Jet Propulsion Laboratory
California Institute of Technology

InSAR Timeseries Analysis: theory and overview

Scott Staniewicz, Heresh Fattahi

Jet Propulsion Laboratory
California Institute of Technology

Earthscope 2025
Aug 20 2025

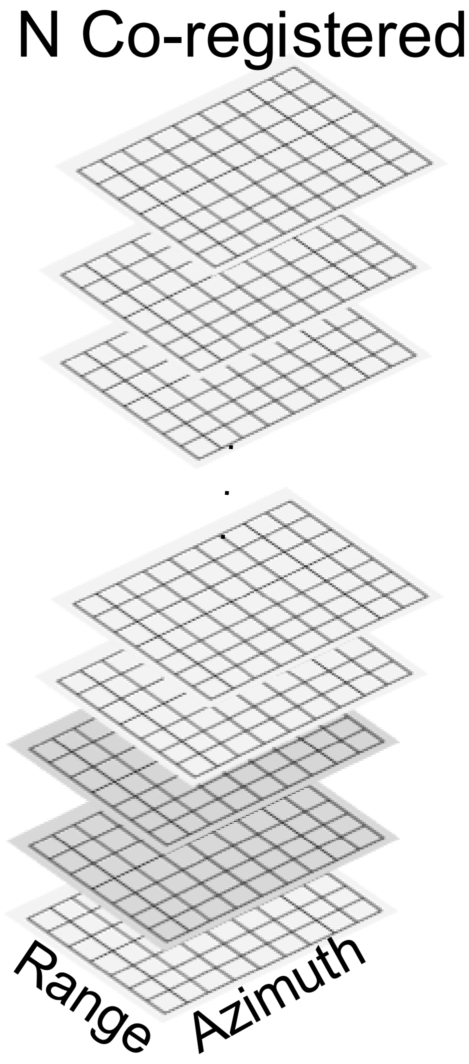
Acknowledgement

With contributions from many colleagues:

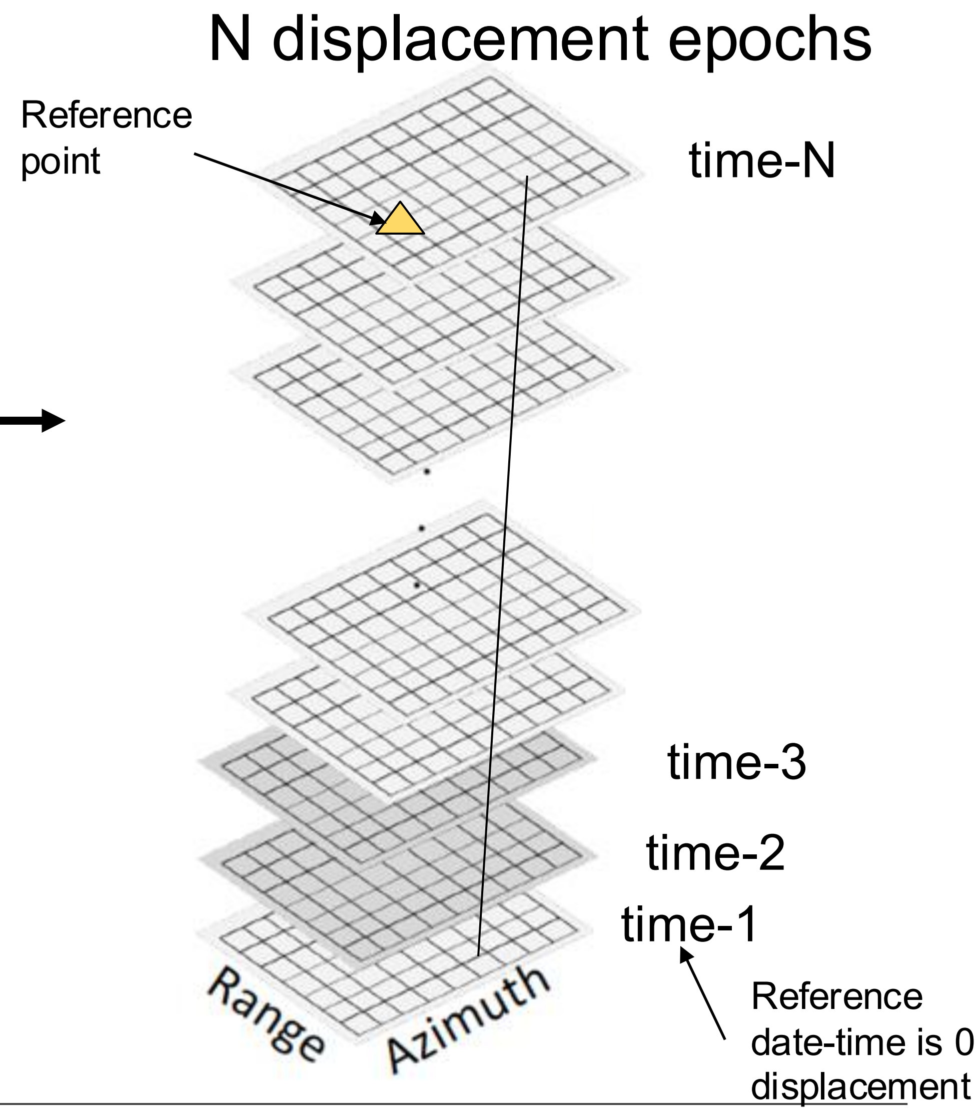
Heresh Fattahi, Sara Mirzaee, Virginia Brancato, Yujie Zheng, Piyush Agram, Falk Amelung and other colleagues at JPL, Caltech and University of Miami

Goal of time-series analysis

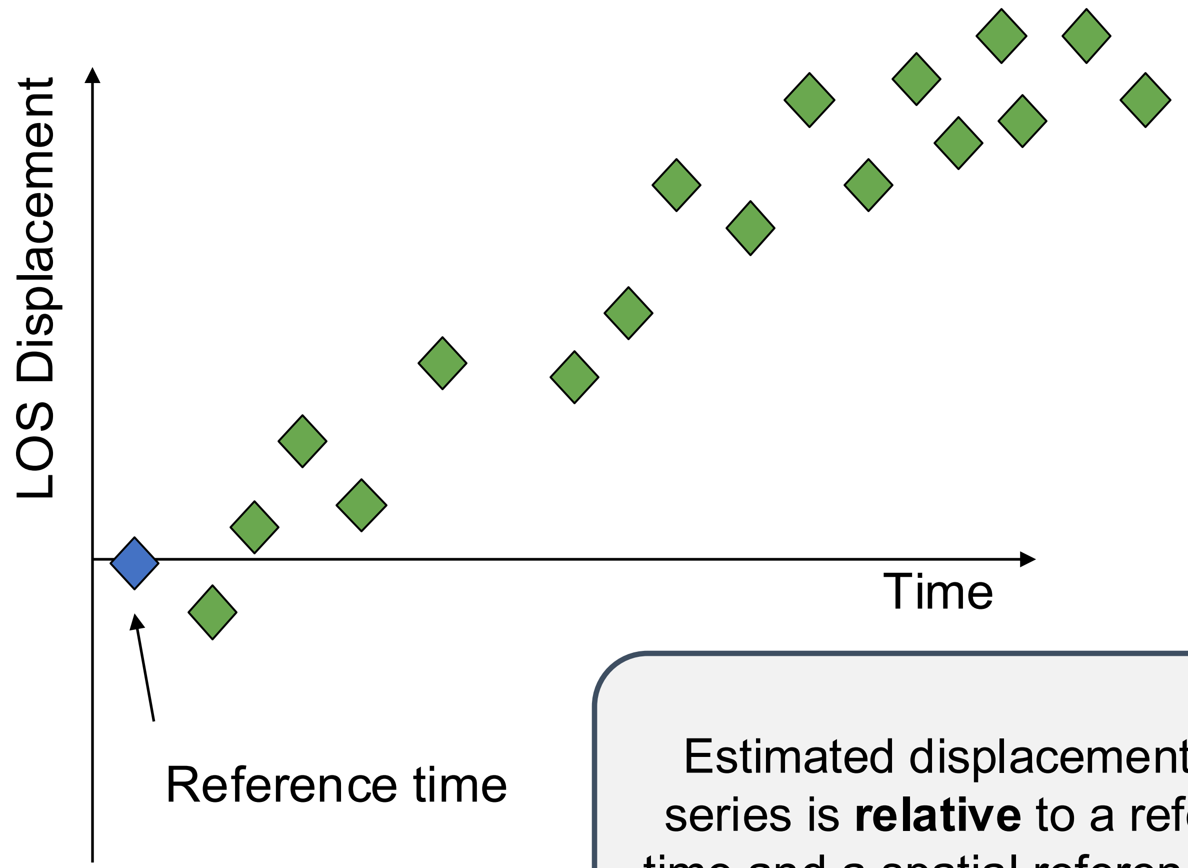
National Aeronautics and Space Administration



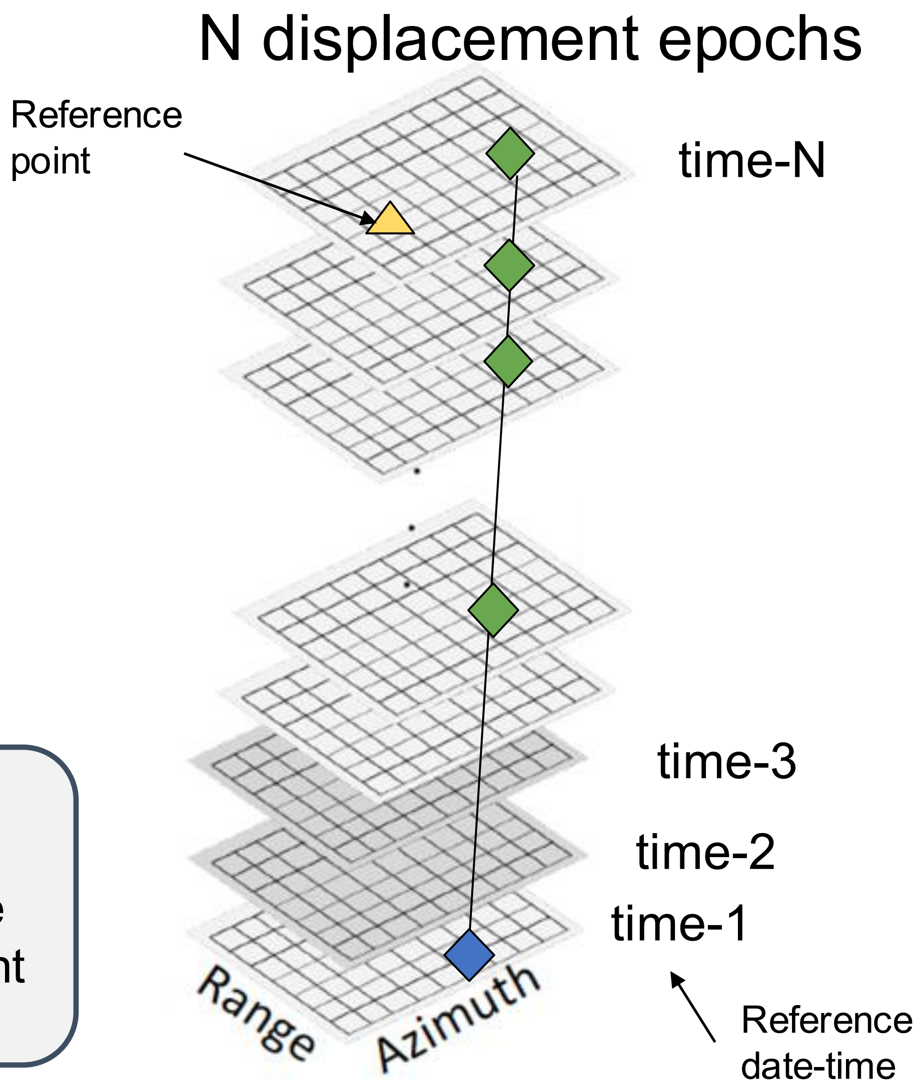
Time-series analysis



Goal of time-series analysis



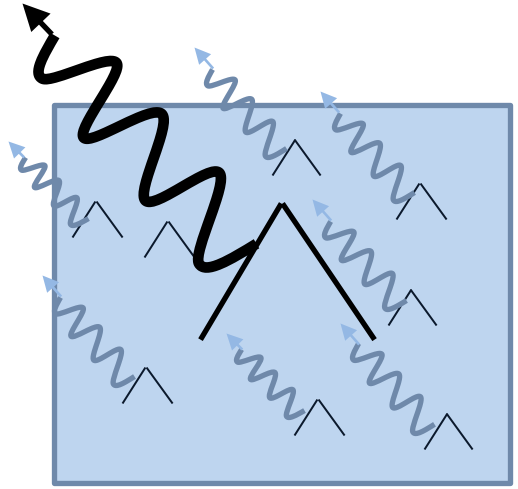
Estimated displacement time-series is **relative** to a reference time and a spatial reference point



InSAR Time-series analysis techniques based on types of scatterers

Types of scatterers

- **One resolution cell (pixel) contains many scatterers**
- A pixel may:
  a) be largely dominated by a single point scatterer (**Persistent Scatterers (PS)**)

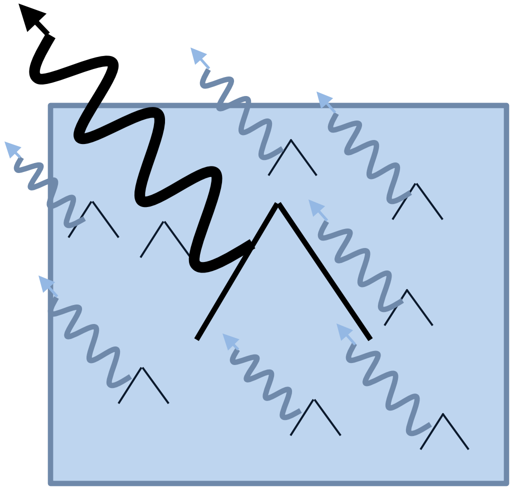


Permanent Scatterer dominates the resolution cell

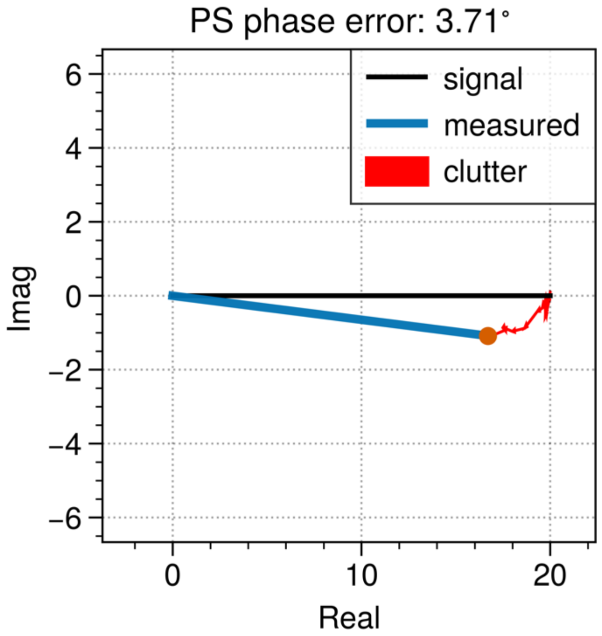
Types of scatterers

National Aeronautics and Space Administration

- **One resolution cell (pixel) contains many scatterers**
- A pixel may:
  a) be largely dominated by a single point scatterer (**Persistent Scatterers (PS)**)



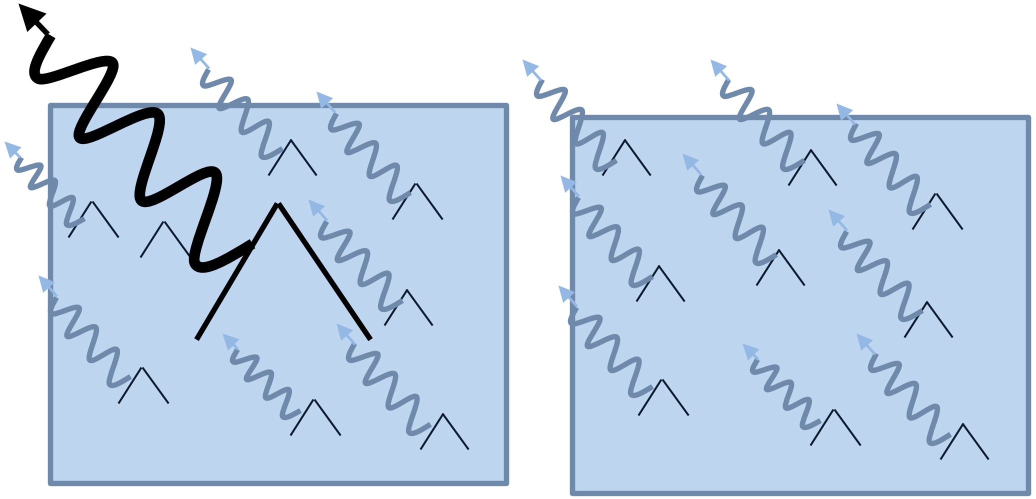
Permanent Scatterer dominates the resolution cell



