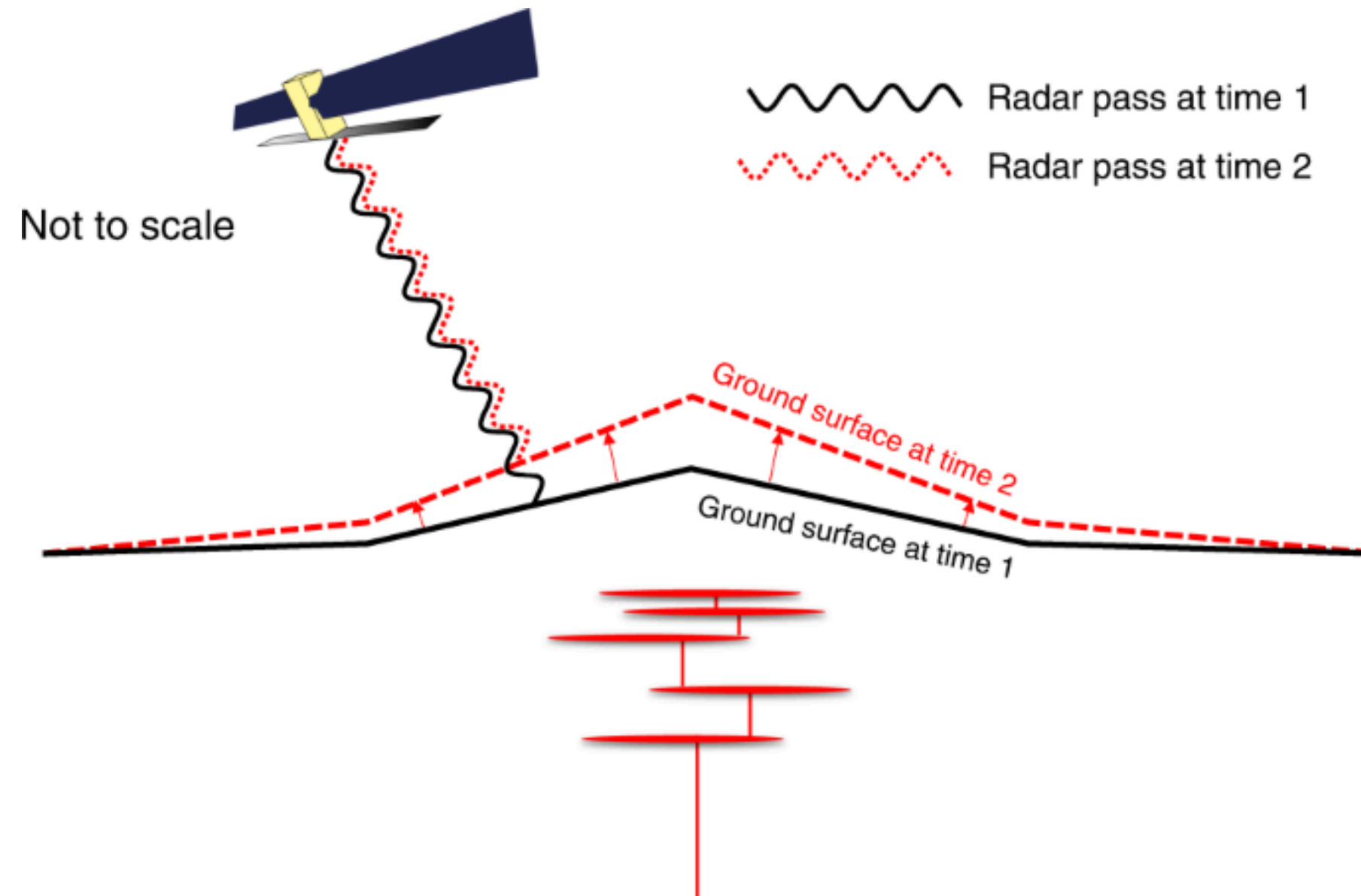


Using **neural networks** to retrieve deformation source **parameters** from InSAR **displacement maps**

Grégoire Vest^{1,2}, Yajing Yan¹, Fabien Albino²

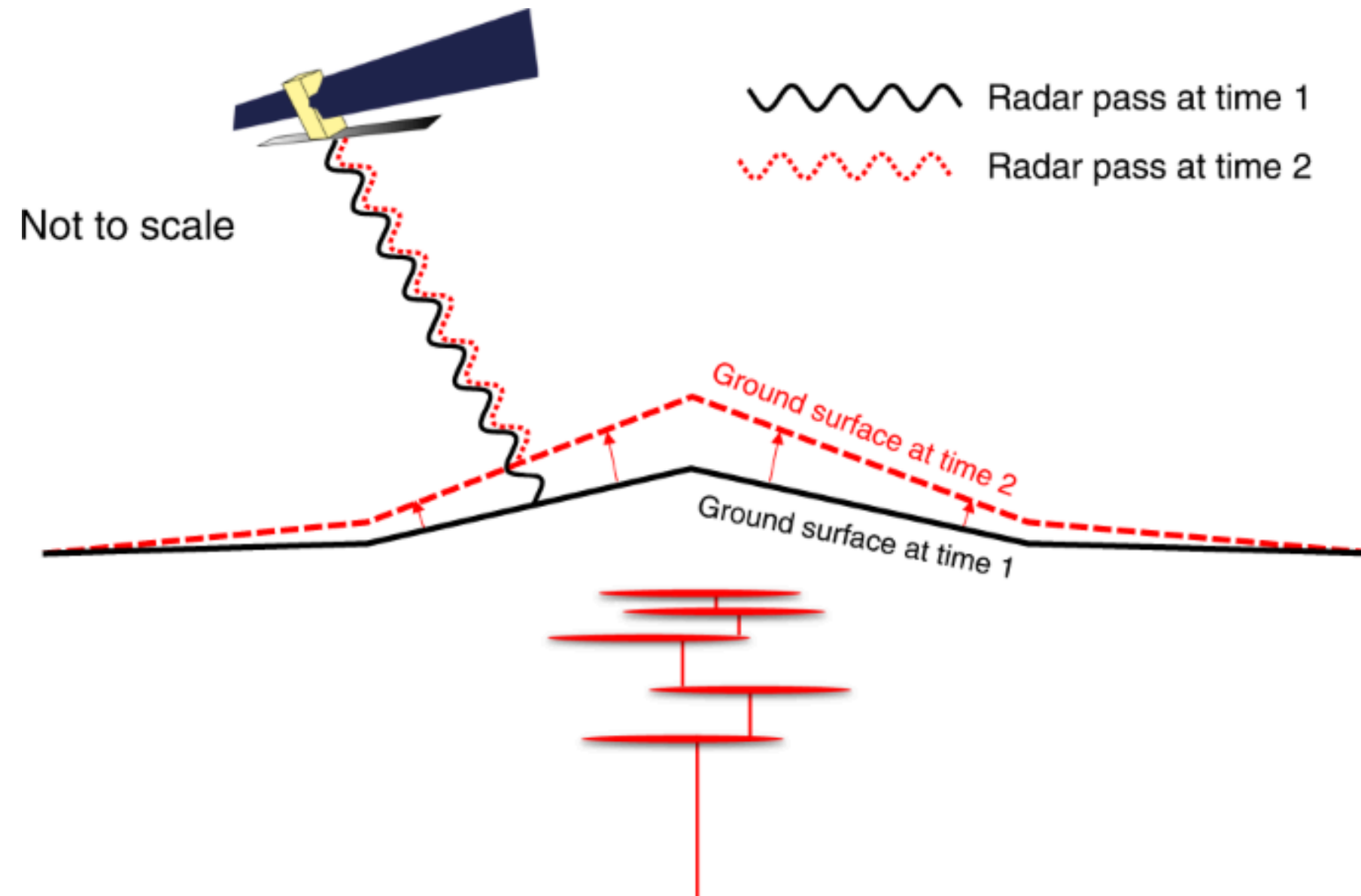
¹ LISTIC, Université de Savoie Mont-Blanc

² ISTERRE, Université Grenoble Alpes



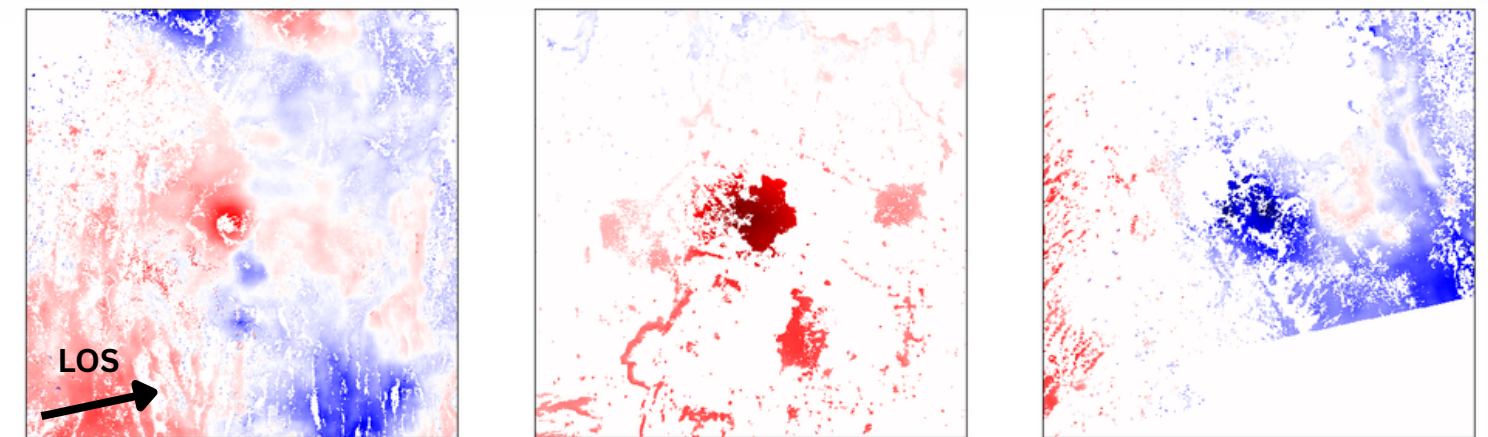
Source: Biggs & Wright (Nature) 2020

1. The source beneath the volcano produces **ground displacement**
2. This displacement is observed **by radar satellite (in the line of sight)**
3. **Artifacts** (atmospheric noise) are acquired at the same moment as the displacement
4. Large uncertainties is associated with **low coherence pixel** (masked in post-processing)



Source: Biggs & Wright (Nature) 2020

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Examples of processed acquisitions that I use

 Towards satellite

 From satellite

We model ground displacement using the analytical solution Mogi (1958)

