Signal extraction and characterization from geodetic datasets using AI approaches

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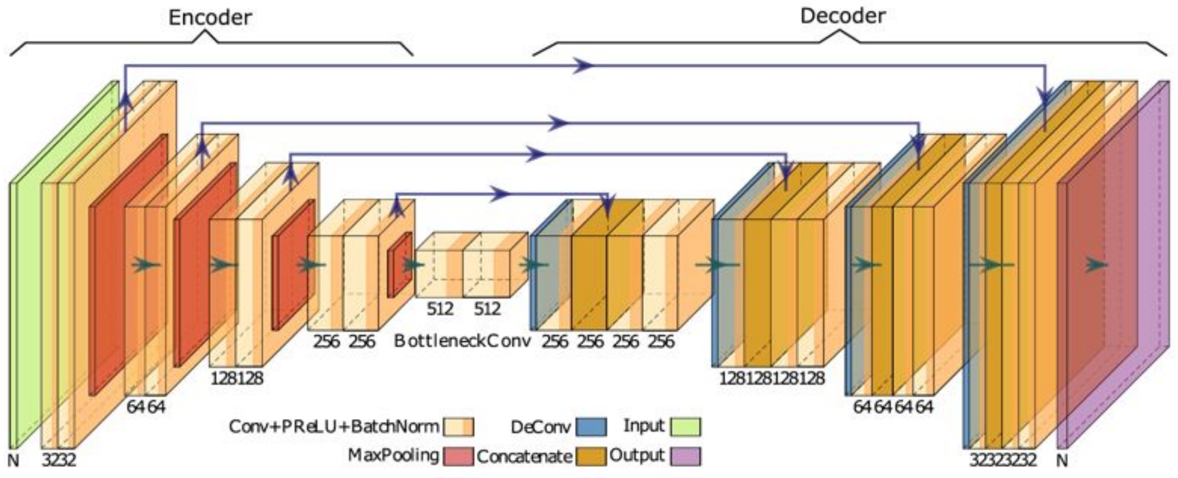
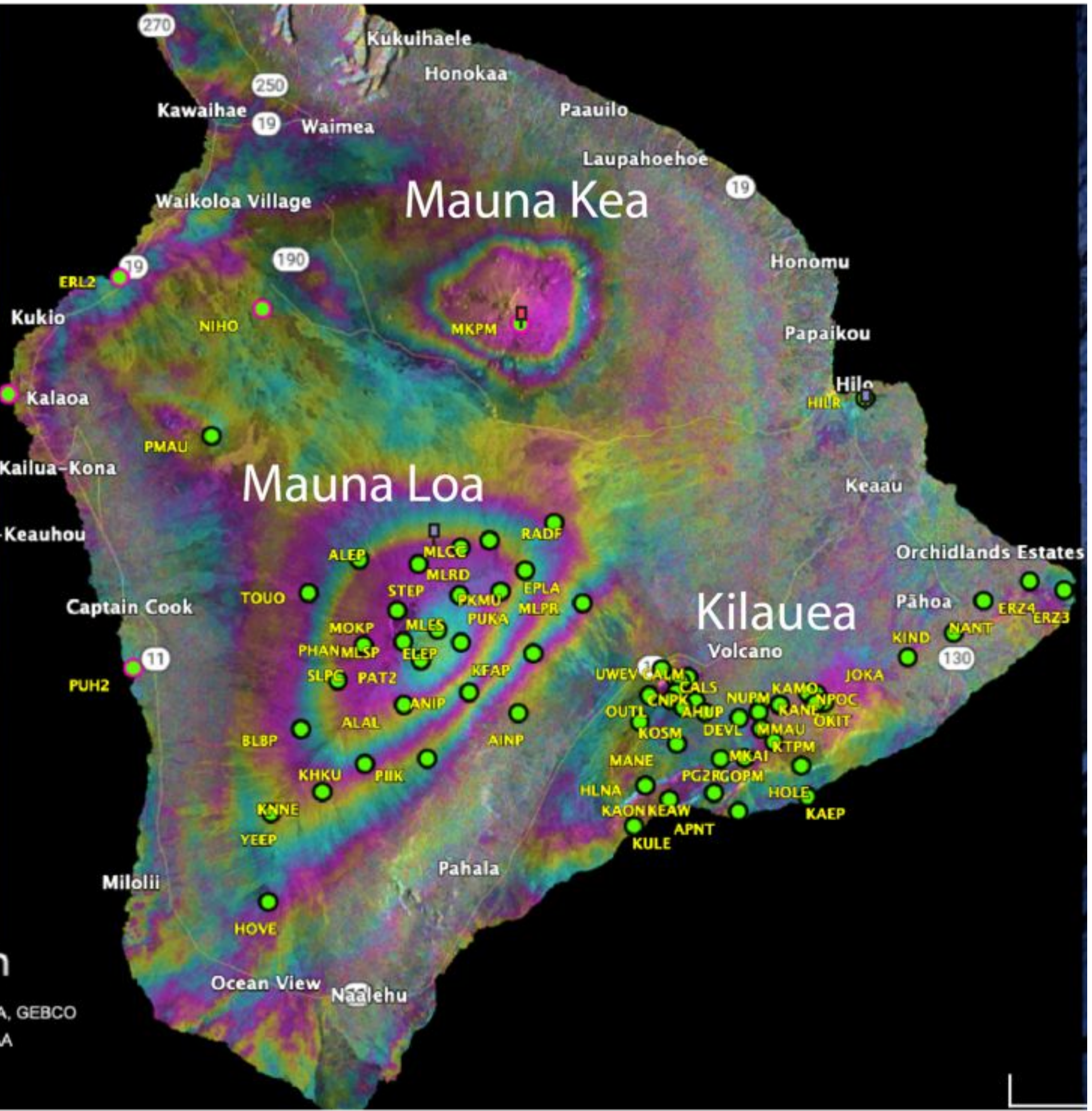