PS pixels have **low noise**, even at single-look resolution

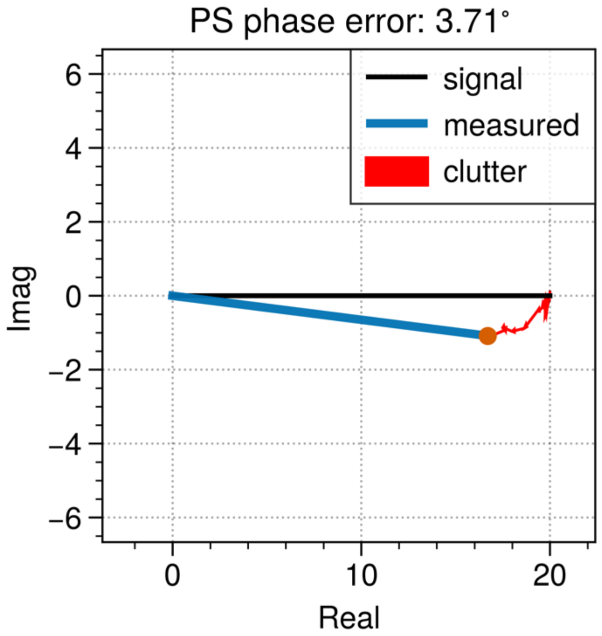
Types of scatterers

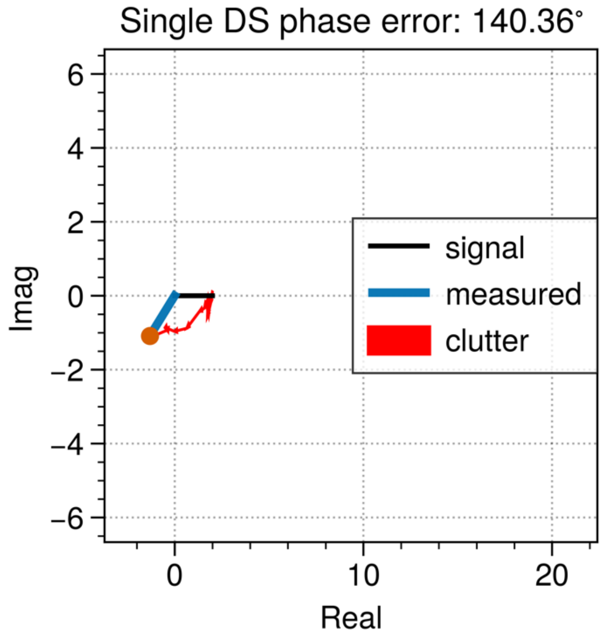
- **One resolution cell (pixel) contains many scatterers**
- A pixel may:
  a) be largely dominated by a single point scatterer (**Persistent Scatterers (PS)**)
  b) contain many scatterers contributing to the sum of the backscattered signal (**Distributed Scatterers (DS)**)



Permanent Scatterer dominates the resolution cell

Distributed Scatterers

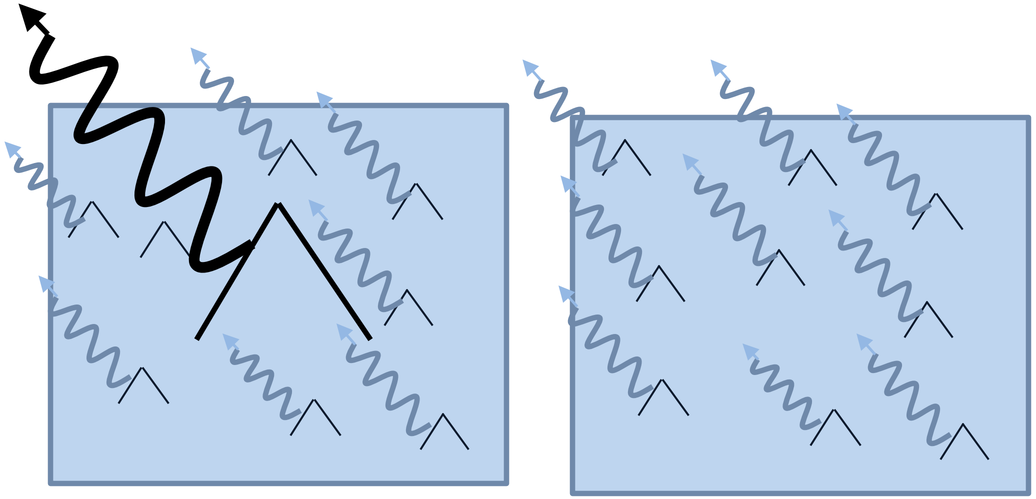


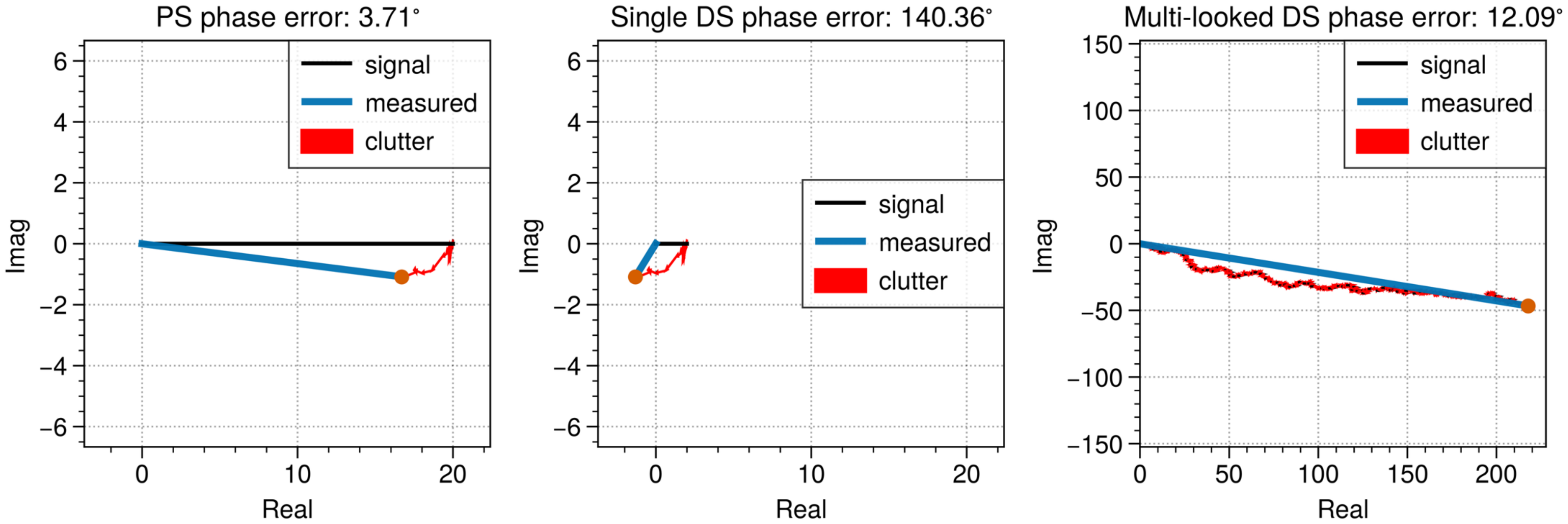


Large error in phase of single pixels!

Types of scatterers

- **One resolution cell (pixel) contains many scatterers**
- A pixel may:
  a) be largely dominated by a single point scatterer (**Persistent Scatterers (PS)**)
  b) contain many scatterers contributing to the sum of the backscattered signal (**Distributed Scatterers (DS)**)
- We can **reduce DS noise by multi-looking** (averaging)





Multi-looking **reduces noise** at the expense of **coarser resolution**

Persistent scatterer (PS) time-series analysis

Persistent scatterer time-series analysis: PS selection

National Aeronautics and Space Administration

1- Amplitude based PS selection to detect stable natural and man-made reflectors (e.g., building) [Ferretti et al 2001]

- The goal is to identify pixels with stable phase over time. The challenge is that the phase is dominated by contributions from atmospheric delay, displacement, geometrical phase and therefore estimating the phase noise is not trivial
- Amplitude is minimally affected by these environmental and geometrical contributors
- Ferretti et al, 2001 proposed amplitude dispersion index as a measure of phase stability

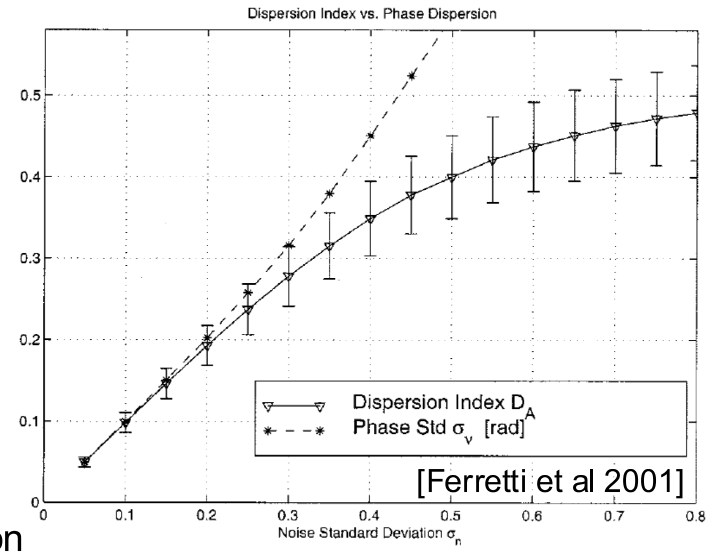
Amplitude standard deviation

$$\sigma_\nu \simeq \frac{\sigma_A}{m_A} \triangleq D_A$$

Phase dispersion

Amplitude mean

Amplitude Dispersion index



[Ferretti et al 2001]

Over high SNR pixels, amplitude dispersion seems to be a good measure of phase dispersion

Persistent scatterer time-series analysis, PS selection

2- Phase-based PS selection [Hooper et al, 2004]

- In order to identify PS pixels (stable phase over time) with low SNR, Hooper et al 2004 suggested to evaluate the phase noise to identify PS pixels
- As mentioned in previous slide, the phase is dominated by atmosphere, geometrical residuals and displacement and therefore can not be readily analyzed to identify low noise pixels
- Assuming a model for interferometric phase, Hooper et al suggest to filter out or estimate different phase components (atmosphere, orbit, DEM error, etc) to isolate noise which then can be evaluated to identify PS pixels

$$\phi_{x,i} = \phi_{def,x,i} + \phi_{\alpha,x,i} + \phi_{orb,x,i} + \phi_{\varepsilon,x,i} + n_{x,i}$$

- It is assumed that deformation, atmosphere and orbital errors are spatially correlated, over a certain spatial length and therefore can be estimated (e.g, averaging or low pass filtering)
- The DEM error is baseline dependent and can be estimated
- Starting with initial PS pixels (with relaxed threshold of amplitude dispersion), the temporal coherence is iteratively computed and thresholded to identify PS pixels (i.e., pixels with high temporal coherence or small phase residual which is assumed to represent noise)

$$\gamma_x = (1/N)\left|\sum_{i=1}^{N} \exp\{j(\phi_{x,i} - \bar{\phi}_{x,i} - \hat{\phi}_{\varepsilon,x,i})\}\right|$$

Persistent scatterer time-series analysis, PS selection

National Aeronautics and Space Administration

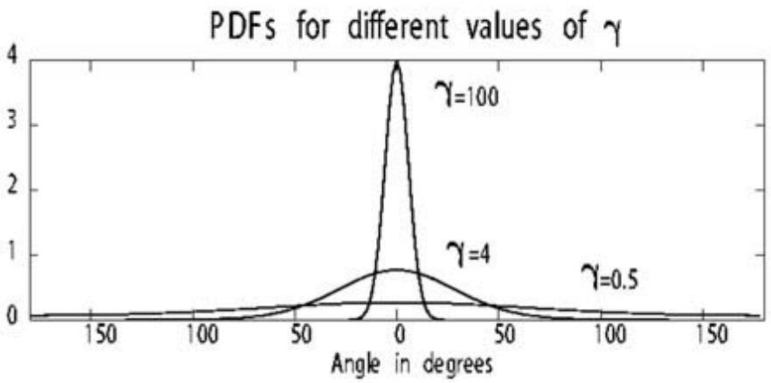
3- Phase based PS selection [Agram and Zebker, 2007]

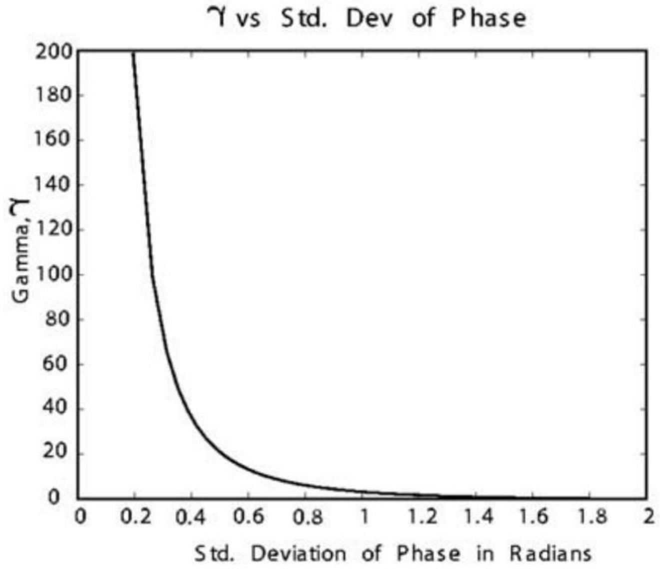
Determine the theoretical phase variation for a pixel as a function of γ, and compare it with the observed interferometric phase (corrected for atmosphere, topography, deformation and other correlated errors) to obtain the maximum likelihood estimate of γ, *which is then thresholded to select PS pixels.*

$$P(\phi) = \frac{1-|\rho|^2}{2\pi} \cdot \frac{1}{1-\beta_\phi^2} \cdot \left\{ 1 + \frac{\beta_\phi . \arccos(-\beta_\phi)}{\sqrt{1-\beta_\phi^2}} \right\}$$

where $\beta_\phi = |\rho| \cos \phi$ and the interferometric correlation ρ depends on γ through

$$|\rho| = \frac{1}{1+\gamma^{-1}}$$





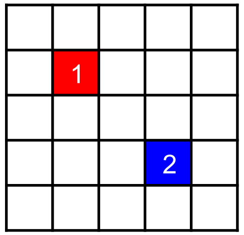
[Agram & Zebker 2007]

Agram and Zebker 2007 use the same signal model of Hooper et al 2004 to isolate phase noise.

Permanent scatterer time-series analysis, PS selection

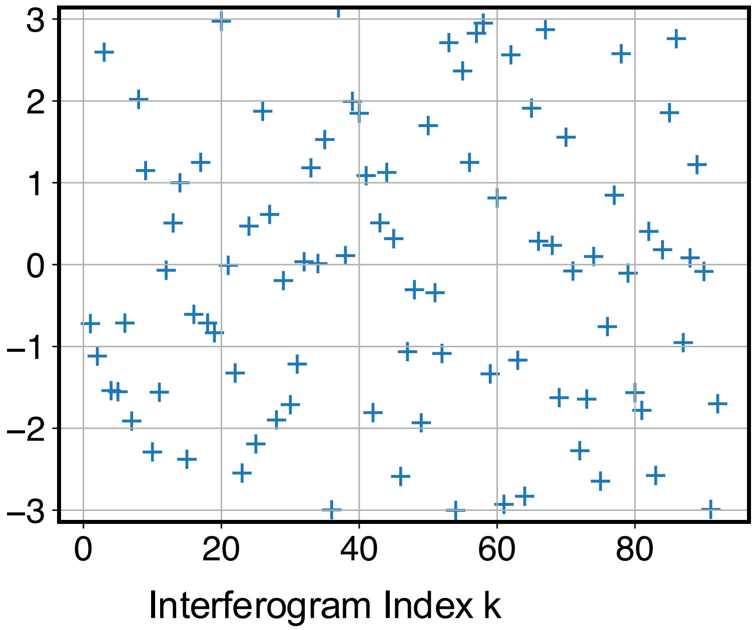
4- Phase based PS using similarity [Wang and Chen, 2022]

$$s_{1,2} = \frac{1}{K-1}\sum_{k=1}^{K-1}\cos\left(\varphi_k^{(1)} - \varphi_k^{(2)}\right)$$



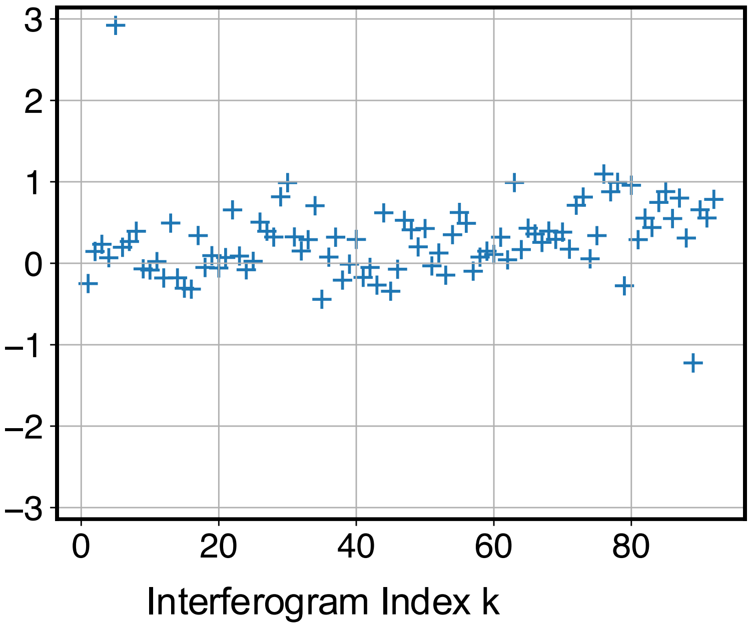
After initial selection of the PS pixels using MLE approach, Wang and Chen evaluate the cosine similarity between the possible PS candidates and through multiple iterations they converge to final identified PS pixels