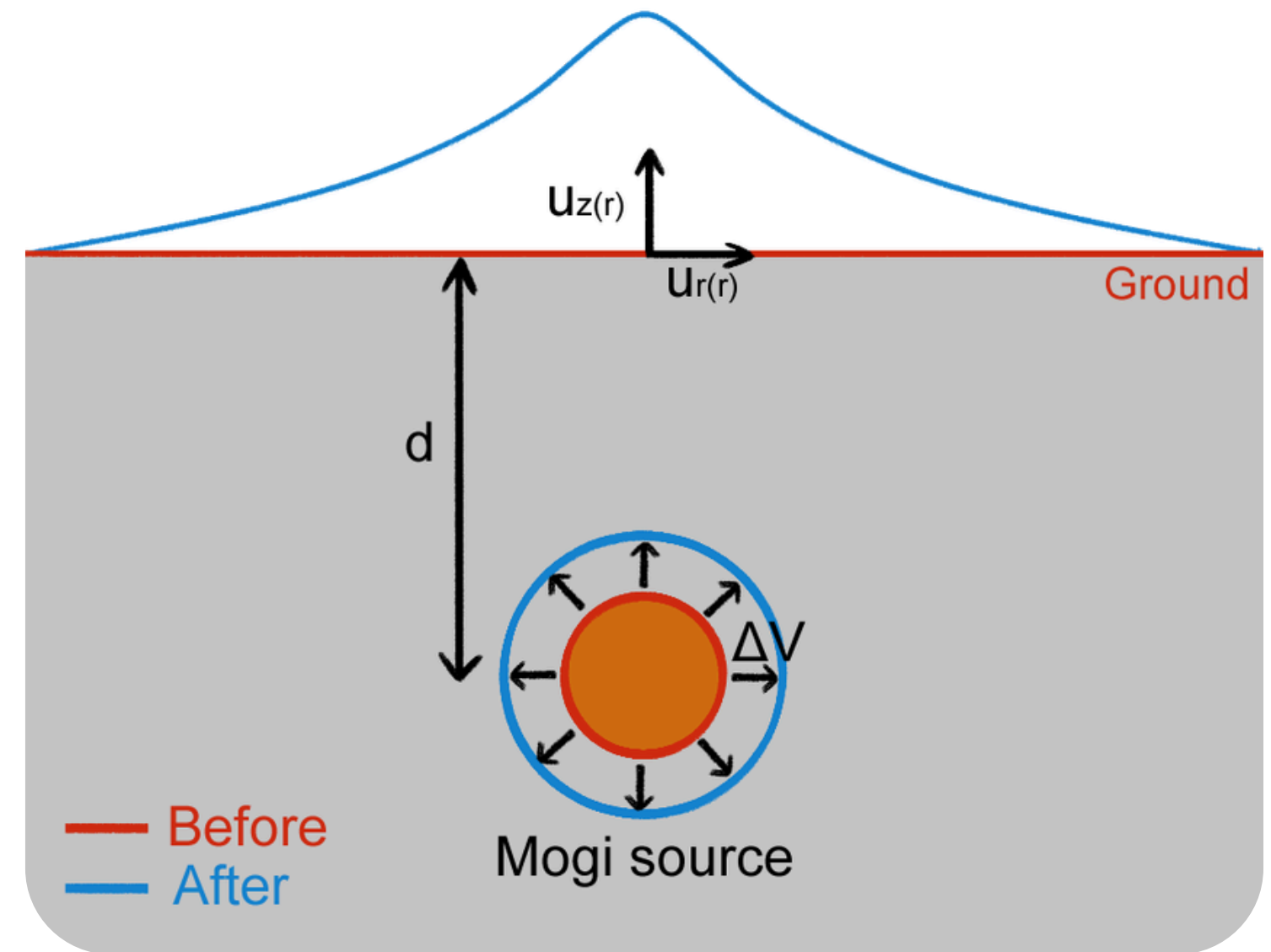
Radial surface displacement :

$$u_r(r) = \frac{r\Delta V}{(r^2 + d^2)^{\frac{3}{2}}} \frac{1 - \nu}{\pi}$$

Vertical surface displacement :

$$u_z(r) = \frac{d\Delta V}{(r^2 + d^2)^{\frac{3}{2}}} \frac{1 - \nu}{\pi}$$

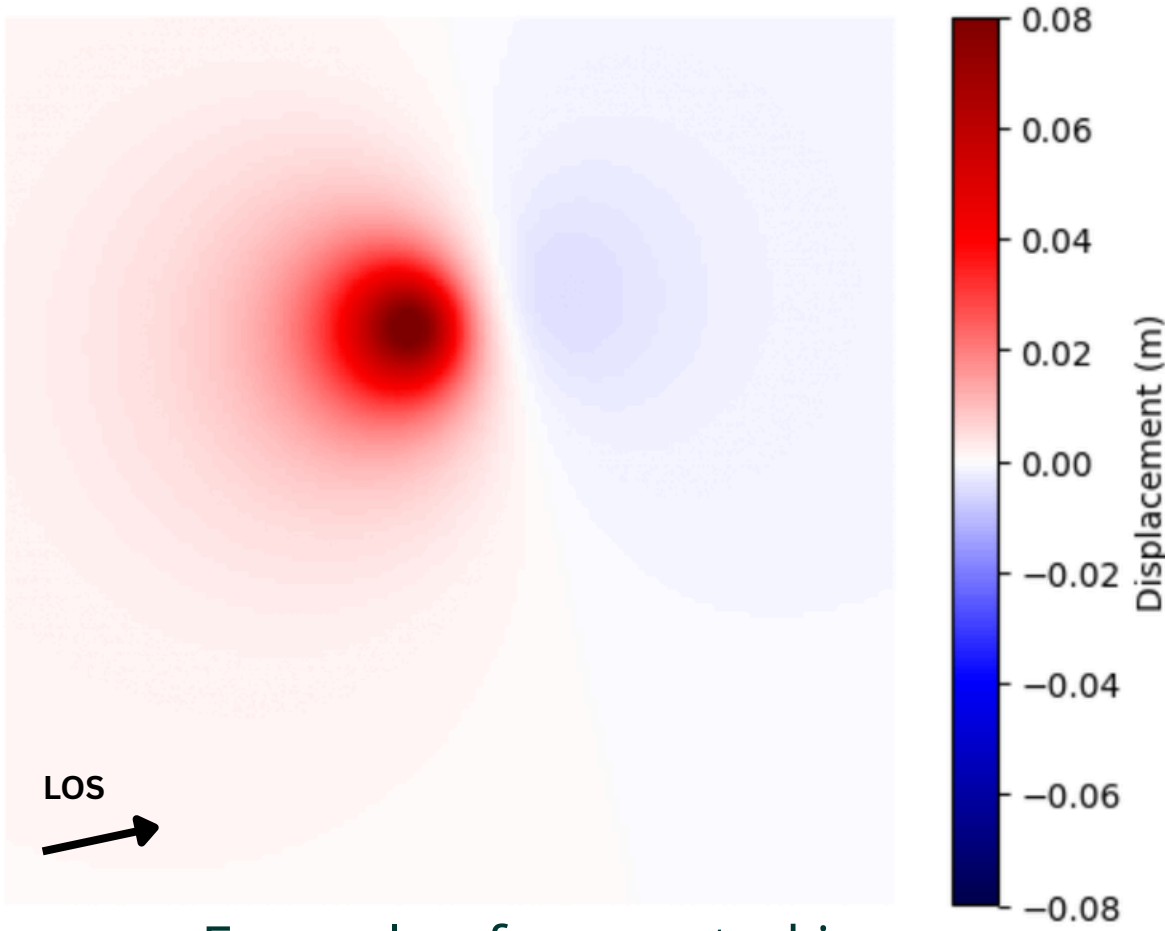
d : depth - ΔV : volume change - $\nu = 0.25$ (Poisson ratio)



Mogi parameter	Value
$d \text{ (km)}$	5
$\Delta V \text{ (}10^6\text{m}^3\text{)}$	8
$X \text{ (km)}$	-2
$Y \text{ (km)}$	10

d : depth – **ΔV** : volume change – **X/Y** : source position

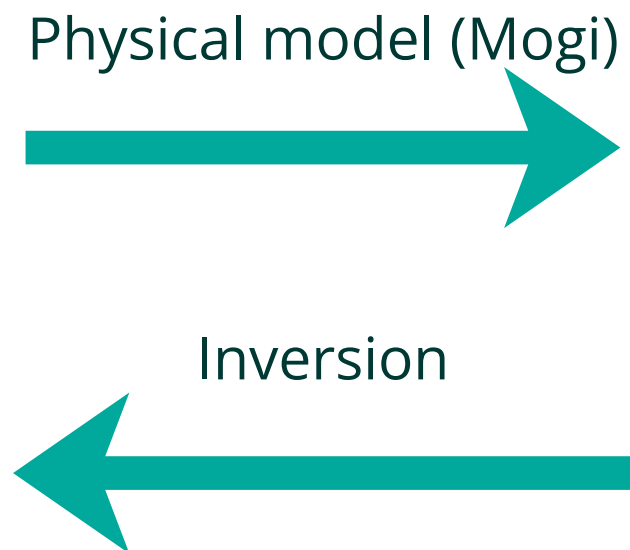
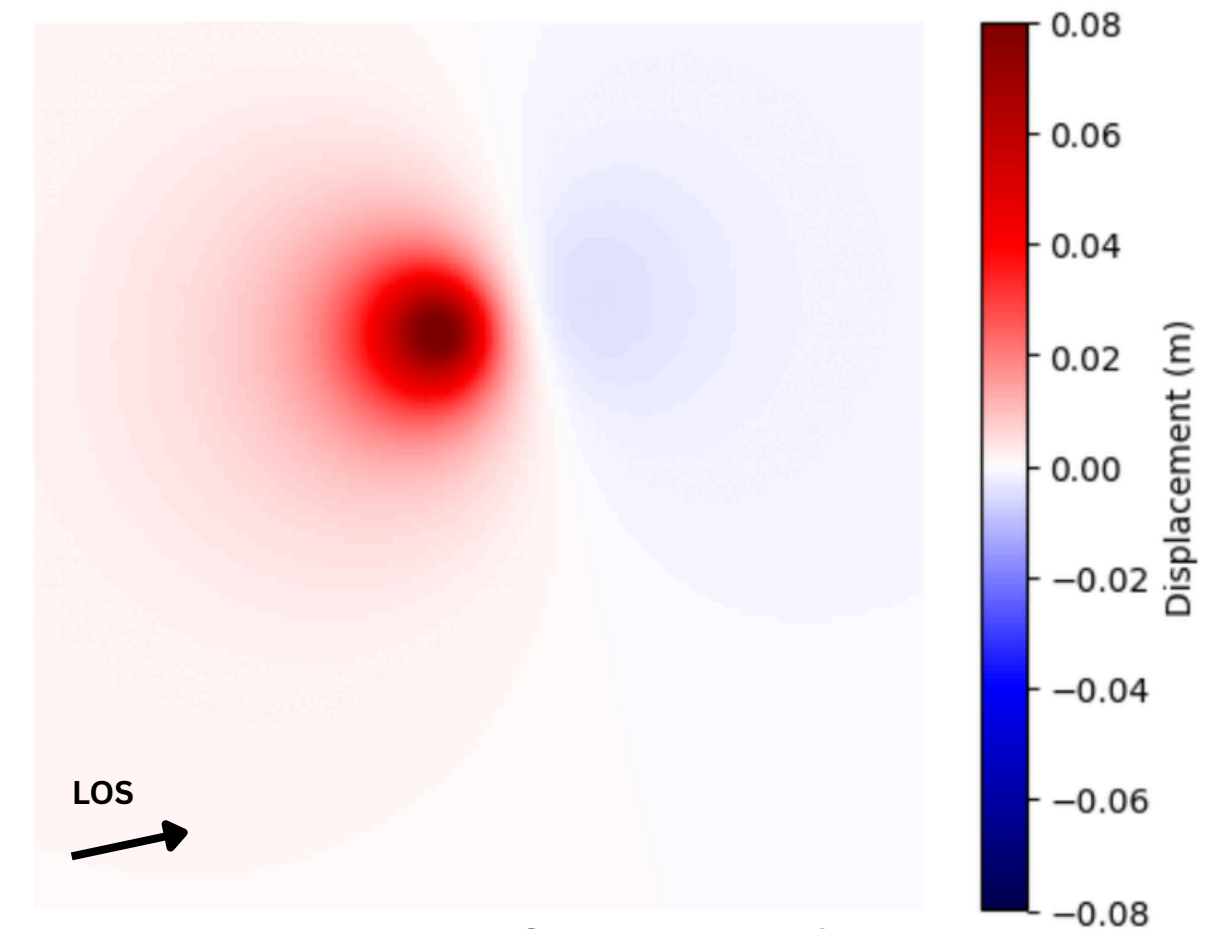
Physical model (Mogi)



