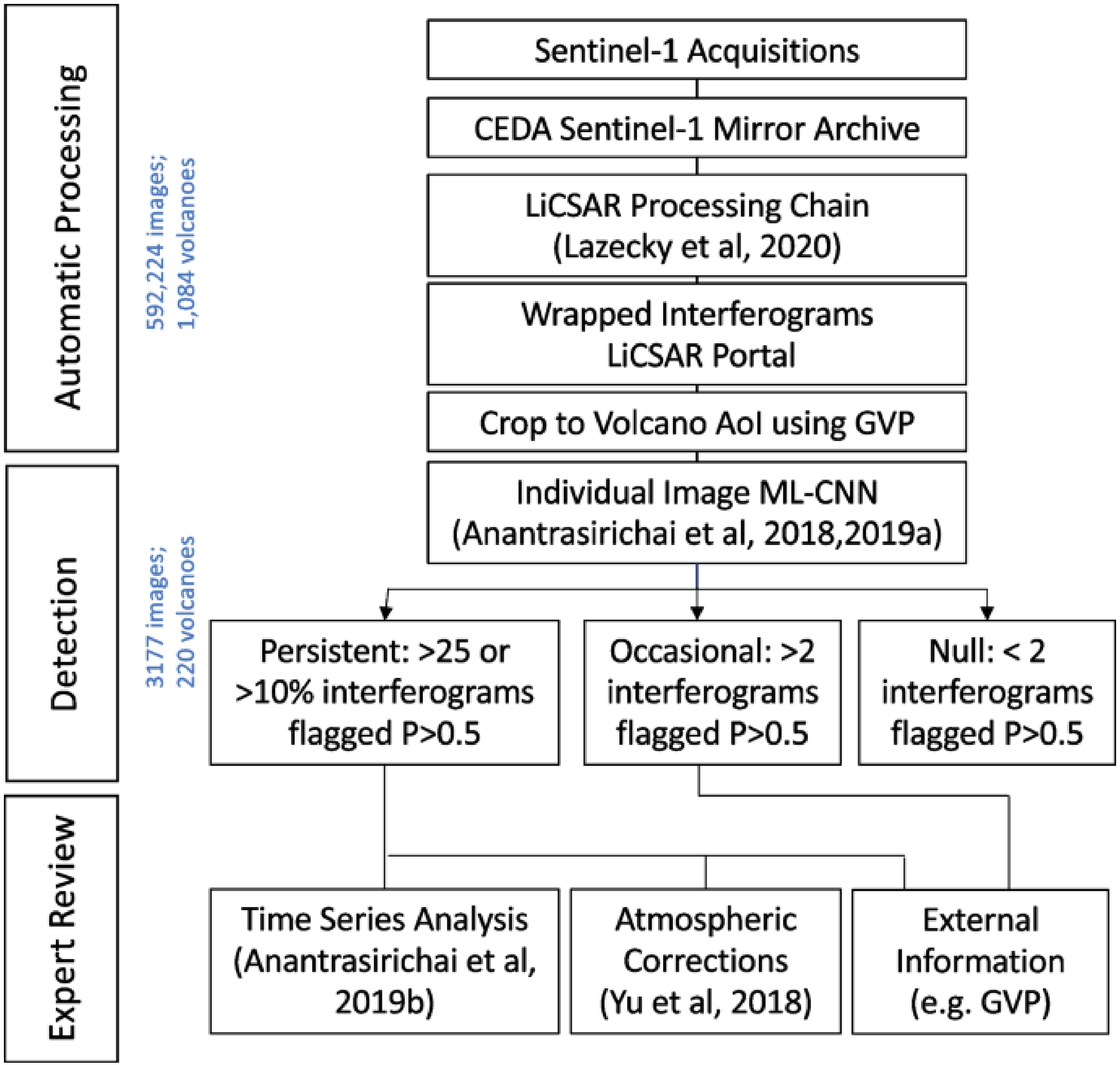


Transfer Learning



LicSAR test dataset: 30,249 interferograms.
Classification Accuracy: 0.981
Detection Threshold: 3-4 cm depending on conditions

Anantrasirichai et al, 2018, 2019a,b



Biggs et al, Bull Volc, 2022

Automatic Processing

592,224 images;
1,084 volcanoes

Sentinel-1 Acquisitions

CEDA Sentinel-1 Mirror Archive

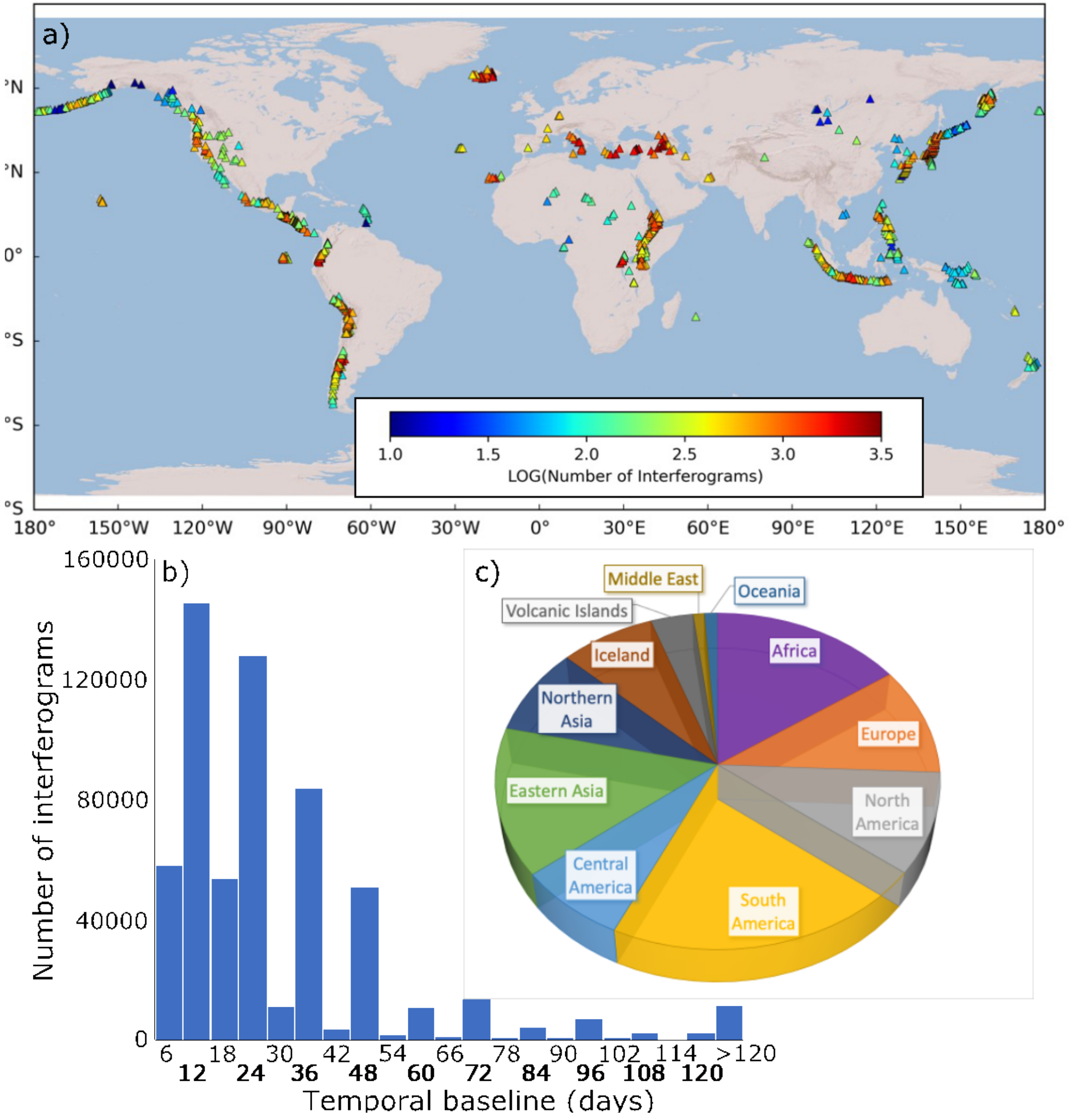
LiCSAR Processing Chain
(Lazecky et al, 2020)