Pixel1 or Pixel2 is non-PS



Phase similarity = 0.093

Pixel1 and Pixel2 are PS



Phase similarity = 0.876

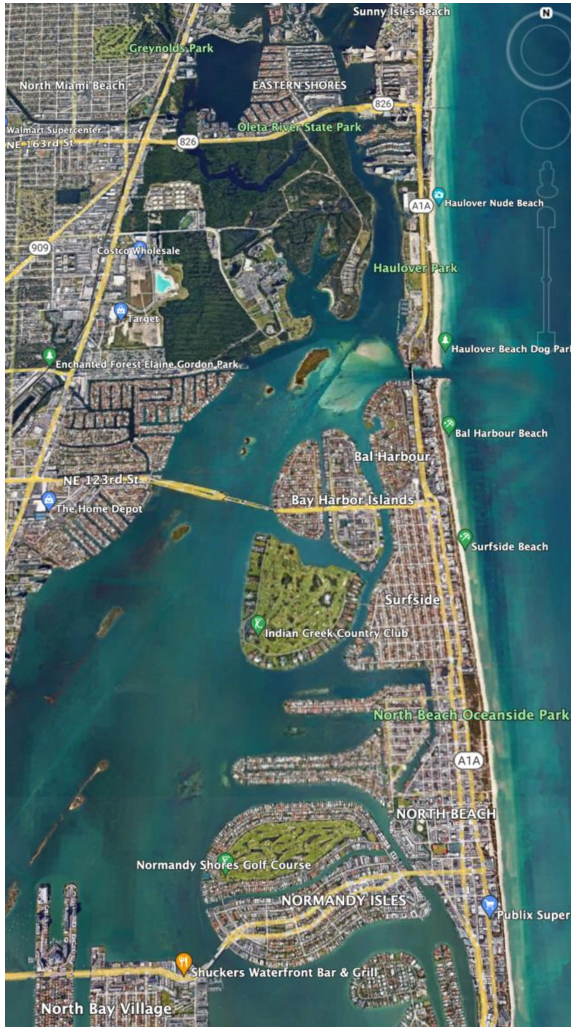
[Wang & Chen 2022]

Persistent scatterer time-series analysis

National Aeronautics and
Space Administration

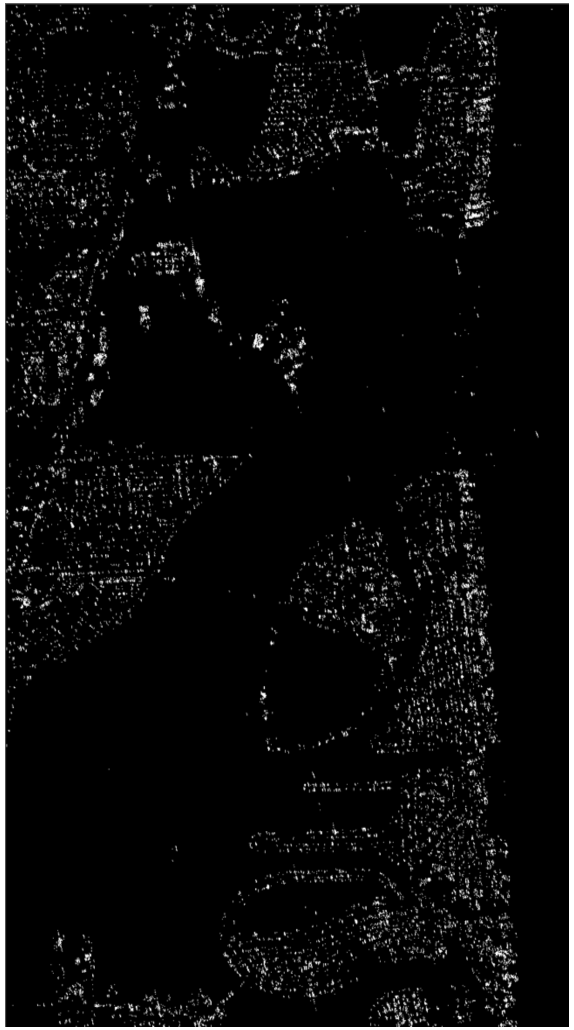
- Amplitude dispersion computed from a stack of 161 SLCs from Sep 2015 to May 2022 over north Miami beach
- Dark pixels in the amplitude dispersion are PS candidates
- PS pixels identified by thresholding the amp dispersion

Optical image (Landsat/ Google)



Amplitude dispersion

PS pixels



Permanent scatterer time-series analysis

National Aeronautics and Space Administration

No PS pixels identified over the Golf course, because the grass land does not contain strong scatterers and

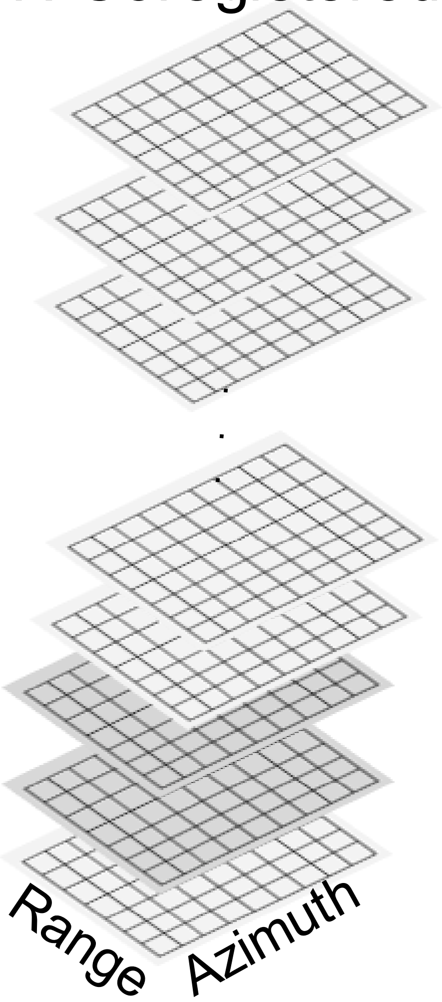
Clear subsidence signal in Miami beach [Mirzaee et al, 2023]

Most PS pixels are identified over buildings

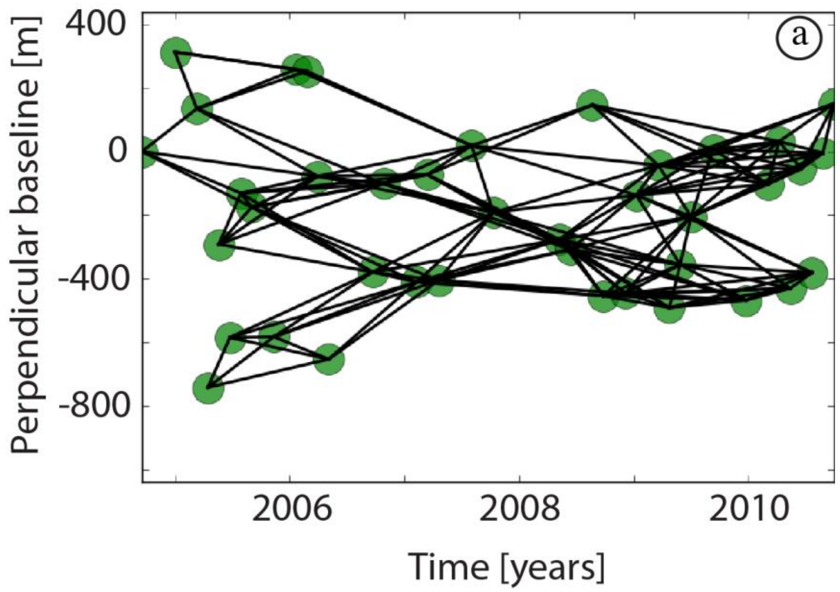
Distributed scatterer (DS) time-series analysis

DS time-series analysis: SBAS

N Coregistered SLCs



Create a network of multi-looked interferograms



<u>SBAS Core Idea</u>

Interferograms made with **short temporal** and **short perpendicular baselines** are **more coherent**

- Each green circle in this plot represents one SAR image
- Each line represents one interferogram

DS time-series analysis: SBAS

Observations
vector of unwrapped phases at a pixel

Design Matrix

Unknowns
Unwrapped phase time-series relative to a reference date-time

$$\delta\varphi = A\phi$$

$$\delta\hat{\varphi}_{ij} = \hat{\phi}(t_j) - \hat{\phi}(t_i)$$

$$\gamma = \left| \frac{1}{M} \sum_{i=1}^{M} \exp\left[j(\delta\varphi_i - \delta\hat{\varphi}_i) \right] \right|$$

$$0 \le \gamma \le 1$$

Temporal coherence

The unwrapped phase time-series is found by minimizing the of the residual vector.

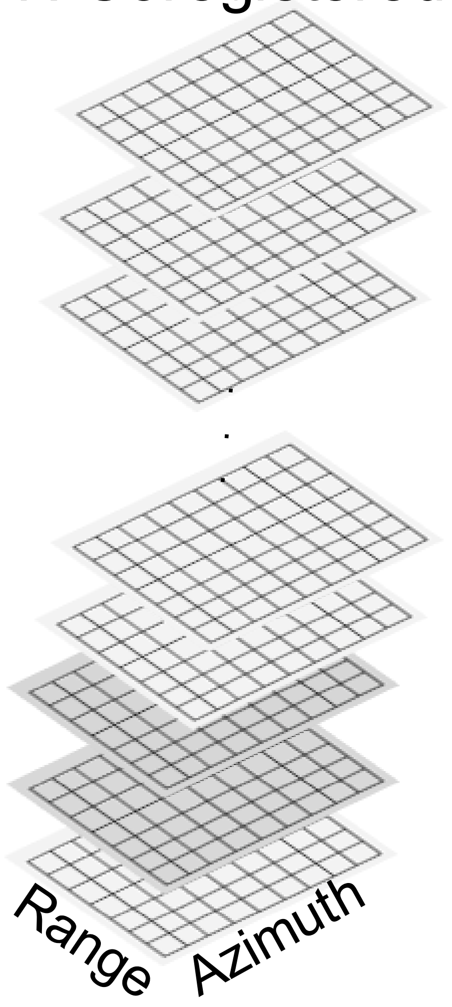
This can be L1 norm, L2 norm (least squares*), and can be a weighted by noise variances.

Temporal coherence derived from the unwrapped residual vector describes quality of inversion

*Or, if under-determined, SVD minimum-norm solution

DS time-series analysis: phase linking

N Coregistered SLCs



Create **all** multi-looked interferograms

Optimize to find N-1 wrapped phase differences

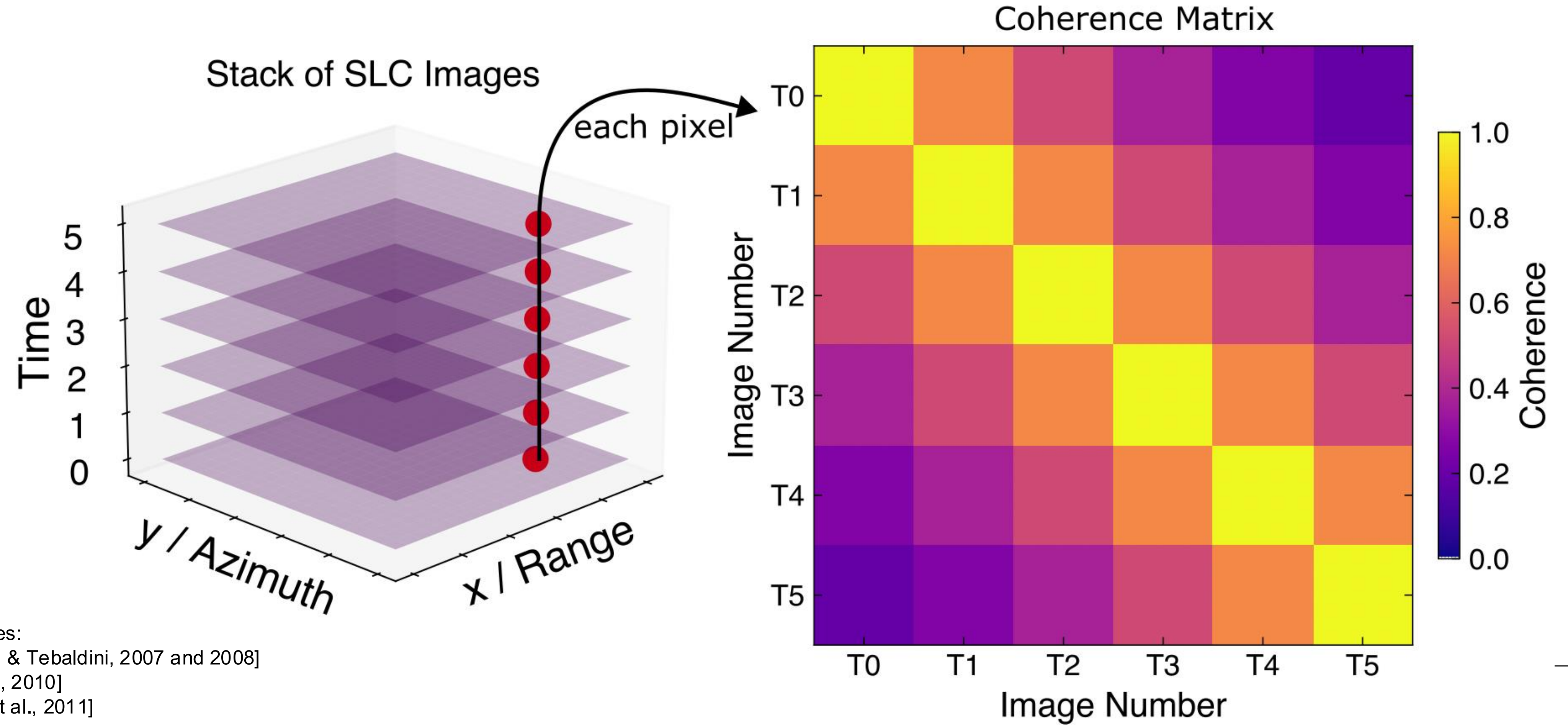
Unwrap
(either single-look like PS, or redundant network)

Phase linking core Idea

- Estimate the “best” N-1 wrapped interferometric phases from N SLCs.
- Make a DS behave like a PS (remove phase mis-closure before unwrapping)

DS time-series analysis: phase linking

For N SAR images, at every pixel:
- Create $N \ x \ N$ coherence matrix with all possible multi-looked interferograms
- Perform optimization to get N filtered, "cleaner" phases

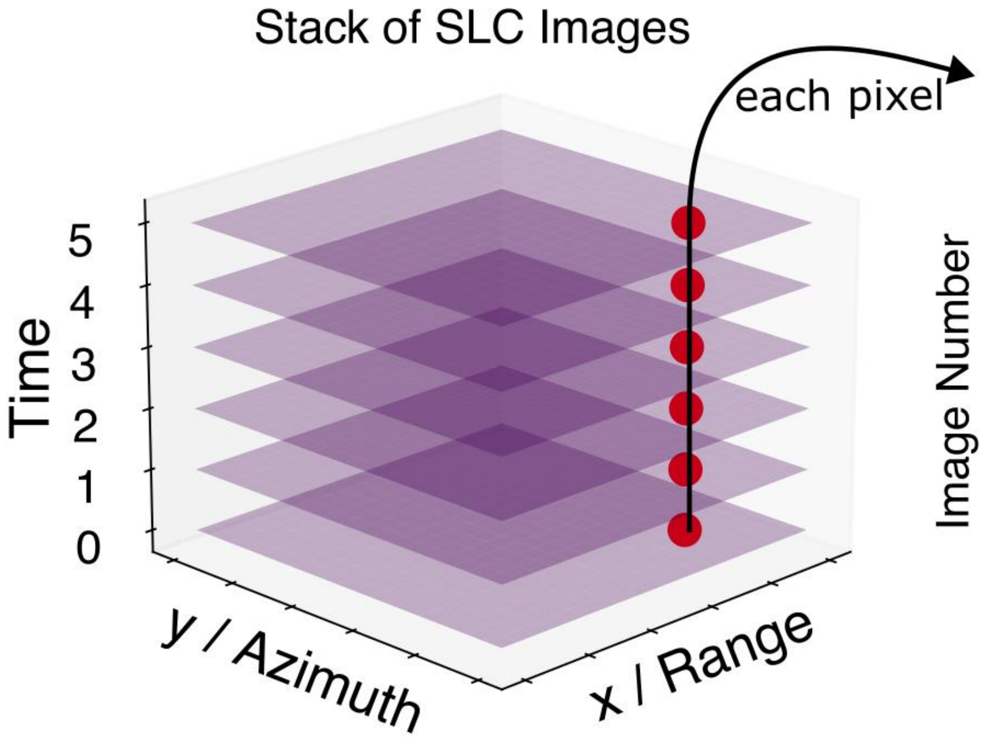


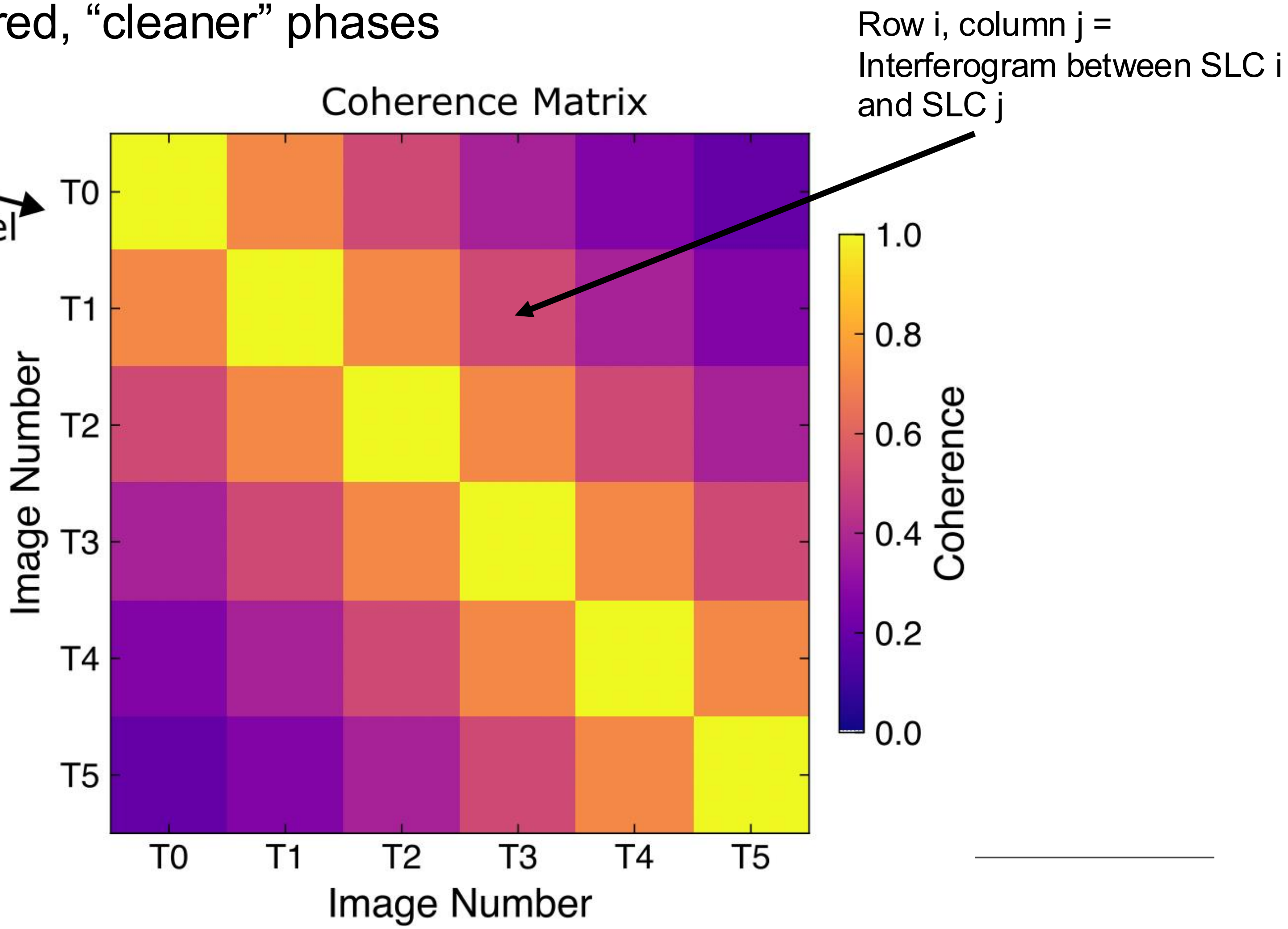
References:
[Guarnieri & Tebaldini, 2007 and 2008]
[Tebaldini, 2010]
[Ferretti et al., 2011]