Exemple of generated image

Mogi parameter	Value
d (km)	5
ΔV ($10^6 m^3$)	8
X (km)	-2
Y (km)	10

d : depth – ΔV : volume change – X/Y : source position



Exemple of generated image

→ Our inversion aims to determine the parameters of the physical model using a displacement field

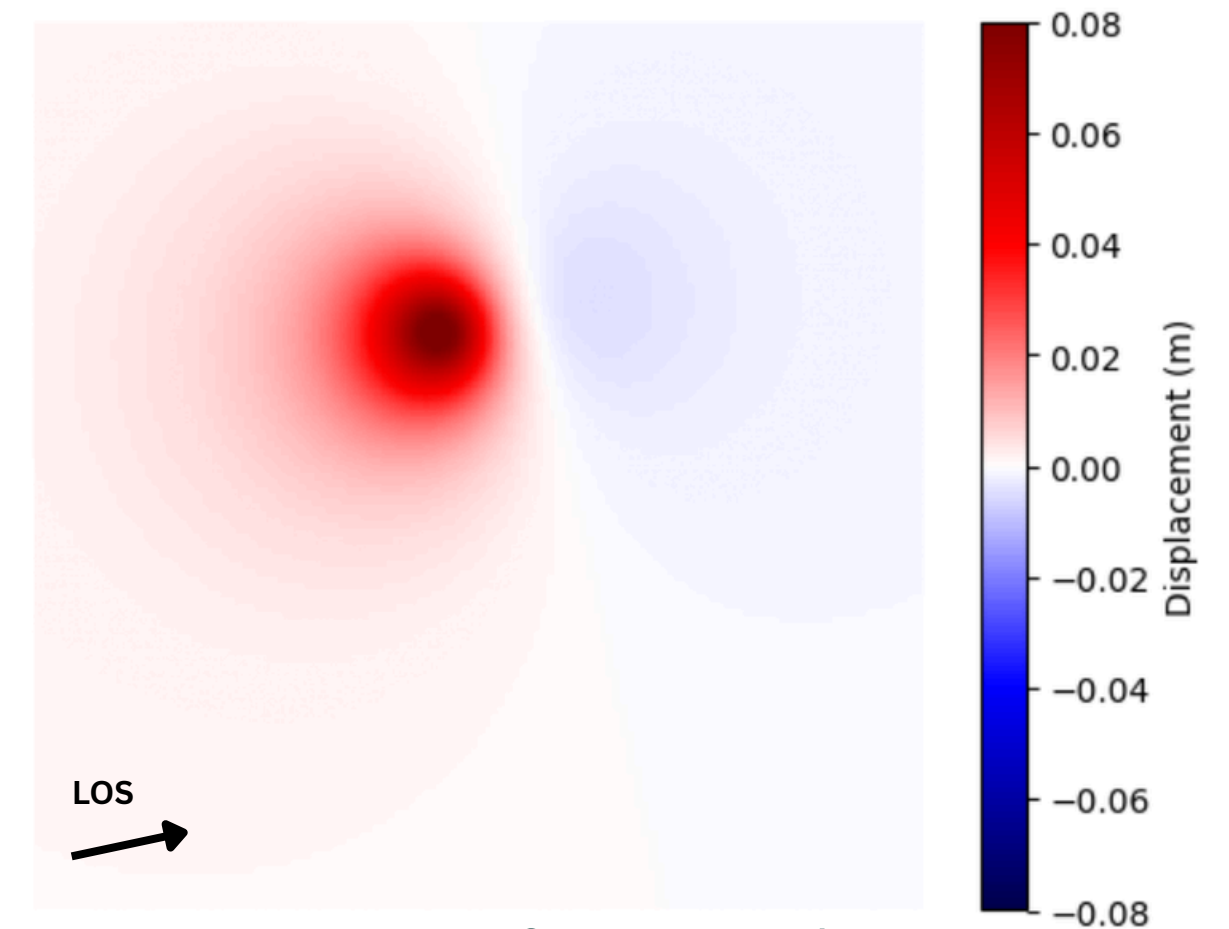
Mogi parameter	Value
d (km)	5
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X (km)	-2
Y (km)	10

d : depth – ΔV : volume change – X/Y : source position

Physical model (Mogi)



Inversion



Exemple of generated image

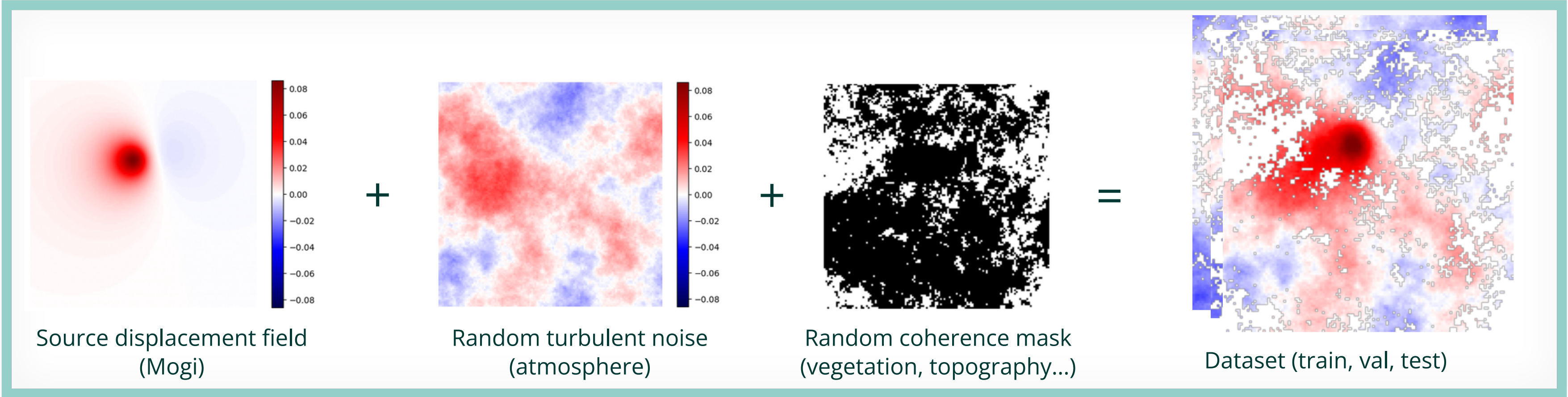
→ Our inversion aims to determine the parameters of the physical model using a displacement field



State of the art for inversion : Gridsearch / Gradient descent / Bayesian approaches (MCMC most used)

- Work well but are **slow** and computationally expensive !
- Do not meet the need for operational risk monitoring !

→ Study of the use of deep learning to meet these time constraints



Mogi parameter	Explored domain
$d \text{ (km)}$	$1 - 10$
$\Delta V \text{ (} 10^6 \text{m}^3 \text{)}$	$(-100) - 100$
$X \text{ (km)}$	$(-10) - 10$
$Y \text{ (km)}$	$(-10) - 10$

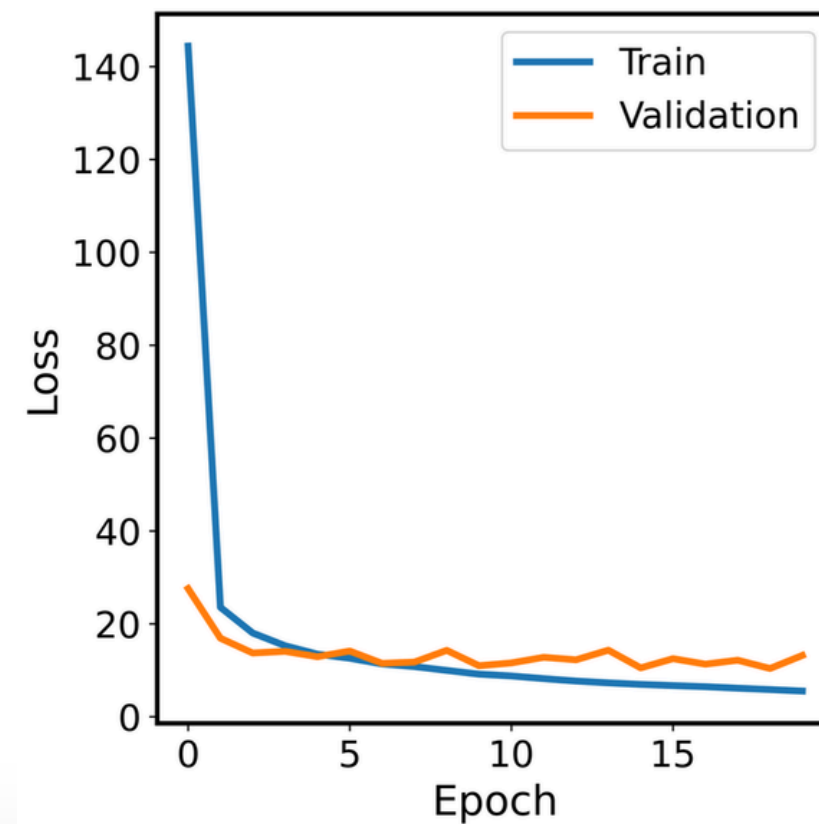
d : depth – **ΔV** : volume change – **X/Y** : source position