Wrapped Interferograms
LiCSAR Portal

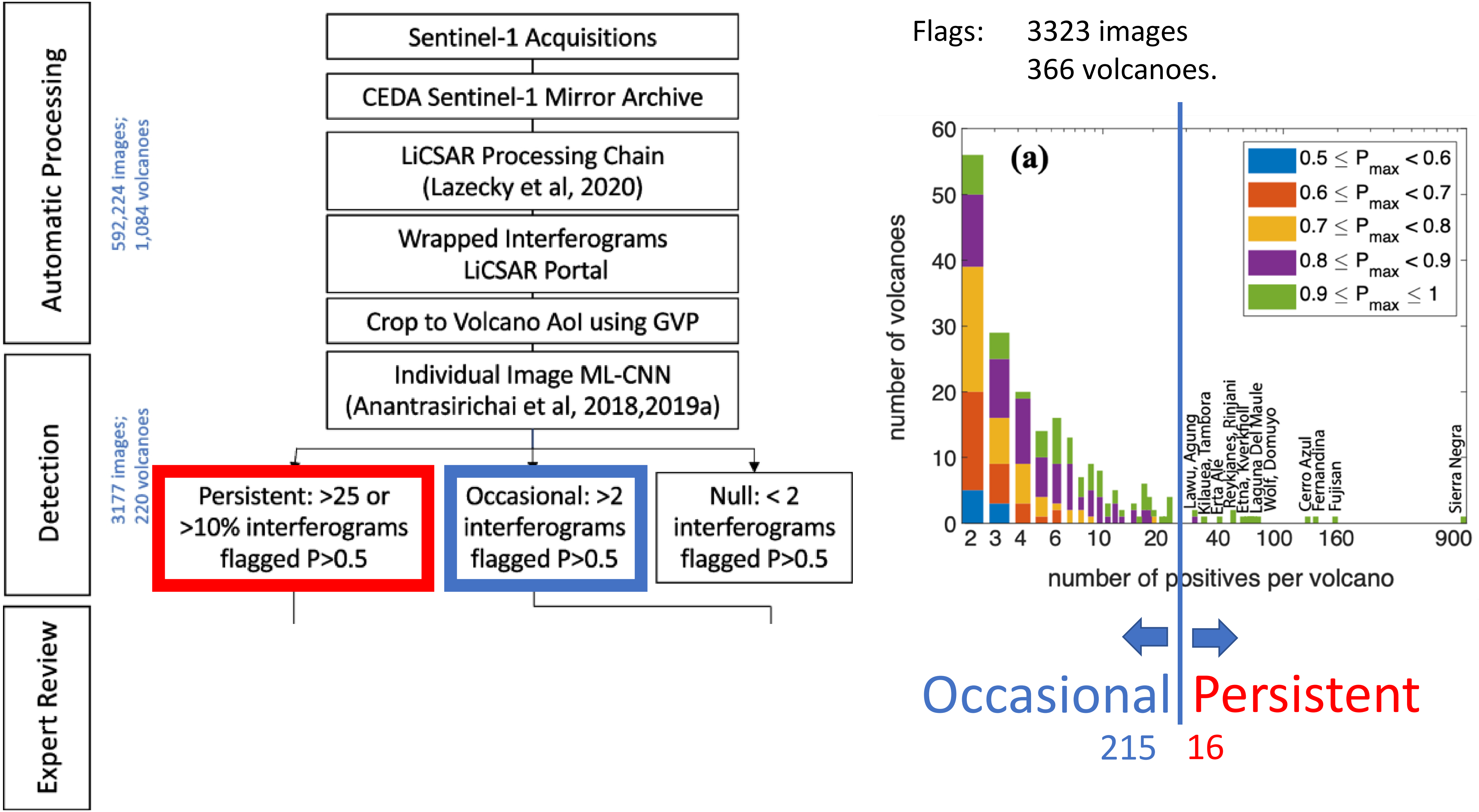
Crop to Volcano AoI using GVP

Detection

Expert Review



Global Dataset: 592,224 images
1084 volcanoes.
Nov 2015-Nov 2020



Automatic Processing
592,224 images;
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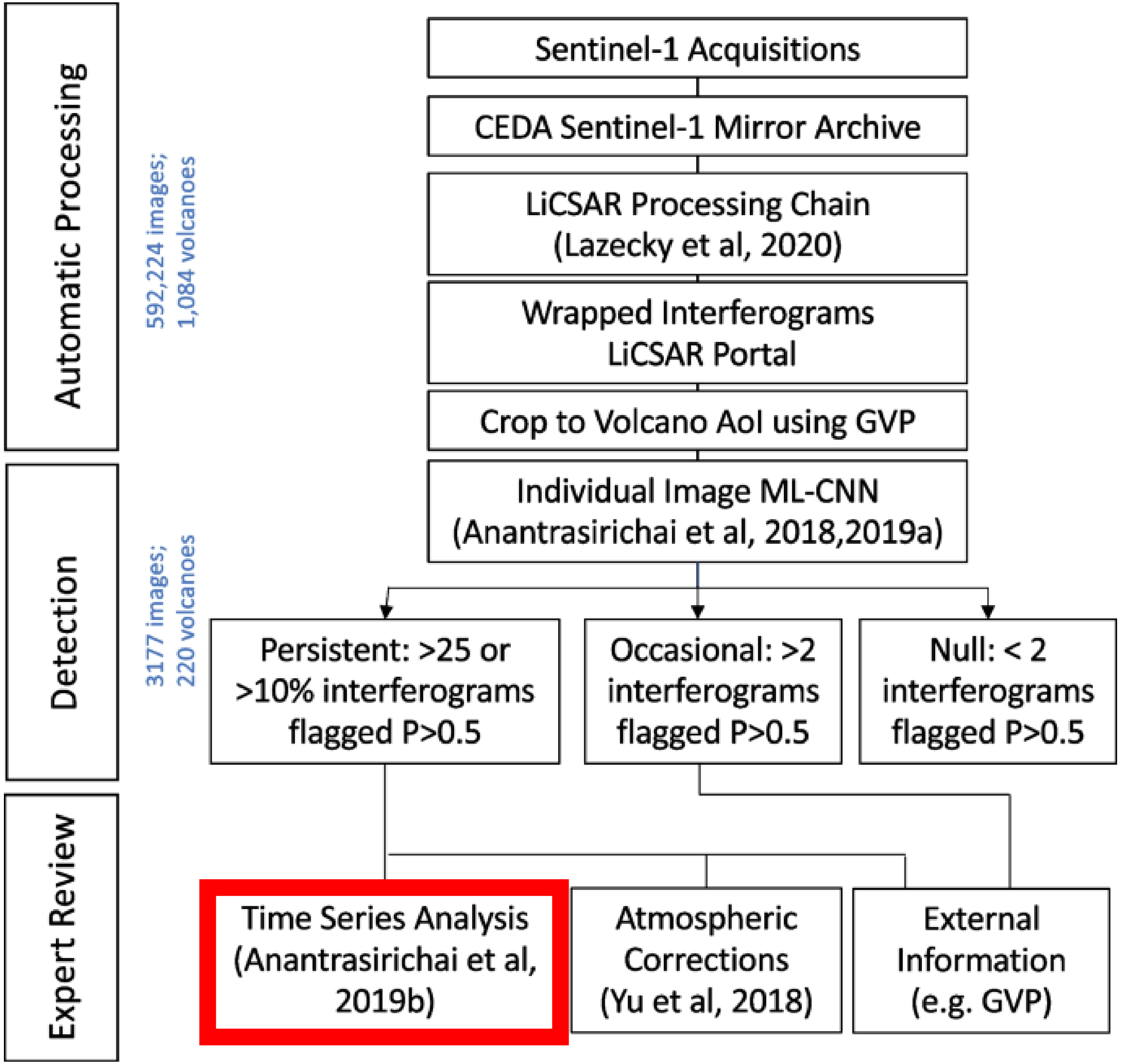
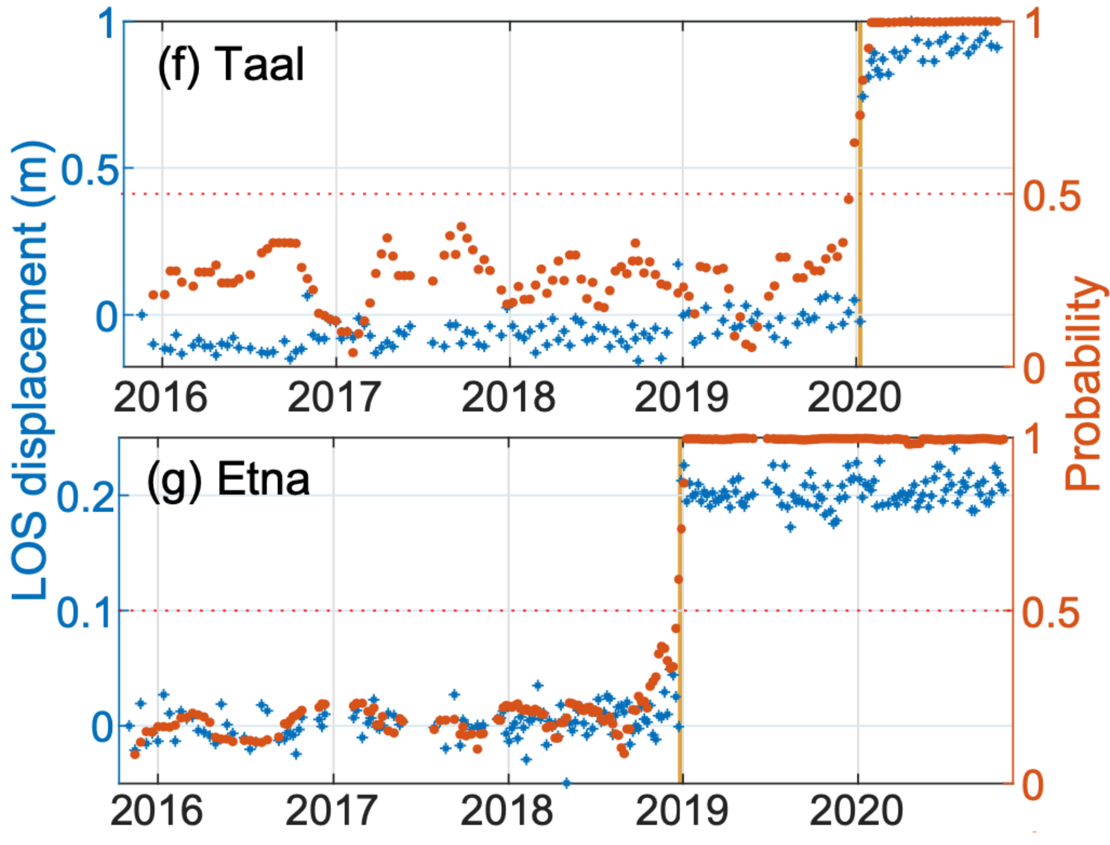
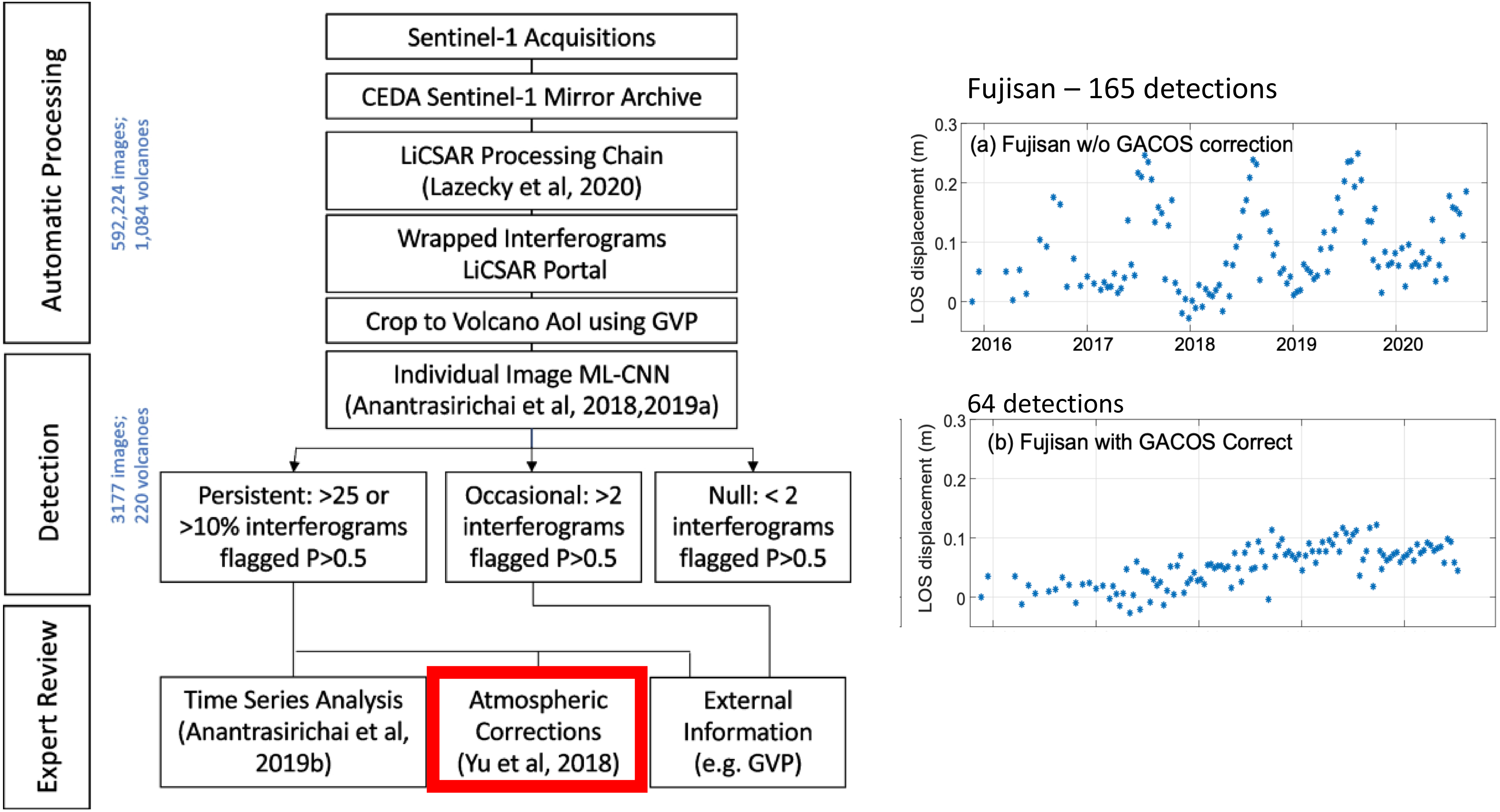
CEDA Sentinel-1 Mirror Archive
LiCSAR Processing Chain
(Lazecky et al, 2020)
Wrapped Interferograms
LiCSAR Portal
Crop to Volcano AoI using GVP
Detection
3177 images;
220 volcanoes
Individual Image ML-CNN
(Anantrasirichai et al, 2018,2019a)
Persistent: >25 or
>10% interferograms
flagged P>0.5
Occasional: >2
interferograms
flagged P>0.5
Null: < 2
interferograms
flagged P>0.5
Expert Review
Flags: 3323 images
366 volcanoes.
(a)
number of volcanoes
number of positives per volcano
0.5 ≤ P max < 0.6
0.6 ≤ P max < 0.7
0.7 ≤ P max < 0.8
0.8 ≤ P max < 0.9
0.9 ≤ P max ≤ 1
Lawu, Agung
Kilauea, Tambora
Erta Ale
Reykjanes, Rinjani
Etna, Kverkfjoll
Laguna Del Maule
Wolf, Domuyo
Cerro Azul
Fernandina
Fujisan
Sierra Negra
Occasional
Persistent
215
16