DS time-series analysis: phase linking

For N SAR images, at every pixel:

- Create $N \times N$ coherence matrix with all possible multi-looked interferograms
- Perform optimization to get N filtered, "cleaner" phases



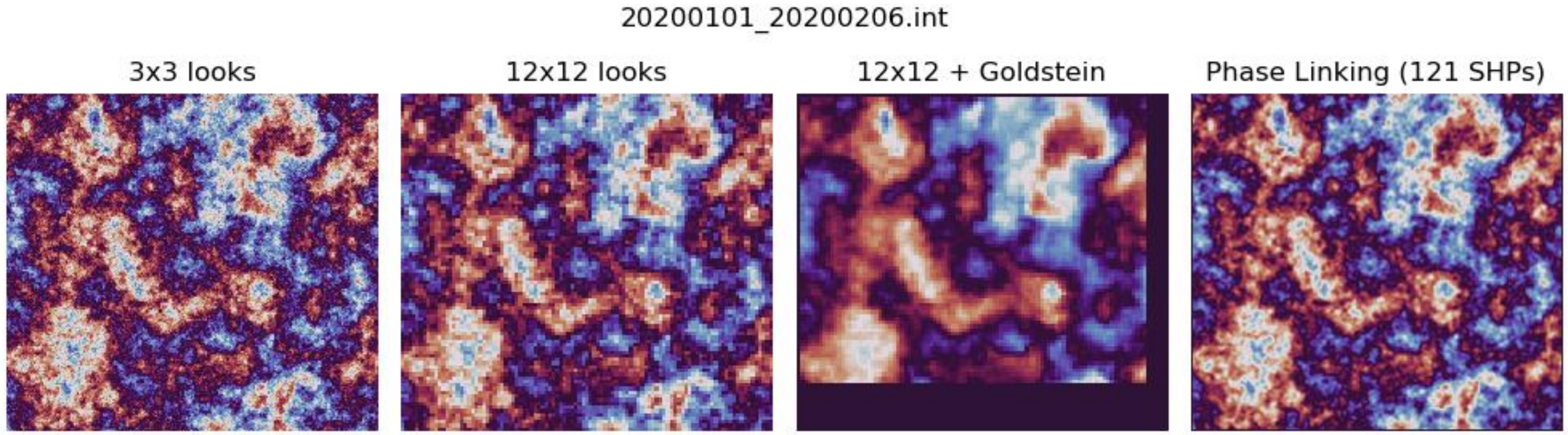


References:
[Guarnieri & Tebaldini, 2007 and 2008]
[Tebaldini, 2010]
[Ferretti et al., 2011]

DS time-series analysis: phase linking

Synthetic example

- Simulate turbulence atmosphere and exponential decaying correlation: $\rho(t) = e^{-t/\tau}, \tau = 60$ days
- Compare 3x3 multilooked interferograms, 12x12, 12x12 + Goldstein filtering, phase linking



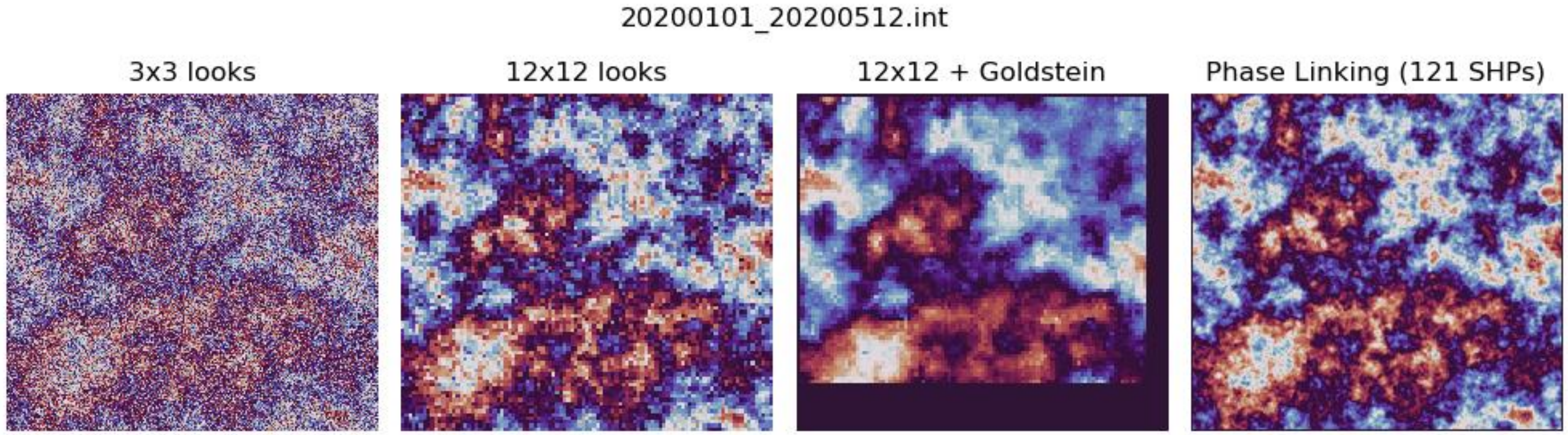
After **1 month**, little difference better multi-looked interferograms and phase linking

DS time-series analysis: phase linking

National Aeronautics and Space Administration

Synthetic example

- Simulate turbulence atmosphere and exponential decaying correlation: $\rho(t) = e^{-t/\tau}, \tau = 60$ days
- Compare 3x3 multilooked interferograms, 12x12, 12x12 + Goldstein filtering, phase linking

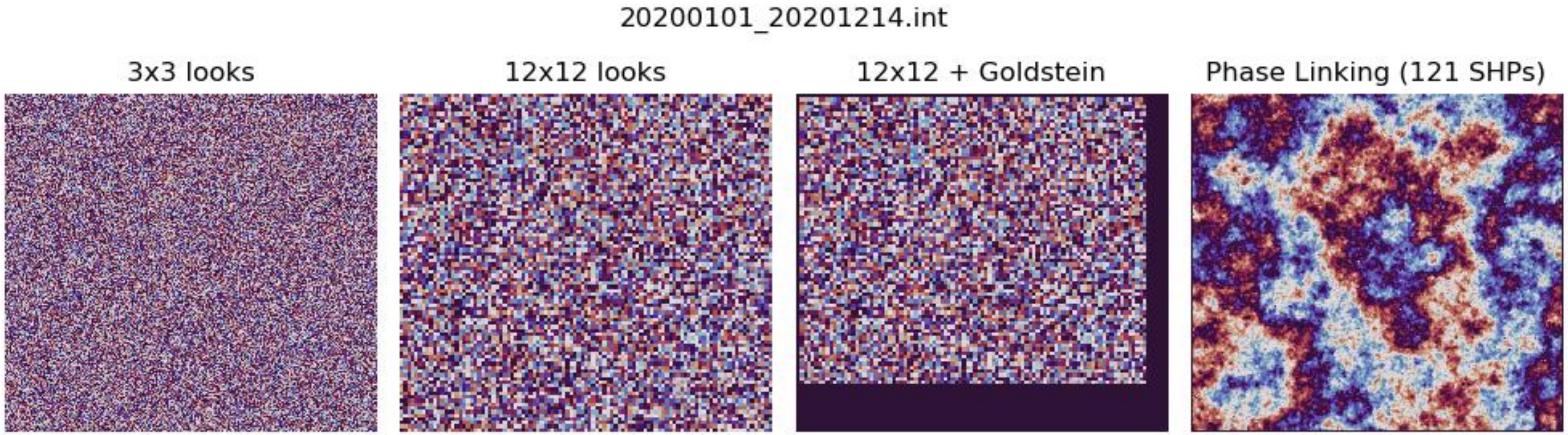


After **4 month**, more looks are required to maintain coherence

DS time-series analysis: phase linking

Synthetic example

- Simulate turbulence atmosphere and exponential decaying correlation: $\rho(t) = e^{-t/\tau}, \tau = 60$ days
- Compare 3x3 multilooked interferograms, 12x12, 12x12 + Goldstein filtering, phase linking



After **11 months**, only phase linking maintains coherence

DS time-series analysis – phase linking algorithms

National Aeronautics and Space Administration

1) Maximum Likelihood Estimator (MLE) [Guarnieri and Tebaldini]:

[Ferretti et al, 2011] in the SqueeSAR algorithm, propose PTA algorithm to maximizing the probability distribution function of the data using repetitive optimization algorithms

$$\boldsymbol{\Theta} = \arg max_{\boldsymbol{\Theta}}\{\boldsymbol{\Theta}^H (\left|\hat{\Gamma}\right|^{-1} \circ \hat{\Gamma})\boldsymbol{\Theta}\}$$

2) Classic Eigenvalue Decomposition (CED) [Fornaro et al 2015]

Also known as EVD or CEASAR, the CED estimator suggest that the phase of the eigenvector corresponding to the largest eigenvalue of the complex covariance matrix represents the wrapped phase time-series

$$\hat{\Gamma}\,\hat{\boldsymbol{v}} = \lambda_m \hat{\boldsymbol{v}}$$

3) Eigenvalue Based Maximum Likelihood Estimator (EMI)

Instead of using PTA for estimating the MLE of the wrapped phase time-series, [Ansari et al, 2018] suggest to simply take the eigenvector corresponding to the minimum eigenvalue of $\left|\hat{\Gamma}\right|^{-1} \circ \hat{\Gamma}$

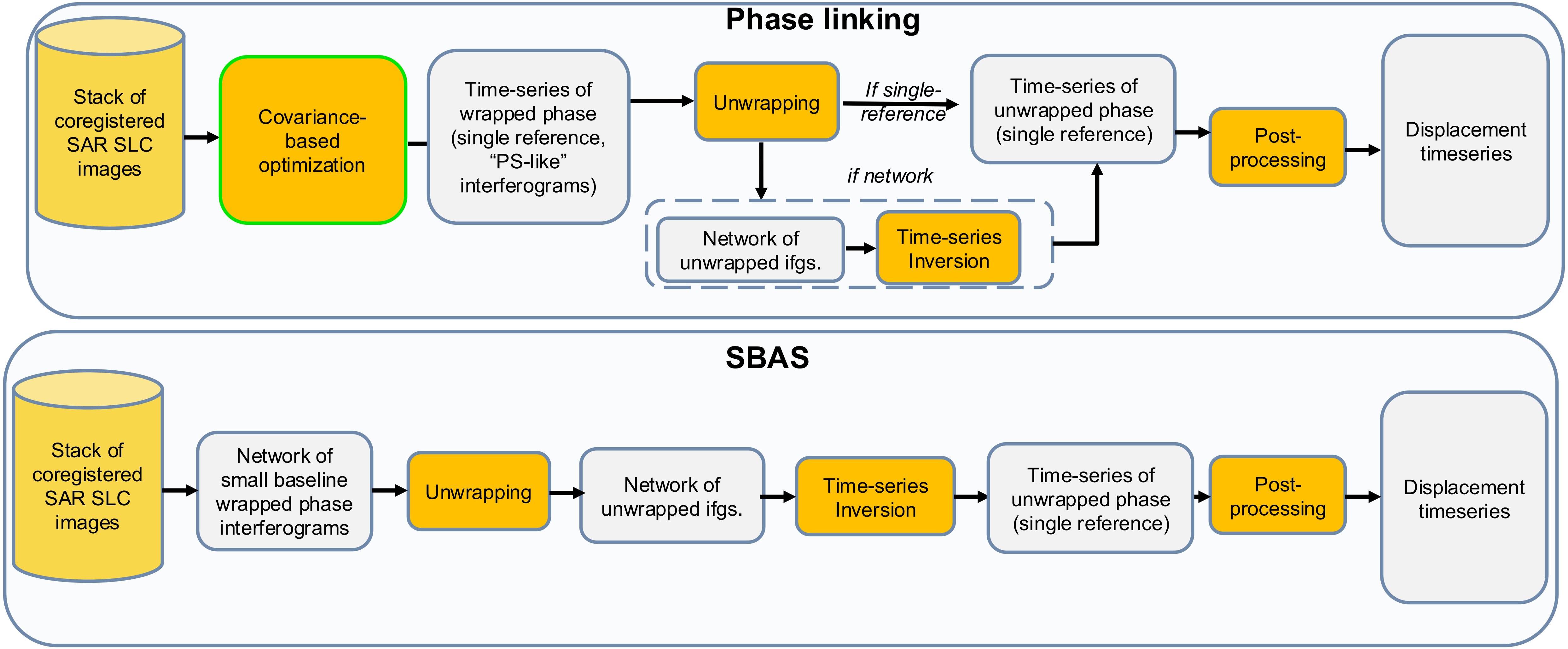
$$(\left|\hat{\Gamma}\right|^{-1} \circ \hat{\Gamma})\hat{\boldsymbol{v}} = \lambda_m \hat{\boldsymbol{v}}$$

DS time-series analysis: phase linking benefits

National Aeronautics and Space Administration

- Interferometric phase can show much lower noise after phase linking
- Less parameter-tuning required / less network thresholds selection for each site
- Reduces impact of closure phase on displacement estimates
- Computational impact is low to moderate (interferograms are formed “on the fly”)

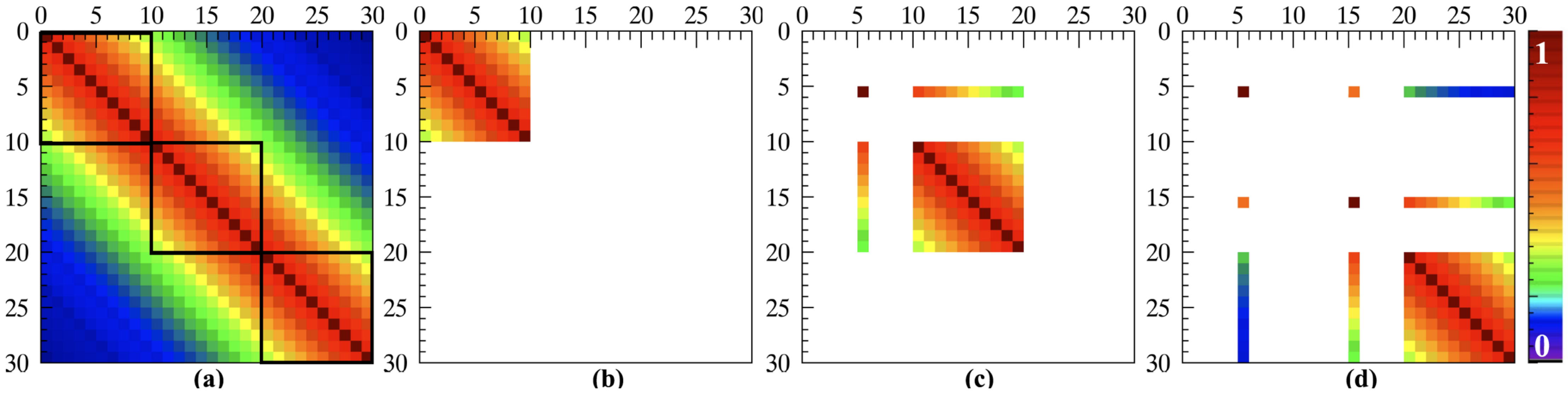
DS time-series analysis - Full covariance algorithms



DS time-series analysis - Full covariance algorithms for Big data

National Aeronautics and Space Administration

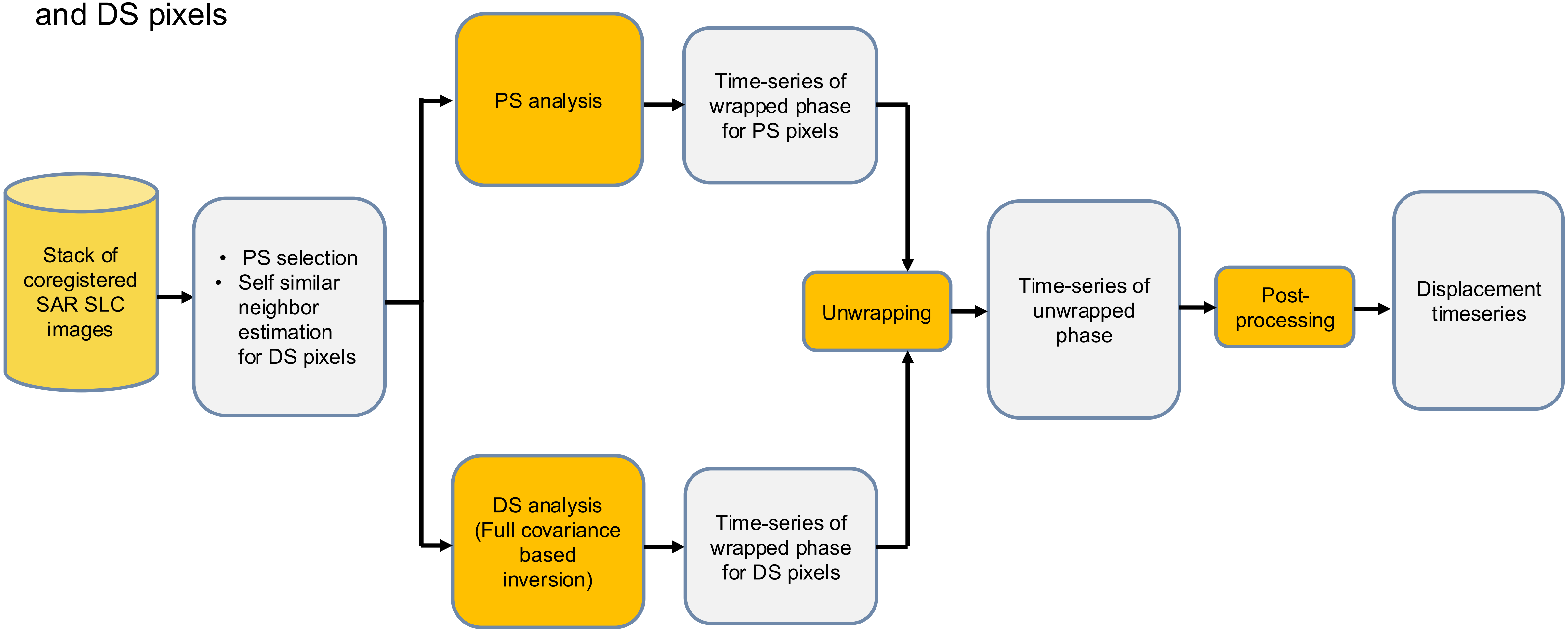
- Regardless of the choice of the estimator, the wrapped phase time-series from a full covariance matrix formed from a large stack of SLCs is an expensive operation.
- With new acquisitions added to the existing stacks, there is a need for time-series update in opposite to reprocessing the entire stack with every new acquisition.
- Ansari et al, 2017 proposed Sequential Estimator algorithm which processes a covariance matrix in batch and allows to update an existing time-series without processing the full covariance matrix.