Noise parameter	Explored domain
$sill \text{ (m}^2\text{)}$	$10^{-6} - 10^{-4}$
$range \text{ (km)}$	$10 - 100$

sill : field amplitude variance – **range** : spatially correlated scale

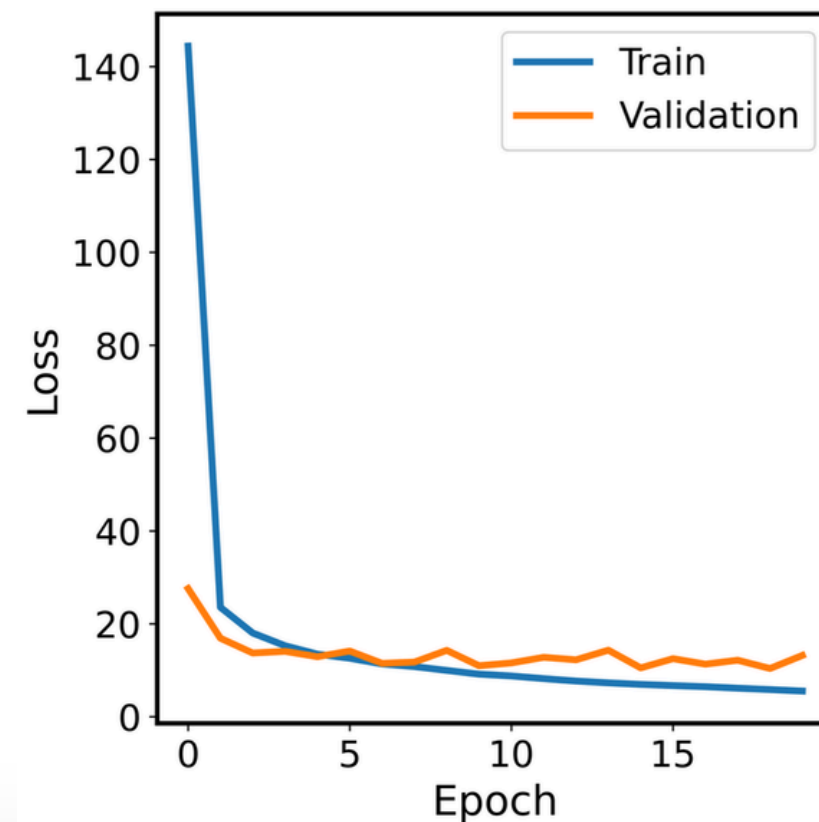
TRAIN

- Resnet Architecture
- **100 000/200 000** data for training
- Input image dimension : **64x64**
- **30** trained models

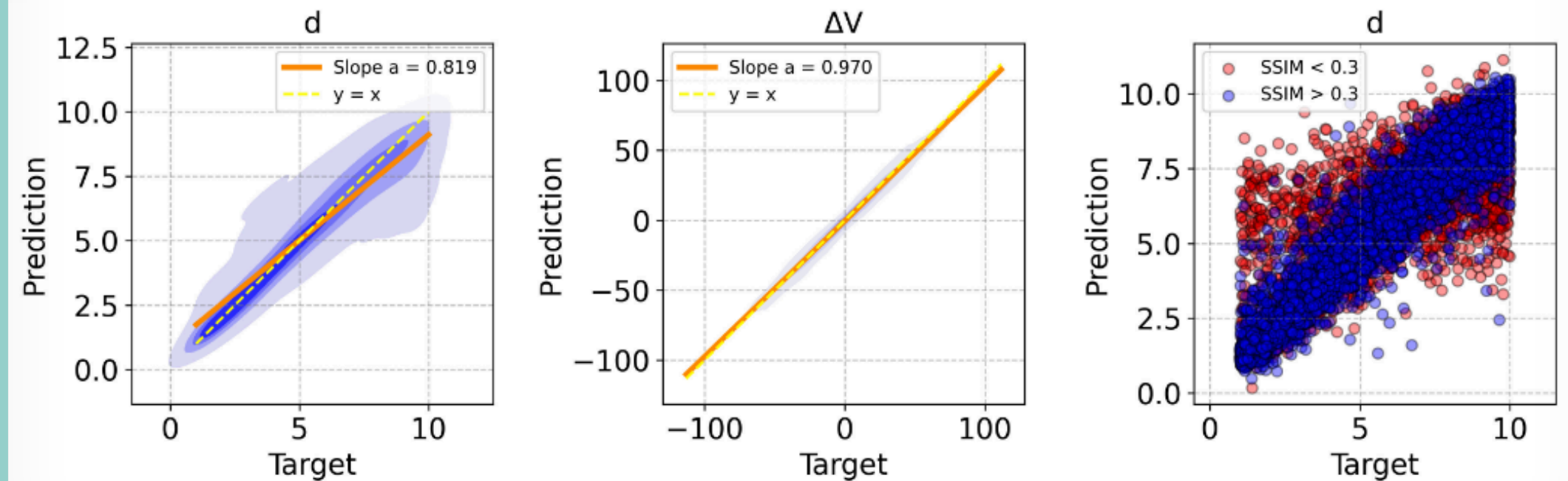


TRAIN

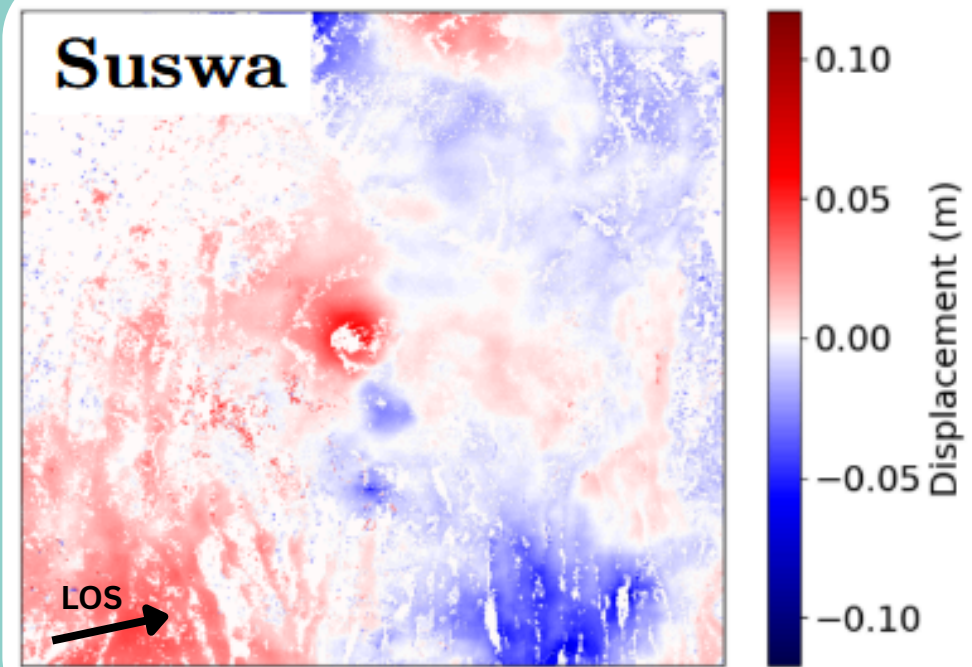
- Resnet Architecture
- **100 000/200 000** data for training
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TEST

