Denoising Unwrapped Interferograms using Deep Learning

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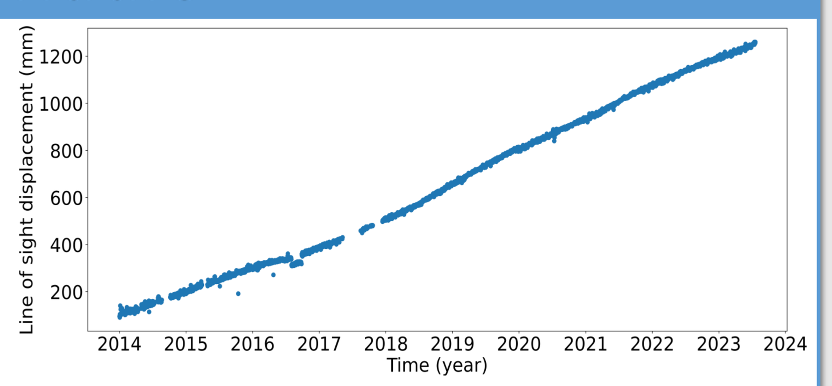
Aim: To study the use of deep learning for noise removal from InSAR images

Problem statement

- Interferograms encompass both deformation and atmospheric effects along the radar path. The presence of atmospheric artefacts can resemble or distort the deformation signal, leading to less precise detection of deformation.
- Current atmospheric removal methods such as GACOS or ERA5 corrections are based on global weather models with limited spatial resolution.
- Deep learning techniques are good at removing noise from natural images.