3 August 2023, SZ4D AI Workshop

Motivation

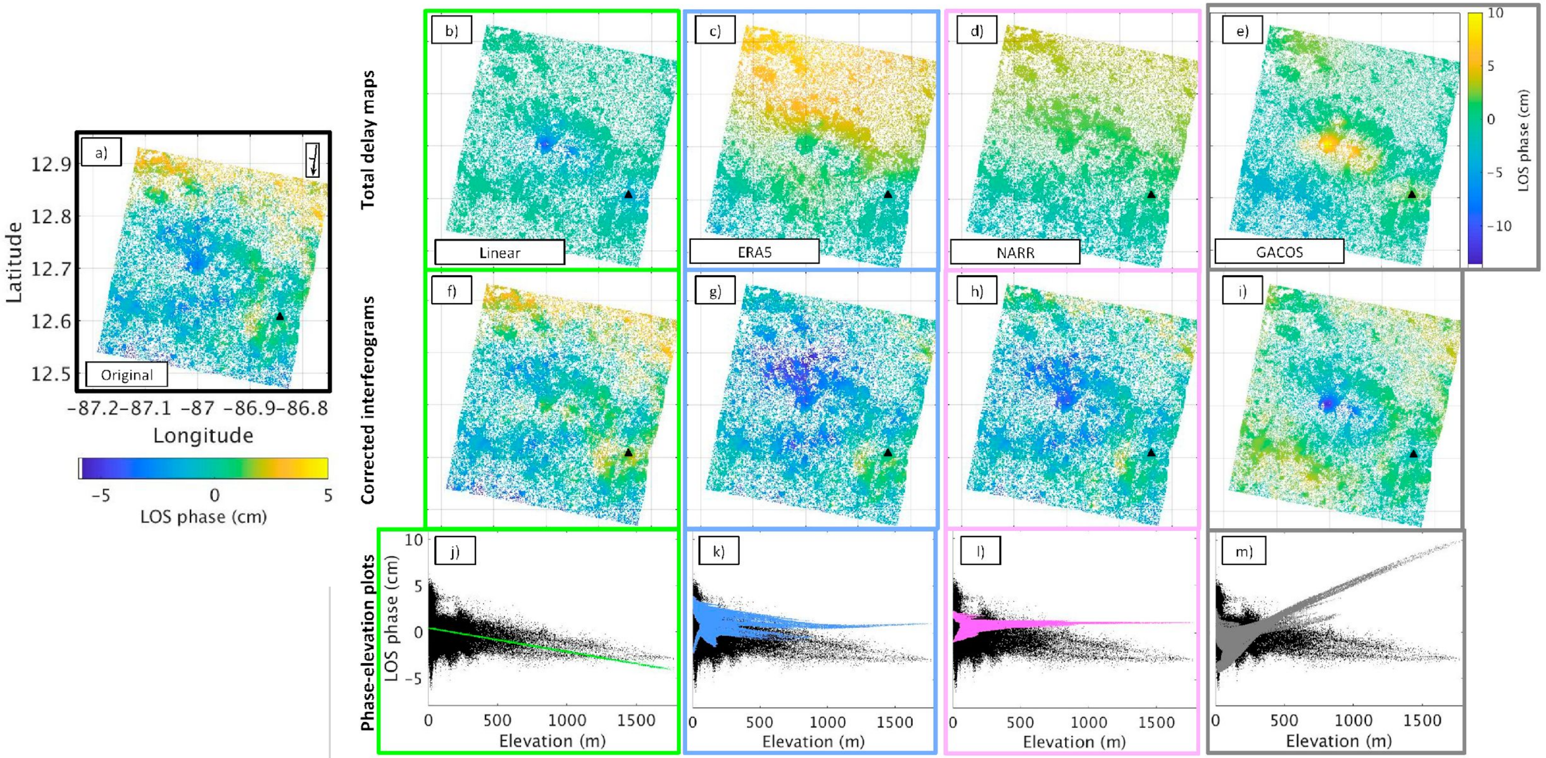


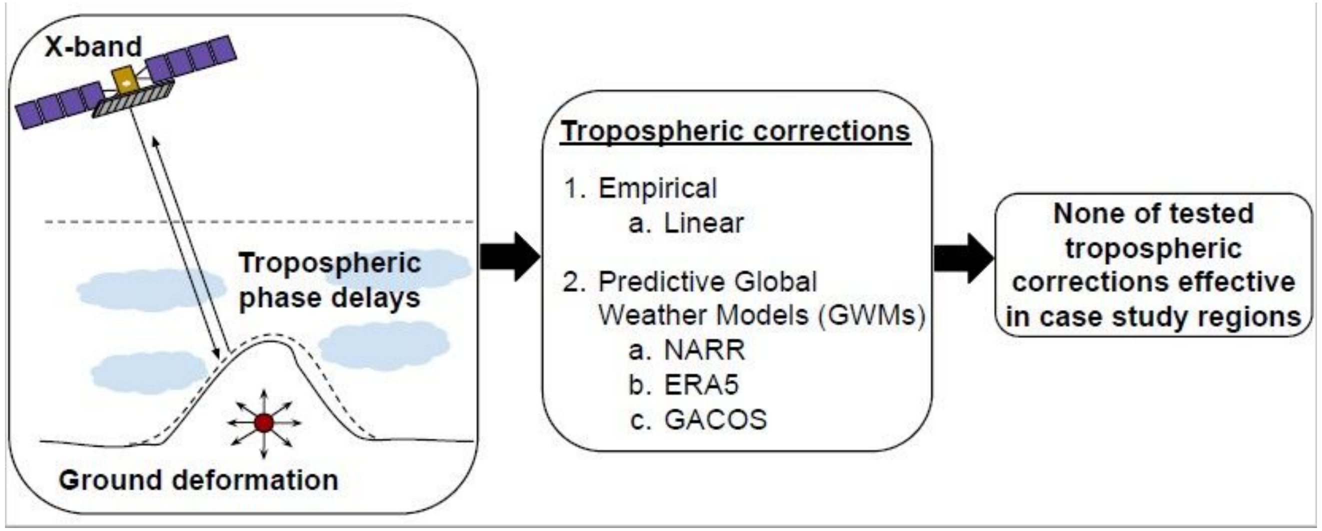
- Interferometric Synthetic Aperture Radar (InSAR) and time series datasets contain many signals of various origin and are thus complex to analyze temporally and spatially:
  - Several deformation sources (magmatic, seismic, loading/unloading etc.)
  - Atmospheric signals

Methods to correct for atmosphere – separate signals?

- Global weather models

=> Do not always work
(issues with coarse spatial resolution and high topography variability at volcanoes)





(Stephens et al., 2020)

Methods

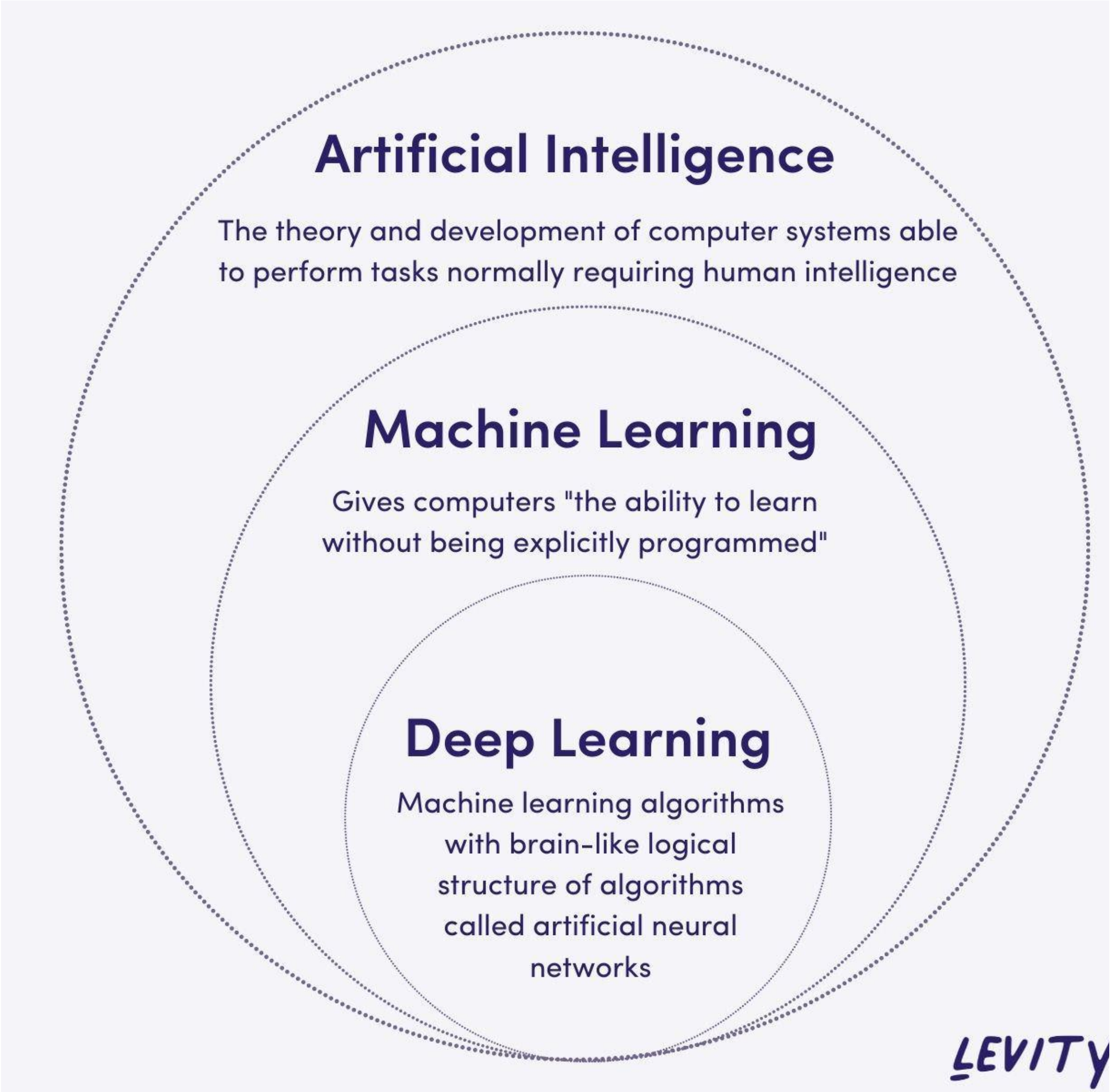
- Global weather models

- Machine learning:
  - Purely data-driven (no *a priori* information): Principal Component Analysis (PCA) / Independent Component Analysis (ICA), etc.

  (e.g., Ebmeier , 2016; Larochelle et al., 2018; Gaddes et al., 2019; Walwer et al., 2022, etc.)

  - Deep learning

  (e.g., Rouet-Leduc et al., 2021; Anantrasirichai et al., 2018; 2019; Sun et al., 2020 etc.)