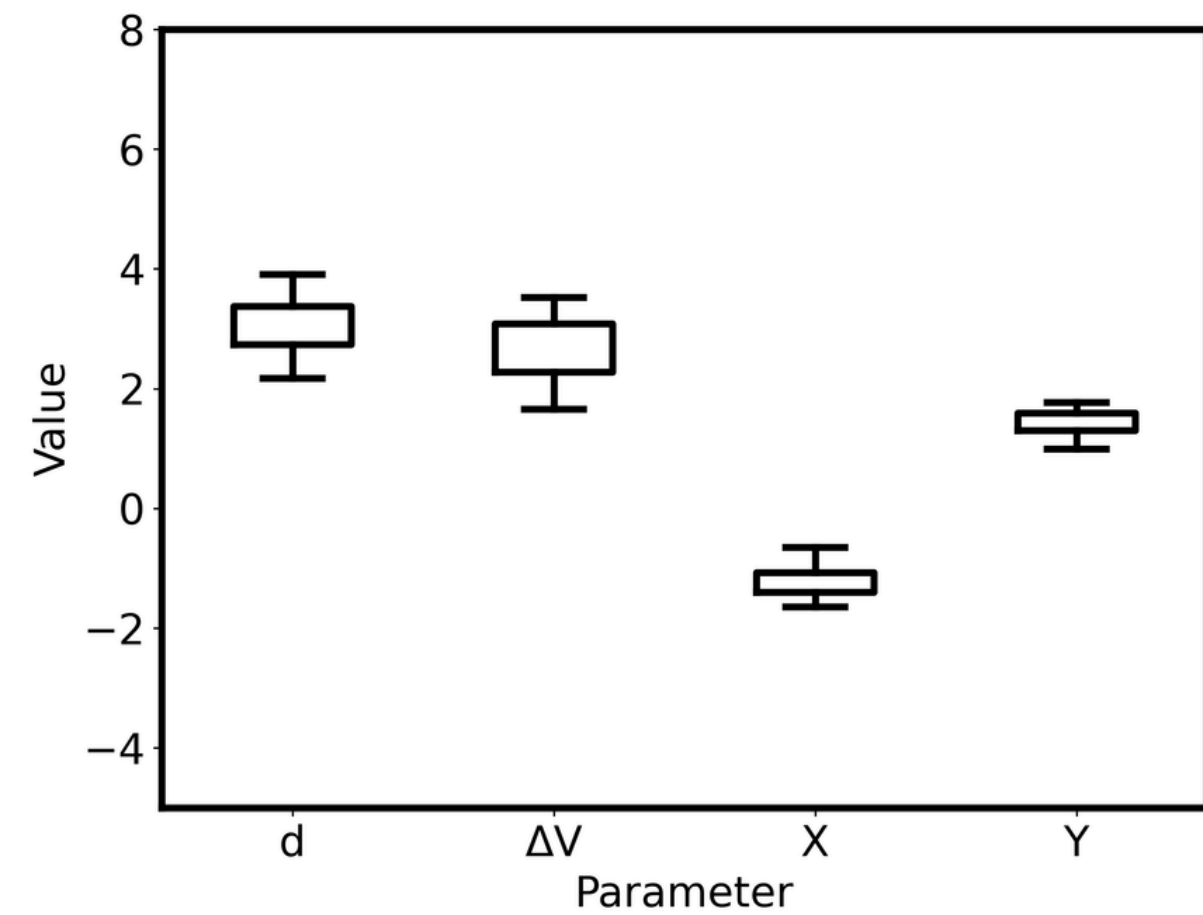


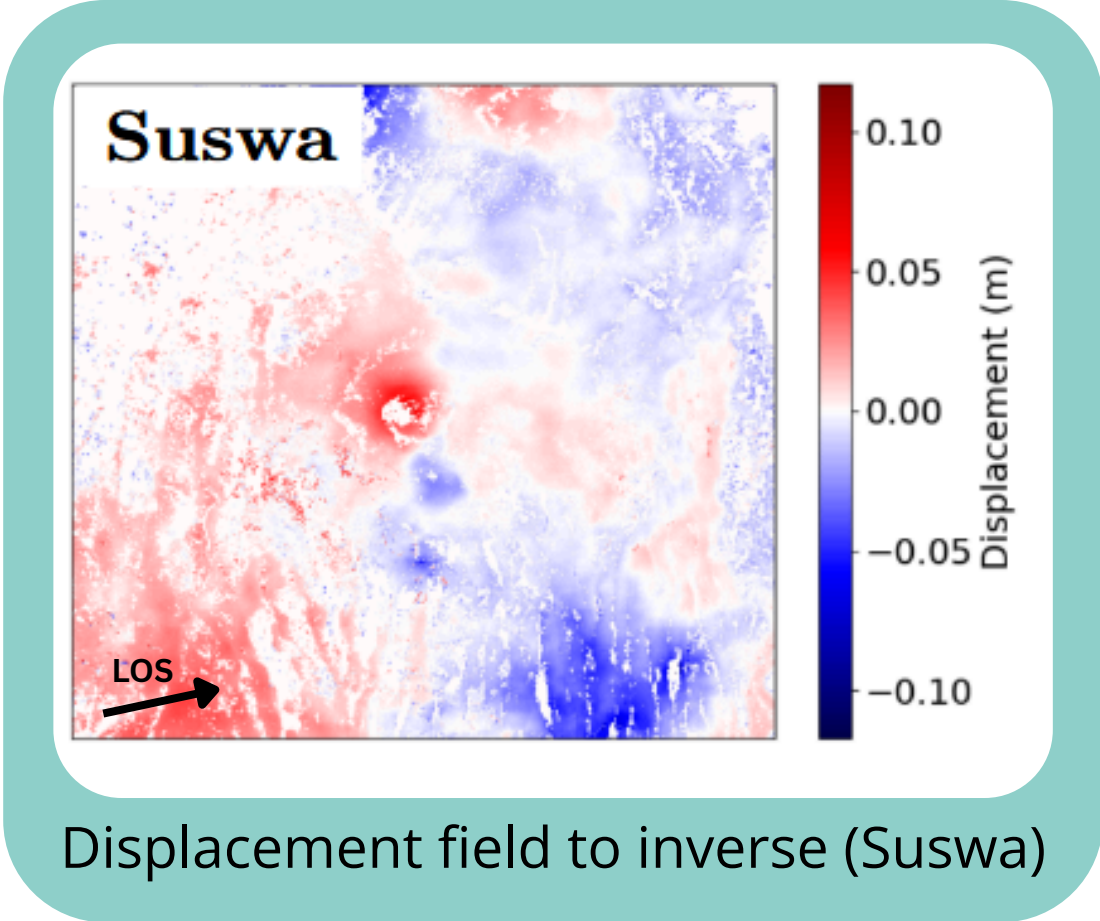
Train and test are made on two different synthetic datasets



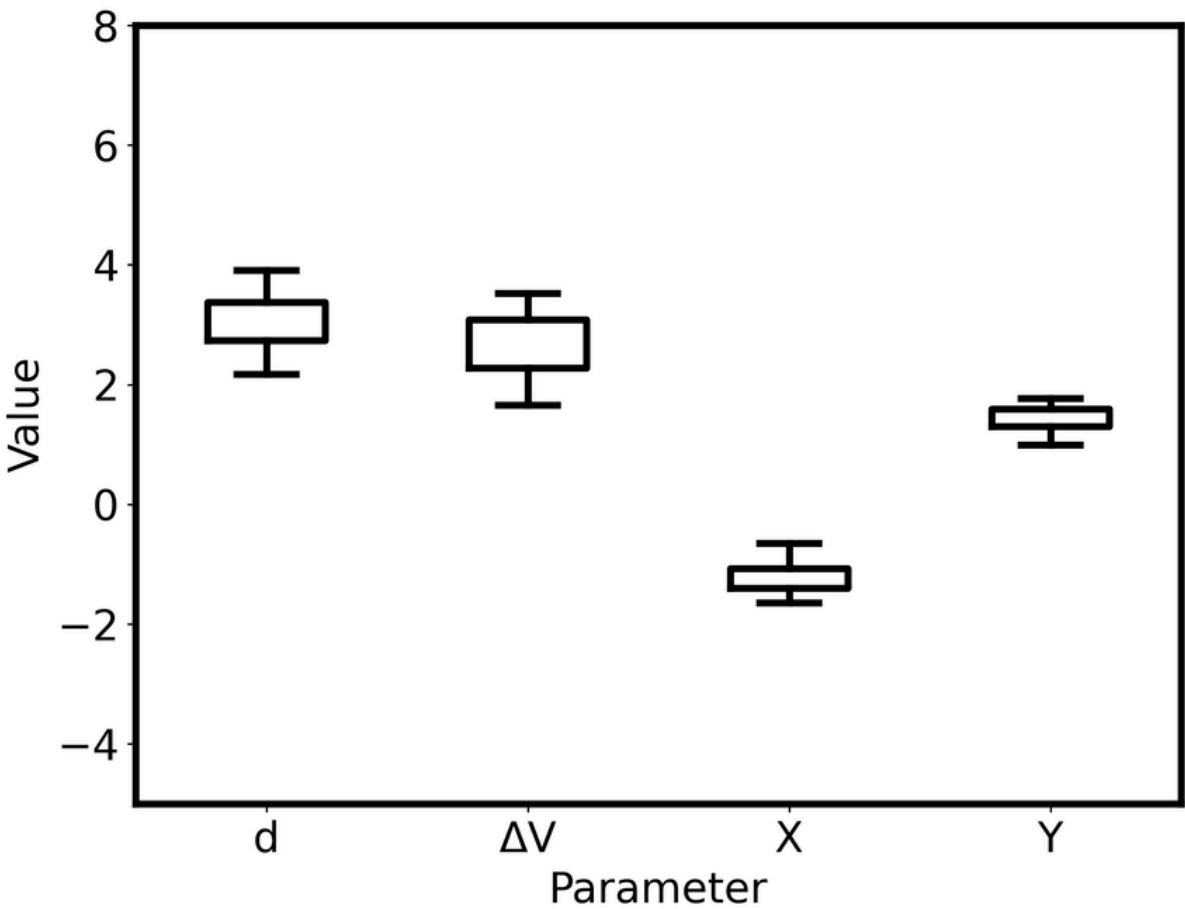
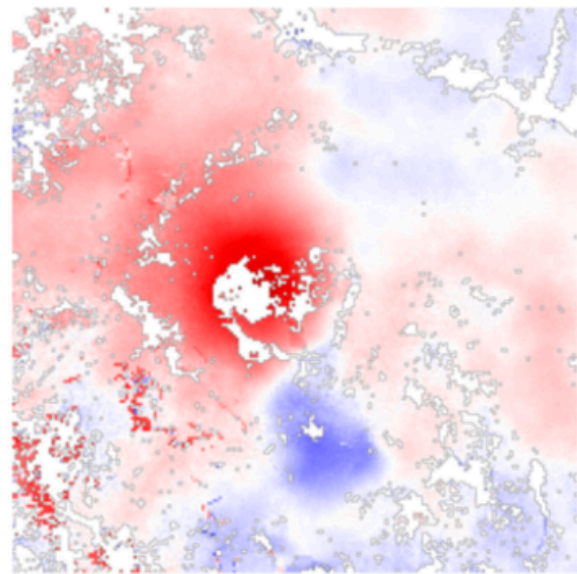
Displacement field to inverse (Suswa)