[Ansari et al, 2017]

PS+DS time-series analysis

The combined PS+DS time-series analysis algorithms provide estimated time-series for both PS and DS pixels

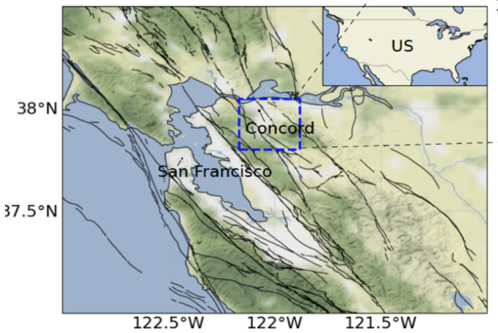


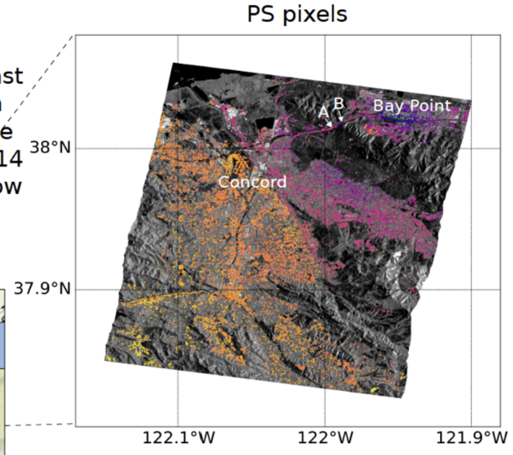
PS+DS time-series analysis- Examples

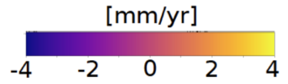
National Aeronautics and Space Administration

Example 1: Concord Fault

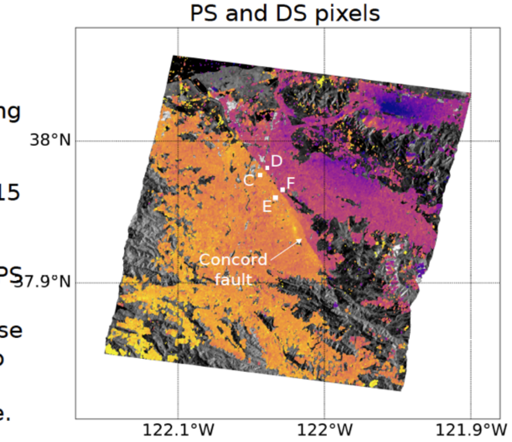
Concord fault, a strike-slip fault running through Concord city, California in the east of San Francisco bay area is under a high stress level and therefore may be capable of producing earthquakes larger than 2014 South Napa earthquake (USGS). At shallow depths, the fault may release part of the strain aseismically with episodic events.

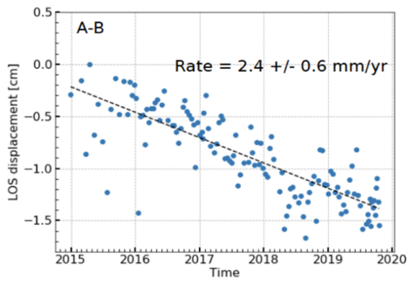




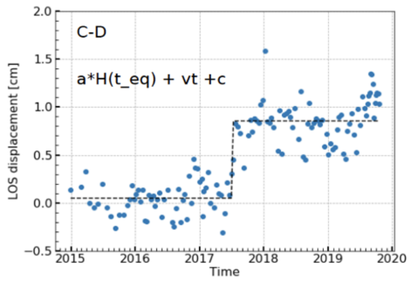


138 SAR acquisitions acquired by Sentinel-1 were coregistered using ISCE. We estimated the neighborhood map using KS2 test and the estimated the wrapped phase time-series of DS pixels using the Sequential approach with mini-stacks of 15 acquisitions and with the eigen-decomposition as the solver. We used an amplitude dispersion of 0.4 for choosing PS pixels and then unwrapped the phase series of PS and DS pixels together. We use 2D unwrappers to simultaneously unwrap the PS and DS pixels.
The DS and PS rate maps generally agree.

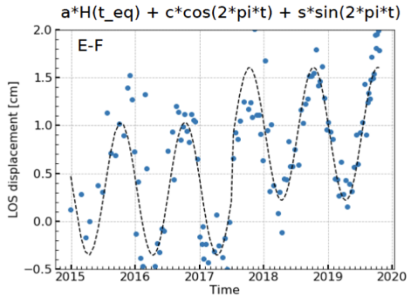




Strong subsidence signal



A creep event



Strong seasonal deformations are c
series can be best explained with a
The latter represents the creep eve
represented.

Seasonal displacement superimposed on the creep event

[Fattahi et al, 2019]

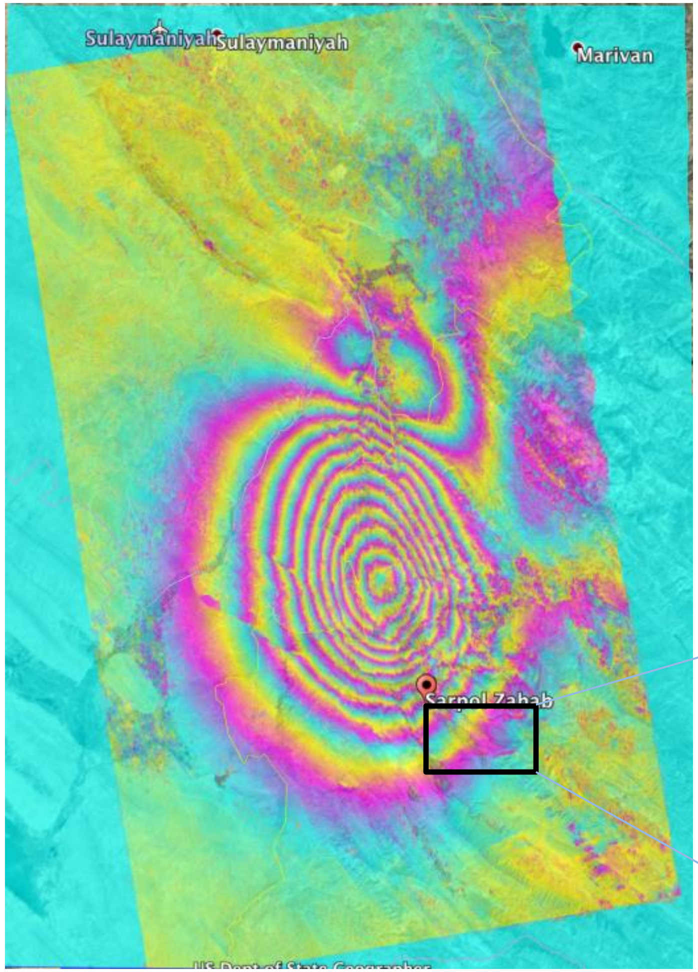
PS+DS time-series analysis- Examples

Magnitude of the normalized full covariance matrix, represents the coherence matrix

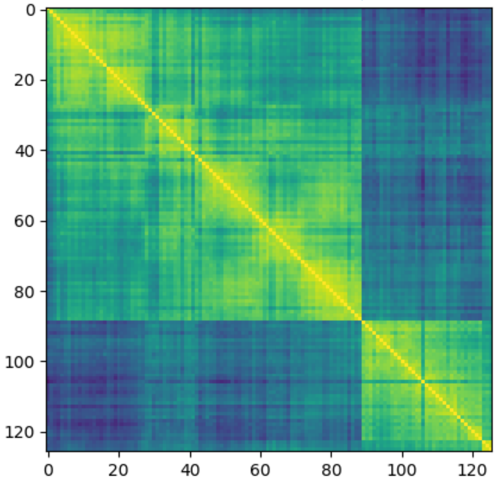
Changes in the scattering properties of the scene can impact coherence

Changes can be potentially detected by coherence time-series

Co-seismic



A change in the coherence magnitude history most likely caused by the damages caused by the Earthquake

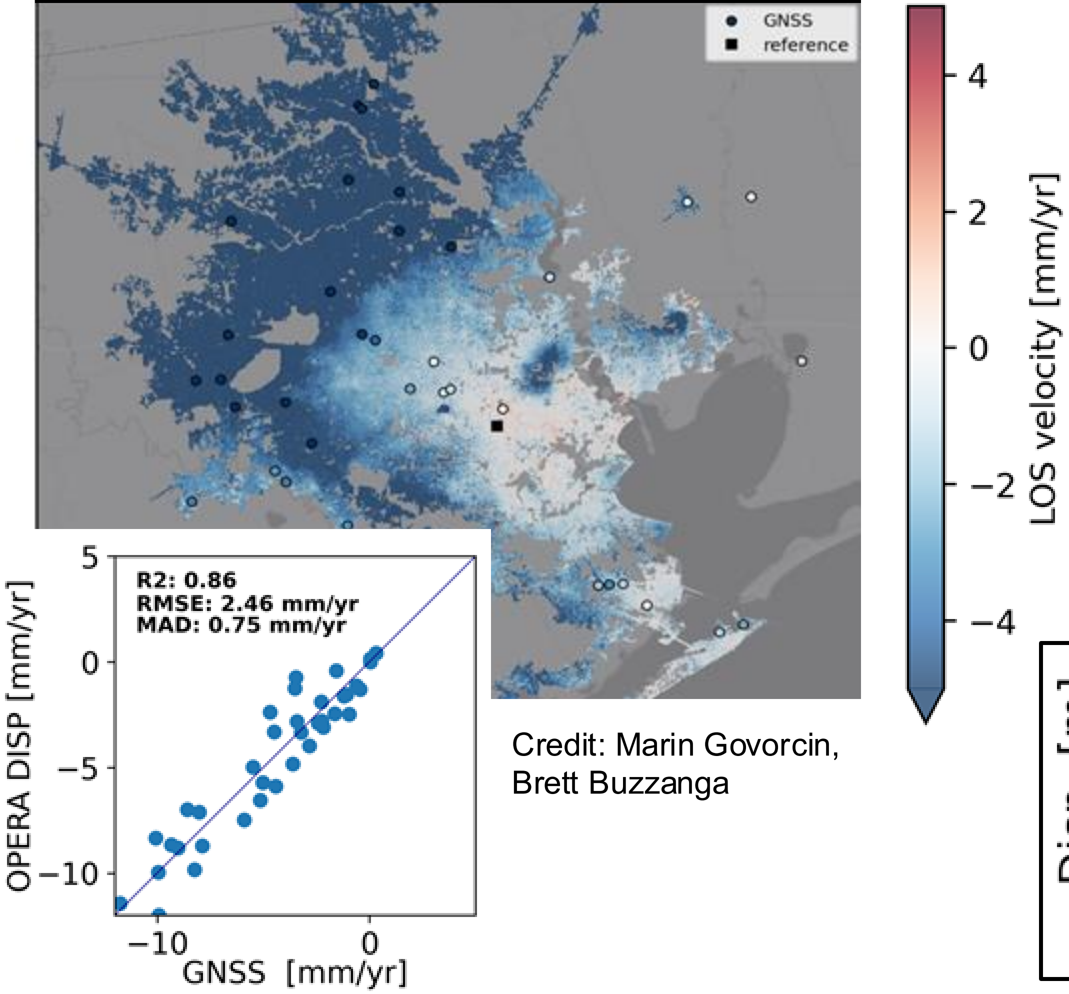


A change in the coherence matrix after the earthquake, demonstrates the potential of full coherence matrix for change detection and damage proxy mapping.

PS+DS time-series analysis- Examples

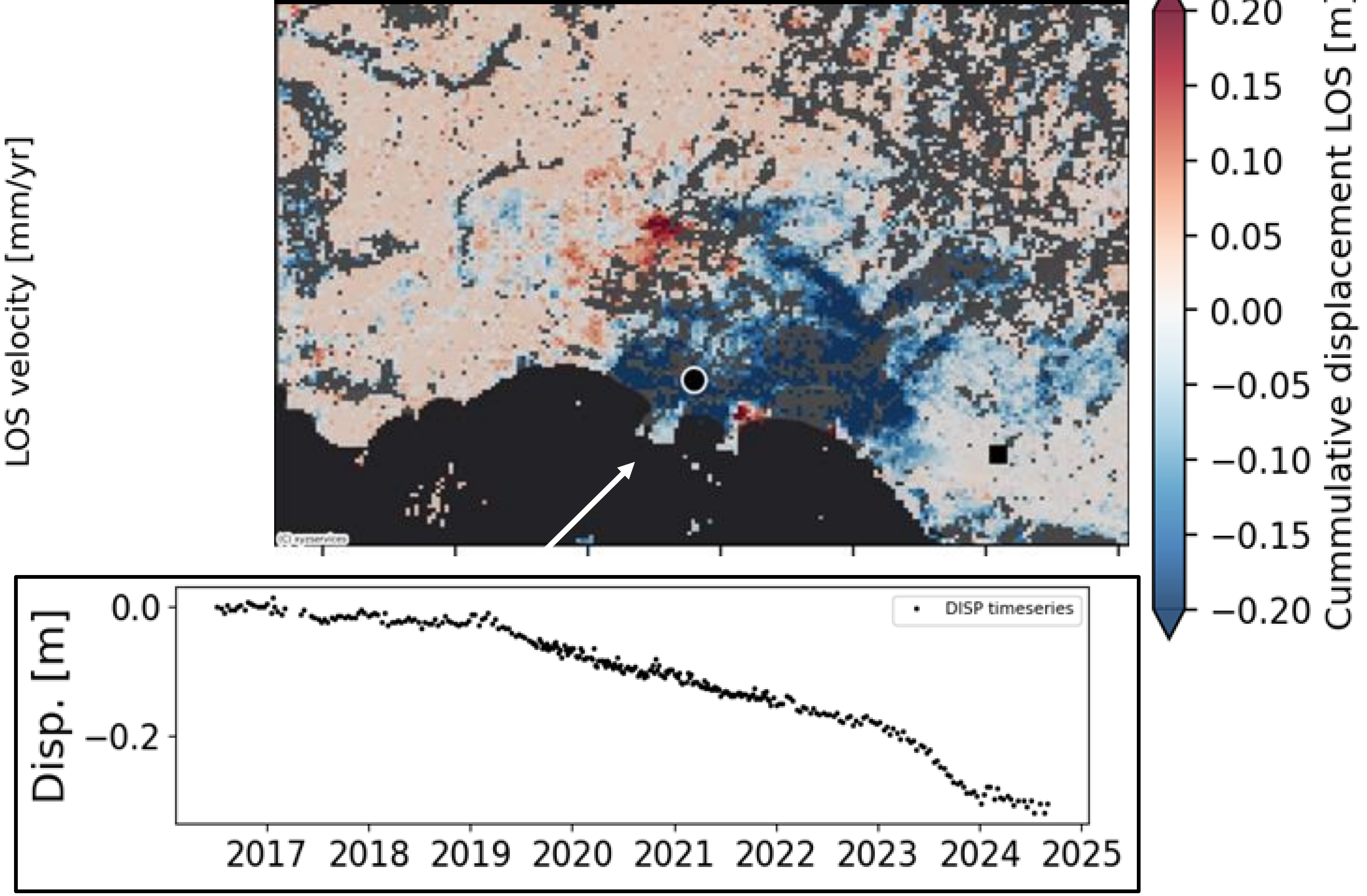
National Aeronautics and Space Administration