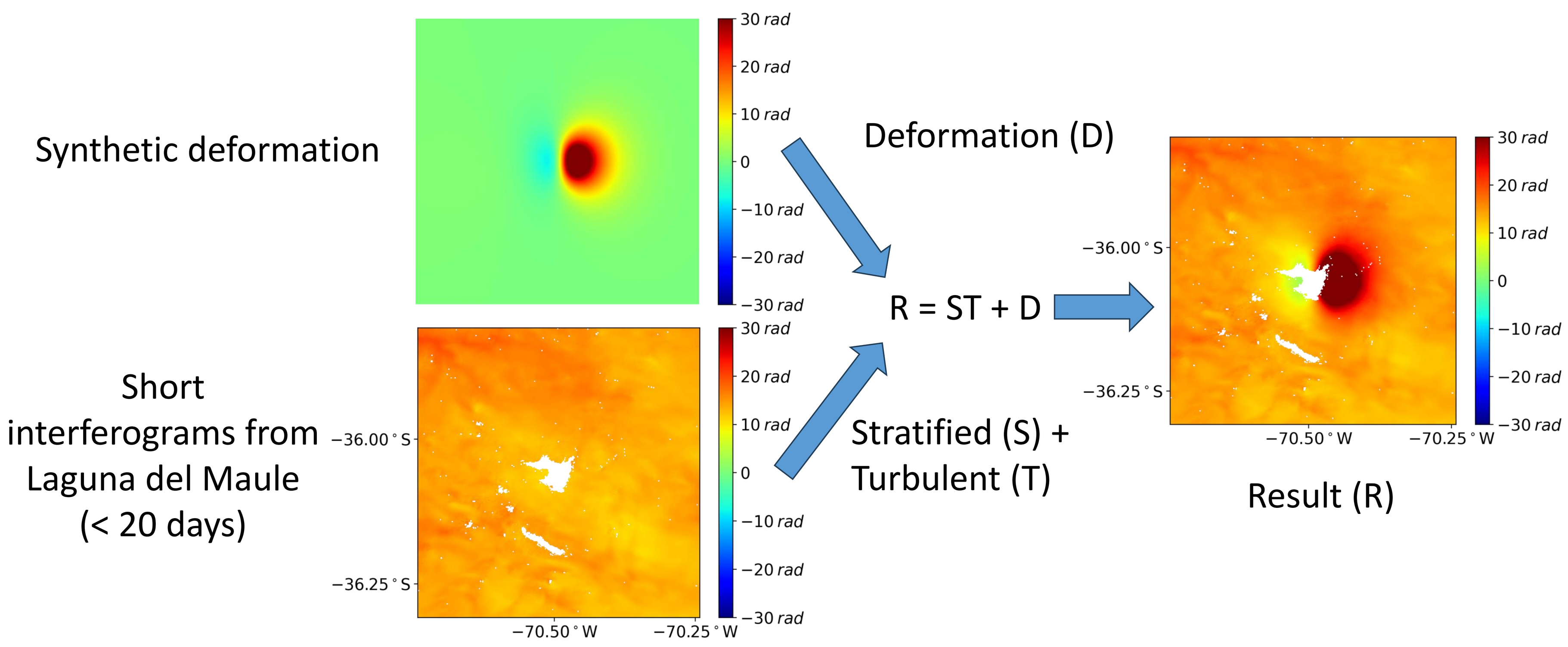
1. Case Study – Laguna del Maule

- Relatively steady deformation is present at Laguna del Maule.
- Short term interferograms may not capture any deformation.
- GPS data is available. This can be used a benchmark for how well a model performs.