Biggs et al, Bull Volc, 2022

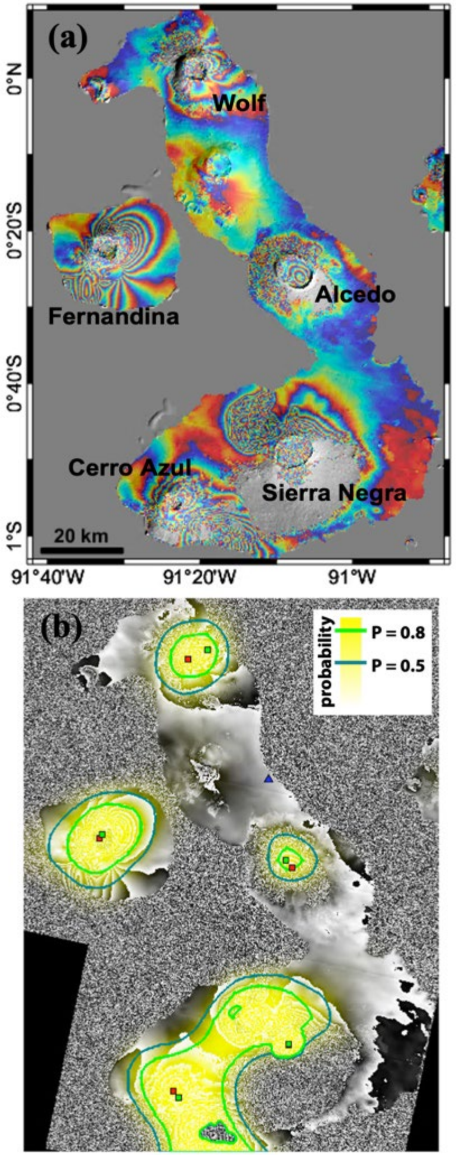


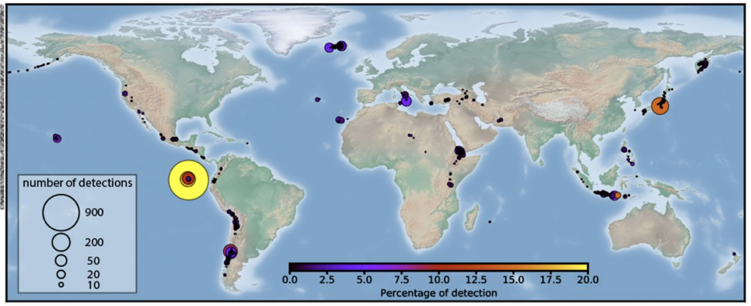
Biggs et al, Bull Volc, 2022

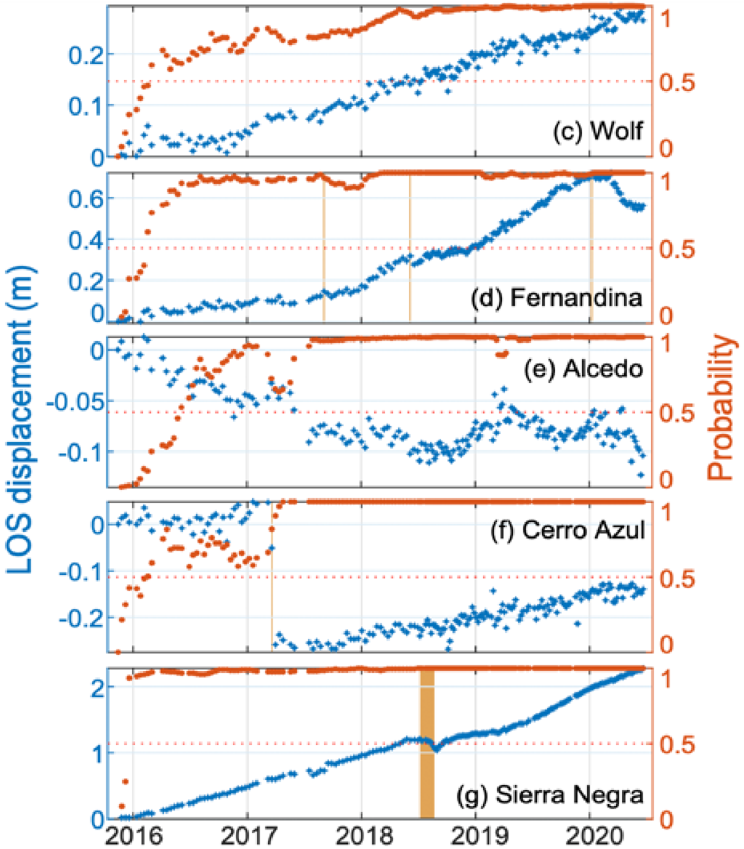
Large Deformation Events

Galapagos:

1,247 (38%) detections, including 904 from Sierra Negra

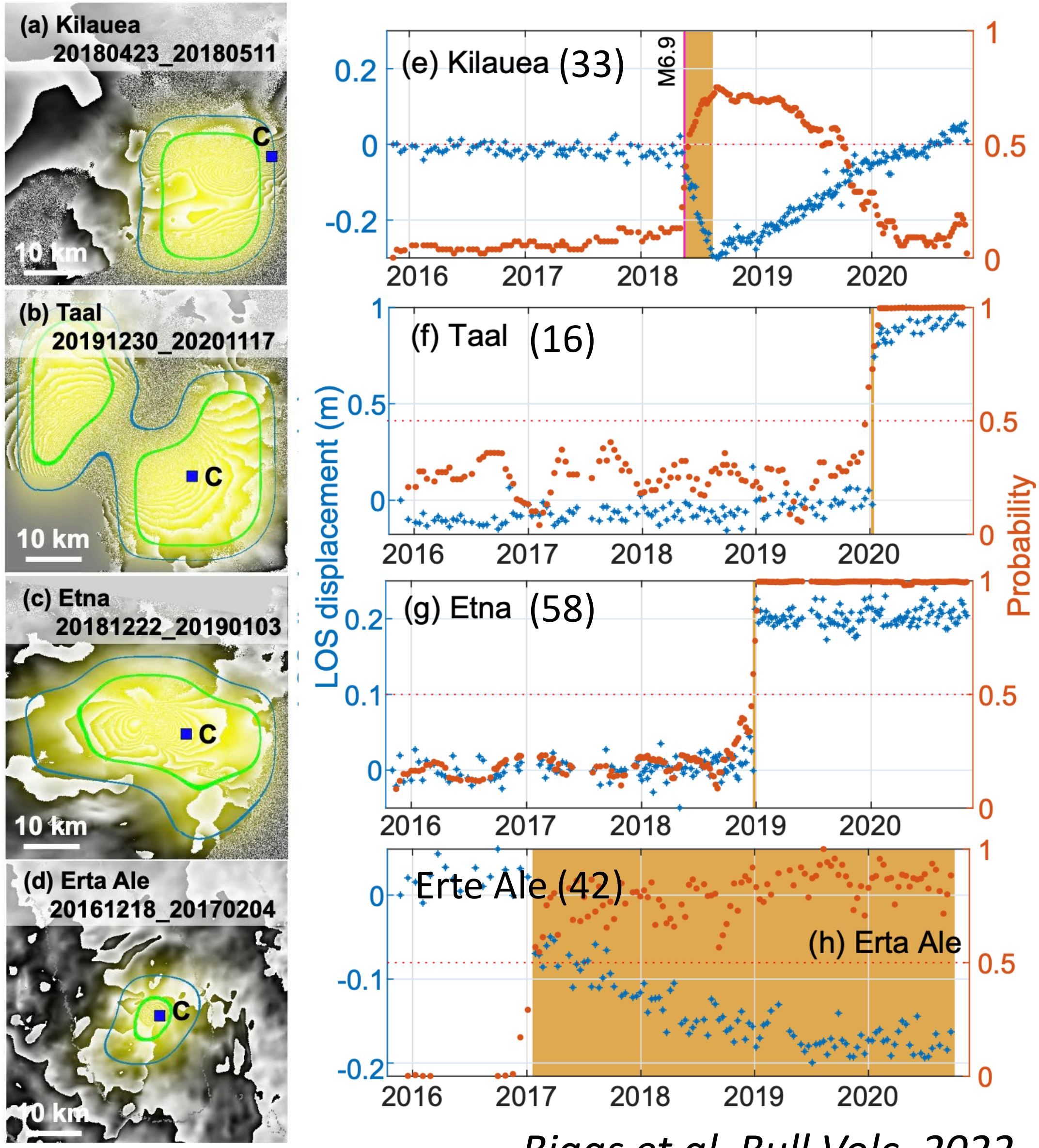






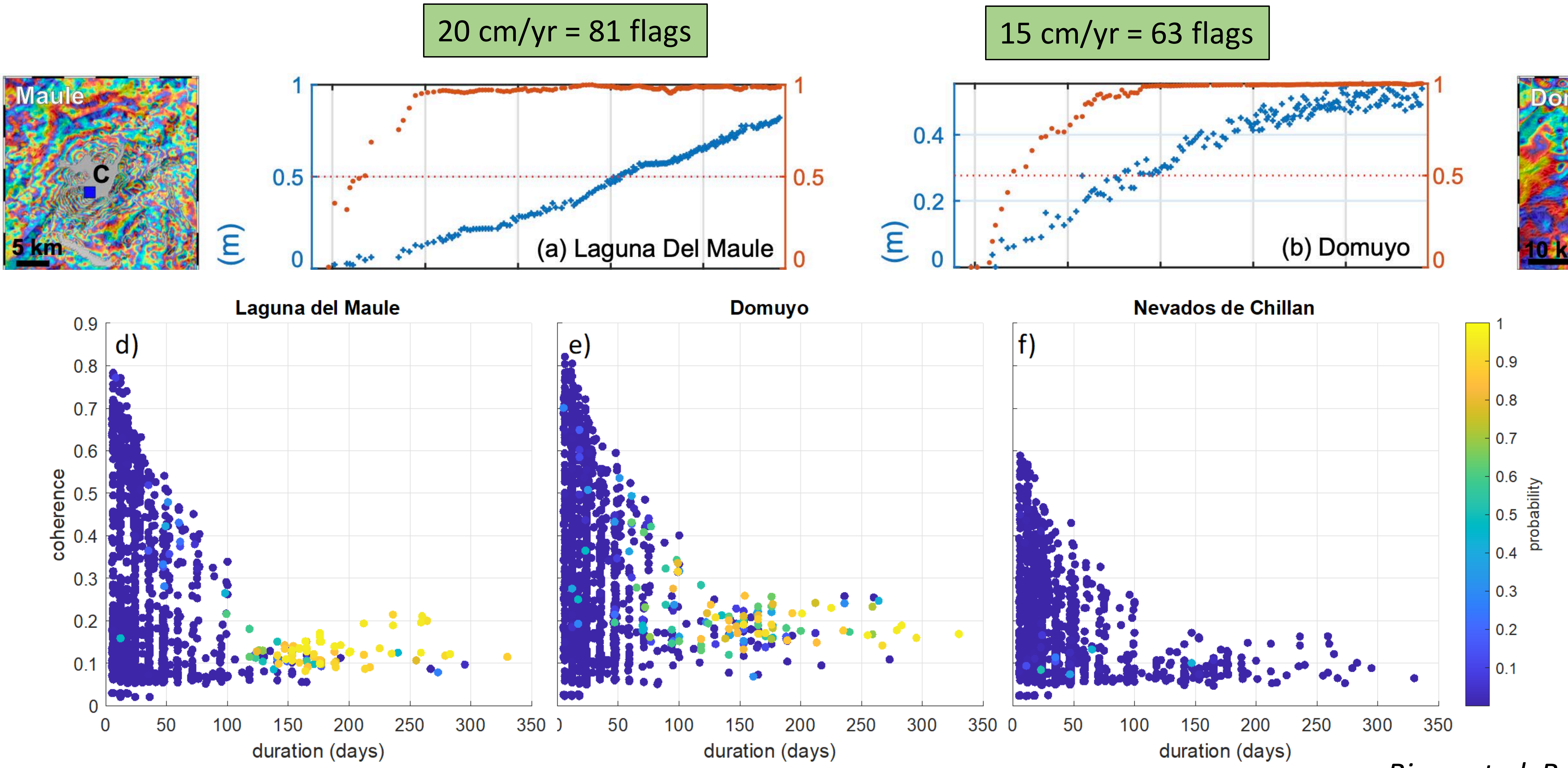
Large Eruptions & Intrusions:

Kilauea + Taal + Etna + Erte Ale = 149 flags



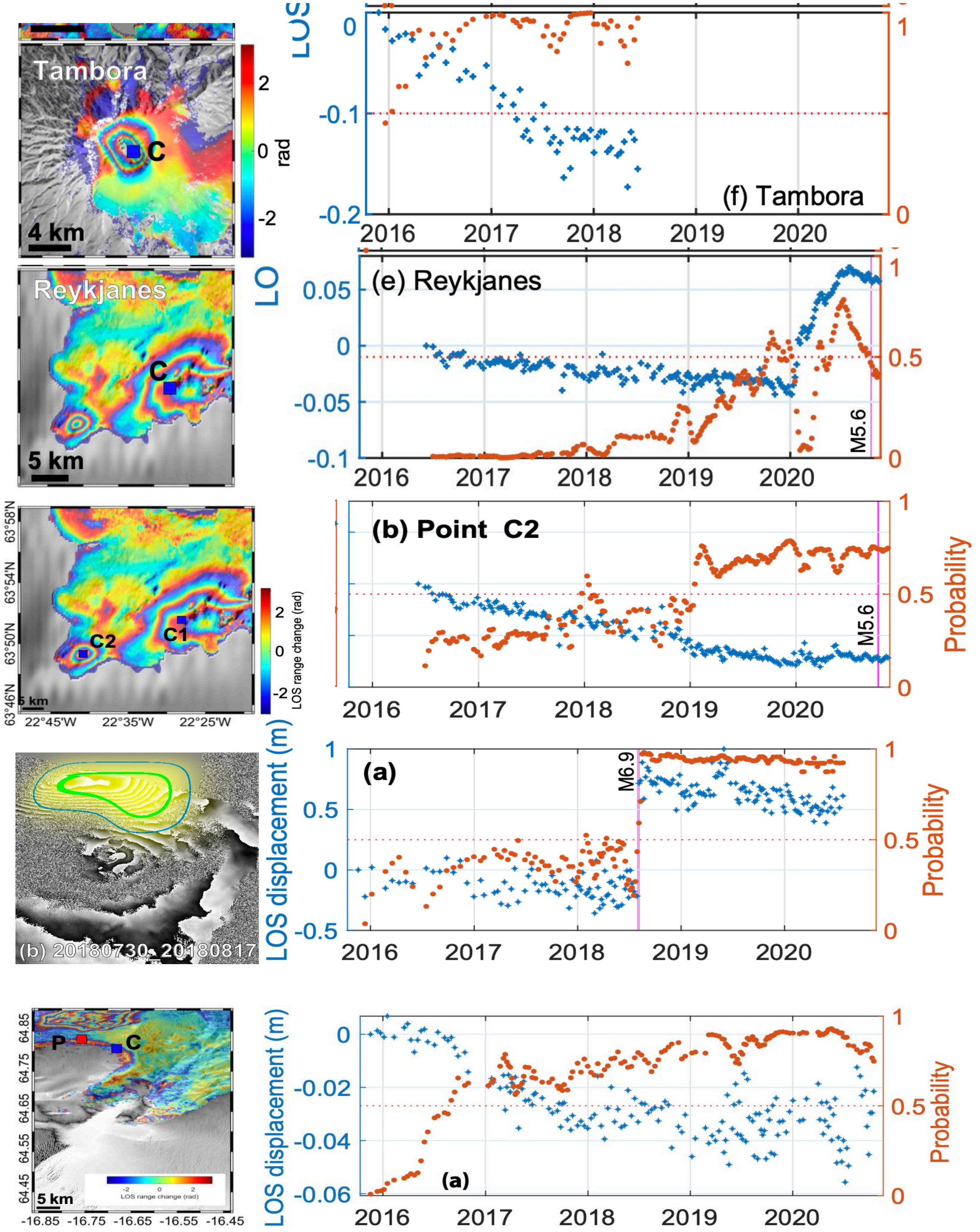
Biggs et al, Bull Volc, 2022

Slow Deformation



Biggs et al, Bull Volc, 2022

Other Signals



Tambora (33 detections):
Subsidence of 8 cm/yr
- Site of largest historical eruption