Average Velocity – Houston, TX



Credit: Marin Govorcin, Brett Buzzanga

Palos Verdes, CA

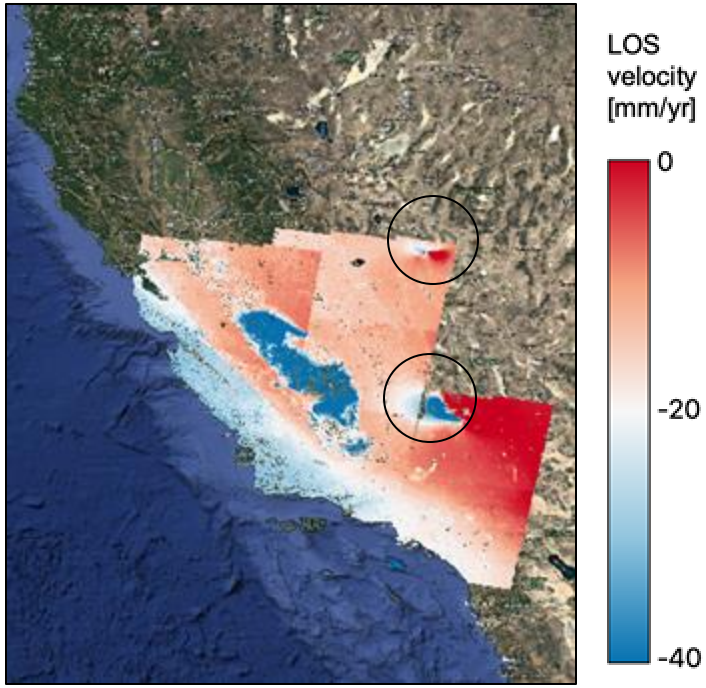


Credit: Al Handwerger

Phase linking results compared to Handcrafted Dataset: California

National Aeronautics and Space Administration

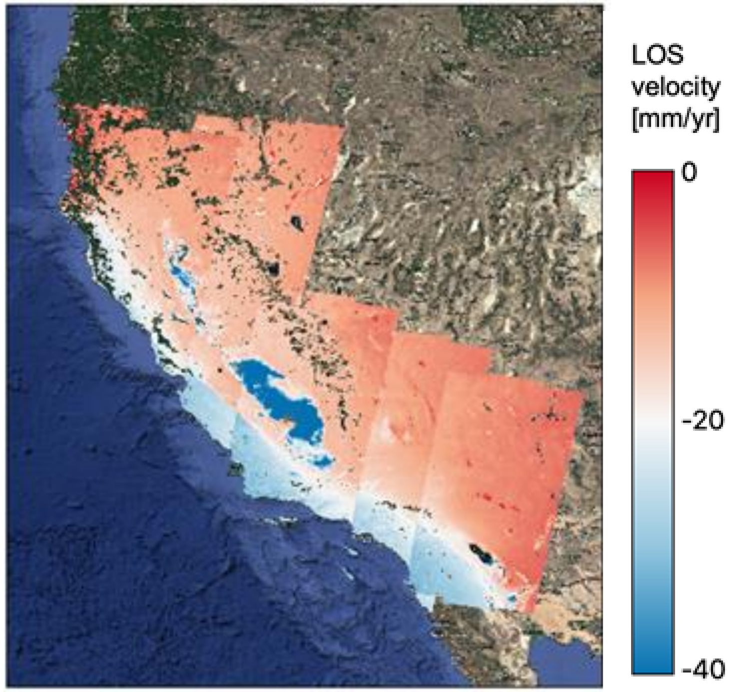
OPERA DISP-S1



Includes coseismic signals filtered by other groups

ARIA research group

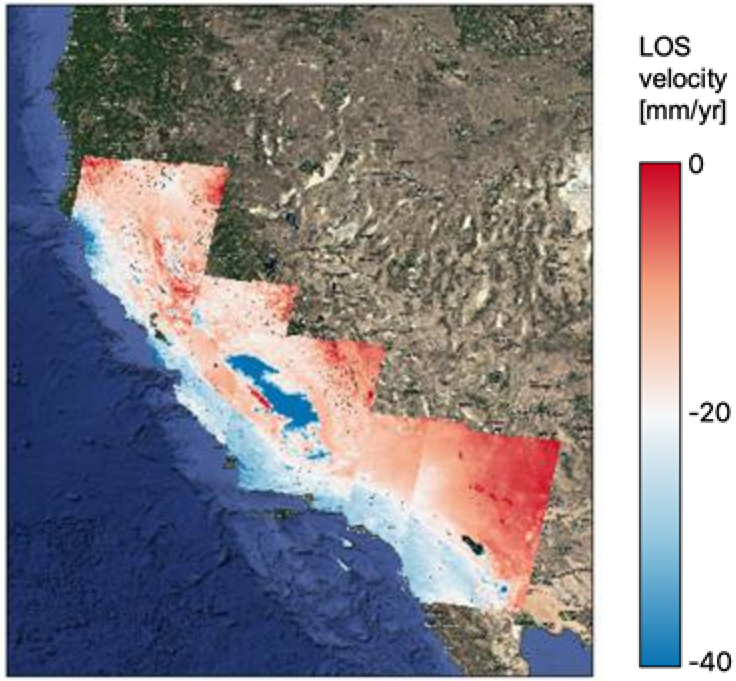
(Govorcin et al., 2024)



Govorcin, M., Bekaert, D., Hamlington, B., Sangha, S., and Sweet, W. (*in press*). Variable vertical land motion for sea level rise projections. Science Advances

UC San Diego

(Xu *et al.*, 2021)



Xu, X., Sandwell, D. T., Klein, E., & Bock, Y. (2021). Integrated Sentinel-1 InSAR and GNSS time-series along the San Andreas fault system. *Journal of Geophysical Research: Solid Earth*, 126, e2021JB022579. https://doi.org/10.1029/2021JB022579

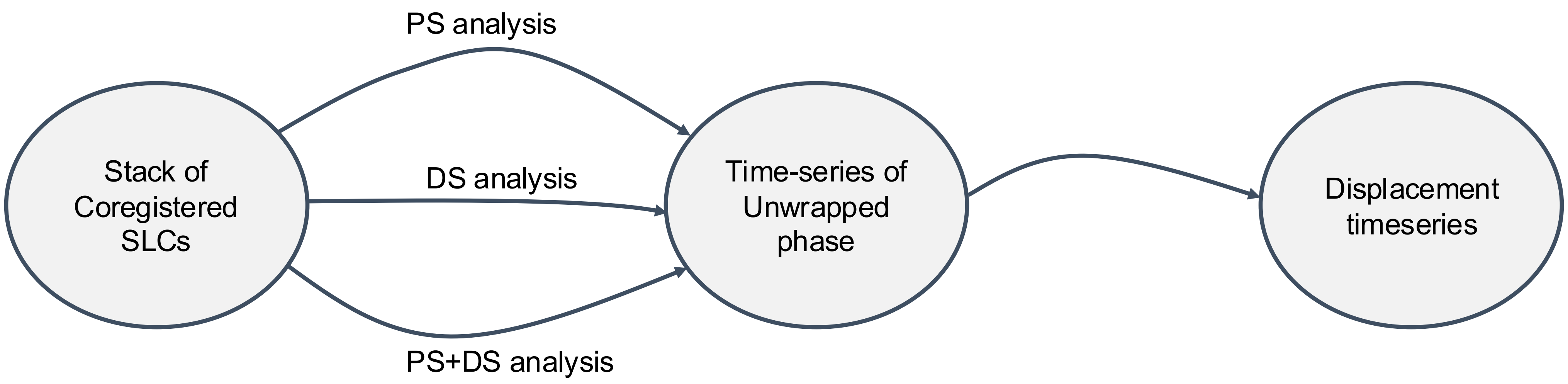
Error analysis of the InSAR timeseries

Error analysis of InSAR time-series

National Aeronautics and Space Administration

The uncertainty of the estimated displacement time-series is a function of:

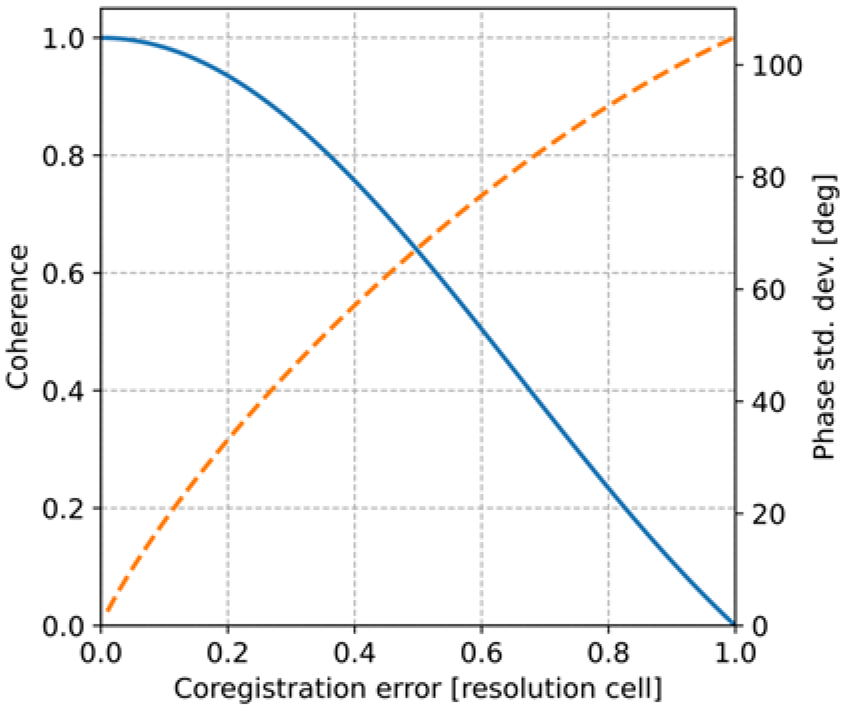
1. the quality of the stack of coregistered SLC
2. the quality of the time-series of unwrapped phase
3. accuracy in isolating the ground displacement from other interferometric phase contributions (tropospheric delay, ionospheric delay, interferometric phase components driven by the dielectric changes, etc)

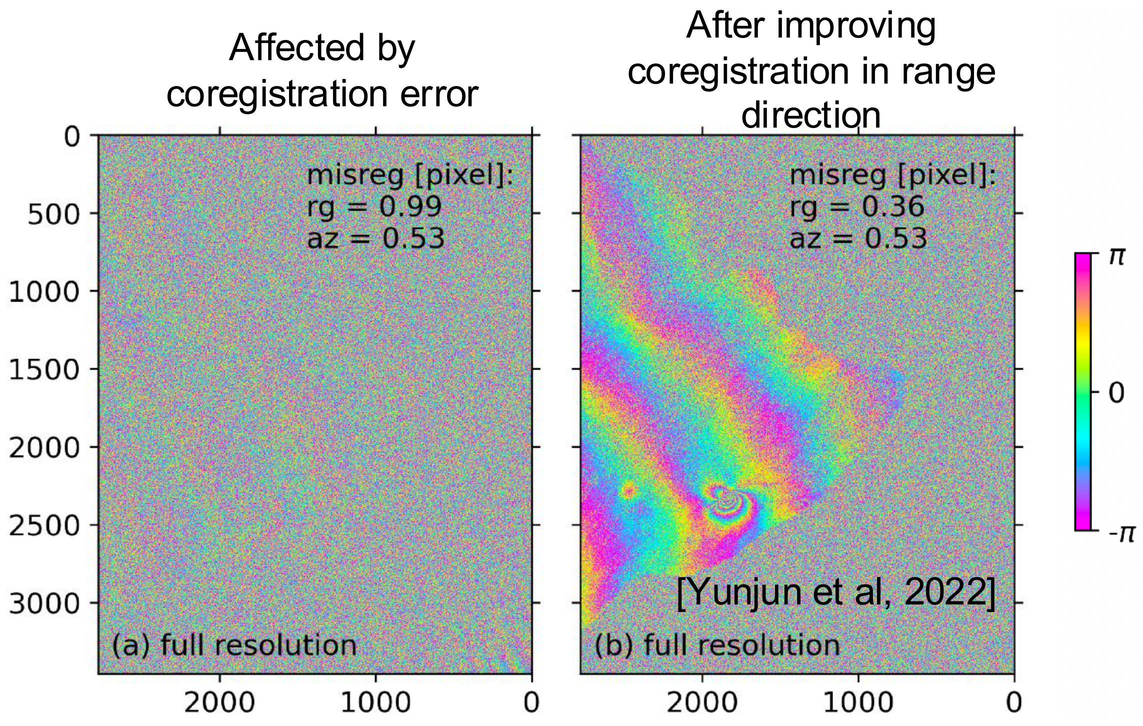


Coregistration error

National Aeronautics and Space Administration

- The input stack of SLC images for InSAR time-series analysis should be aligned (coregistered) with accuracies of ~1/10th of the SLC resolution cell or better
- Coregistration errors (or misregistration) of the stack of SLC images leads to increased interferometric phase noise, i.e., worsens the accuracy of interferometric phase and subsequent time-series products





Unwrapping errors

- Phase unwrapping is the process of reconstructing the phase field by adding integer number of phase cycle to the wrapped interferometric phase

- Unwrapping error: wrong integer cycle (wrong 2*PI) added to the wrapped phase

- Unwrapping errors can lead to non-closing triplets of the Integer cycles

- Evaluating the closure phases of the dense stacks of interferograms helps to identify areas affected by unwrapping errors and potentially correct them

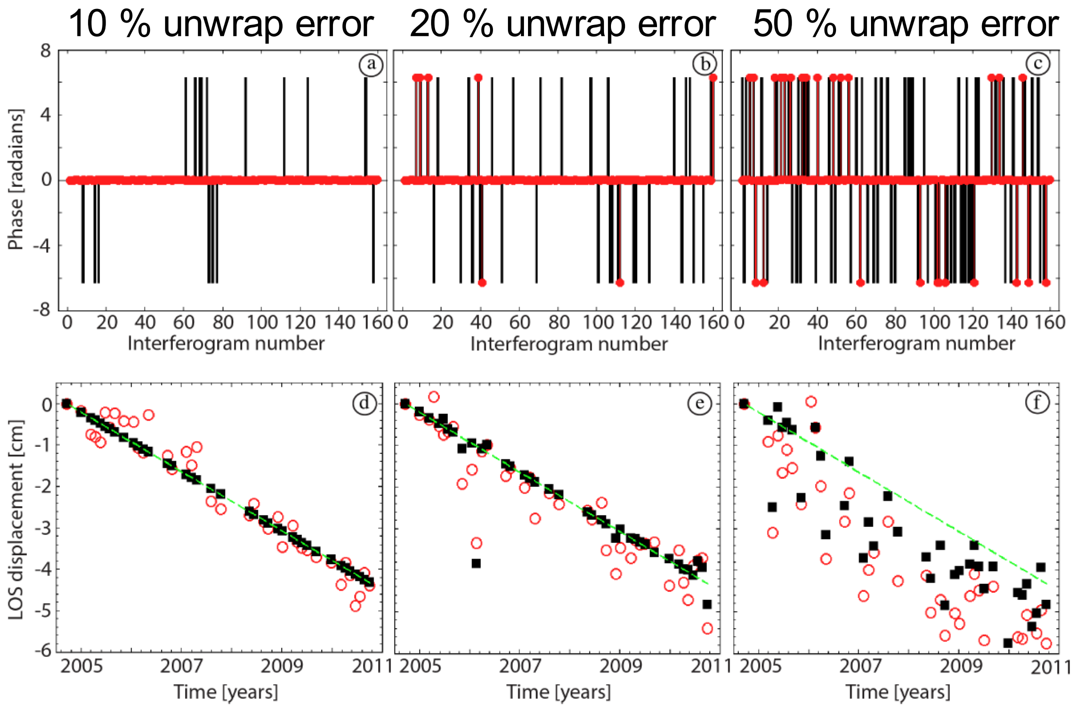


Figure 4.4 Effect of the unwrapping error correction on the interferometric phases and on the estimated displacement history. (a-c): The unwrapping errors in the simulated interferograms before (black bars) and after (red bars) unwrapping error correction for the three simulations with a) 10%, b) 20% and c) 50% of the simulated unwrapping errors. (d-f): The estimated displacement history before (red circles) and after (black squares) unwrapping error correction compared with the simulated displacement (green dashed line) for the three simulations with d) 10%, e) 20% and f) 50% of the unwrapping errors.