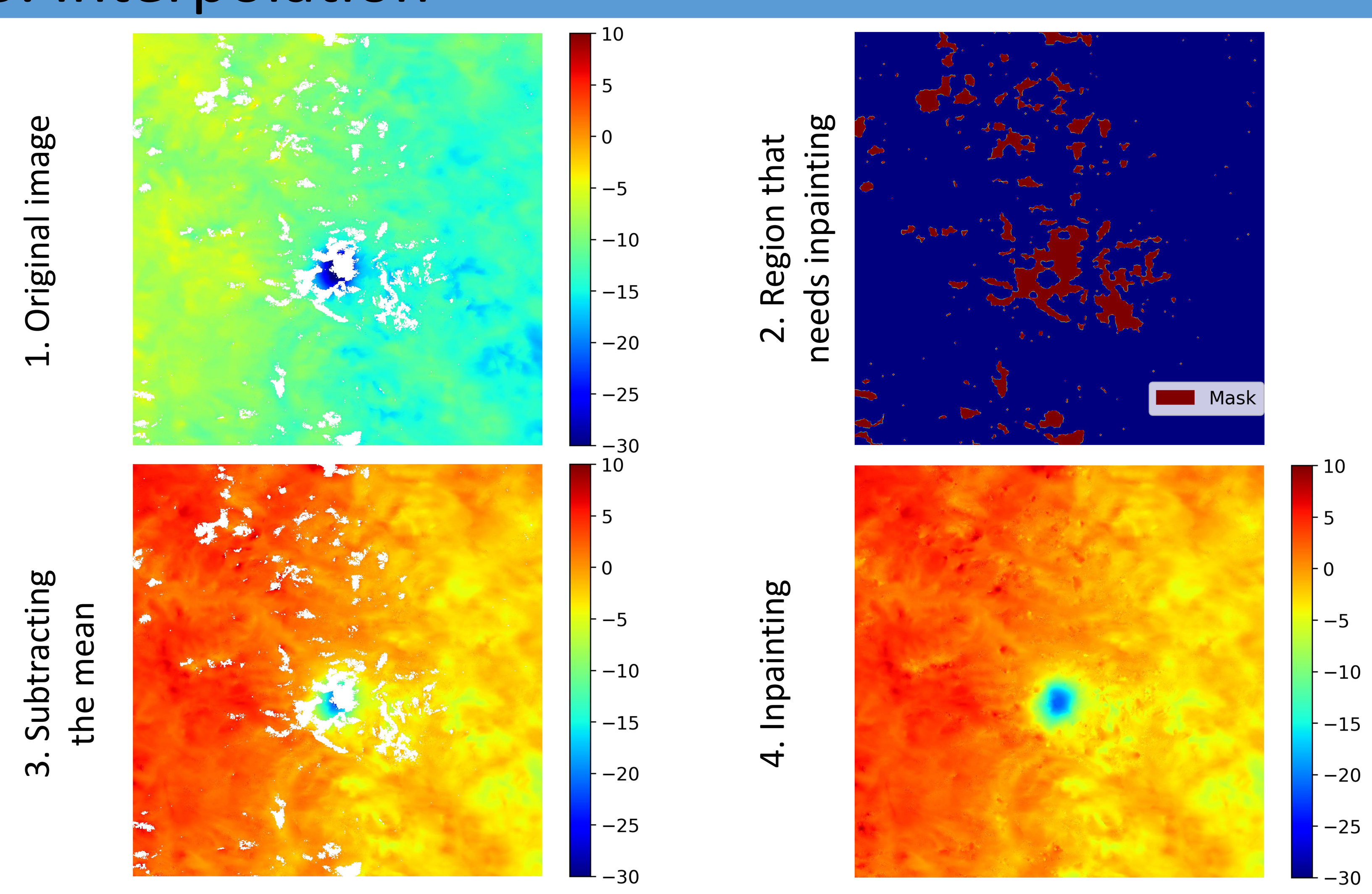
Displacement from MAU2 GPS station

2. Synthetic Training Dataset



- We create a dataset by combining synthetic deformation with real interferograms from Laguna del Maule.
- We generate synthetic deformation using different geological observations with different models: Earthquake, Dike (Okada), Mogi (Magma Chamber), Sill (Penny Crack) and Rectangular Sill.
- We use short interferograms during training to avoid any deformation being present in the images.

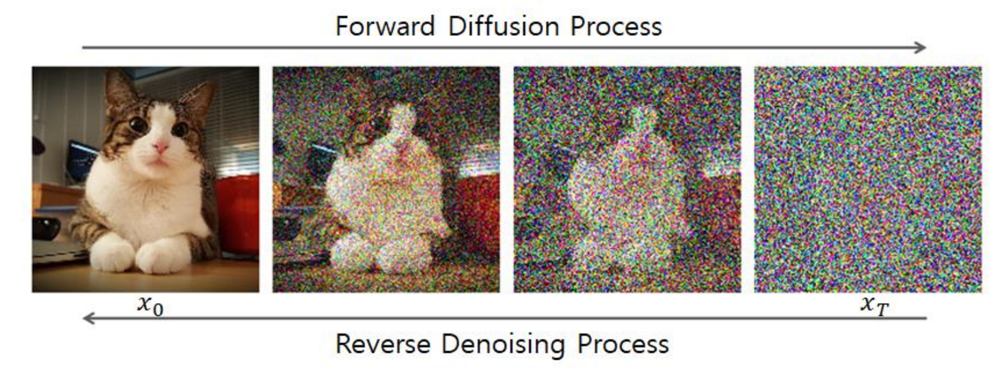
3. Interpolation



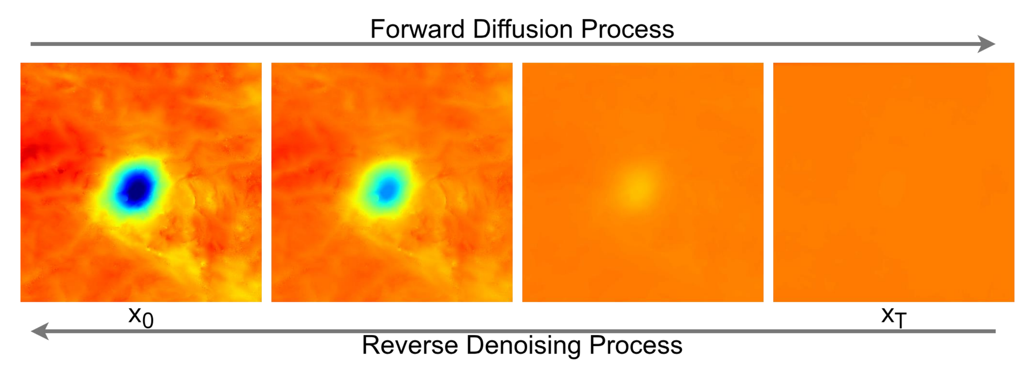
- Most interferograms from Laguna del Maule have missing values (NaN values).
- Deep learning models don't work with input images that have NaN values. The models perform multiple matrix multiplications which propagate and multiply the NaN values present in the input, resulting in an output of only NaN values.
- We could replace the NaN values with zeros, but that will increase the difficulty of our task.
- We will interpolate over the areas with missing values.
- Interferograms with more than 50% of values missing are skipped .