Inversion with 30 models

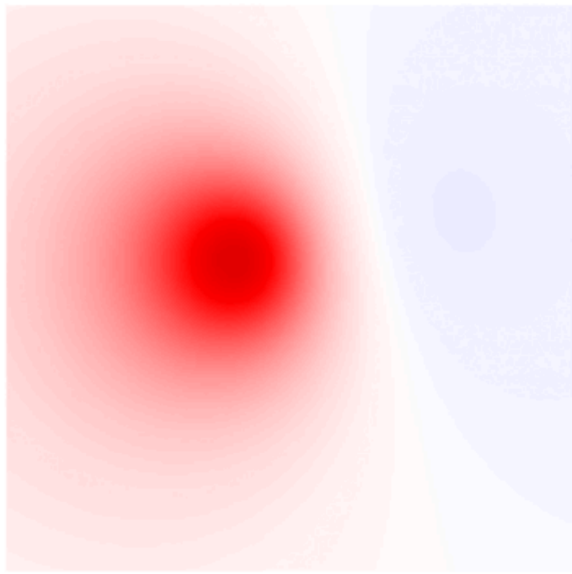




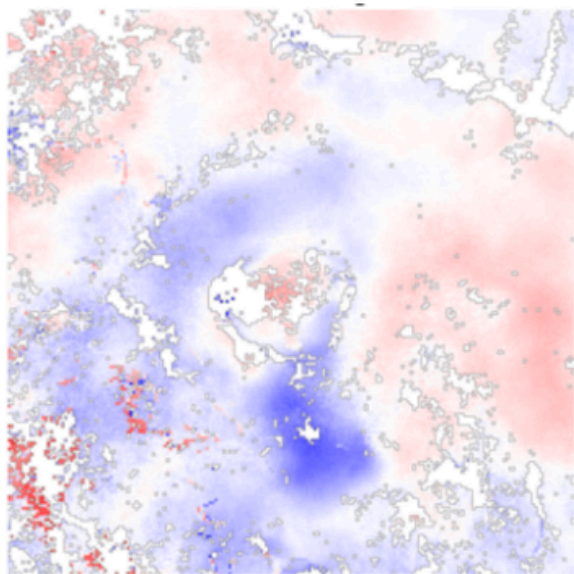
Inversion with 30 models



real image



reconstructed image



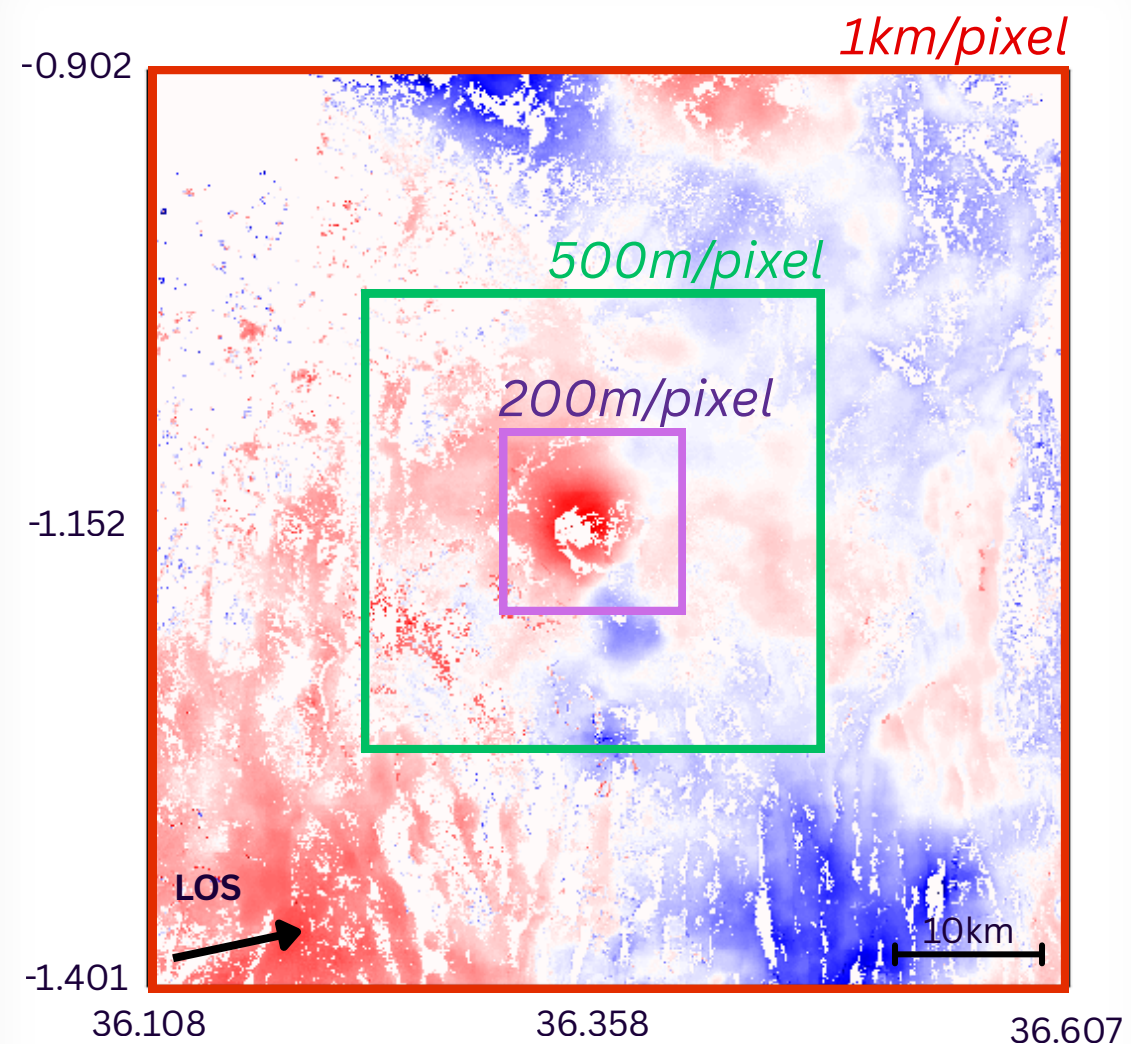
residual image

Selecting the best out of the 30 (RMSE)

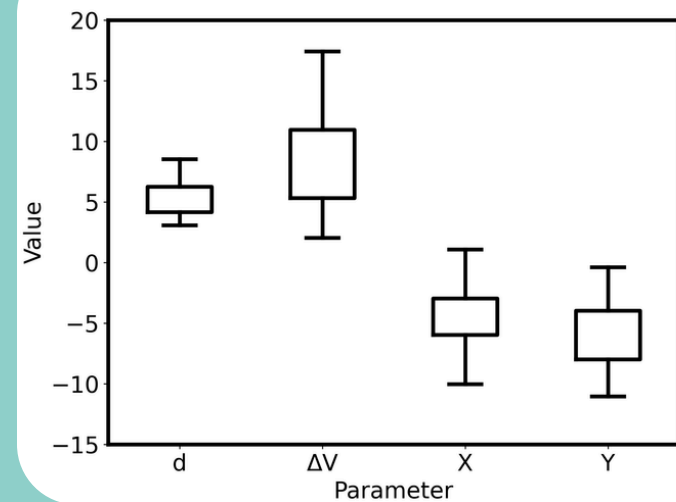


Mogi parameter	Predicted value
$d \text{ (km)}$	3.96
$\Delta V \text{ (} 10^6 \text{m}^3 \text{)}$	3.66
$X \text{ (km)}$	-1.11
$Y \text{ (km)}$	1.69

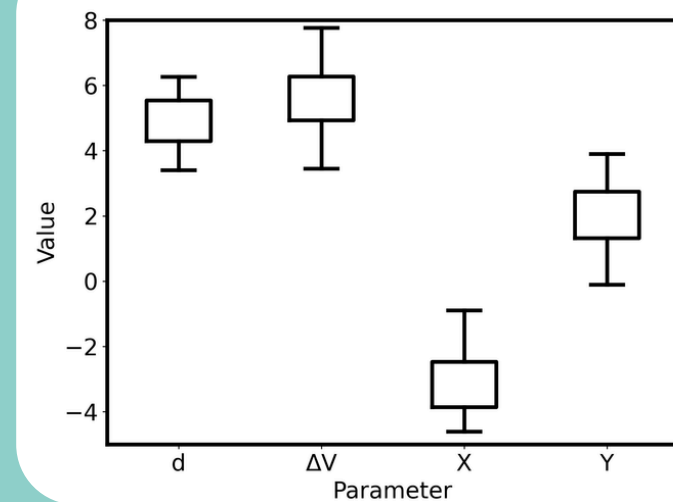
The issue with resolution



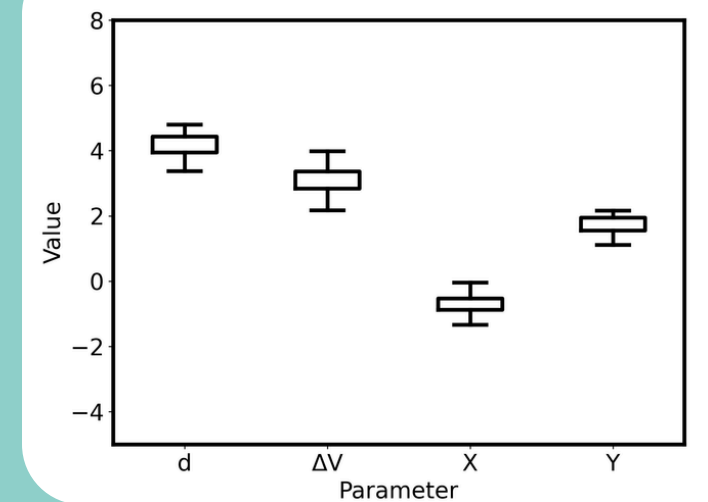
The different resolutions on Suswa
when using dimension of 64x64