Reykjanes (49 detections):
Pre-eruption
- lots of subsequent studies…

Rekjanes (49 detections):
Geothermal Plant

Rinjani (49 detections):
M6.9 Earthquake

Kverfjoll (55 detections):
Ice Cap

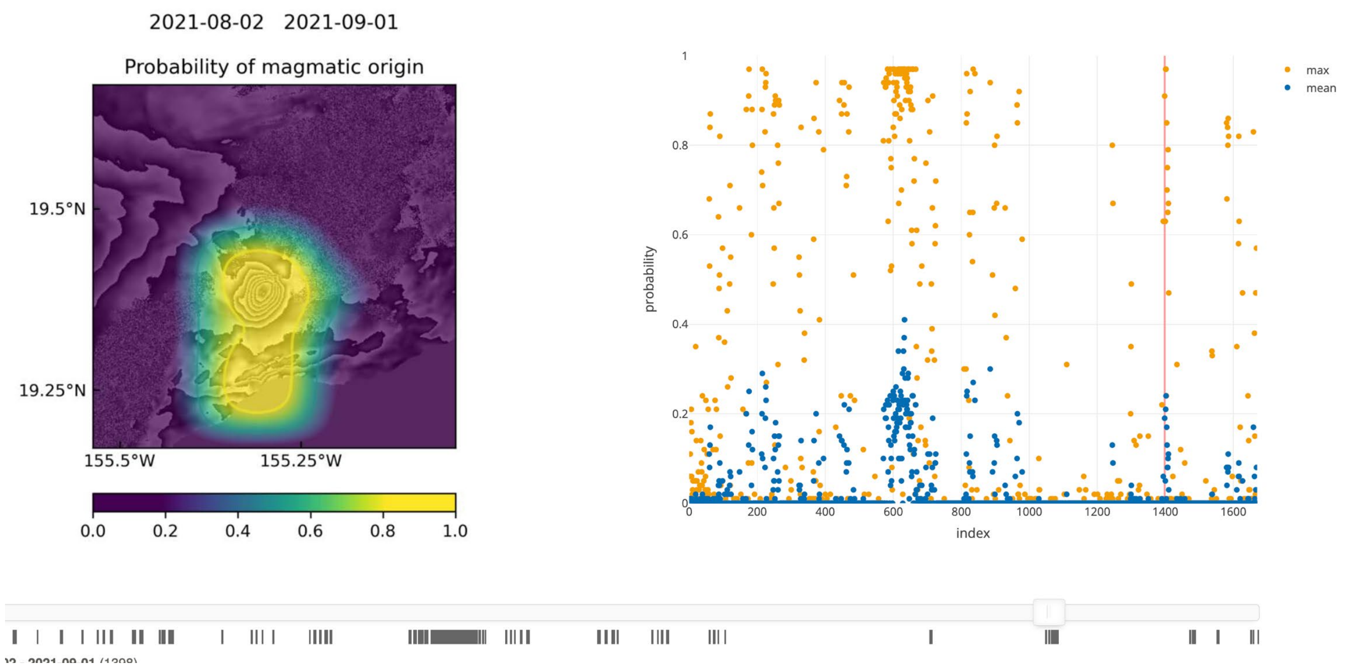
Biggs et al, Bull Volc, 2022

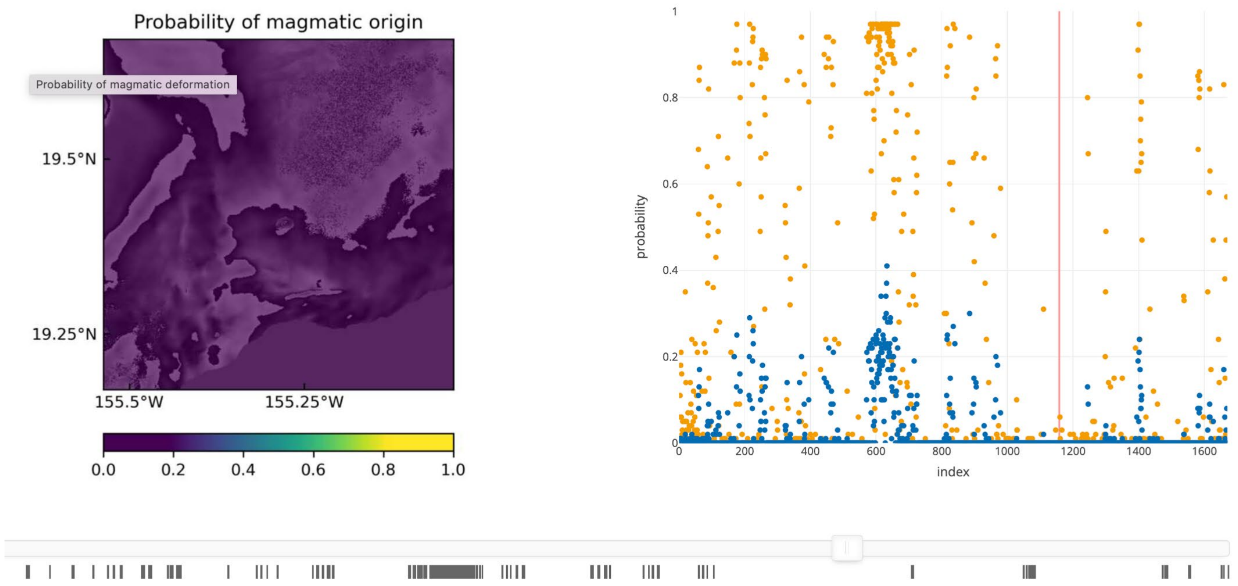
COMET

Volcano Deformation Portal

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

Volcano	Date	
Kilauea	2023-08-04	View
Sierra Negra	2023-08-03	View
Tambora	2023-07-11	View
Bezymianny	2023-06-24	View
fujisan	2023-06-23	View
Rinjani	2023-06-19	View
Asavyo	2023-05-04	View
Erta Ale	2023-04-27	View
Irazú	2023-04-27	View
Turrialba	2023-04-27	View





Towards global volcano deformation monitoring using satellite InSAR

Part 1: CNN

- Large Scale Demonstration of Anantrasirichai et al (2018,2019a,b)

Part 2: Development of New Methods

- New Architectures
- New Applications
- New Catalogues

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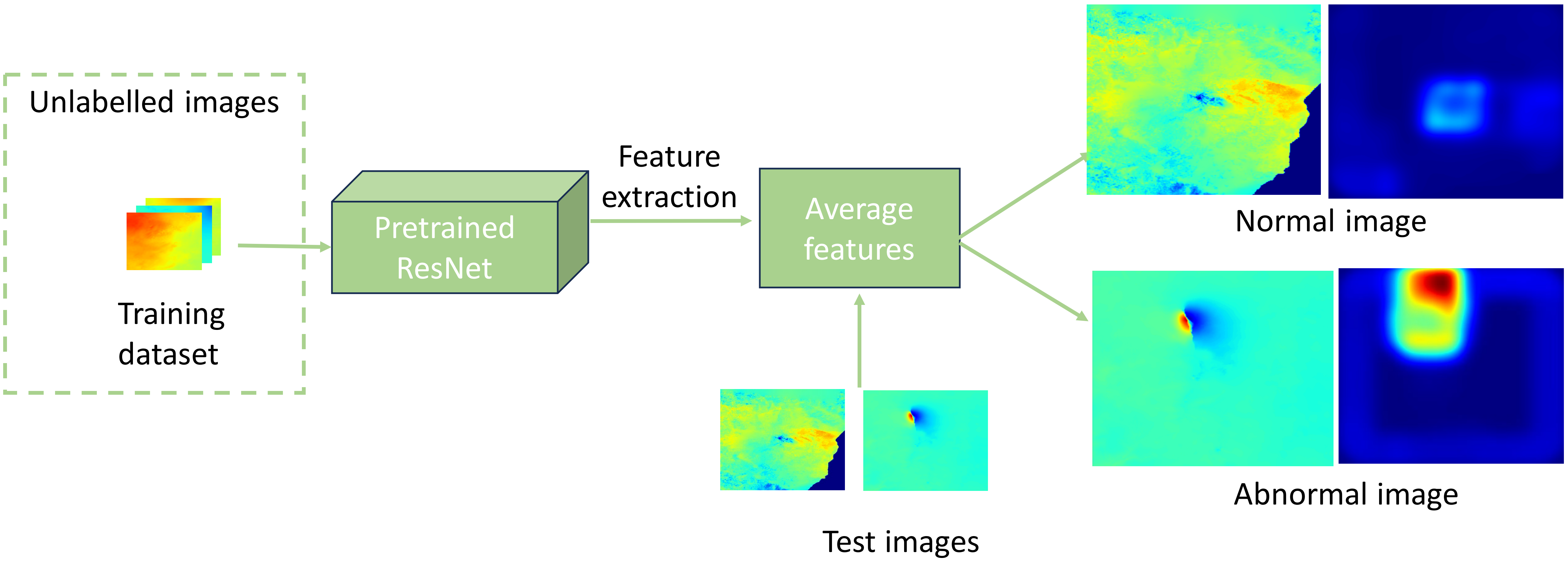
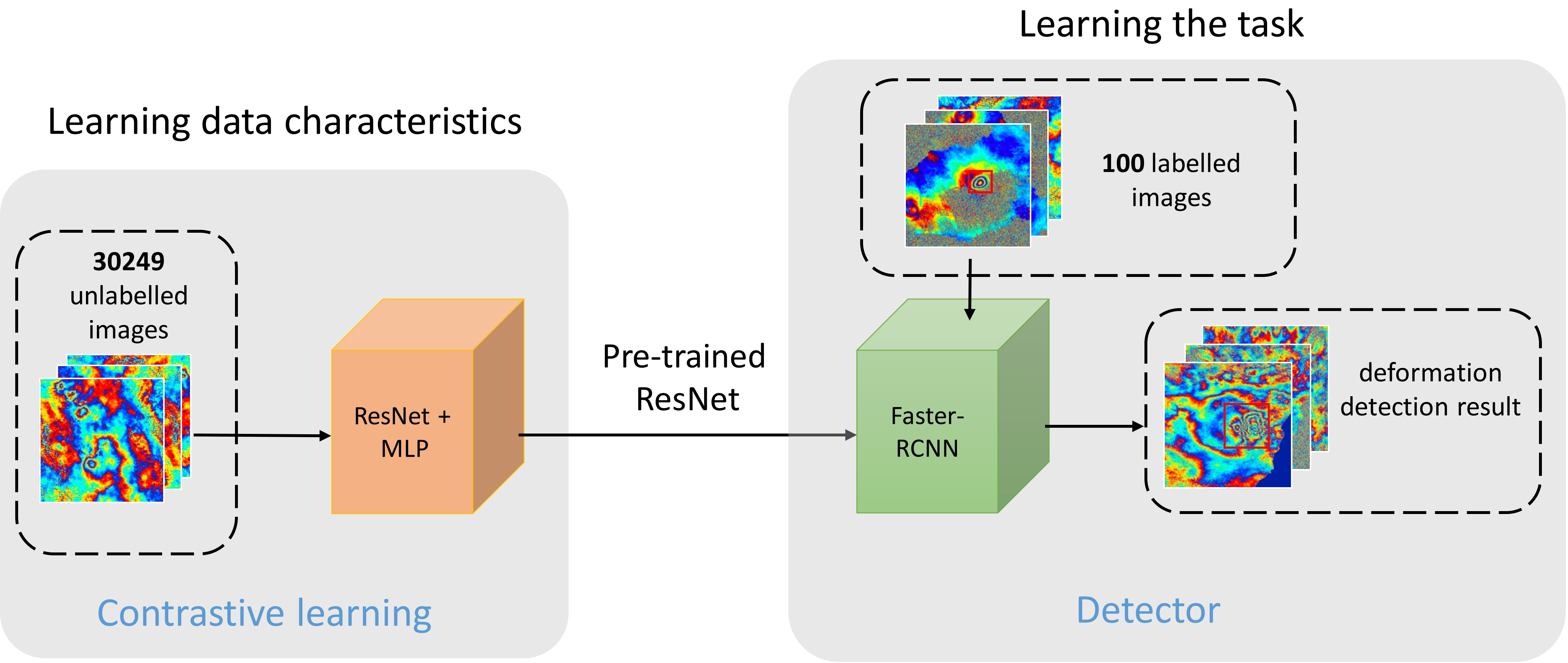
Unsupervised Learning: Anomaly Detection