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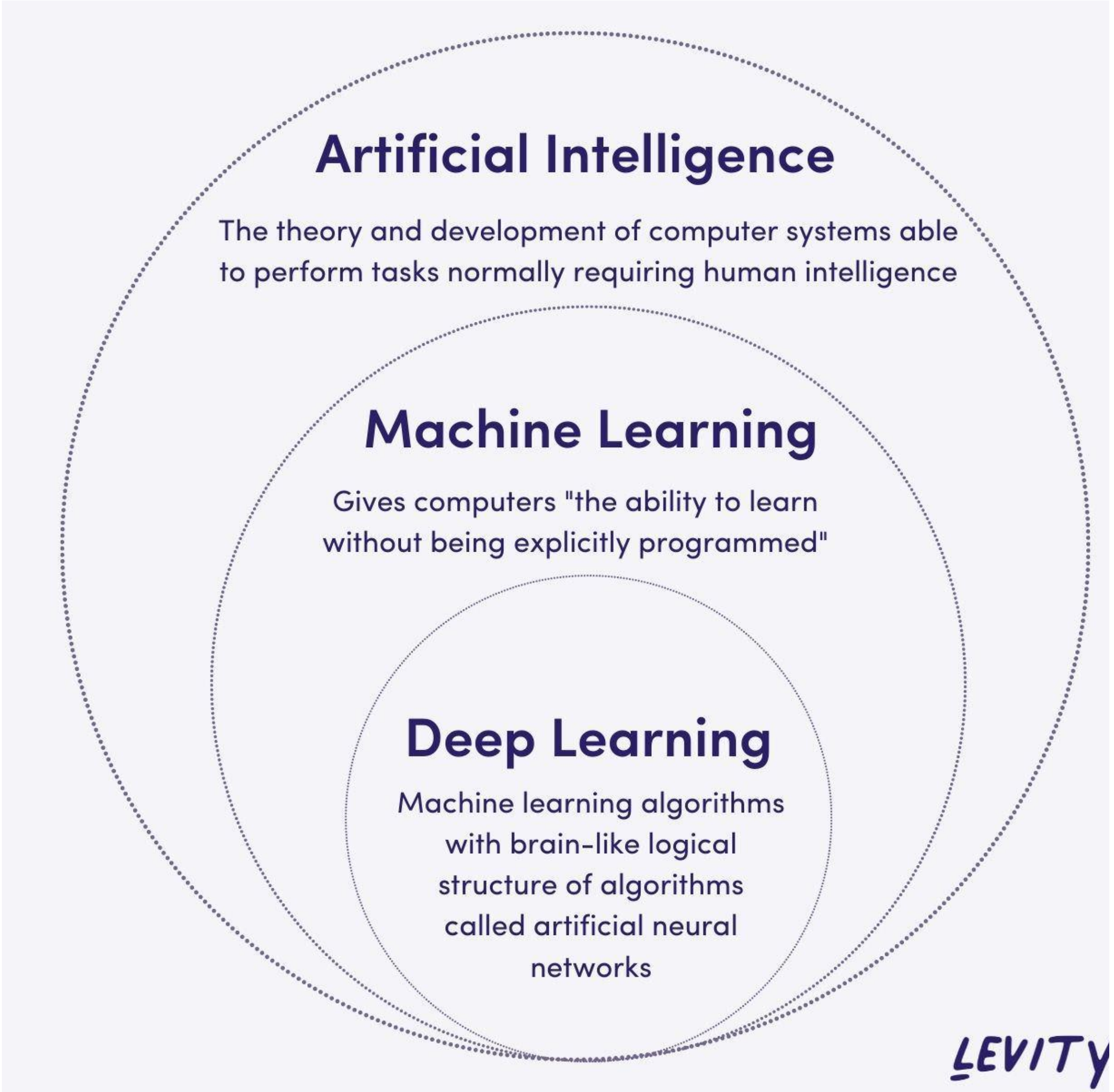
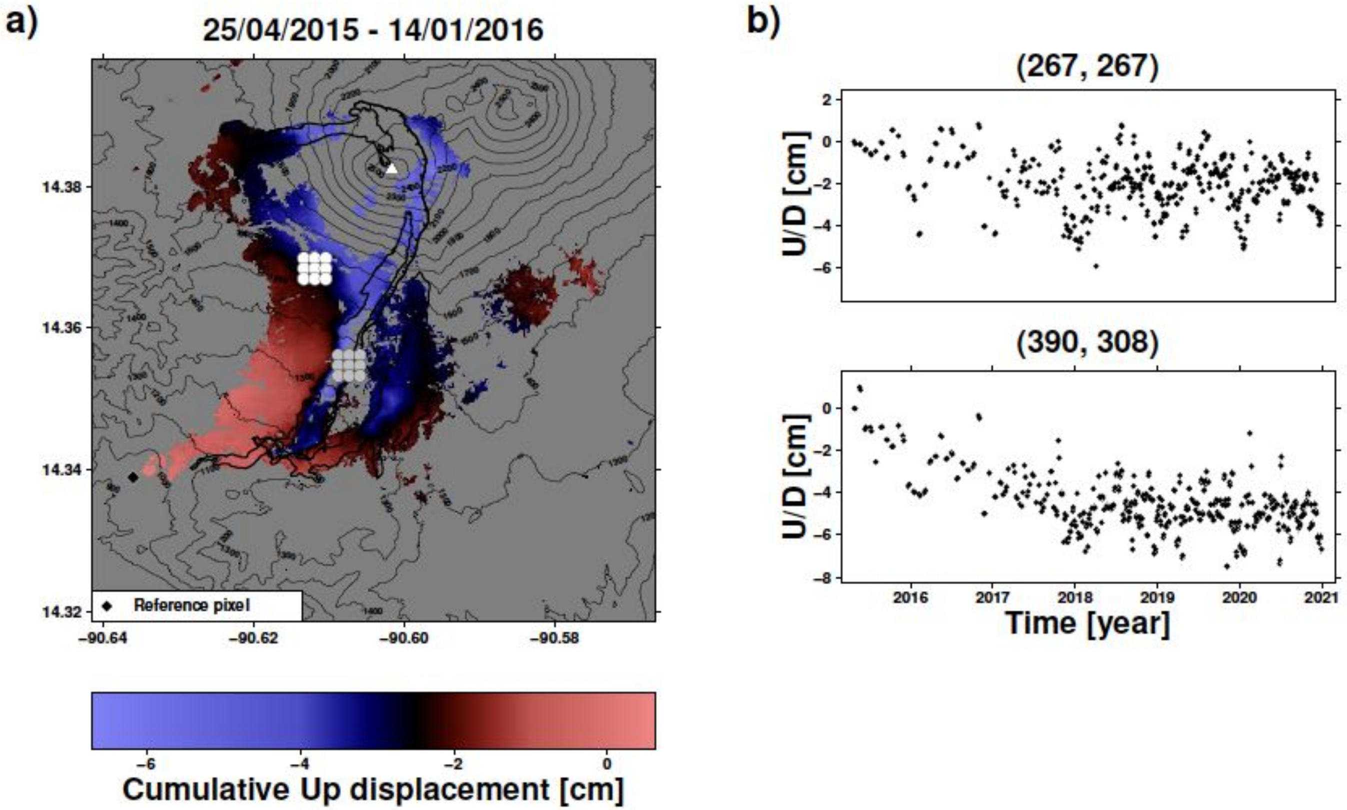


MSS-A (Multichannel Singular Spectrum Analysis)