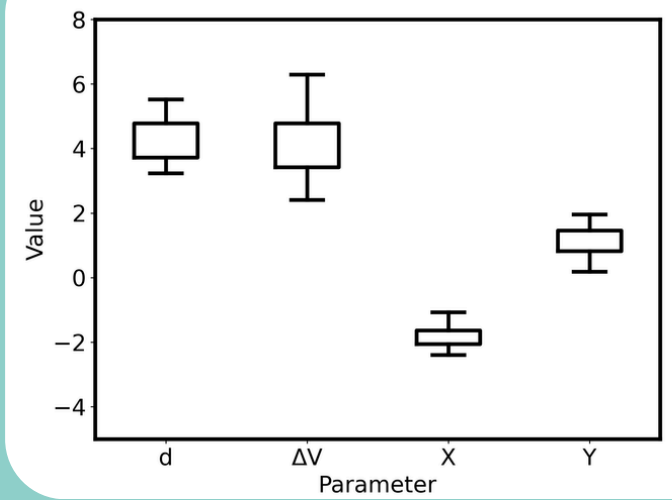
1km/pixel



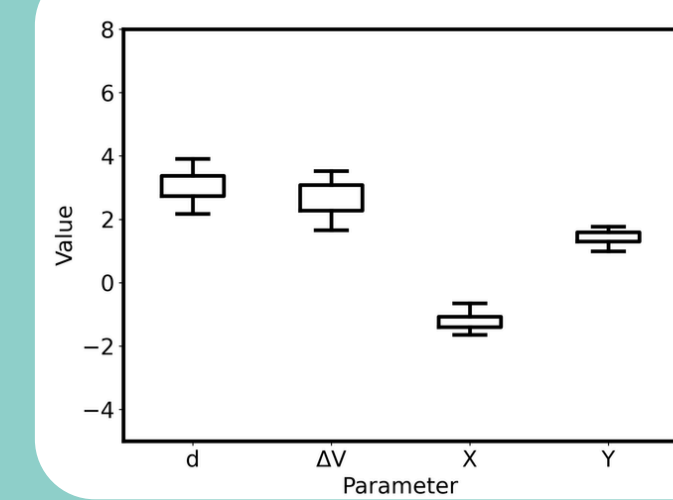
500m/pixel



200m/pixel



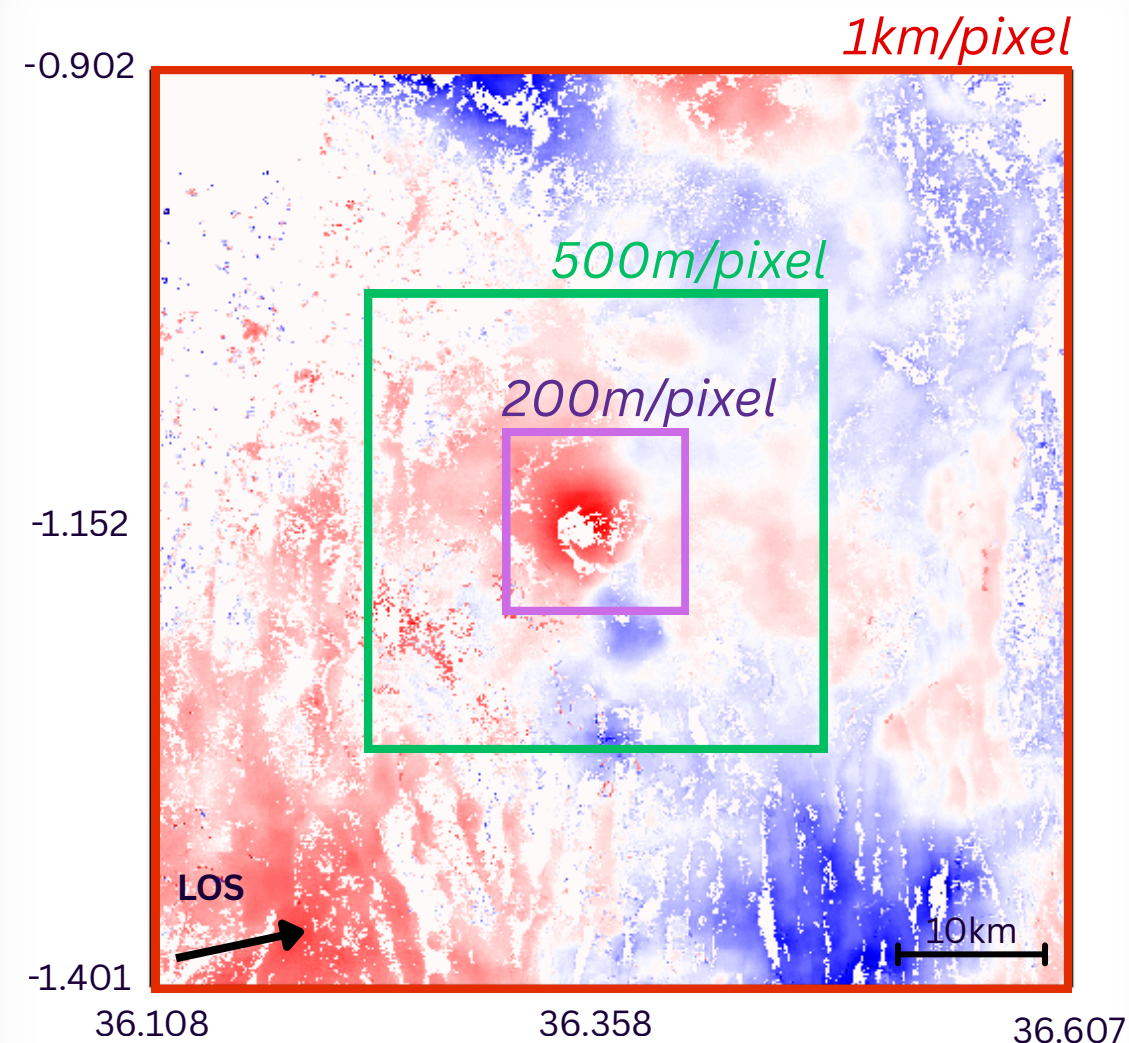
200,500,1000m/pixel



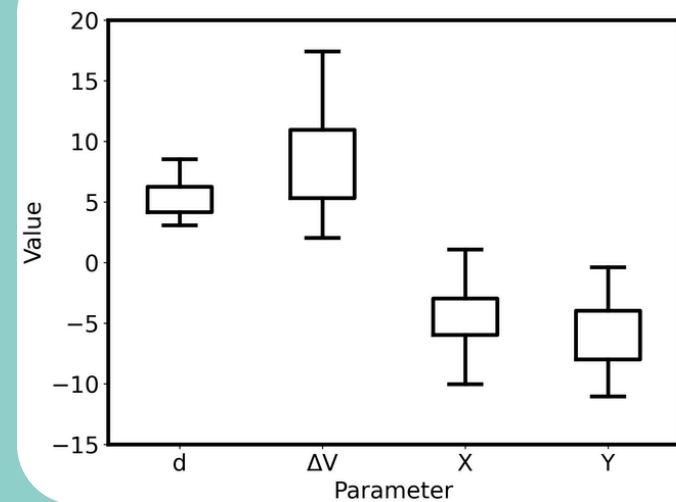
200,300,400m/pixel

Inversion results with different resolutions input set

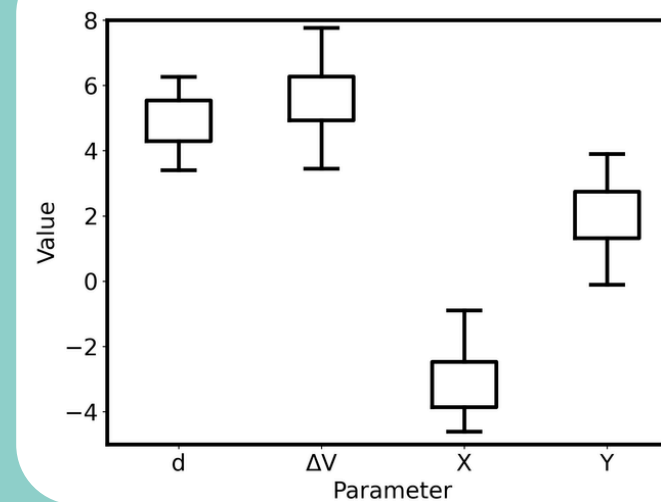
The issue with resolution



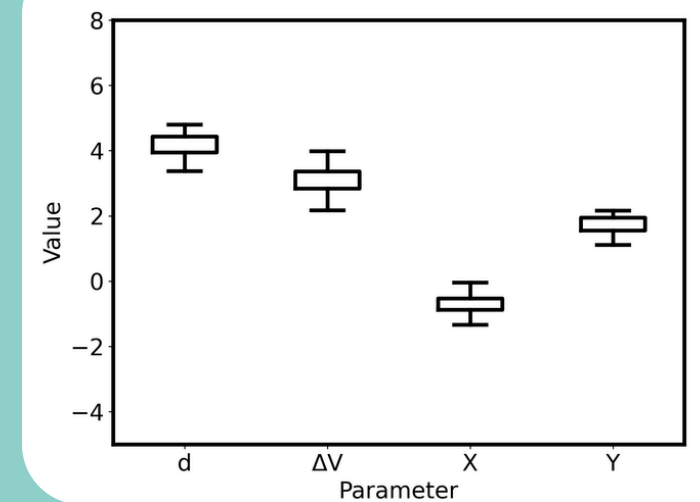
The different resolutions on Suswa
when using dimension of 64x64