See poster session for more details:

- Anomaly Detection For The Identification Of Volcanic Unrest In Satellite Imagery; Robert Gabriel Popescu, Nantheera Anantrasirichai, Juliet Biggs

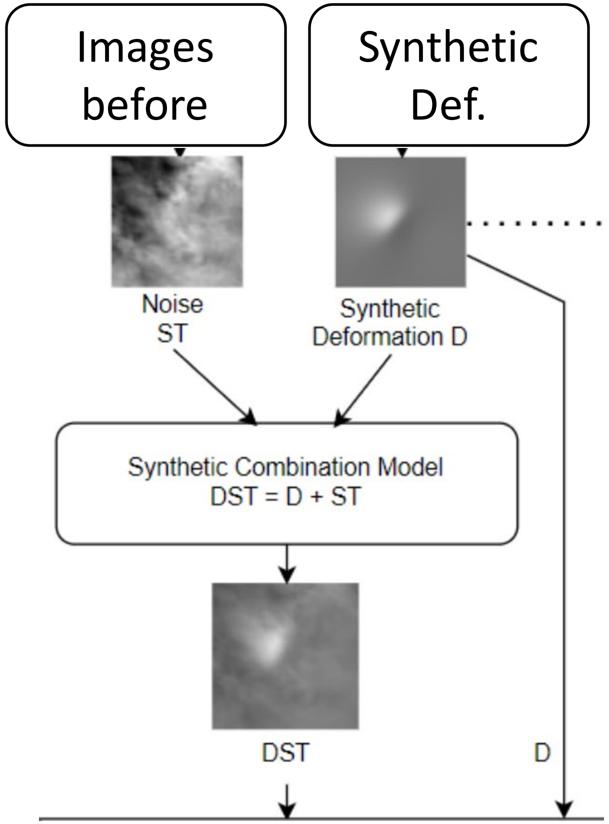
Semi-supervised Learning: Methods

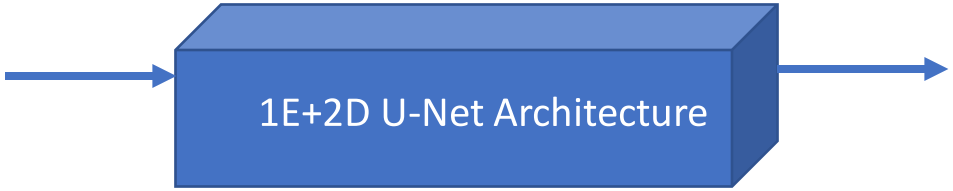


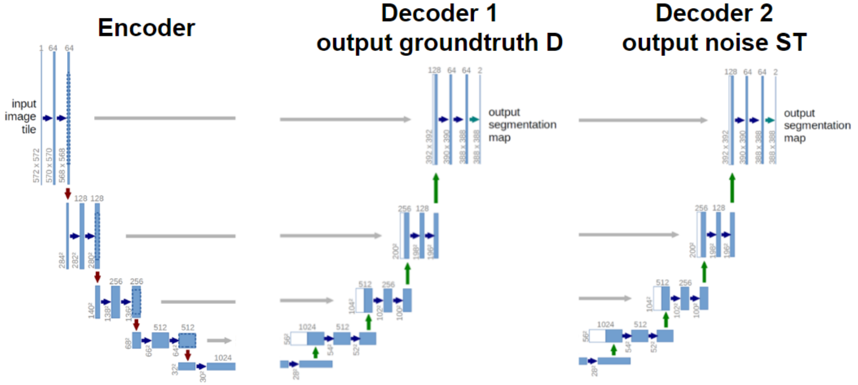
See poster session for more details:

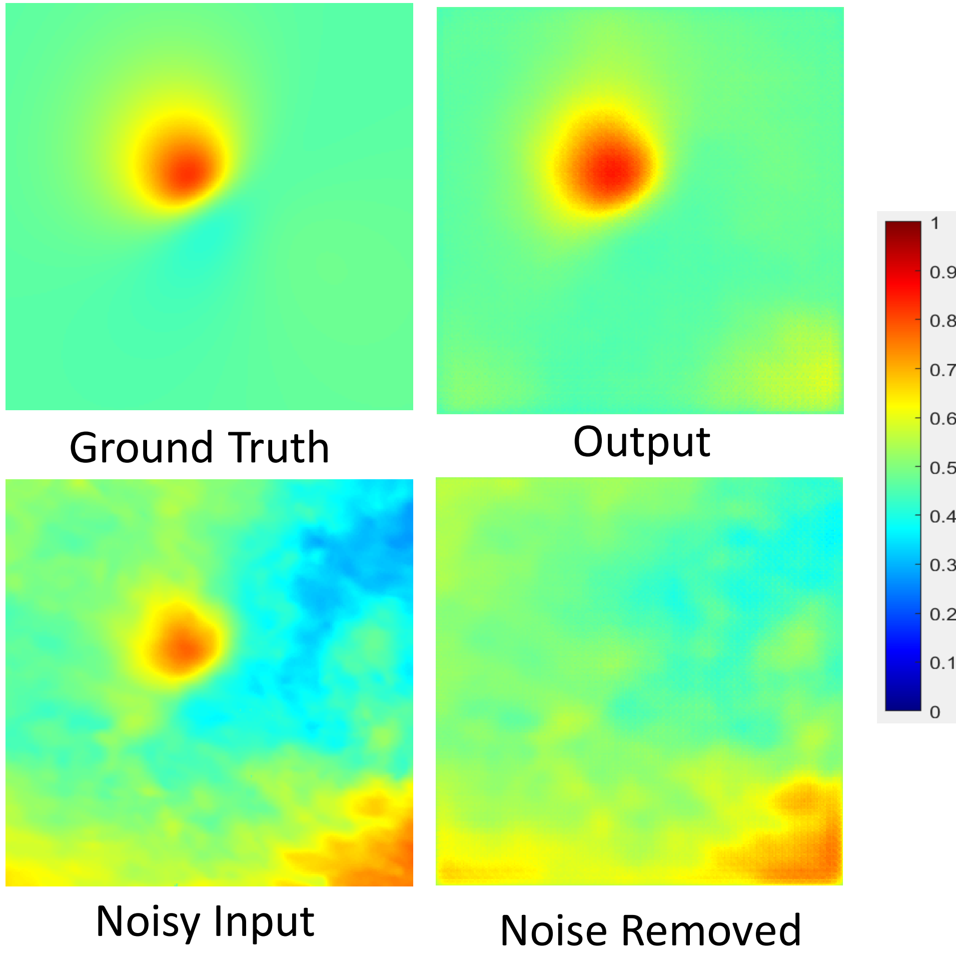
- Semi-supervised Learning Approach for Ground Deformation Detection in InSAR, Nantheera Anantrasirichai, Tianqi Yang, Juliet Biggs