[Fattahi, 2015]

Unwrapping errors – impact of interferogram network

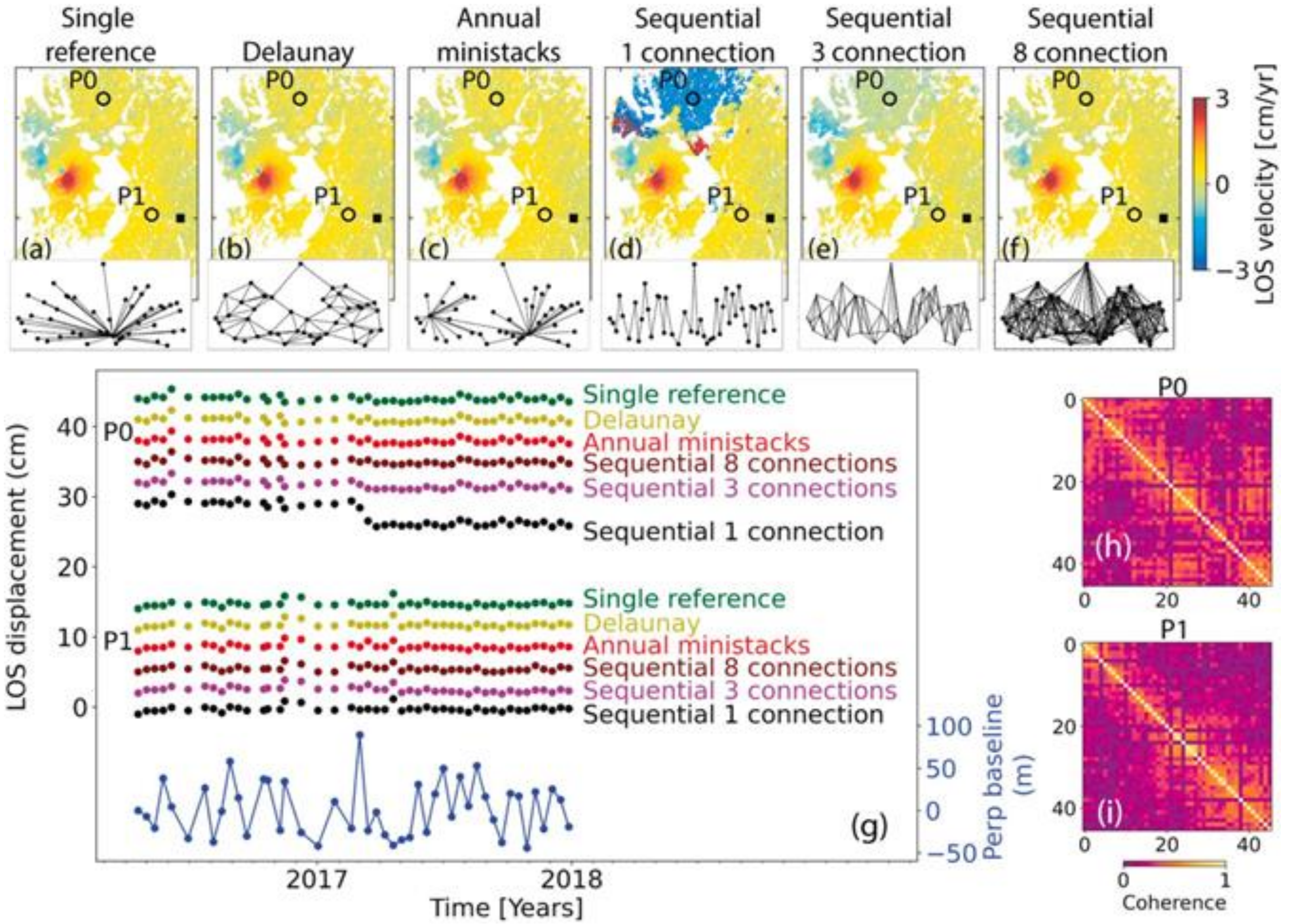
National Aeronautics and Space Administration

Phase unwrapping error in individual interferograms propagate to time-series depending on the interferogram network

Single reference and Delaunay are most robust networks

(i) For cases with long-term coherent interferograms → use a single-reference network: because the unwrap errors don't propagate and because it requires the least memory.

(ii) For cases with strong seasonal decorrelation and cases where correlation is lost rapidly → a Delaunay network may be preferred if overhead extra computation can be afforded



[Mirzaee et al, 2023]

DEM error

National Aeronautics and Space Administration

$$\delta\phi = \delta\phi_{displacement} + \delta\phi_{atmosphere} + \delta\phi_{geometry} + \delta\phi_{scattering} + \delta\phi_{noise}$$

- We use an existing Digital Elevation Model (DEM) to remove topographic component from the interferometric phase.

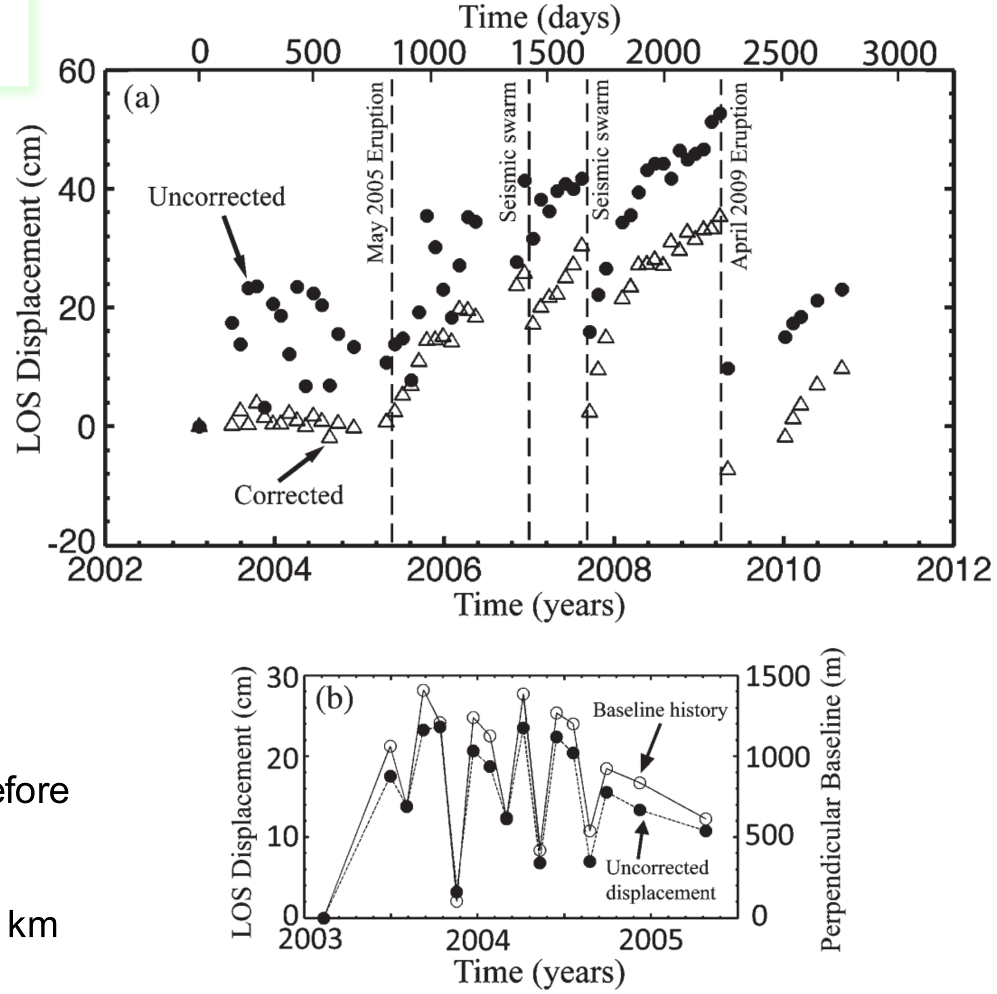
- Any error in DEM will lead to residual topographic effects in the estimated time-series

- The contribution of DEM error in the estimated time-series is a function of the perpendicular baseline time-series. This dependency allows to estimate DEM error from InSAR time-series data when the baseline diversity increases the sensitivity to DEM errors

$$\phi^{\varepsilon}_{\text{topo}}(t_i) = \frac{4\pi}{\lambda}\frac{B_{\perp}(t_i)}{r\sin(\theta)} z^{\varepsilon}$$

- Sentinel-1 and NISAR have small baseline variation (< few hundred m) and therefore are less sensitive to DEM errors

- Missions with large baseline diversity (e.g, CSK Envisat, ERS, ALOS-1) with few km baseline separation, are most affected by DEM error.



[Fattahi & Amelung, 2013]

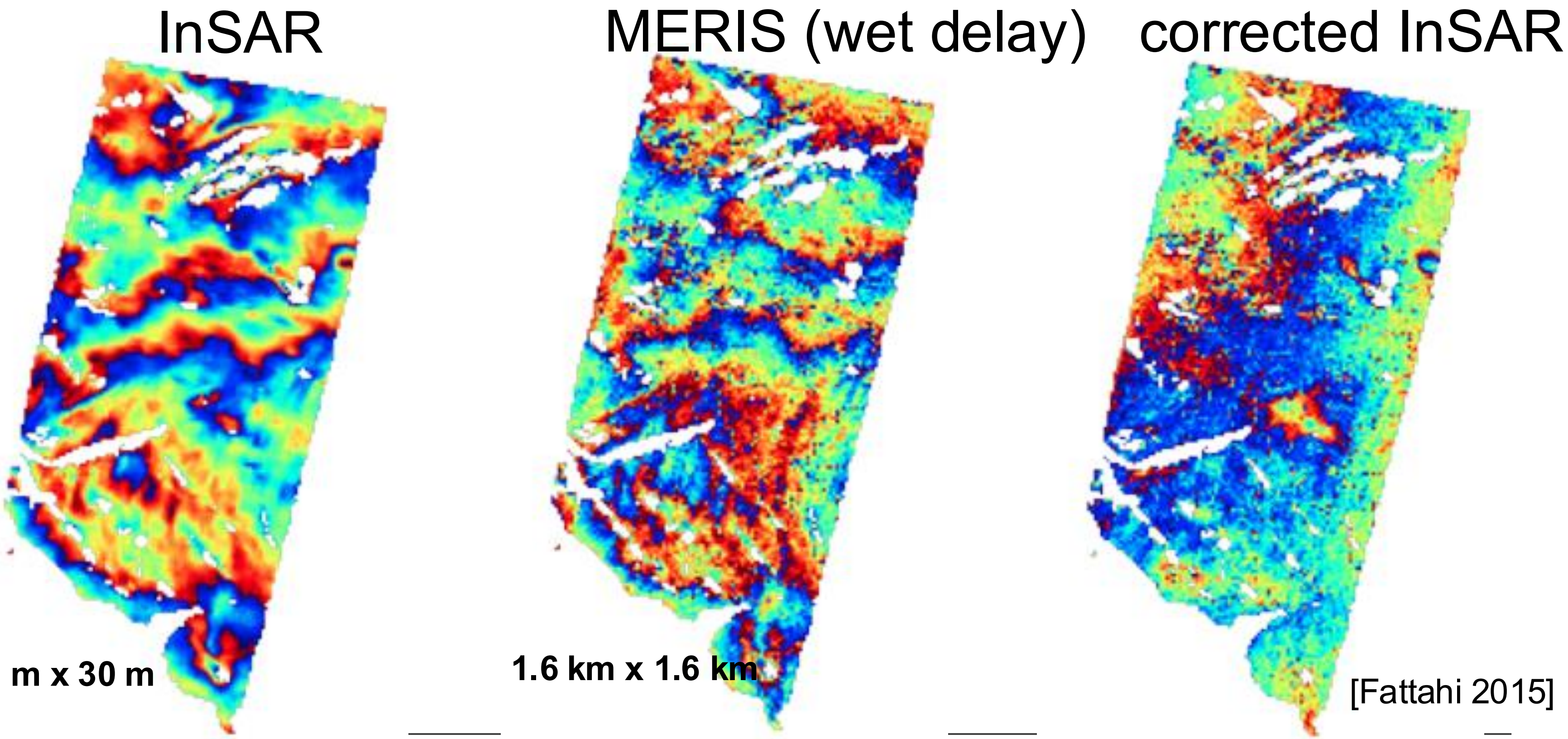
Tropospheric delay

National Aeronautics and Space Administration

$$\delta\phi = \delta\phi_{displacement} + \delta\phi_{atmosphere} + \delta\phi_{geometry} + \delta\phi_{scattering} + \delta\phi_{noise}$$

- Microwave signals experience a delay while propagating through atmosphere.
- The two main components of the delay comes from **troposphere** and **ionosphere** layers of the atmosphere

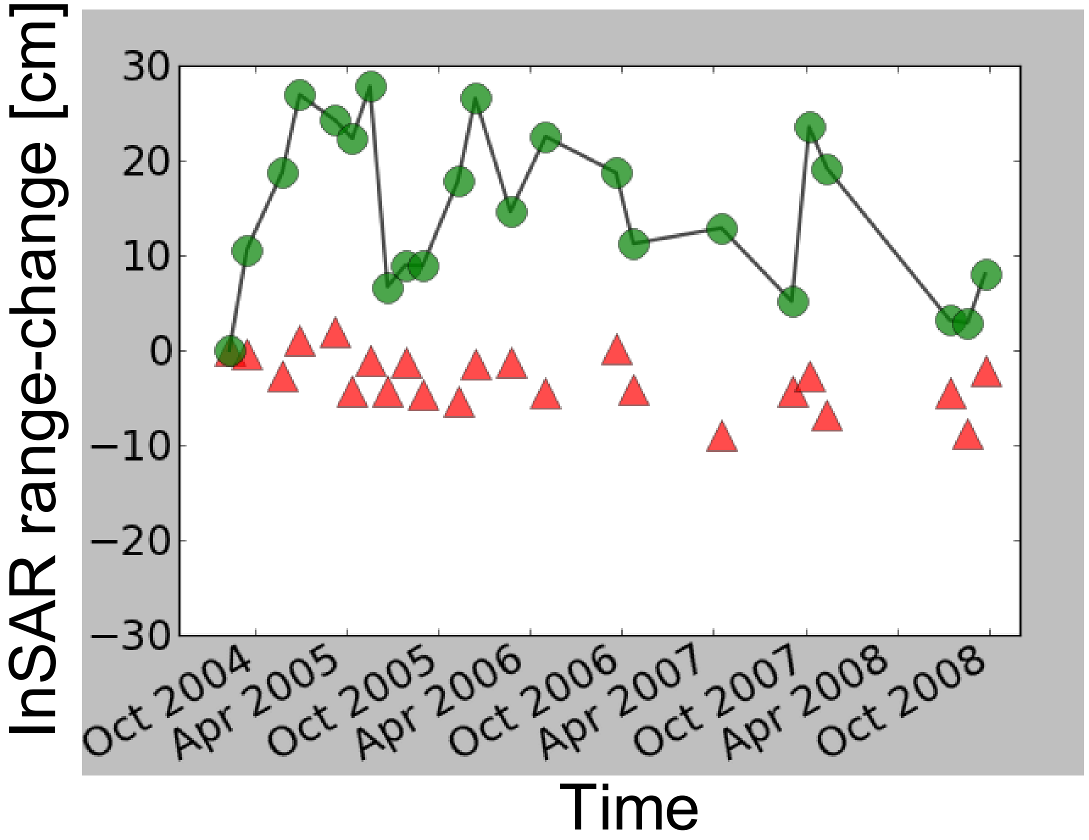
In this example independent observation from optical sensor (MERIS) acquired at the same time as the SAR acquisition predicts the impact of tropospheric delay on InSAR data



Tropospheric delay

- The time-series between two pixels ~200 km away in western Indian plate boundary, significantly improves after tropospheric delay correction.
- The tropospheric delay correction using atmospheric models depends on the spatial resolution of the model, their temporal sampling and accuracy of the model parameters
- The tropospheric delay correction using atmospheric models usually can NOT correct the turbulent component of the delay

Effect of stratified tropospheric delay correction

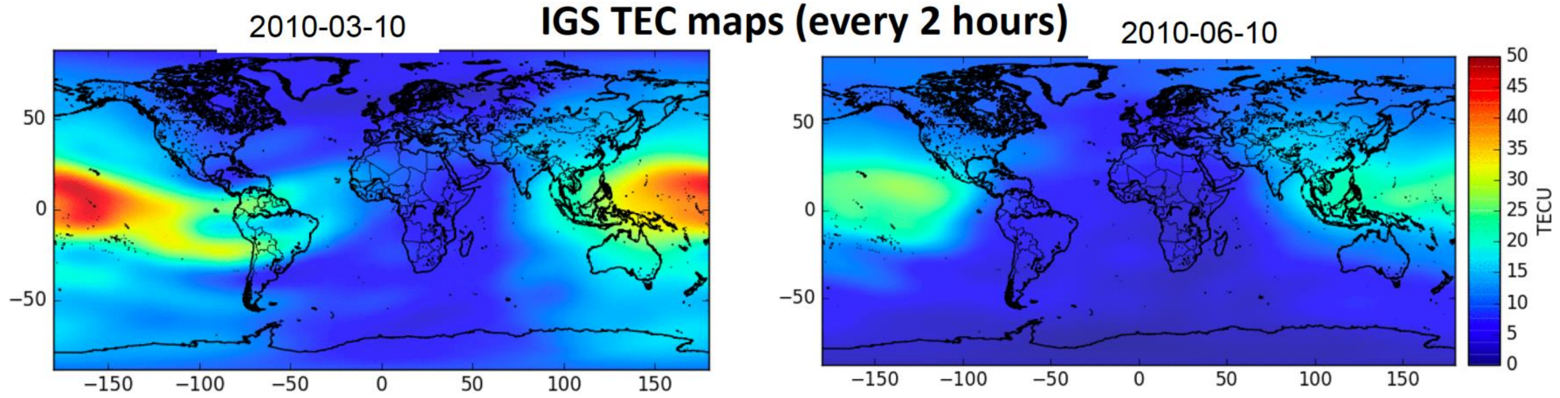


The dramatic improvement of the displacement time-series is due to very long distance and large height variation between the two pixels

Ionospheric delay

National Aeronautics and Space Administration

- Ionosphere is a dispersive media with respect to microwave signal
- Ionosphere impacts SAR data in all different frequencies. However the effect is larger in lows frequencies (e.g., P and L badn compared to high frequencies such as X and C bands)
- The dispersive nature of ionosphere provides an opportunity to estimate the ionospheric delay from SAR data



TEC variation →
- Defocusing the SAR images
- Faraday rotation
- Extra Doppler frequency (azimuth offset)
- Propagation delay (cm to m delay or phase advance)

Repeat-pass interferometric phase components

$$\Delta\phi = \frac{4\pi}{\lambda}(\overbrace{\underbrace{\Delta r_d}_{\text{displacement}} + \underbrace{\Delta r_{geom}}_{\text{geometry}} + \underbrace{\Delta r_{trop}}_{\text{tropospheric delay}}}^{\text{non-dispersive}} \overbrace{+ \underbrace{\Delta r_{iono}}_{\text{ionospheric delay}}}^{\text{dispersive}}) + \Delta\phi_{noise}$$