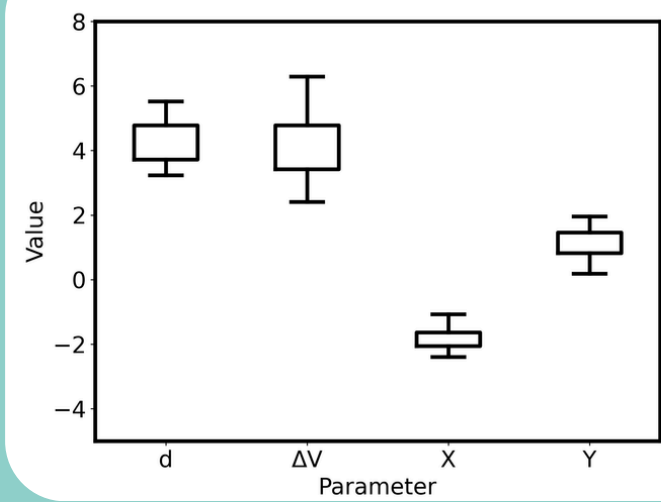
1km/pixel



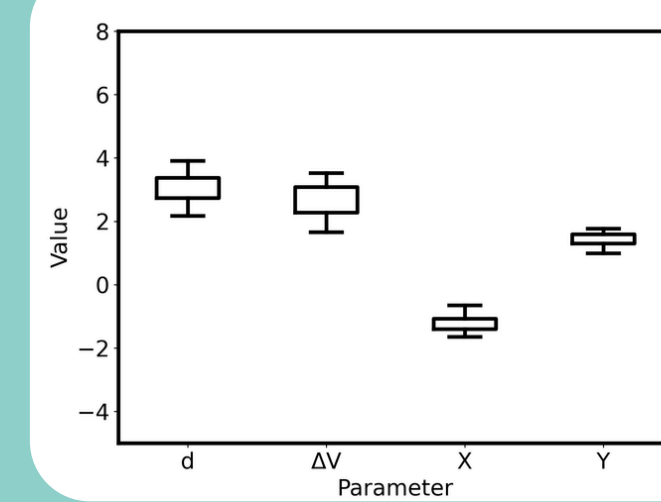
500m/pixel



200m/pixel



200,500,1000m/pixel

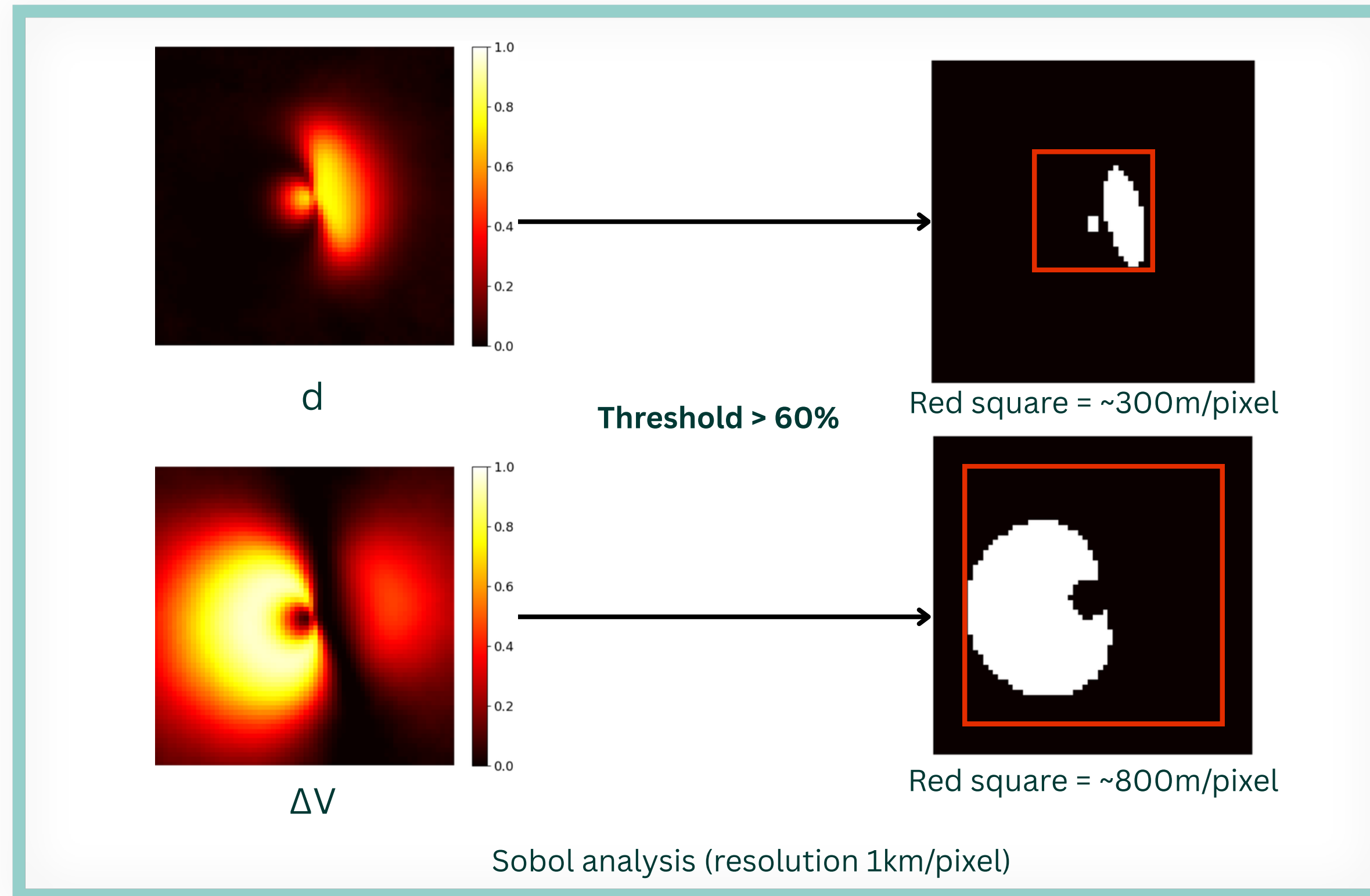


200,300,400m/pixel

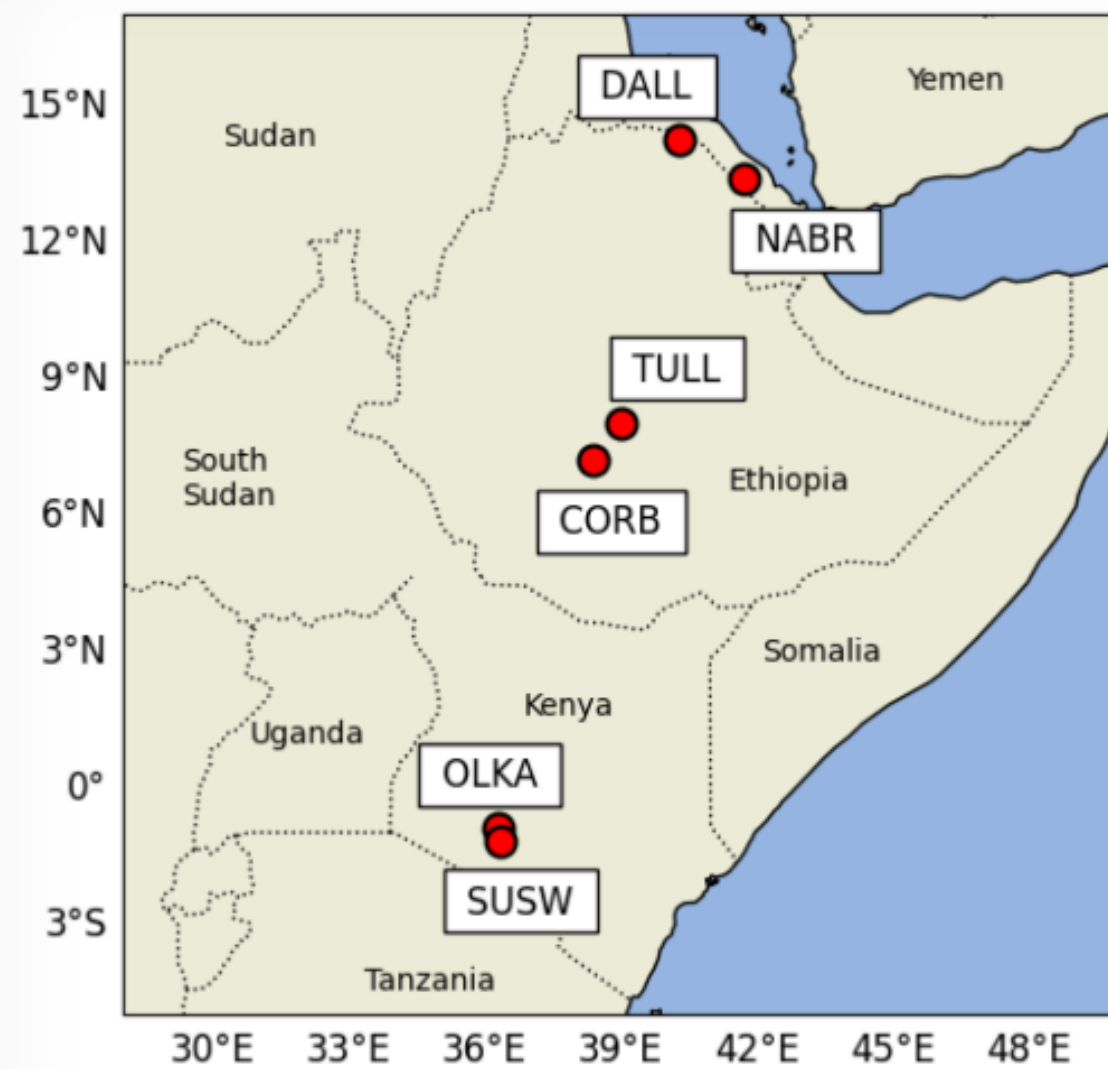
Inversion results with different resolutions input set

→ The chosen resolution significantly affects the results of the inversion

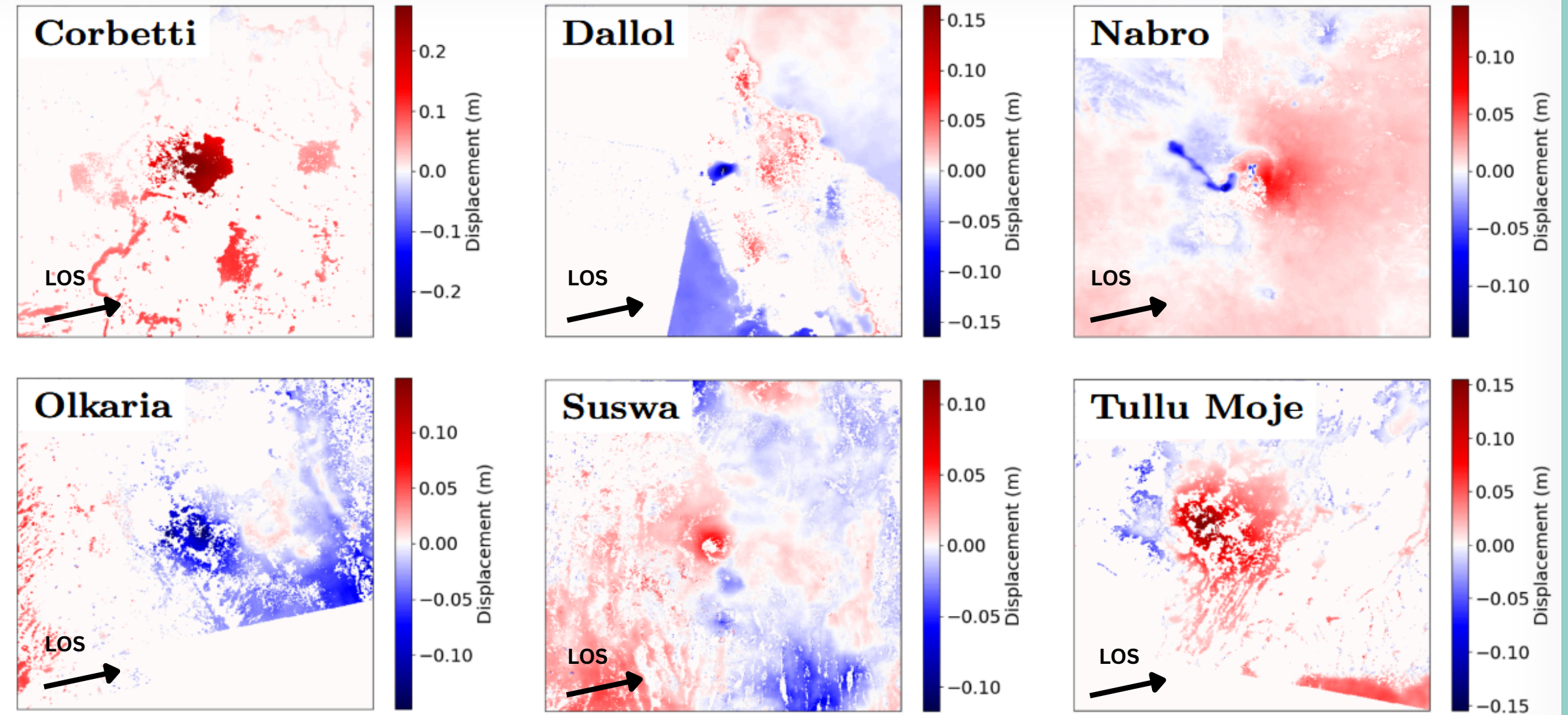
Determining the best resolution set



→ We are using these three resolutions for our model : 300, 550 and 800 m/pixel



Rift East Africa map



Displacement field of each volcano

Each volcano has a very different ground deformation pattern and coherence mask

	$d(km)$		$\Delta V(10^6 m^3)$		$\frac{\Delta V}{d^2}$	
	ResNet	MCMC	ResNet	MCMC	ResNet	MCMC
Corbetti	$5.26^{5.72}_{4.55}$	$7.98^{8.08}_{7.89}$	$31.22^{32.99}_{29.36}$	$76.00^{78.79}_{73.63}$	1.13	1.19
Dallol	$1.66^{2.47}_{1.25}$	$1.14^{1.16}_{1.12}$	$-1.84^{-1.81}_{-3.43}$	$-0.90^{-0.87}_{-0.93}$	-0.67	-0.70
Nabro	$6.78^{6.78}_{4.37}$	$3.99^{4.24}_{3.79}$	$5.02^{7.30}_{4.07}$	$5.01^{5.82}_{4.41}$	0.11	0.31
Olkaria	$4.80^{6.44}_{4.69}$	$6.87^{7.14}_{6.63}$	$-10.82^{-10.81}_{-14.67}$	$-27.79^{-25.43}_{-30.80}$	-0.47	-0.59
Suswa	$4.31^{5.17}_{3.67}$	$3.08^{3.20}_{2.97}$	$3.98^{5.30}_{3.08}$	$3.01^{3.29}_{2.76}$	0.21	0.32
Tullu Moje	$8.05^{8.91}_{7.34}$	$6.13^{6.26}_{6.00}$	$25.35^{28.14}_{22.92}$	$28.53^{30.08}_{26.94}$	0.39	0.76

Results compared with the MCMC algorithm from [1]

[1] Ireland, B., Biggs, J., Anantrasirichai, N., Albino, F., Dualeh, E.W.: Towards systematic modelling of volcano deformation sources using automatically-generated insar products. ESS Open Archive 2025(0912) (2025).

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Results compared with the MCMC algorithm from [1]

→ Our results are similar to classical inversion, but they differ by the metrics we are using

[1] Ireland, B., Biggs, J., Anantrasirichai, N., Albino, F., Dualeh, E.W.: Towards systematic modelling of volcano deformation sources using automatically-generated insar products. ESS Open Archive 2025(0912) (2025).

CONCLUSIONS

- > The value of neural networks for inversion is confirmed
- > We are able to reproduce the results of a standard inversion by training about thirty models
- > Resolution is a key factor that affects the quality of the results

PERSPECTIVES

- > The next step will be to work on more complex physical models
- > Other types of architecture could be explored for this purpose
- > CNNs can be used to process wrapped images

Thank you for your listening !

Contact

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Lab: LISTIC, Université de Savoie Mont-Blanc