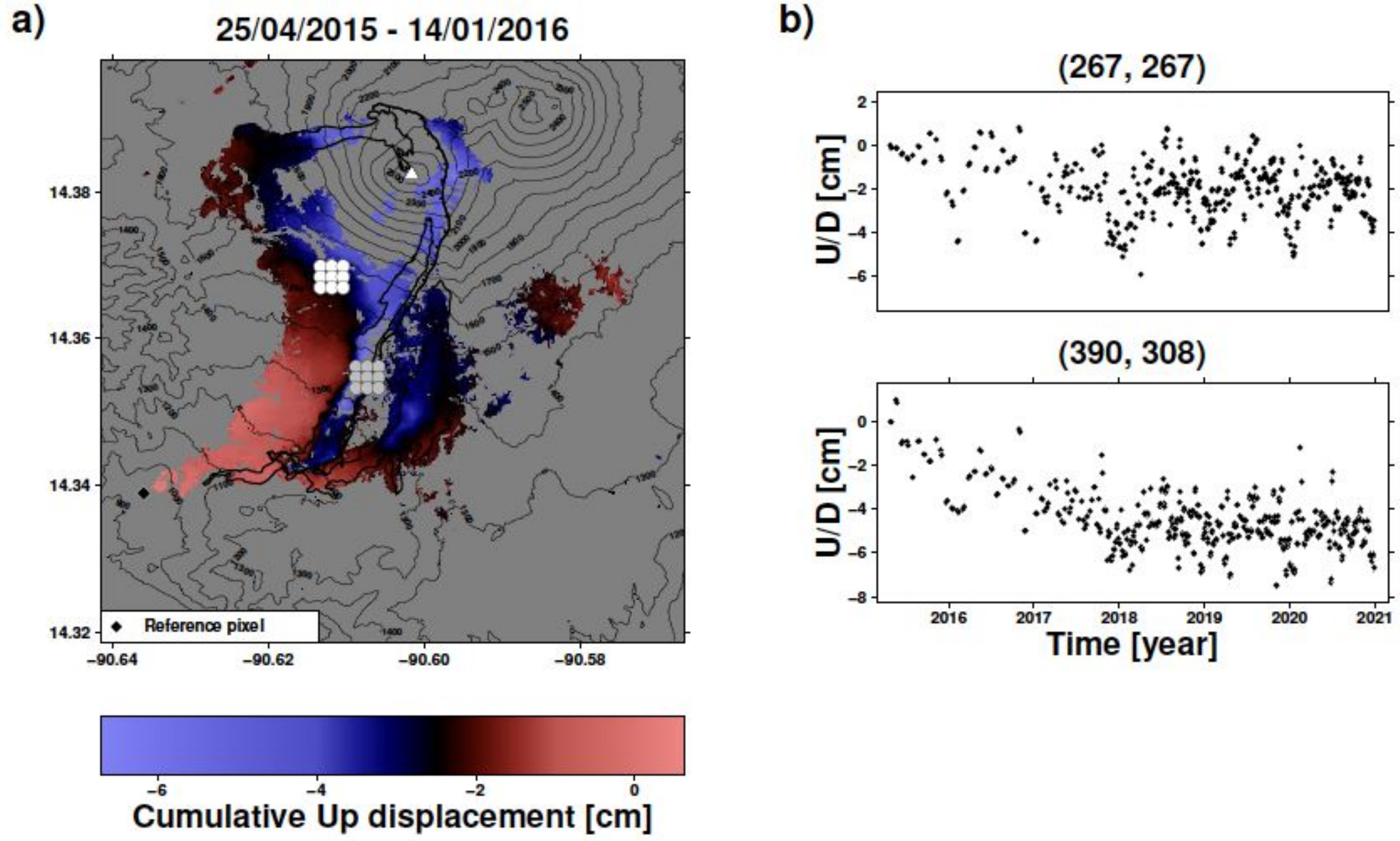
- Generalization of **PCA**: MSS-A (Multichannel Singular Spectrum Analysis)
- Purely **data-driven**: no *a priori* information needed
- Very good at retrieving seasonal (harmonic) signals (atmosphere!)
- MSS-A simultaneously uses temporal and spatial correlations

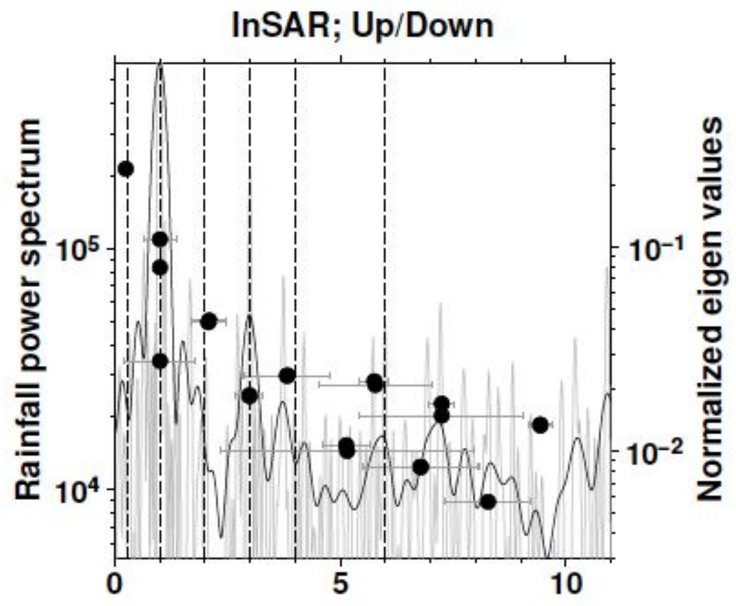


(Walwer et al., 2016; *In Review JGR*)

MSS-A

- Modes of variability are derived from the eigenvector decomposition of a covariance matrix composed of lagged InSAR time series

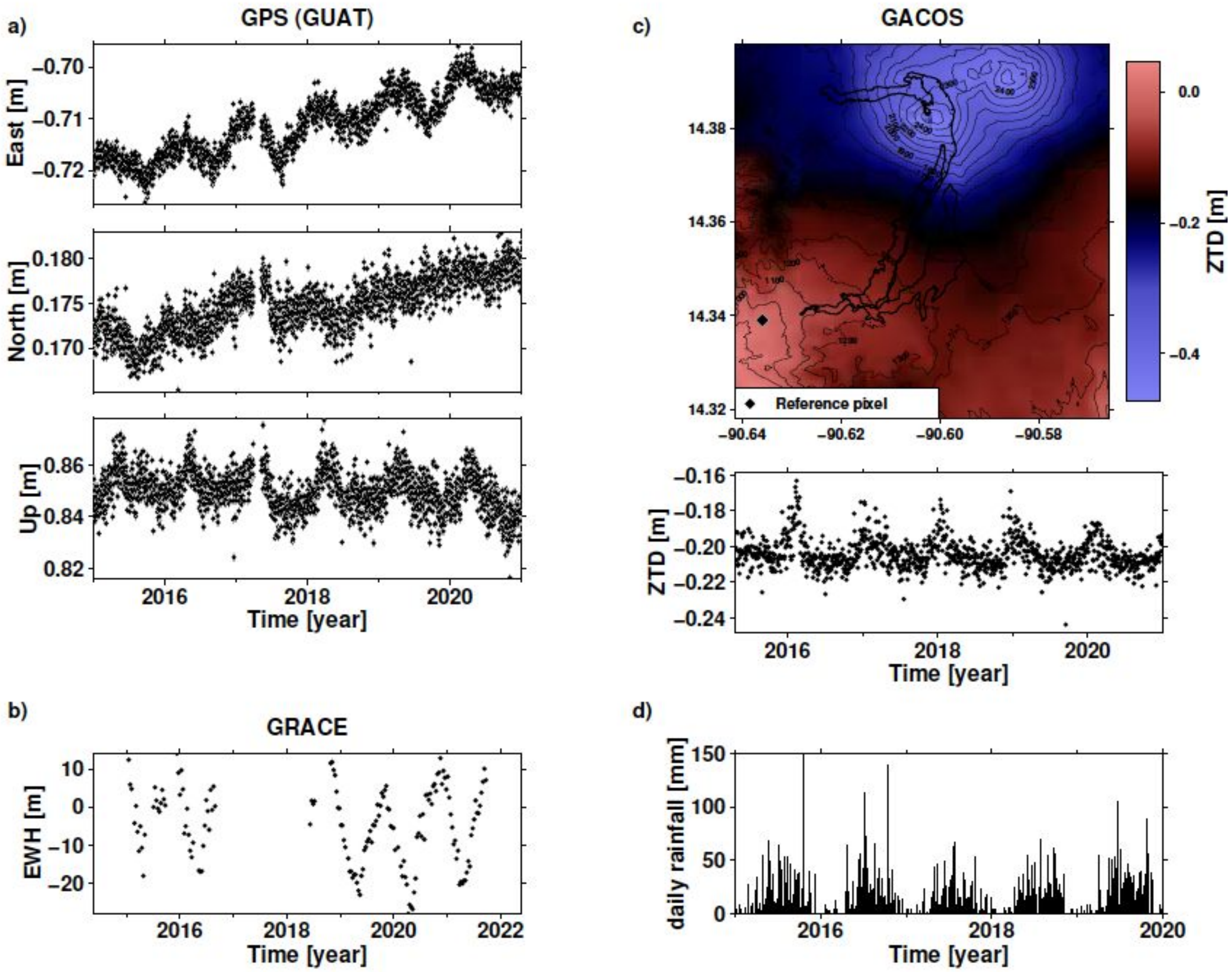




- Signals that are strongly correlated in space and time will have highest eigenvalues

(Walwer et al., *In Review JGR*)