Denoising 1: Deep Learning





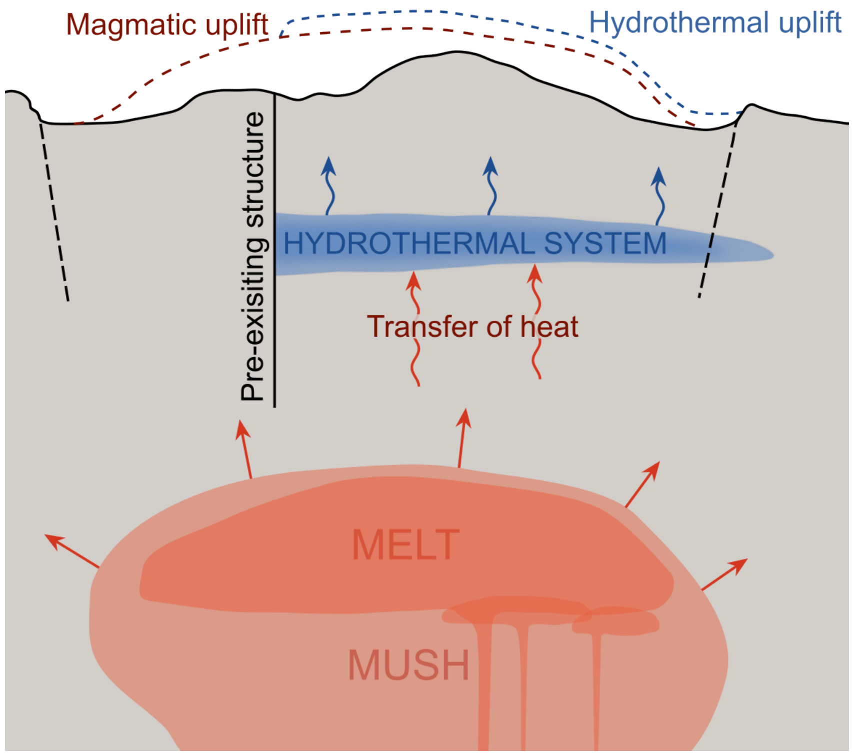


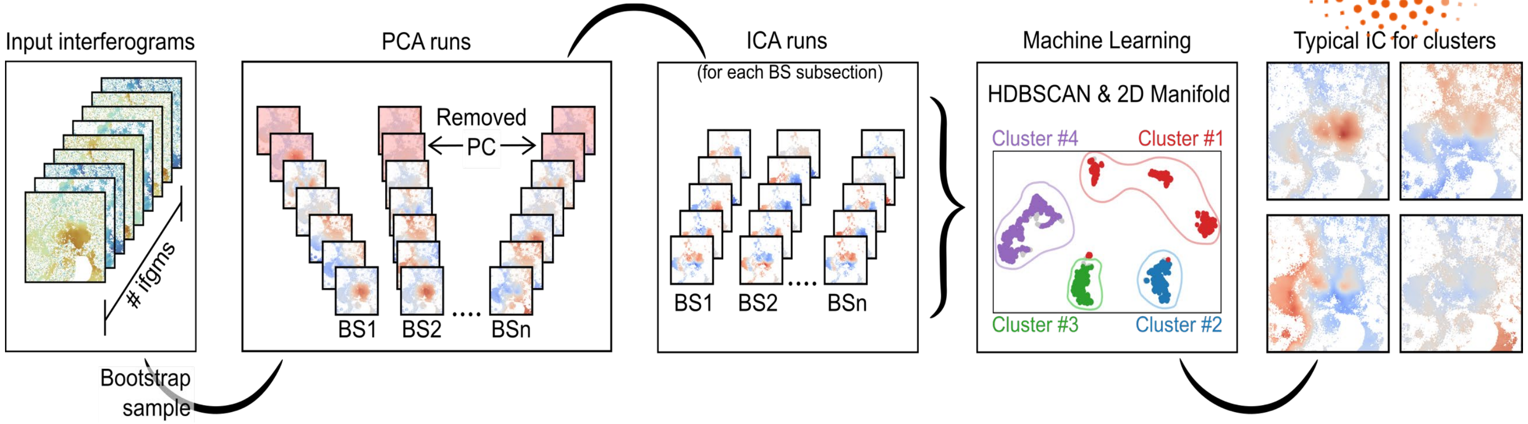


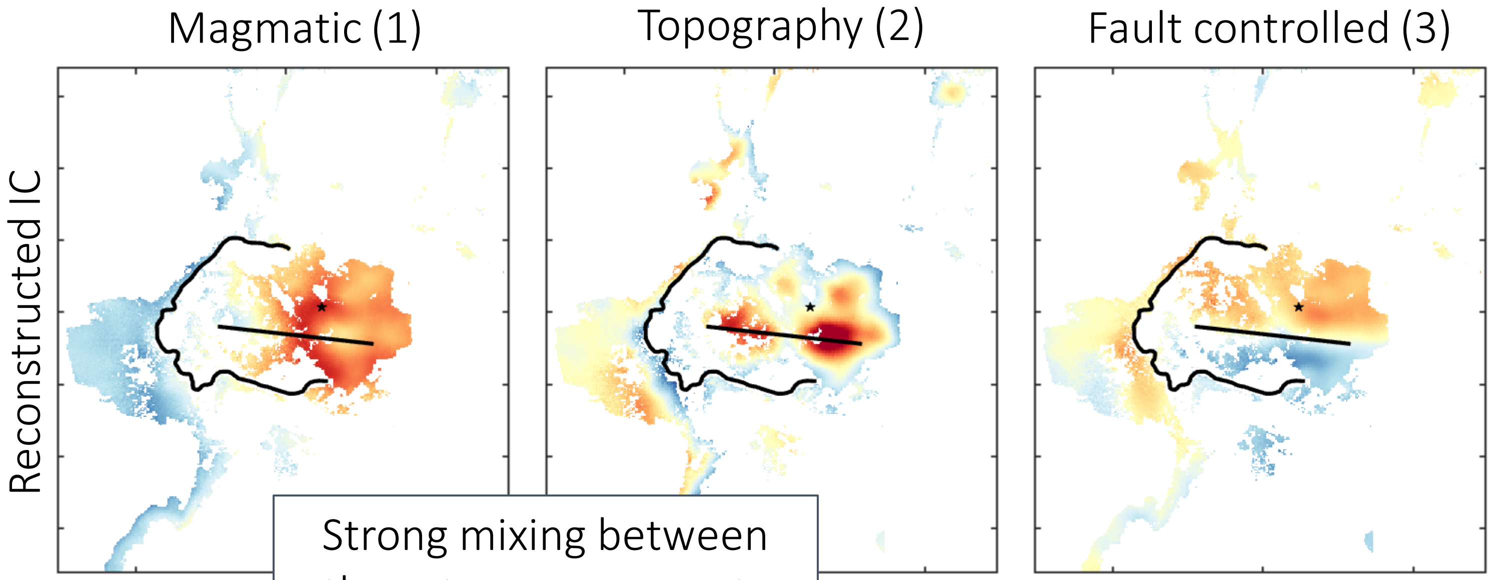
See poster session for more details:

- Semi-supervised Learning Approach for Ground Deformation Detection in InSAR, Nantheera Anantrasirichai, Tianqi Yang, Juliet Biggs

Denoising 2: Spatial ICA







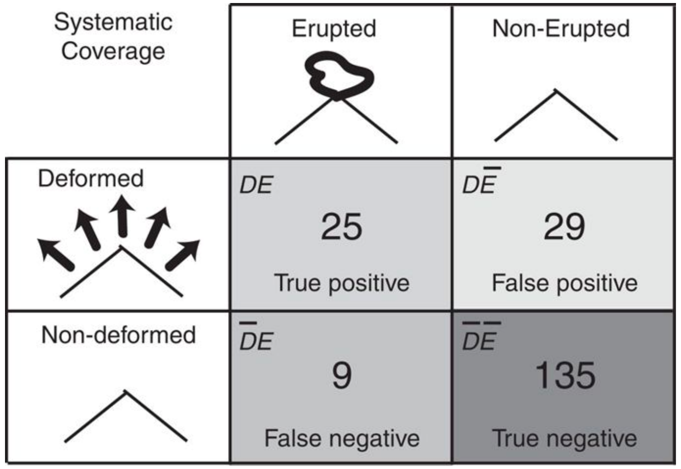
Strong mixing between these two components

See poster session for more details:

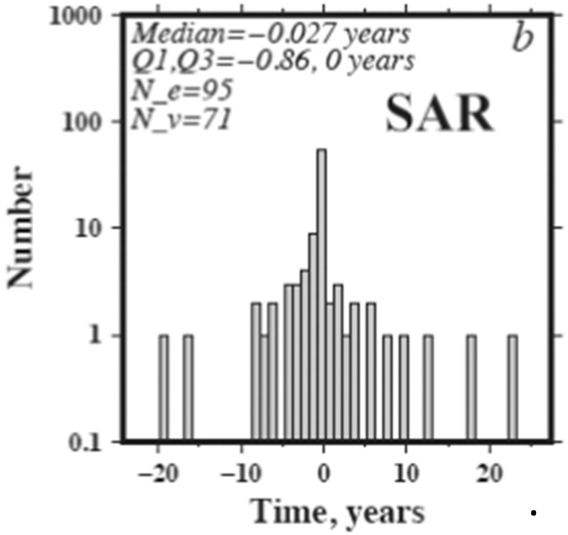
- Separating Volcanic Deformation Signals at Silicic Caldera Systems Using ICA; Edna W. Dualeh, Juliet Biggs

Global InSAR Database: Metadata Studies

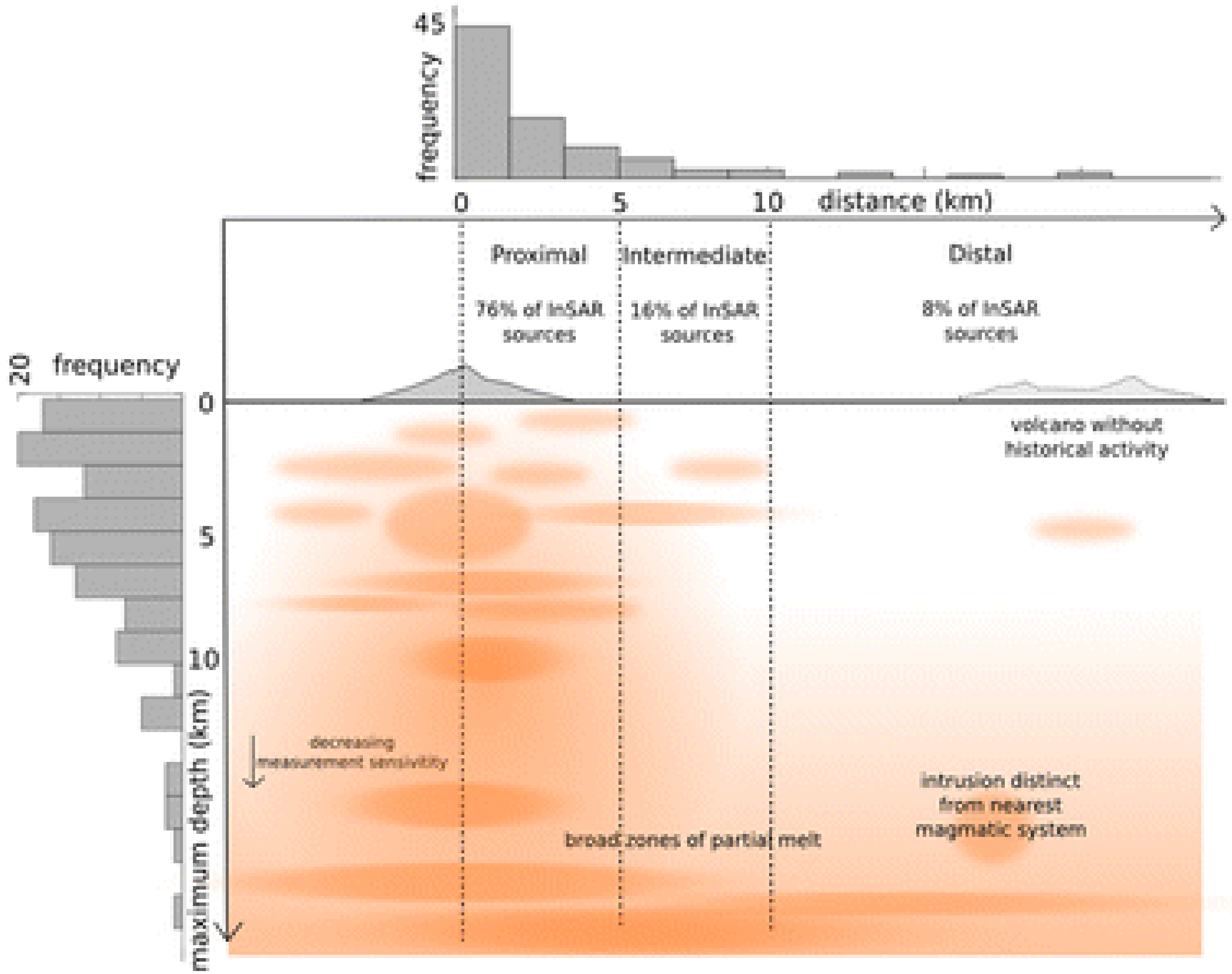
1) A significant statistical link to volcanic eruptions :



2) InSAR detections often pre-eruptive (~50%):



3) Architecture of active magmatic systems:

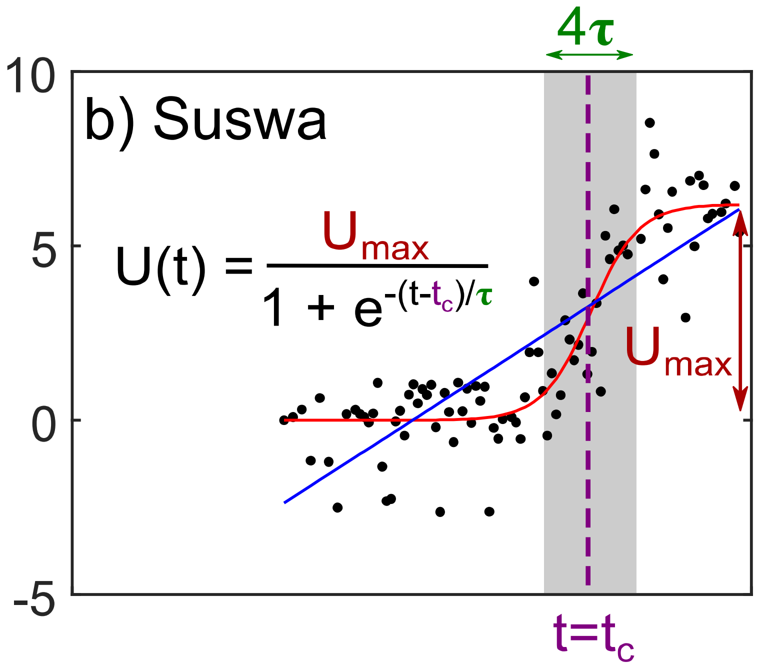


Biggs et al, 2014, Furtney et al, 2018, Ebmeier et al, 2018

Classification of Signals: Time

East African Rift: 64 volcanoes, 4000 interferograms

16 volcanoes with high SNR



Linear (Steady State):

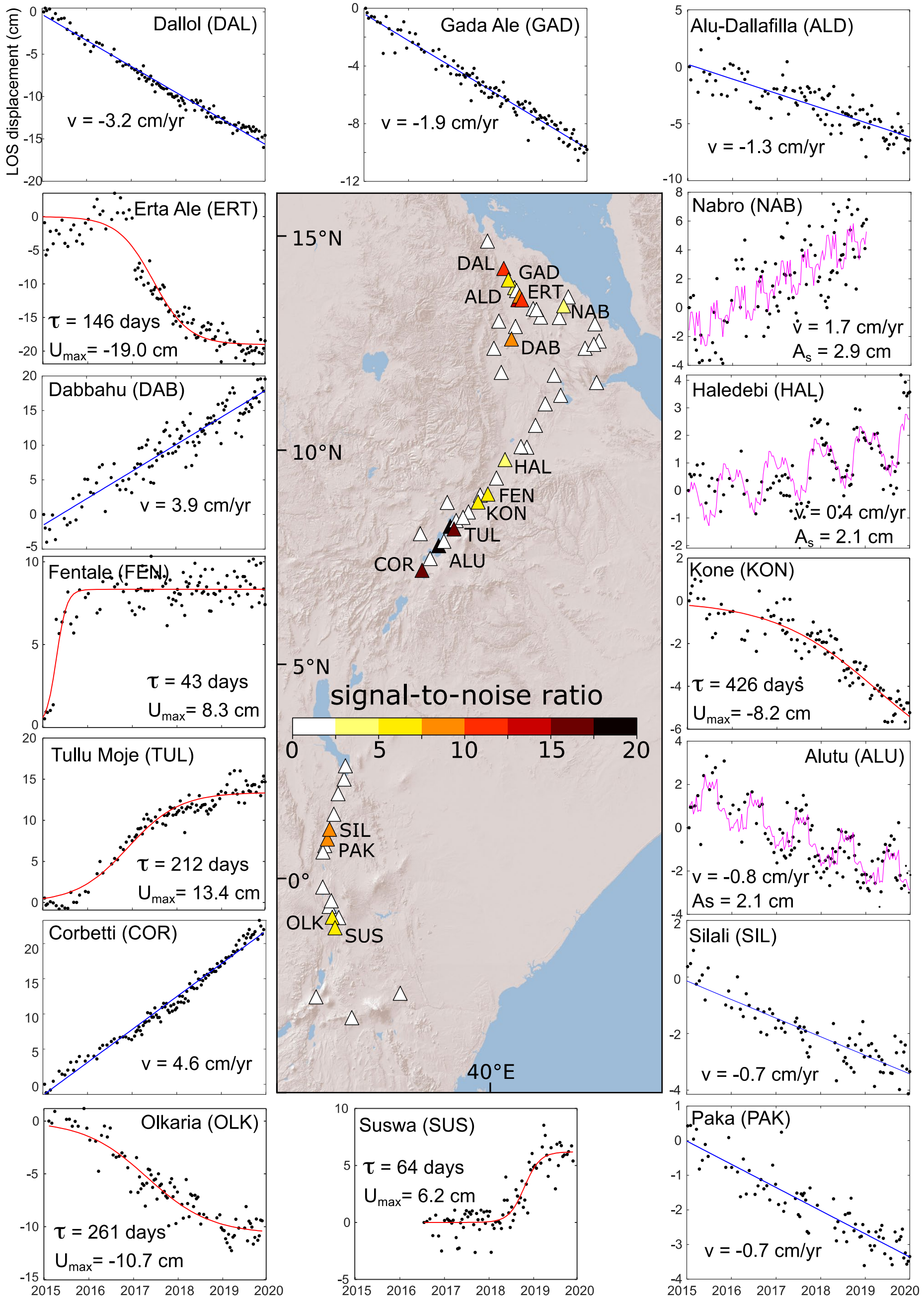
$$U(t) = vt + b,$$

Sigmoidal (Transient):