4. Denoising Diffusion Probabilistic Models

- During training, Gaussian noise is gradually added to an image. The model learns to extract the noise from the noisy image.
- We replaced the Gaussian noise with spatially correlated noise to be more representative of atmospheric noise in InSAR
- During testing, after gradually adding noise to an image, the denoising formula is applied using the noise extracted by the model. This denoising step is applied until all the noising steps are reversed.



Original diffusion process using Gaussian noise

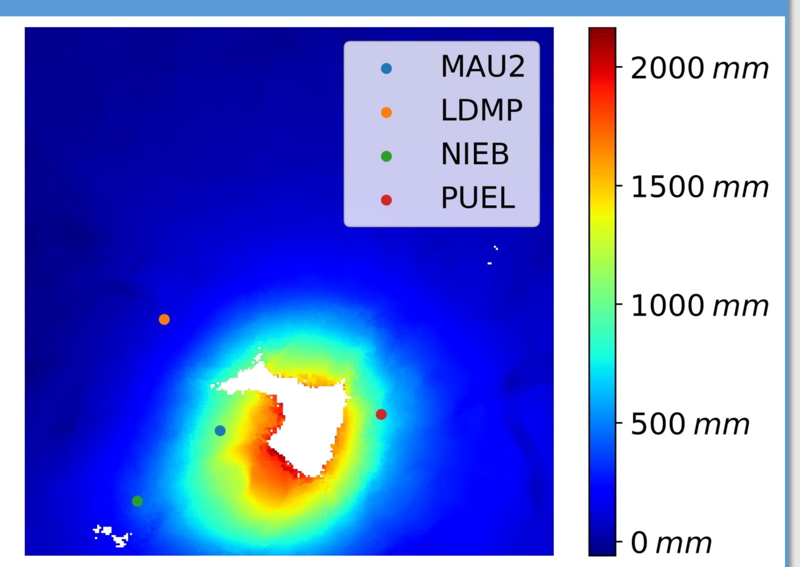


Modified diffusion process using atmospheric noise

5. Results

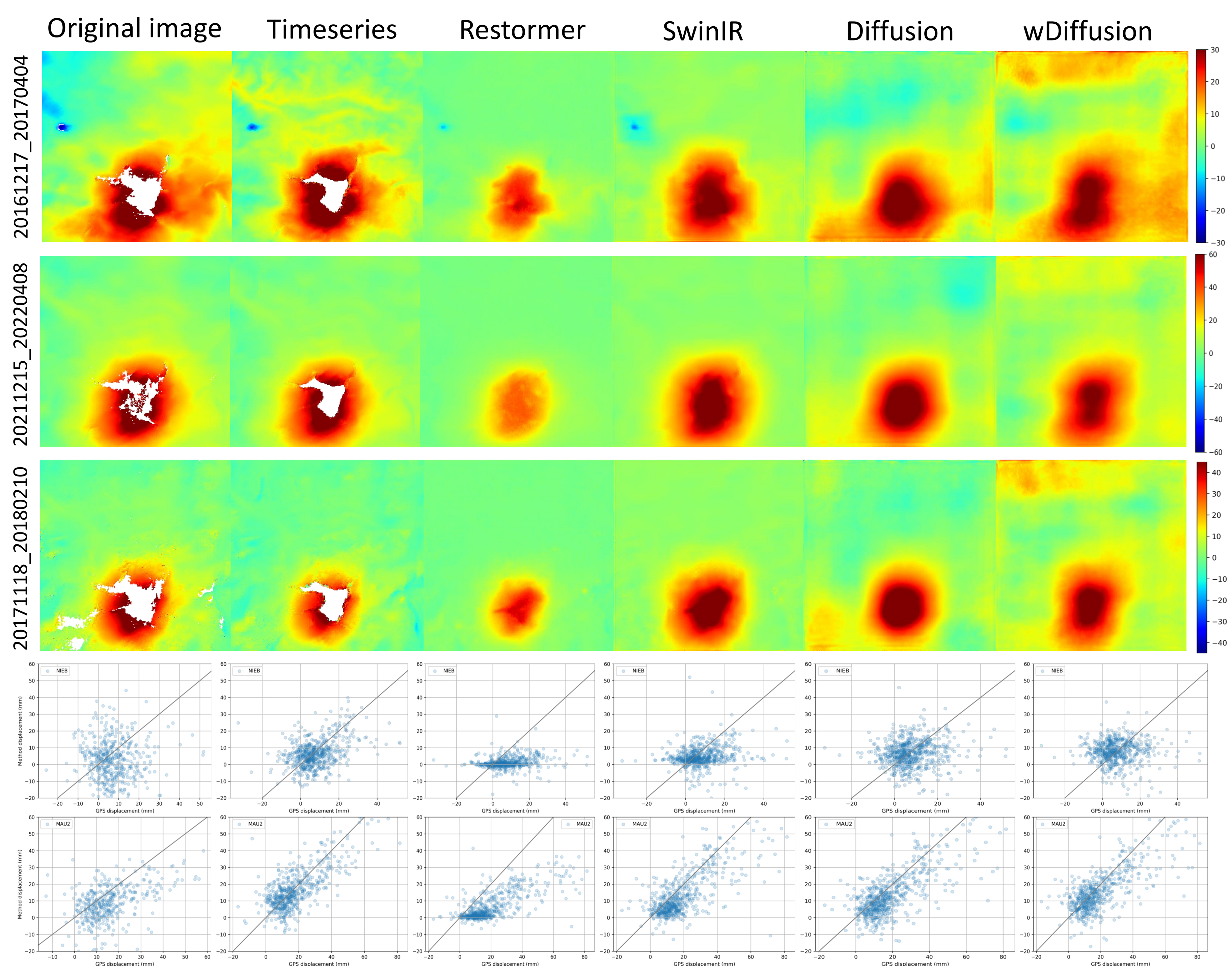
- We test on the long interferograms from Laguna del Maule (> 20 days)
- We use the GPS data as ground truth and calculate the average difference in millimeters
- We test against the time series

$$AVG = \frac{1}{n}\sum_{i=1}^{n}|GPS_i - IMG_i|$$



Cumulative displacement at Laguna del Maule from October 2024 to May 2035 (Zhu et al.)

Model	MAU2	LDMP	NIEB	PUEL	Average error
Original image	10.26 mm	11.17 mm	12.86 mm	11.92 mm	11.28 mm
Timeseries(Zhu et al.)	7.53 mm	6.90 mm	7.60 mm	8.16 mm	7.50 mm