MSS-A



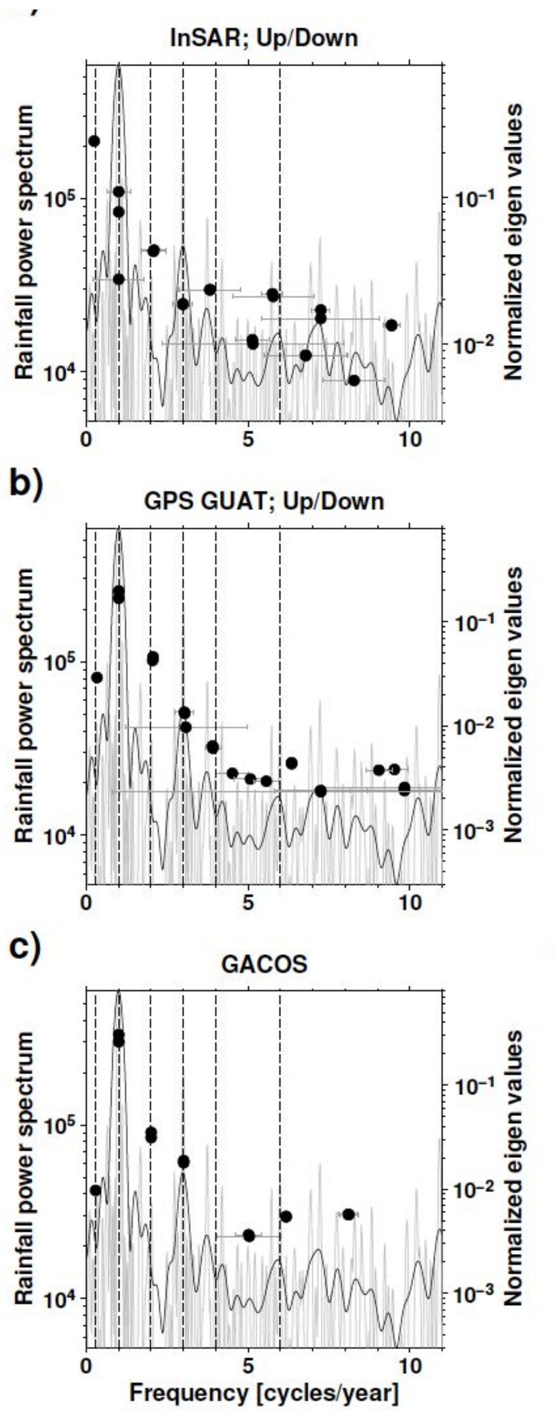
- Other datasets are used and decomposed with the same approach (MSS-A) to help with the interpretation of the extracted PC modes:
  - GPS
  - GRACE (gravity)
  - GACOS (atmosphere)
  - Daily rainfall

(Walwer et al., *In Review JGR*)

MSS-A

- Comparison can help distinguishing between hydrological (loading/unloading) and atmospheric effects.

- Common modes for several datasets show that many non-linear trends modes are associated with hydrological processes: deformation caused by either multiannual variations in groundwater content or in surface water load (i.e., Larochelle et al., 2021).



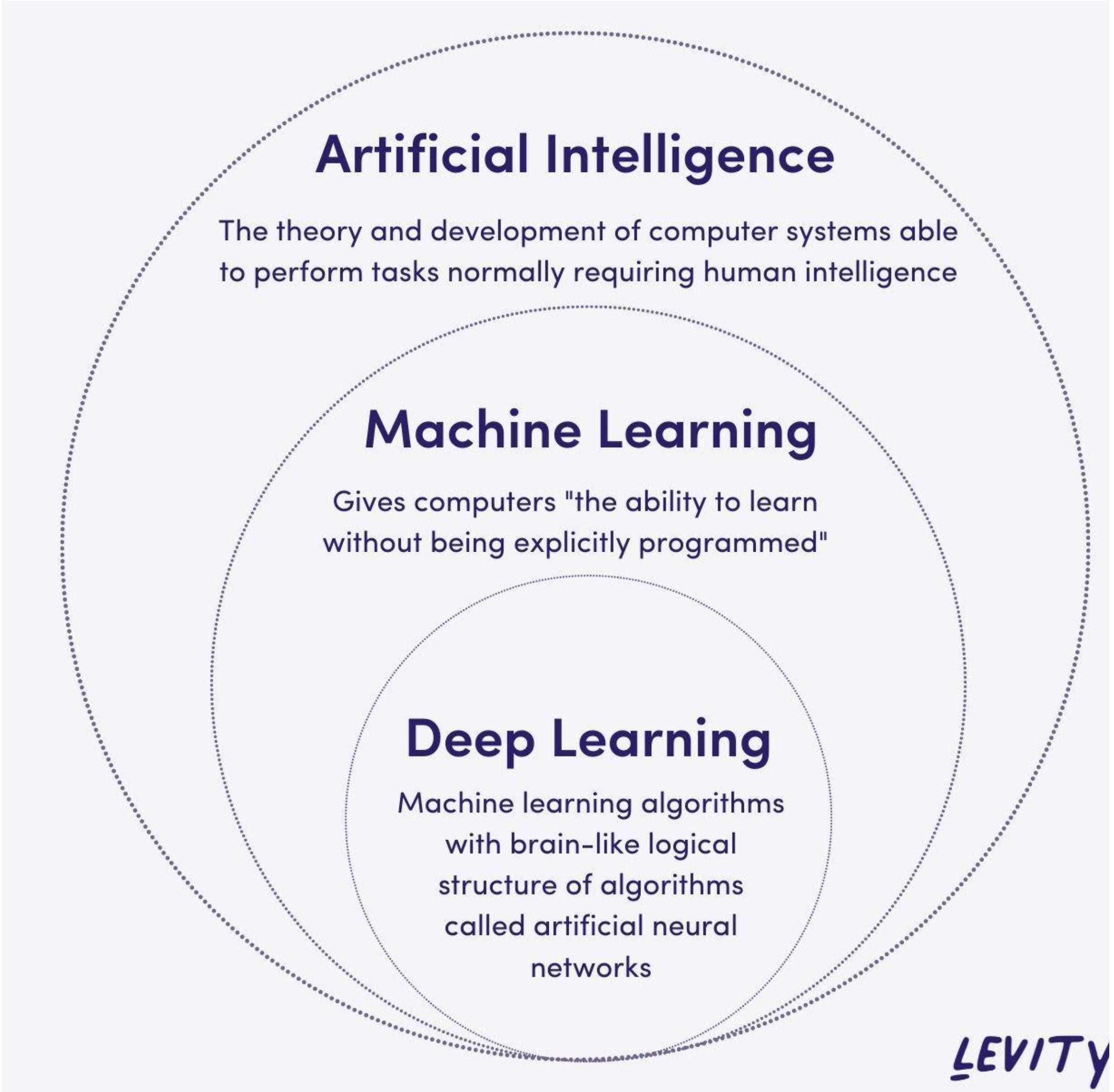
(Walwer et al., *In Review JGR*)