$$U(t) = \frac{U_{max}}{1 + e^{-(\frac{t-t_c}{\tau})}}$$

Use AIC to judge goodness of fit for different models:

$$\Delta AIC = AIC_{sigmoid} - AIC_{linear} = n(\ln \frac{RSS_s}{RSS_l}) + 2$$



Albino et al, Rem. Sens., 2022

Classification of Signals: Time

East African Rift: 64 volcanoes, 4000 interferograms

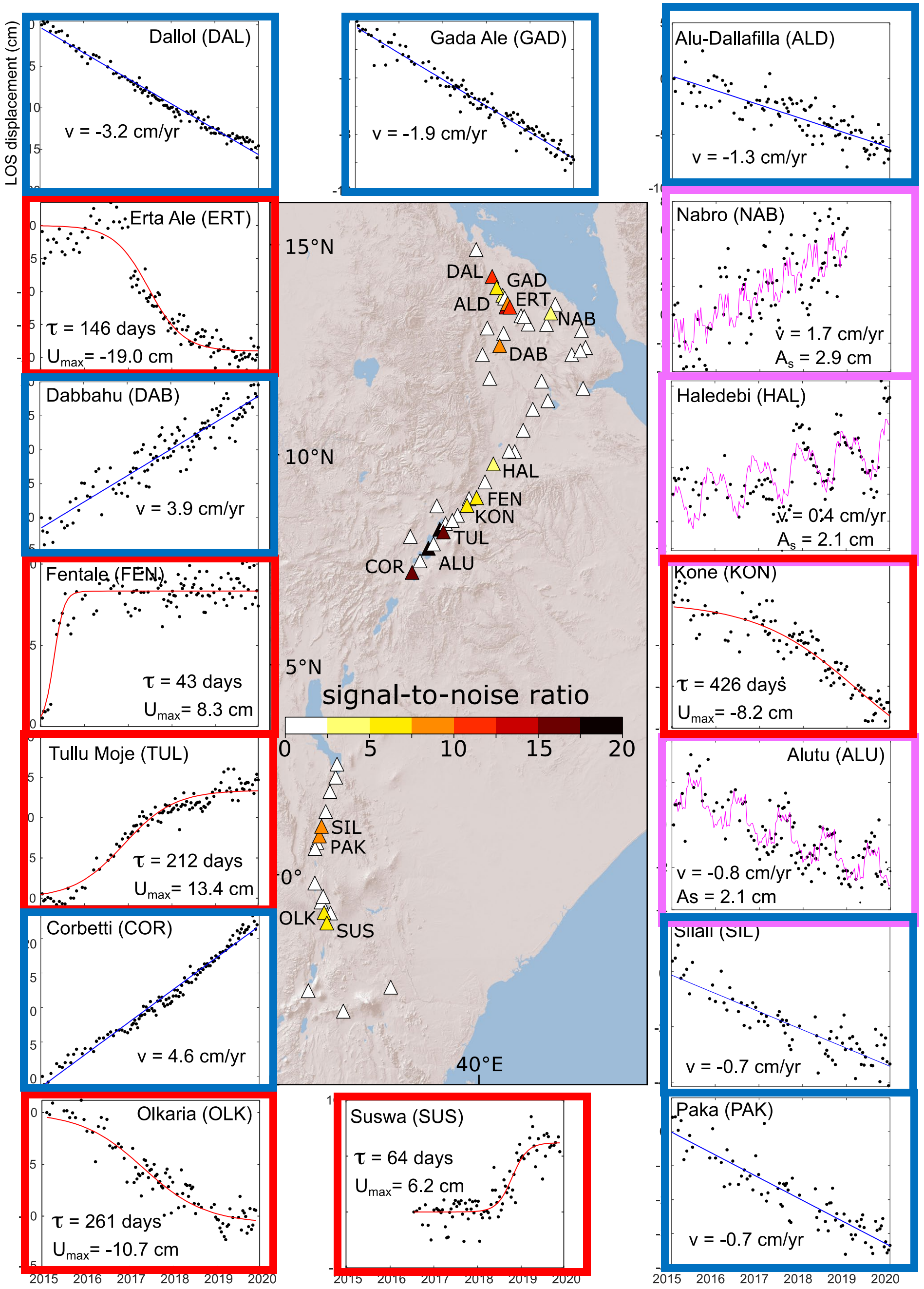
16 volcanoes with high SNR

Volcano	Detection			Model	Sigmoid	$R^2 > 0.75$	
	$\lvert A_B\rvert$ (cm)	σ_A (cm)	$\lvert A_B\rvert/\sigma_A$	ΔAIC	t_c (Days)	τ (Days)	U_{max} (cm)
Fentale	5.8	1.0	5.8	−133	20150422	43	8.3
Erta Ale	18.0	1.9	9.5	−86	20170626	146	−19.0
Tullu Moje	14.7	1.0	14.7	−61	20161130	212	13.4
Suswa	5.5	1.0	5.5	−49	20181025	64	6.2
Kone	6.1	1.2	5.1	−31	20190329	426	−8.2
Olkaria	7.9	1.4	5.6	−10	20170429	261	−10.7
				Model	Linear	$R^2 > 0.75$	
				ΔAIC	v_B (cm/yr)	σ_B (cm/yr)	b
Corbetti	26.1	1.6	16.3	−4	4.6	0.1	1.47
Alu−Dallafilla	6.10	1.5	4.1	−3	−1.3	0.1	1.53
Silali	3.4	0.4	8.5	−2	−0.7	0.05	1.35
Dallol	14.6	1.2	12.2	10	−3.2	0.1	1.45
Paka	4.4	0.5	8.8	11	−0.7	0.06	1.61
Gada Ale	9.9	1.4	7.1	21	−1.9	0.1	1.45
Dabbahu	22.0	2.7	8.1	23	3.9	0.2	1.65
				Model	Linear	+ Seasonal	
					v_B (cm/yr)	A_s (cm)	
Nabro	5.5	1.2	4.6		1.7	2.9	
Alutu	3.8	0.2	19		−0.8	2.1	
Haledebi	5.8	1.3	4.5		0.4	2.1	

Sigmoidal [6]
- transients

Linear [7]
- steady state

Linear + Seasonal [3]



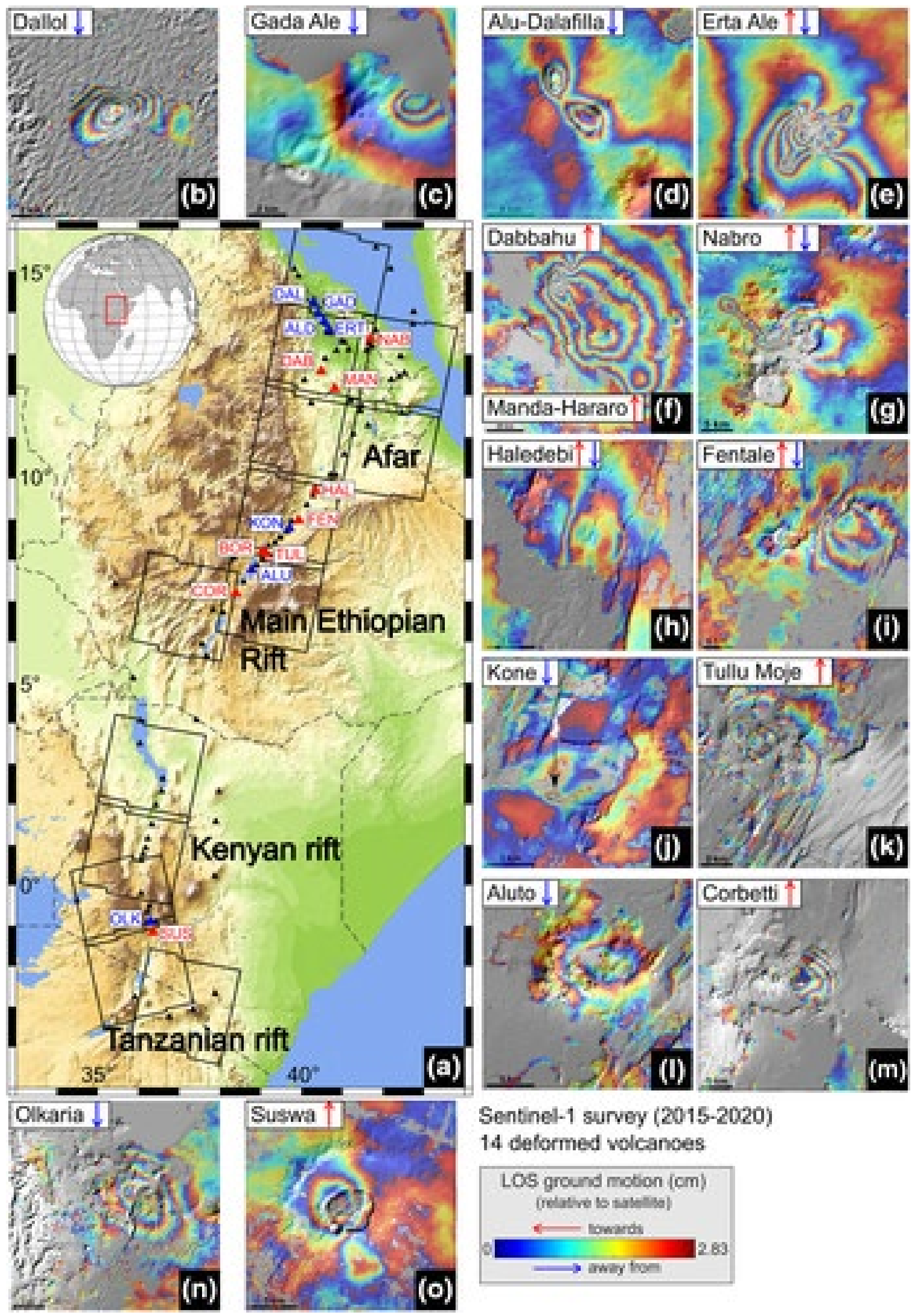
Albino et al, Rem. Sens., 2022

Classification of Signals: Space

East African Rift: 64 volcanoes, 4000 interferograms
16 volcanoes with high SNR

Volcano	Temporal parameters (Albino *et al.* 2022)			Source parameters (This poster)	
	Trend	Time period (days)	Rate (cm/yr)	depth (m)	Volume (m^3)
Alu-Dalafilla	Linear		-1.3	1.2E+03	-4.7E+05
Corbetti	Linear		4.6	7.7E+03	6.9E+07
Dabbahu	Linear		3.9	5.3E+03	1.8E+07
Dallol	Linear		-3.2	1.3E+03	-1.2E+06
Gada Ale	Linear		-1.9	2.2E+03	-2.8E+06
Erta Ale	Sigmoid	146		1.3E+03	-6.3E+05
Olkaria	Sigmoid	261		7.8E+03	-3.8E+07
Suswa	Sigmoid	64		3.8E+03	4.4E+06
Tullu Moje	Sigmoid	212		6.2E+03	3.0E+07

Note: Orange source parameters indicate the inversion results were poor



Albino et al, Gcubed, 2021

See poster session for more details:

- Systematic Extraction of Volcano Deformation Source Parameters from Sentinel-1 InSAR Data; Ben Ireland, Juliet Biggs, Nantheera Anantrasirichai

Conclusions

Operational Methods, CNN:

- Applied to large datasets of interferograms to detect eruptions, intrusions, slow deformation and transients.
- Runs automatically on LICSAR systems and results released through COMET volcano portal.