Restormer[1]	13.87 mm	5.40 mm	8.71 mm	12.59 mm	10.07 mm
SwinIR[2]	8.89 mm	5.81 mm	7.78 mm	8.50 mm	7.72 mm
Diffusion[3]	8.99 mm	7.21 mm	8.93 mm	9.26 mm	8.59 mm
wDiffusion	8.22 mm	7.23 mm	8.87 mm	9.39 mm	8.42 mm



6. Conclusions

- Deep learning can be used to remove atmospheric noise from InSAR images
- It can achieve similar results with a timeseries approach
- Once trained, it can denoise a new interferogram in seconds
- It only needs one image as input to generate the denoised version
- This suggests there is potential in combining deep learning and timeseries

References:

1. S. W. Zamir, A. Arora, S. Khan, M. Hayat, F. S. Khan and M. Yang, "Restormer: Efficient Transformer for High-Resolution Image Restoration," 2022 IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR).
2. J. Liang, J. Cao, G. Sun, K. Zhang, L. Van Gool and R. Timofte, "SwinIR: Image Restoration Using Swin Transformer," 2021 IEEE/CVF International Conference on Computer Vision Workshops (ICCVW).
3. R. Rombach, A. Blattmann, D. Lorenz, P. Esser and B. Ommer, "High-Resolution Image Synthesis with Latent Diffusion Models," 2022 IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR).

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