Methods

- Global weather models

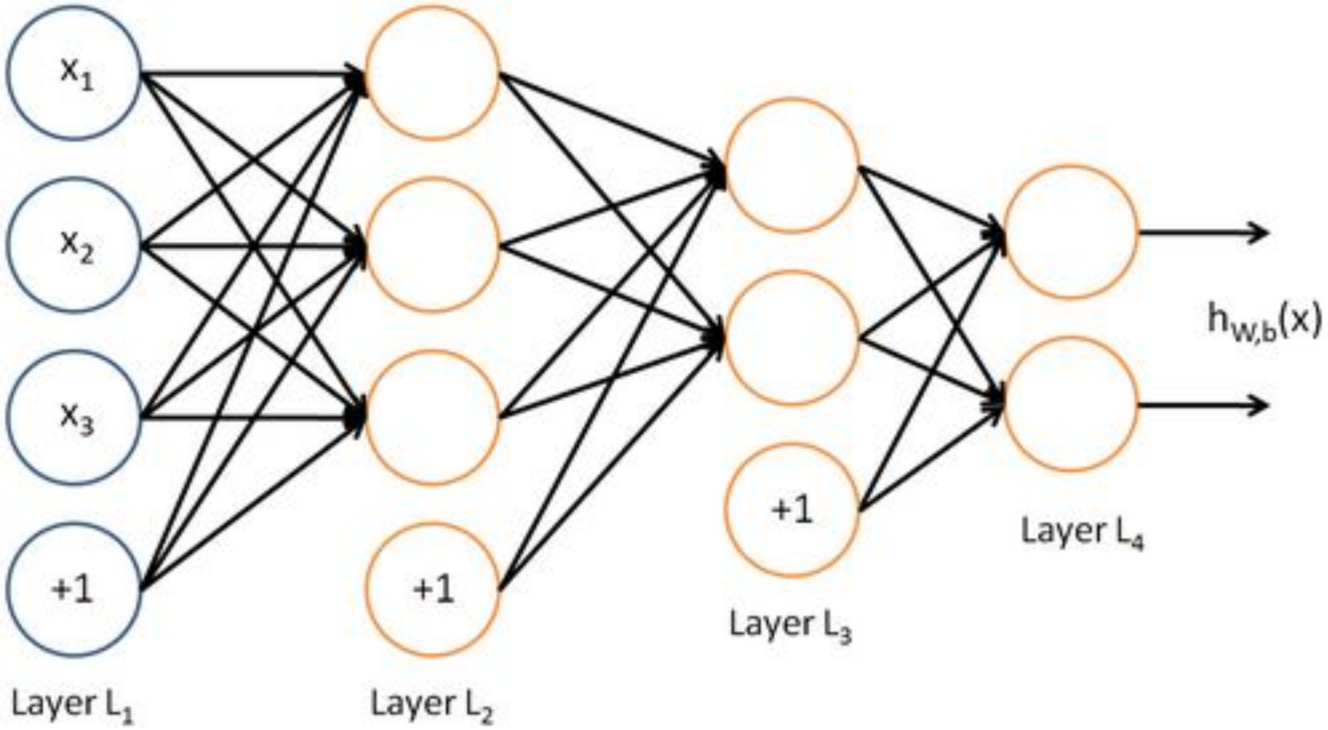
- Machine learning:
  - Purely data driven (no *a priori* information/models/solutions): Principal Component Analysis / Independent Component Analysis (ICA), etc.

  - Deep learning



Deep Learning for Denoising InSAR data: Convolutional Neural Network (CNN)

- Neural Network
- Simulate brain: neurons interconnected to other neurons which forms a network.
- A simple information transits in a lot of them before becoming an actual thing, like “move the hand to pick up this pencil”
- Enter variables as inputs: for example, an image, and after some calculations, an output is returned: giving an image of a cat should return the word “cat”



INPUT → 2 internal layers (hidden layers): some math operation → OUTPUT

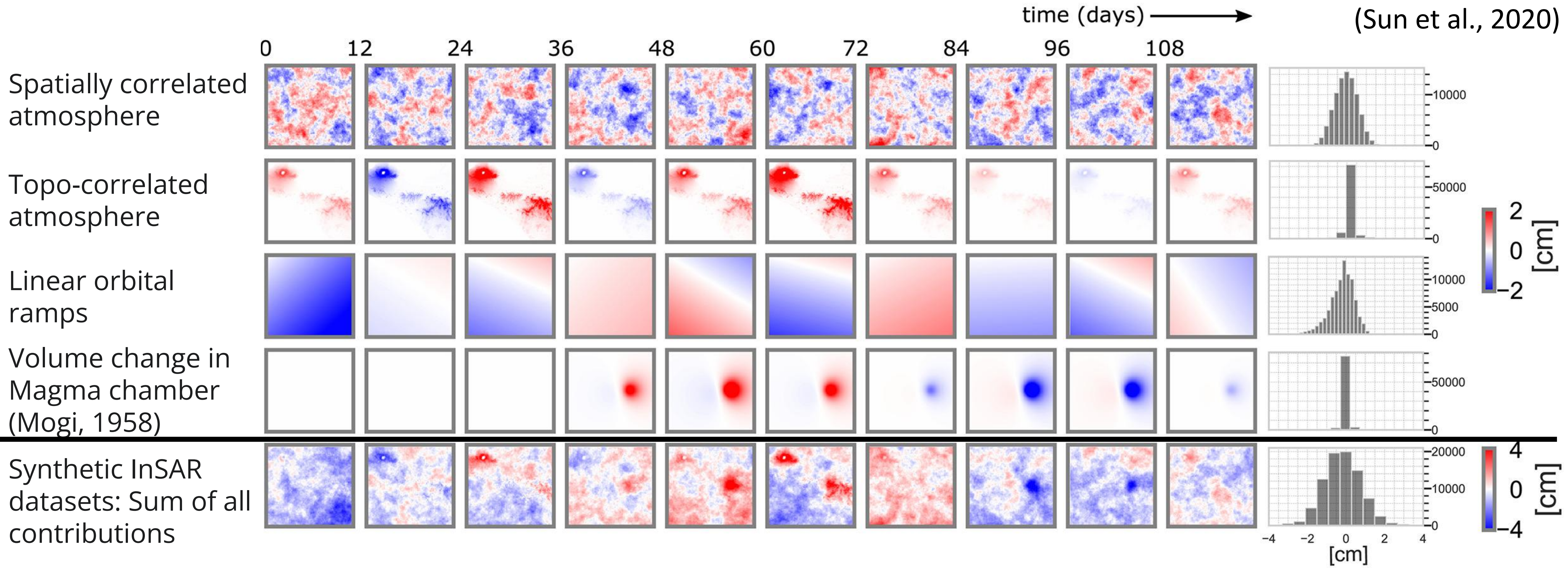
Source: https://towardsdatascience.com


NETFLIX

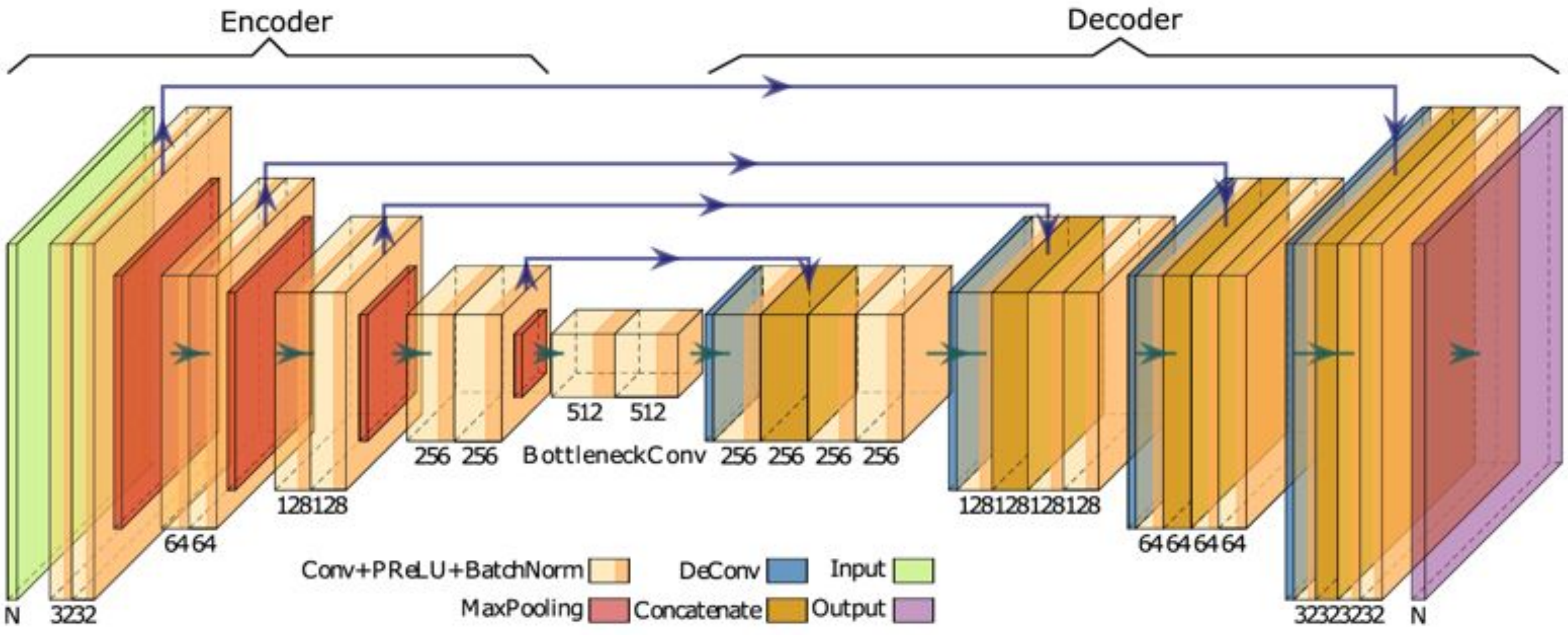
Deep Learning for Denoising InSAR data

- First step: **training stage**
- Synthetic dataset: simulate the InSAR phase from various signal contributions