New Methods:

- Proof-of-concept studies using new architectures for anomaly detection and semi-supervised learning.
- New applications to separating signals and noise
- Developing a systematic global database of volcano deformation

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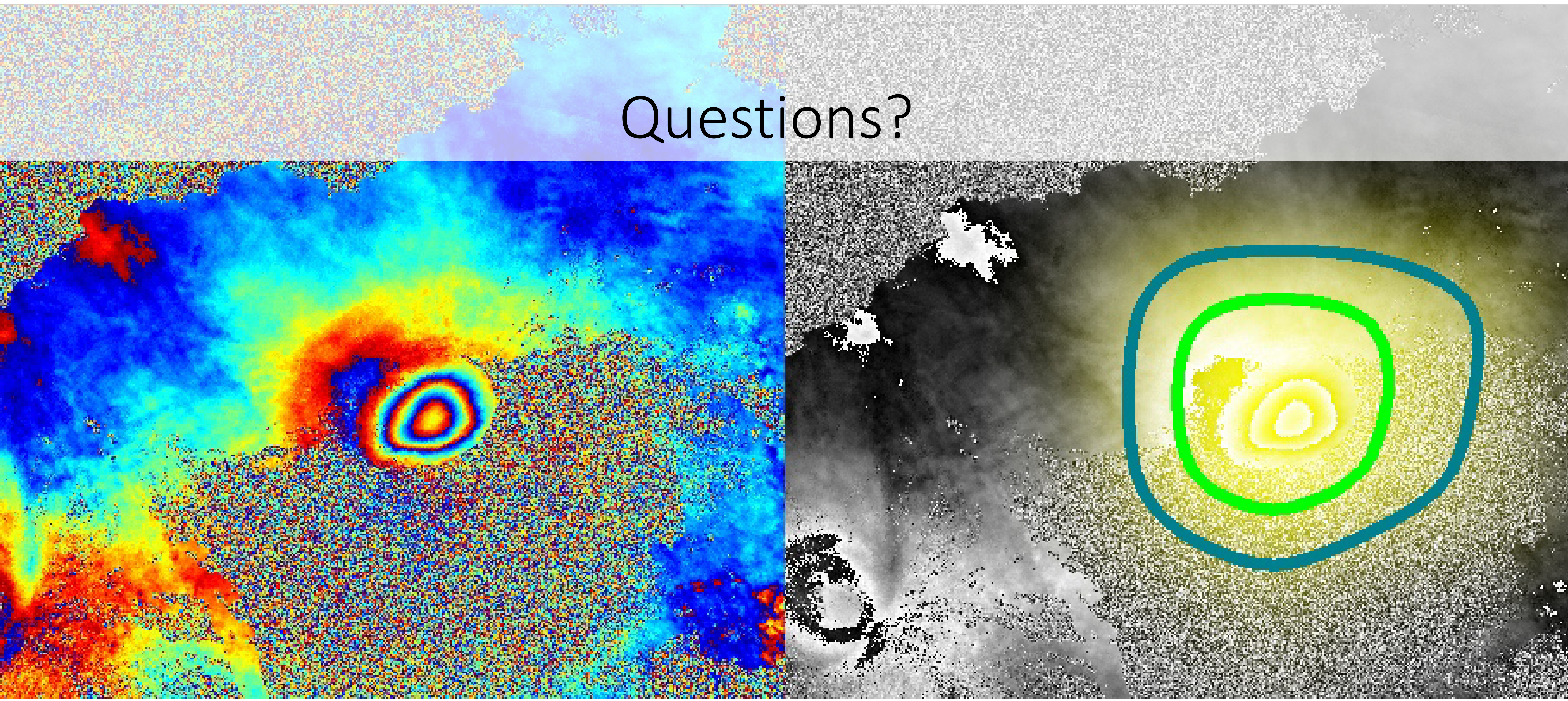
Questions?



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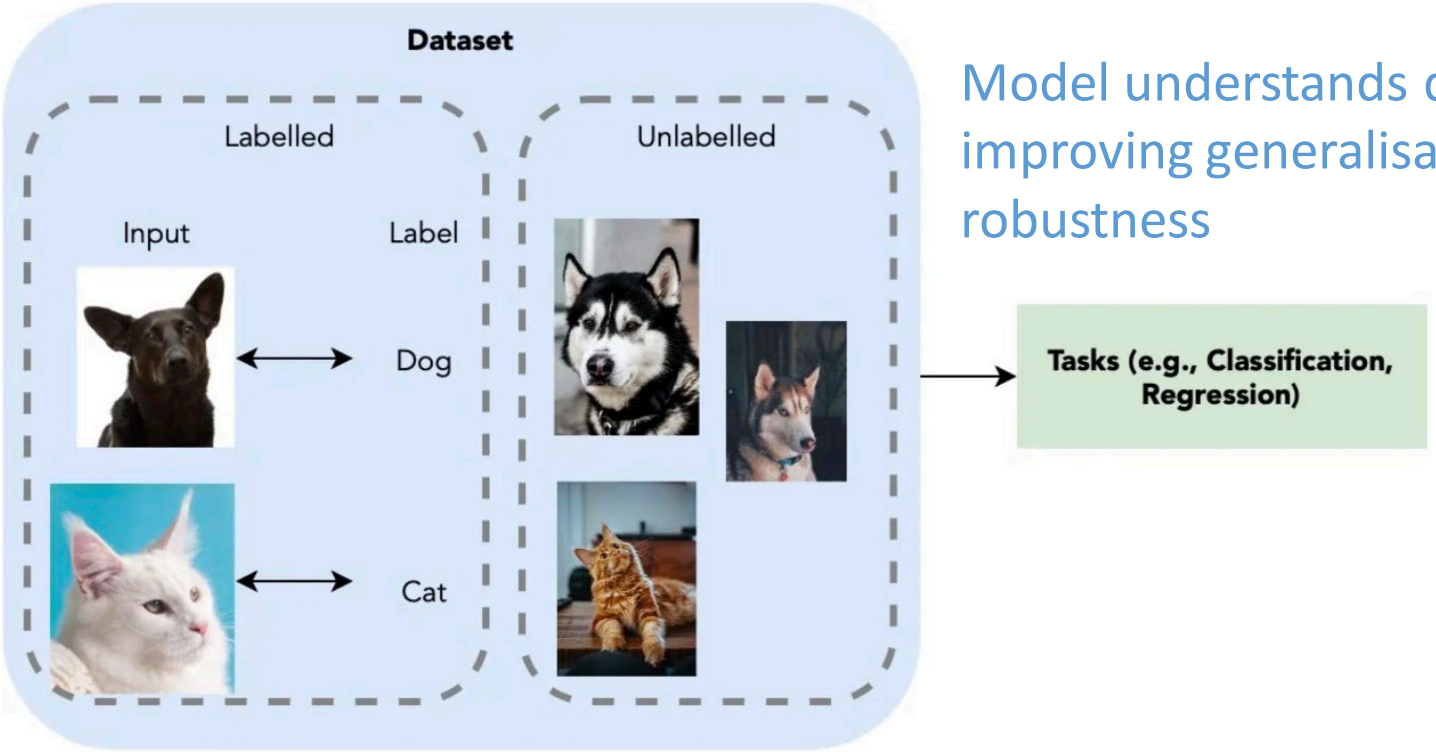
Semi-Supervised Learning

- A small portion of the training data is labeled, and the majority is unlabeled.

Model understands the task



Model understands data, improving generalisation and robustness

https://towardsdatascience.com/supervised-semi-supervised-unsupervised-and-self-supervised-learning-7fa79aa9247c

Semi-supervised Learning: Results

- LiCSAR test dataset (30,249 interferograms)

Training Data	#P	#TP	#FP	#FN	Paper
Envisat	1369	42	1327	0	Application of Machine Learning to Classification of Volcanic Deformation in Routinely Generated InSAR Data, 2018
Envisat + FP	104	42	62	0	
Synthetic + FP	50	41	9	1	A deep learning approach to detecting volcano deformation from satellite imagery using synthetic datasets, 2019
Semi-supervised	45	40	5	2	Contrastive learning + Faster-RCNN

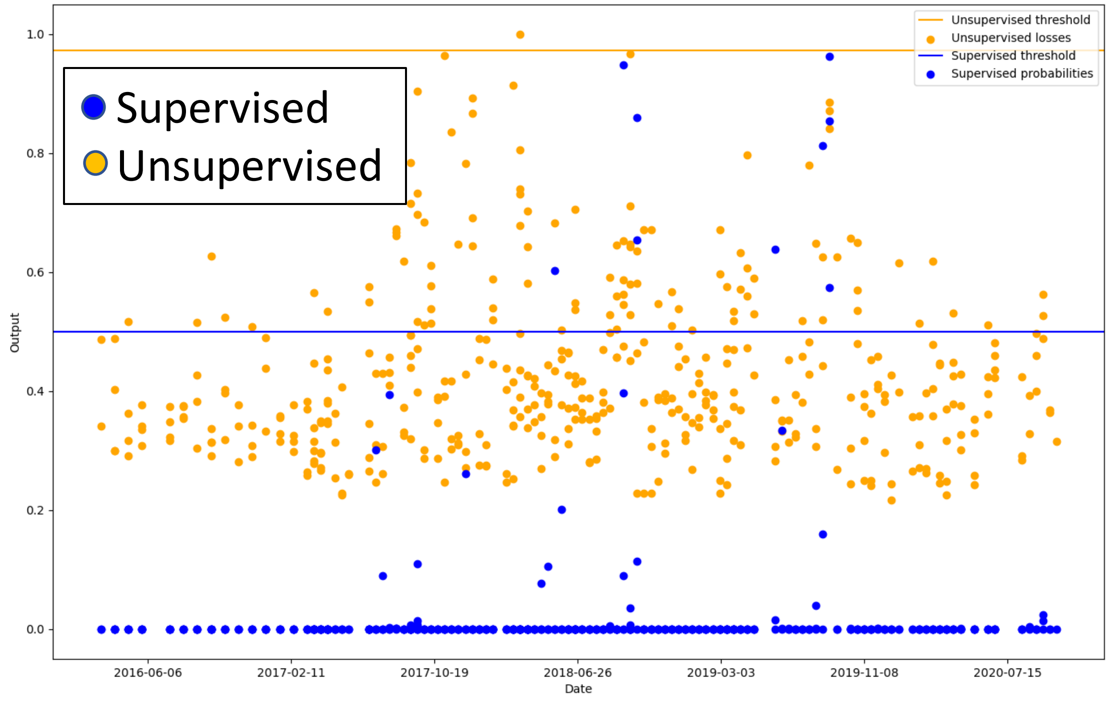
See poster session for more details:

- Semi-supervised Learning Approach for Ground Deformation Detection in InSAR, Nantheera Anantrasirichai, Tianqi Yang, Juliet Biggs

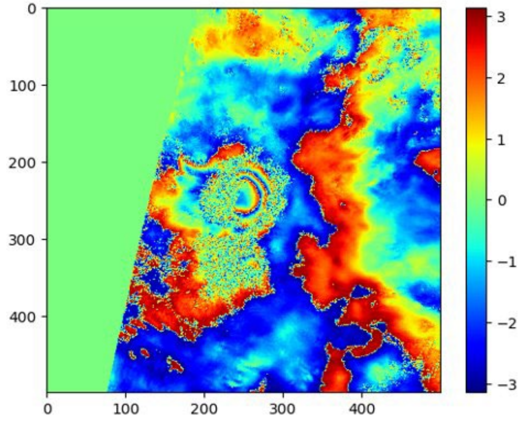
Unsupervised Learning: Results

Example: Lawu, Indonesia

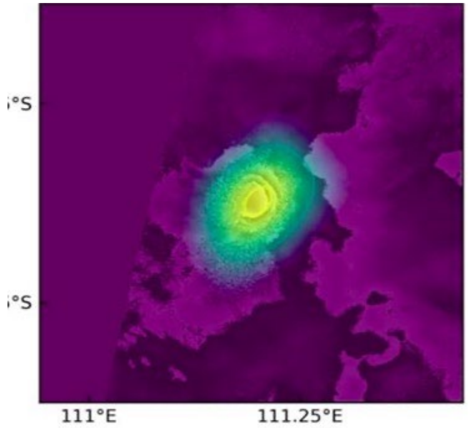
Toprgraphically-correlated atmospheric noise



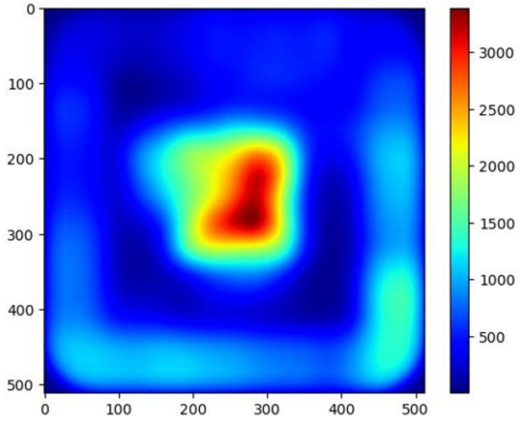
Input



Supervised: Flagged



Unsupervised: Normal



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