(Sun et al., 2020)



Deep Learning for Denoising InSAR data: Convolutional Neural Network (CNN)



INPUT

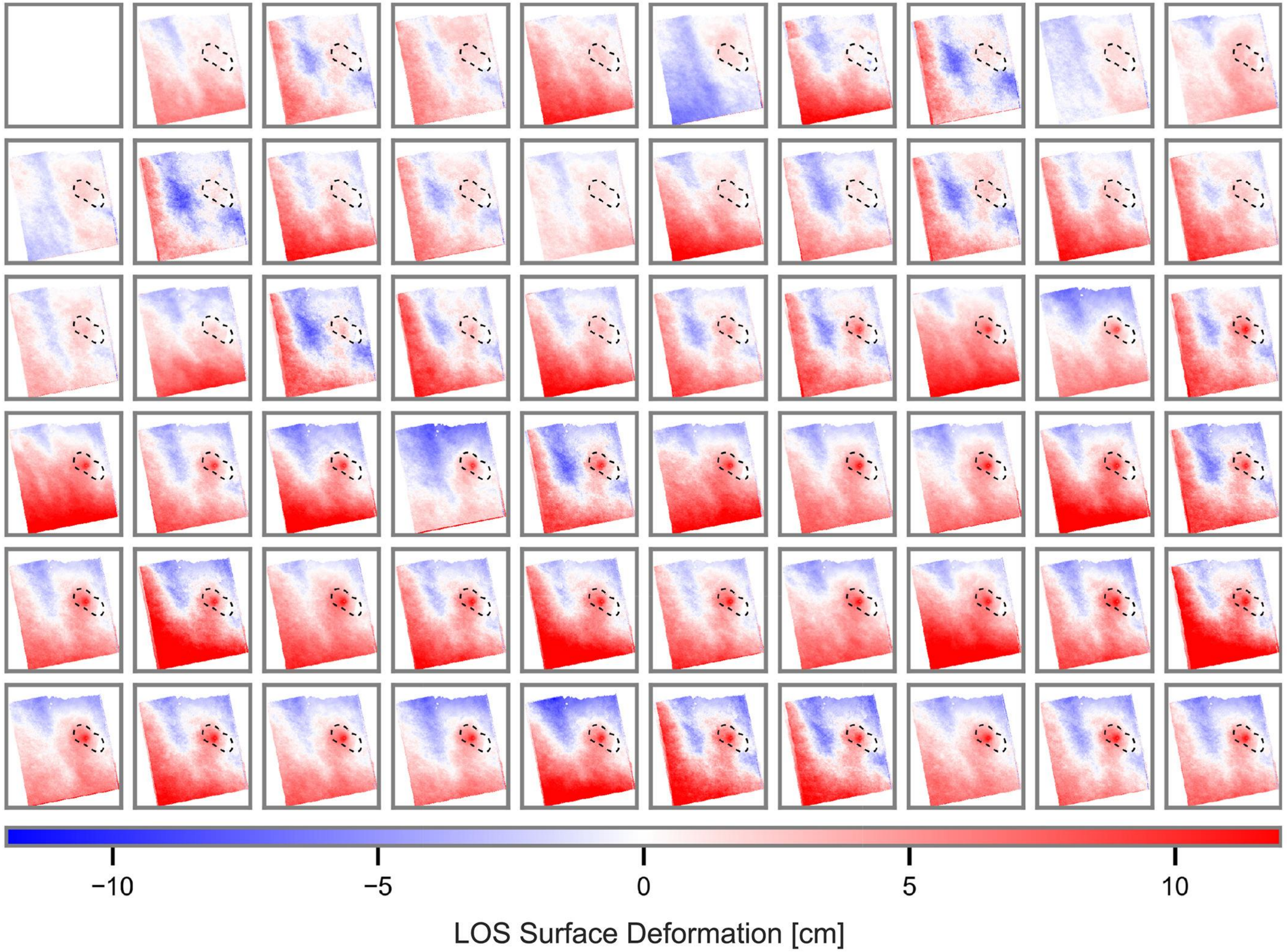
Hidden layers: reduce input dimensions (encode), convolution operation, decode and export same output dimensions and input

OUTPUT

(Sun et al., 2020)

Deep Learning for Denoising InSAR data: Application to **real InSAR dataset**

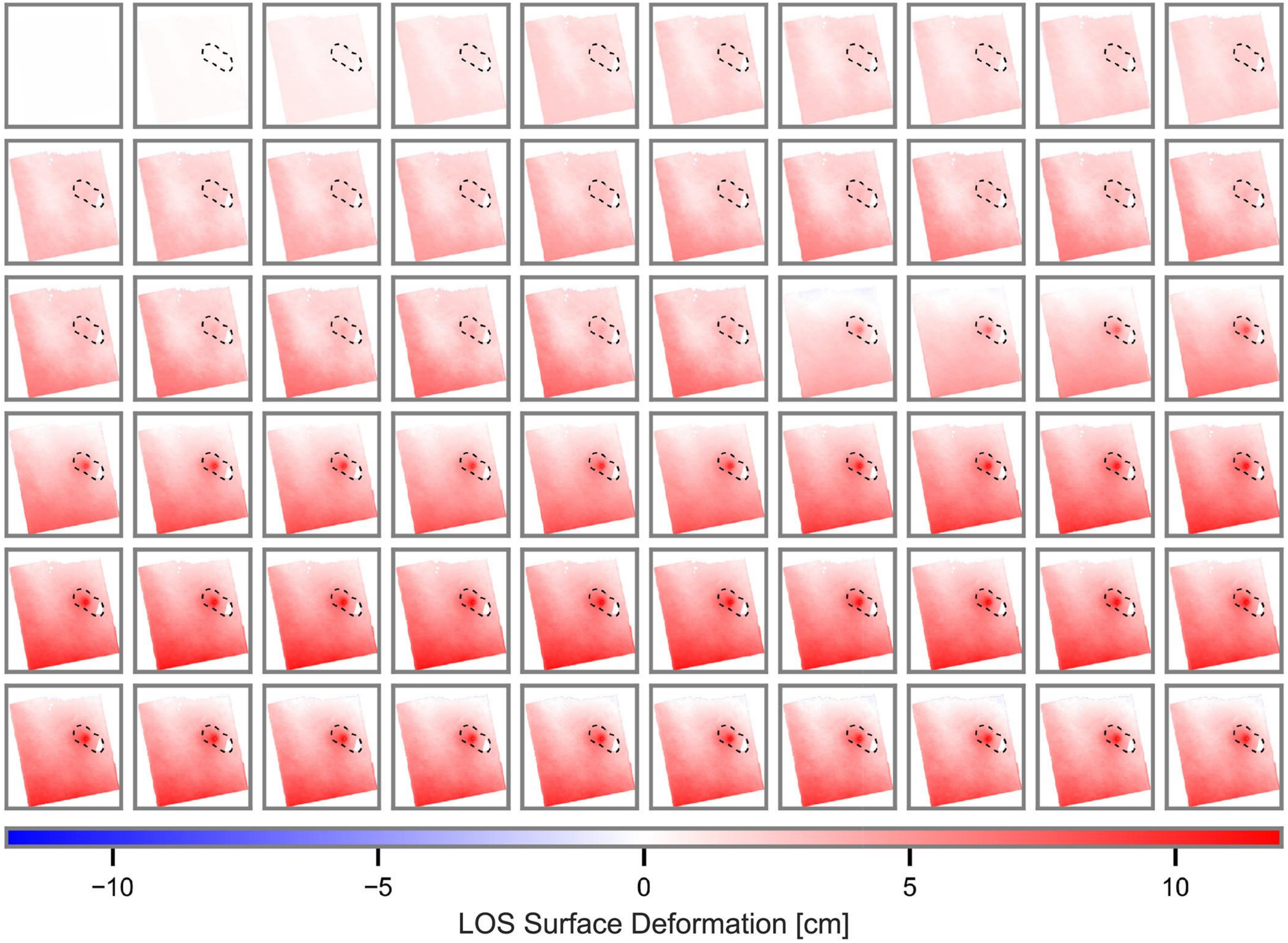
- **INPUT** = Sixty consecutive InSAR surface displacement maps at Masaya caldera (Nicaragua) obtained with InSAR time-series approach (SBAS, Berardino et al., 2002)



(Sun et al., 2020)

Deep Learning for Denoising InSAR data: Application to **real InSAR dataset**

- **OUTPUT** = Sixty predicted consecutive InSAR DENOISED surface displacement maps



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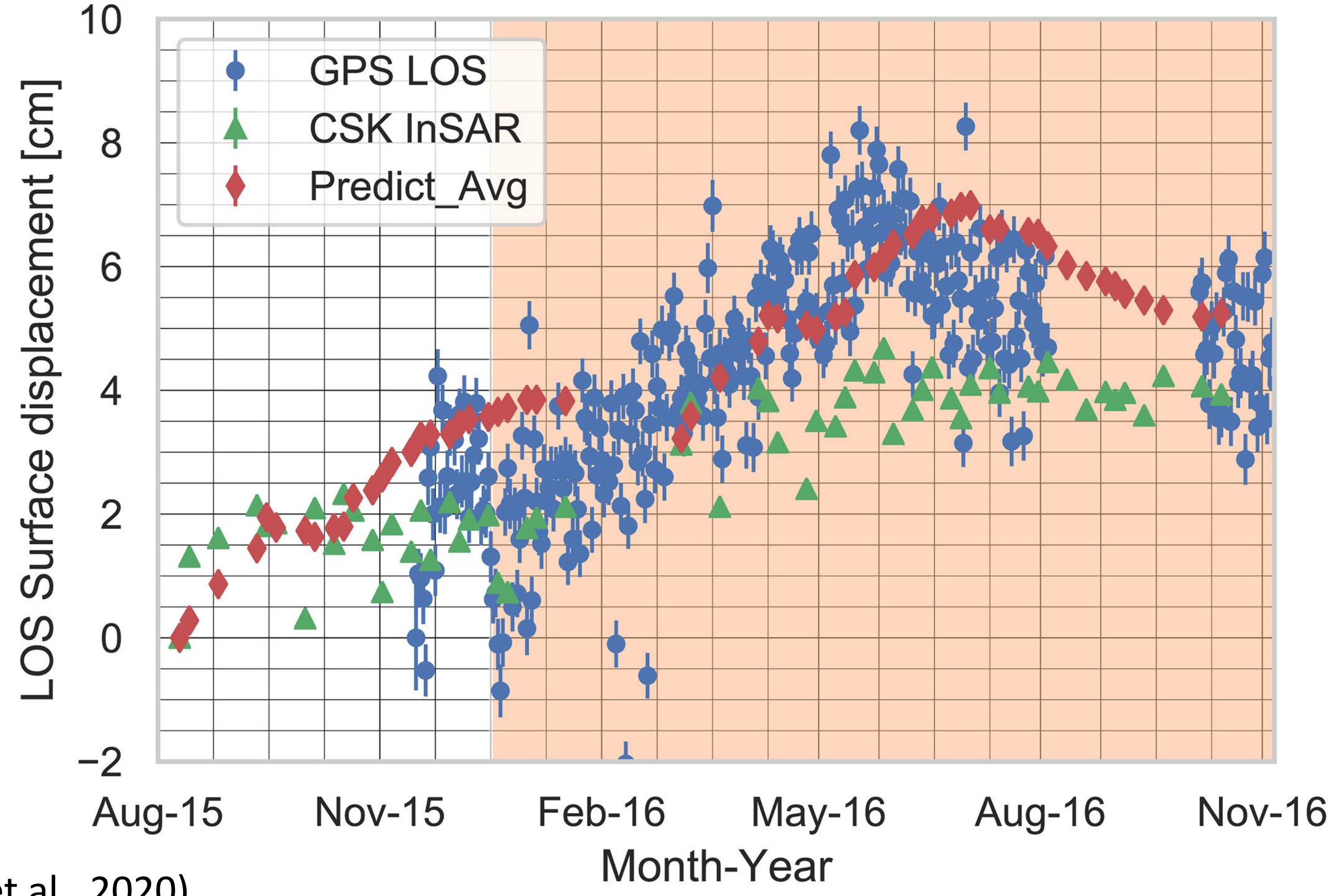
Deep Learning for Denoising InSAR data: Application to real InSAR dataset

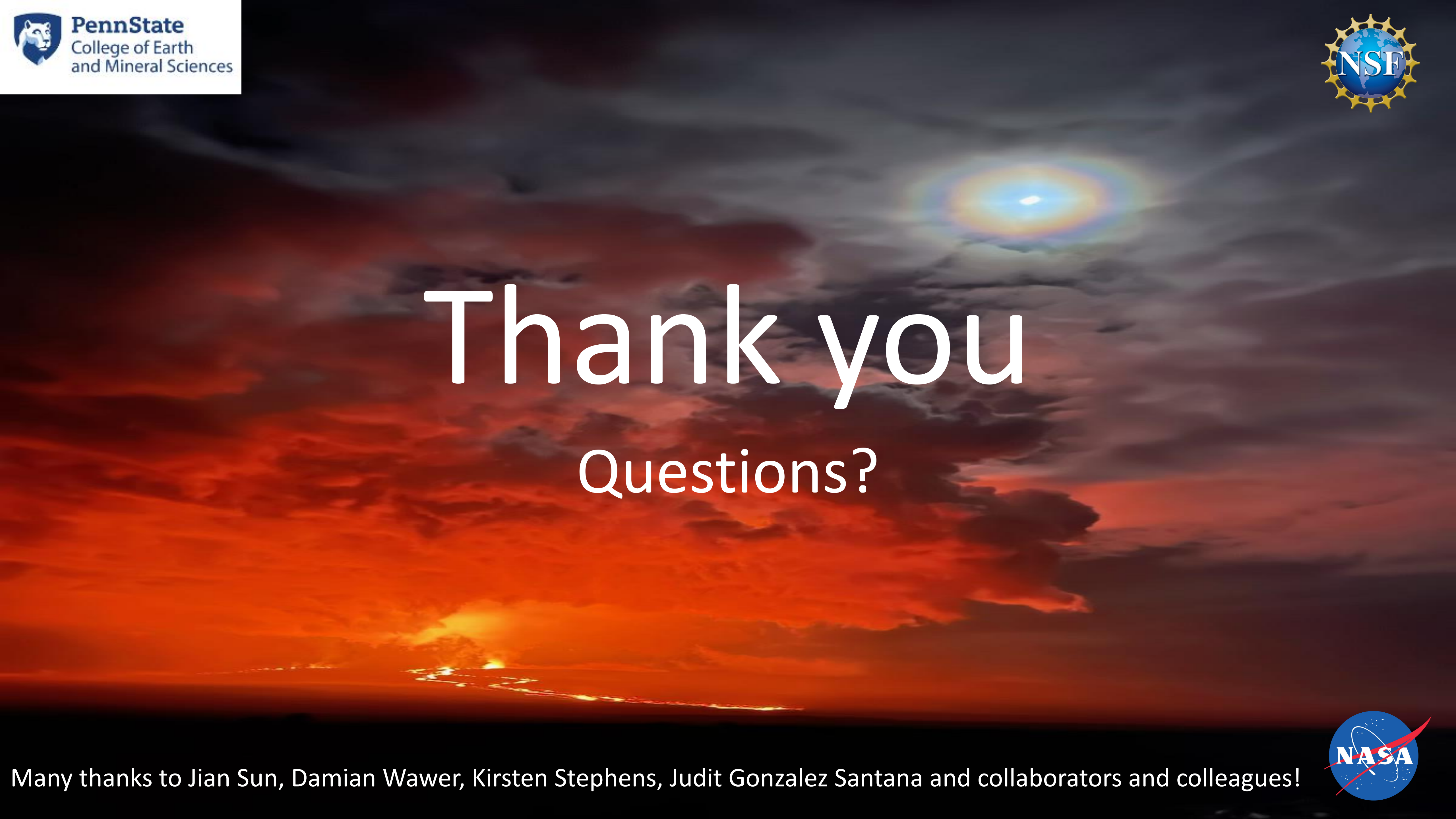


- Comparison of
  - Input (InSAR)
  - Output (CNN Predictions)
  - GPS

(Sun et al., 2020)

Future work

- *"On man's trash is another man else's treasure*": work with "the others" aka atmospheric scientists to use more accurate weather models – locally tested and perhaps improved back from the deep learning results / or use Weather data assimilation
- Test for various atmospheric conditions
- Expand to S – L band (longer radar wavelengths) for upcoming NASA NISAR mission: need to consider ionospheric effects too
- Improve CNN to train and test for more deformation source types and avoid geodetic inversions all together!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Thank you
Questions?
NASA
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