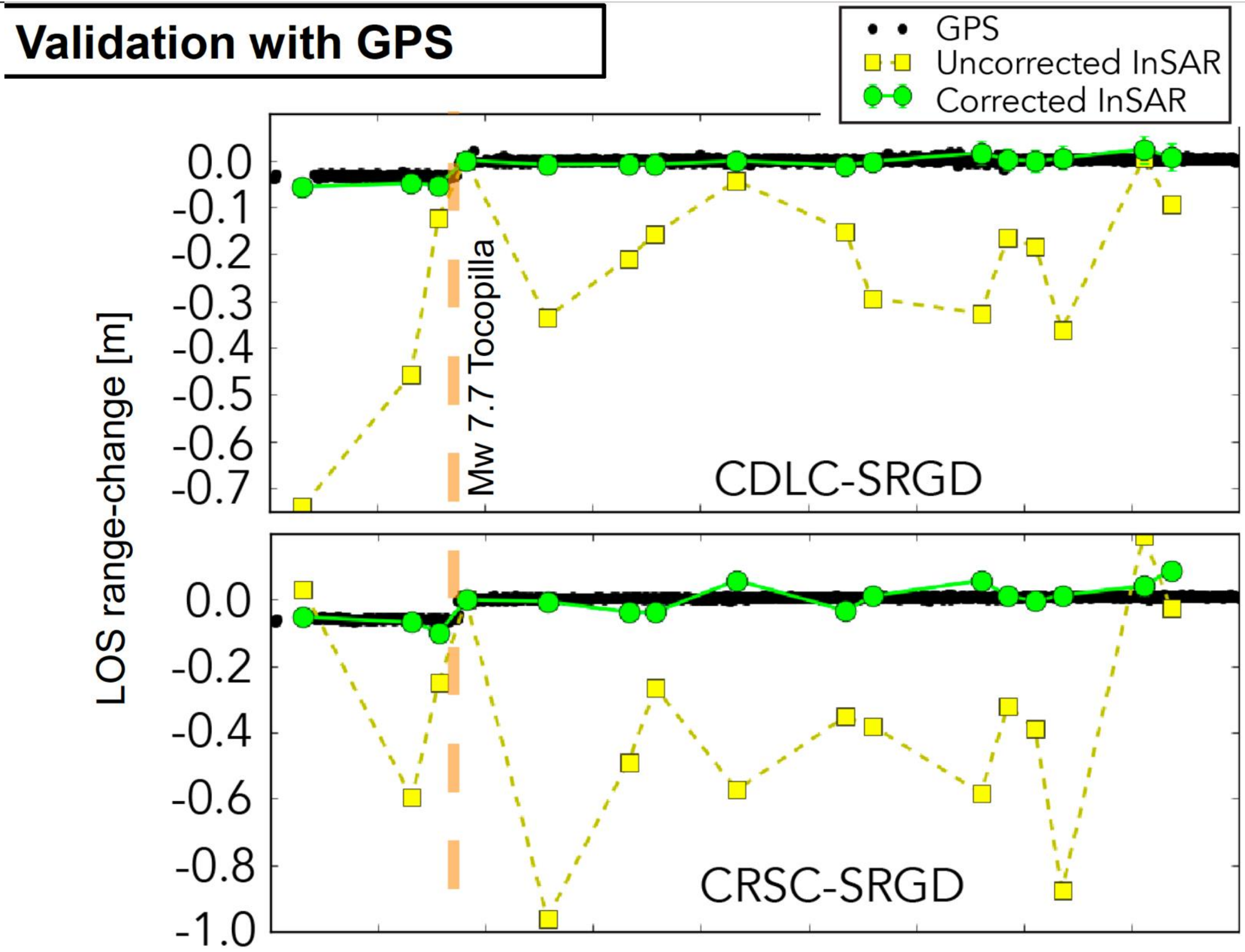
Ionospheric delay is dispersive (frequency dependent)

$$\Delta r_{iono} = -\frac{40.31}{f_0^2}\Delta TEC$$

Ionospheric delay

- The InSAR time-series before and after ionosphere correction compared with GNSS time-series demonstrates the impact of ionospheric phase on InSAR time-series in L-band.

- The impact of ionosphere is smaller in higher frequency radar data, however several studies have demonstrated that the ionosphere contribution is not negligible in C-band data.



Closure phase

Phase triplet is the sum of three interferometric phases formed from three SAR acquisitions at times i, j and k

$$\Delta\phi_{ijk} = \Delta\phi_{ij} + \Delta\phi_{jk} + \Delta\phi_{ki}$$

Zero closure phase is the intrinsic assumption of all InSAR time-series analysis algorithms

For single look interferograms $\Delta\phi_{ijk} \equiv 0$, for multi-looked interferograms $\Delta\phi_{ijk} \neq 0$

Multi-looking gives rise to non-closing triplets

Zheng et al, suggest **spatial and temporal inhomogeneity** as the source of non-closing triplet

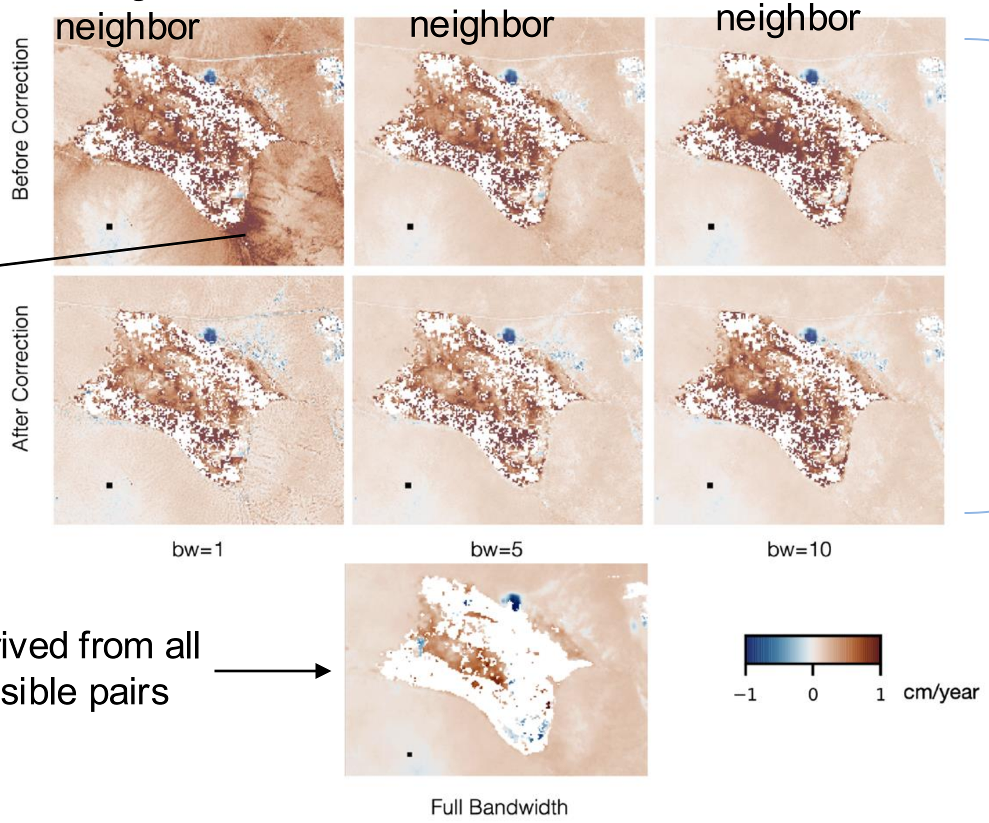
Closure phase

National Aeronautics and Space Administration

Using 1 nearest neighbor

5 nearest neighbor

10 nearest neighbor

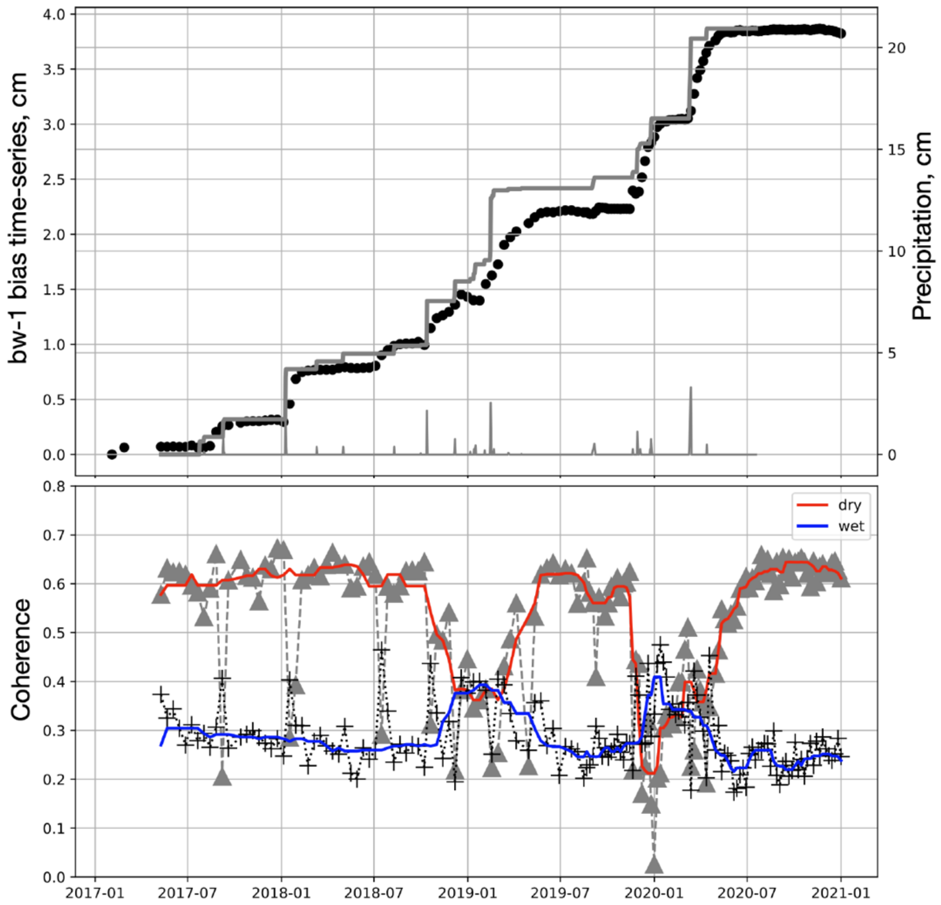


bias

SBAS

Derived from all possible pairs

Estimated bias from cumulative closure phase is correlated with cumulative precipitation



[Zheng et al, 2022]

How to treat the displacement bias in short temporal baseline time-series:

1- Use cumulative closure phase to estimate the bias

2- Use **all possible interferometric pairs** to minimize the bias

References

Mirzaee, Amelung, Fattahi, Nonlinear phase-linking using joint permanent and distributed scatterers, Computers and Geosciences, 2023 https://www.sciencedirect.com/science/article/pii/S0098300422002400

Fattahi and Amelung, DEM error correction in InSAR time-series, IEEE-TGRS https://ieeexplore.ieee.org/abstract/document/6423275

Yunjun, Fattahi, Amelung, 2019, “Small baseline InSAR time series analysis: Unwrapping error correction and noise reduction”, Computer and Geoscience, https://www.sciencedirect.com/science/article/pii/S0098300419304194

Zheng, Fattahi, Agram, Simons, Rosen,
On Closure Phase and Systematic Bias in Multilooked SAR Interferometry, IEEE TGRS
https://ieeexplore.ieee.org/abstract/document/9758802

Ferretti, Fumagalli, Novali, Prati, Rocca and Rucci, A New Algorithm for Processing Interferometric Data-Stacks: SqueeSAR, IEEE-TGRS
https://ieeexplore.ieee.org/abstract/document/5765671

Ansari, DeZan, Bamler, Sequential Estimator: Towards Efficient InSAR Time-series,IEEE-TGRS
https://ieeexplore.ieee.org/abstract/document/8024151

Ansari, DeZan, Parizzi, Study of Systematic Bias in Measuring Surface Deformation With SAR Interferometry,
https://ieeexplore.ieee.org/abstract/document/9130052

Open source tools

National Aeronautics and Space Administration

ISCE2
https://github.com/isce-framework/isce2

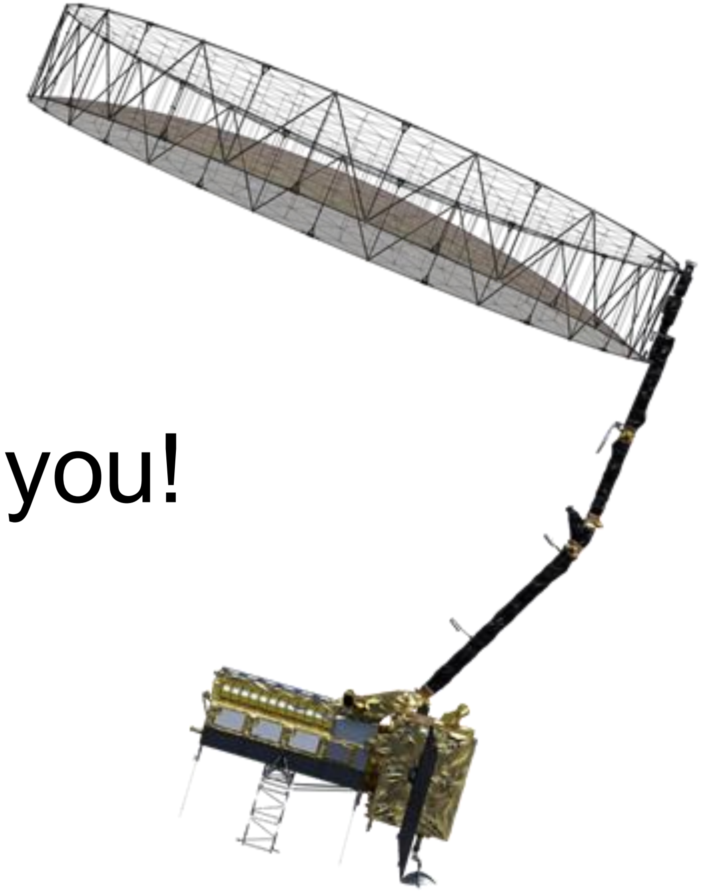
ISCE3
https://github.com/isce-framework/isce3

Mintpy
https://github.com/insarlab/MintPy

Dolphin
https://github.com/isce-framework/dolphin

FRInGE
https://github.com/isce-framework/fringe

MiaplPy
https://github.com/insarlab/MiaplPy



Thank you!

Appendix and Old Slides

Time series: High level overview

Inputs: Coregistered stack of SLCs

Outputs: Displacement time series at each epoch

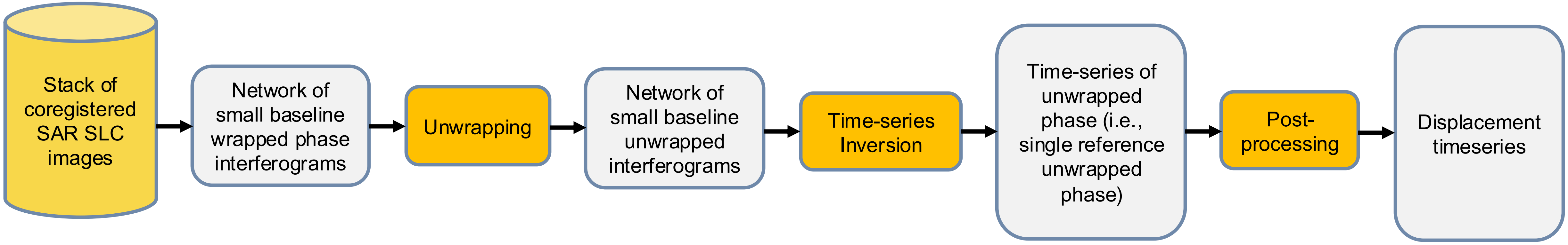
- Find the good pixels
- Unwrap inteferograms successfully
- (if necessary) invert your network
- (if necessary) post process for additional noise sources

People have development many methods to accomplish this for varying data quality!

DS time-series analysis algorithms- Small Baseline algorithms

National Aeronautics and Space Administration

- Taking a coherent network of small baseline interferograms, the Small Baseline Subset (SBAS) algorithms attempt to improve signal to noise ratio in individual interferograms [Berardino et al, 2002]
- The redundant network of unwrapped interferograms are inverted to estimate a singe-reference network of unwrapped interferograms (i.e., the unwrapped phase timeseries) and converted to meters (range-change = $\frac{\lambda}{4\pi} \cdot \phi$)
- The estimated range change time-series can be post processed to correct for different contributions such as tropospheric delay, DEM errors etc to isolate the displacement time-series signal [Yunjun et al, 2019; Fattahi & Amelung 2013]



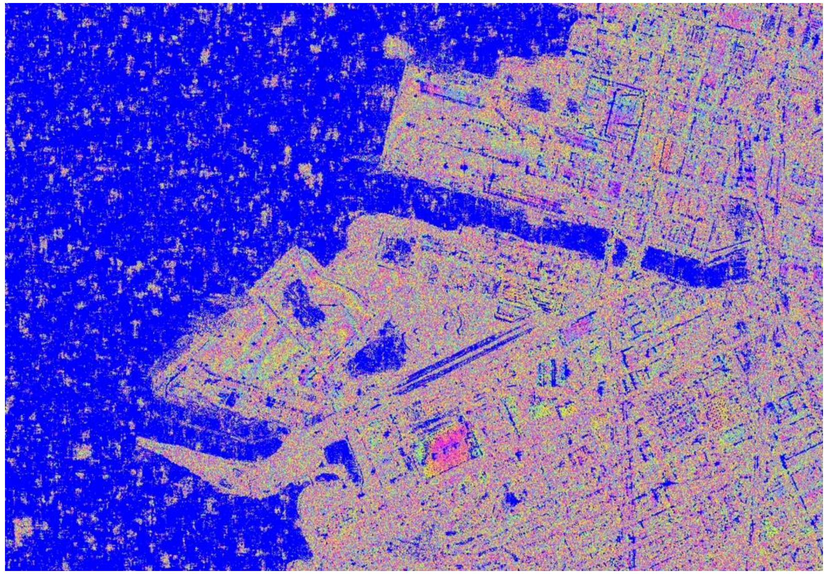
Outline

- InSAR
- Why InSAR time-series analysis
- InSAR time-series analysis techniques based on scatterers
  - PS time-series
  - DS time-series
    - DS analysis algorithms based on interferogram networks
      - Small Baseline algorithms (subsets of interferograms)
      - Full covariance-based algorithms
  - PS+DS time-series techniques
- Error analysis of InSAR displacement time-series
  - Propagation delay (Troposphere, Ionosphere)
  - Geometrical residuals
  - Phase unwrapping error
  - Phase scattering

Why InSAR Time-series analysis?
a) to reduce the impact of decorrelation

National Aeronautics and Space Administration

A regular interferogram over ~2.5 years



An X-band interferogram is fully decorrelated over 2.5 years

Same interferogram from time-series analysis

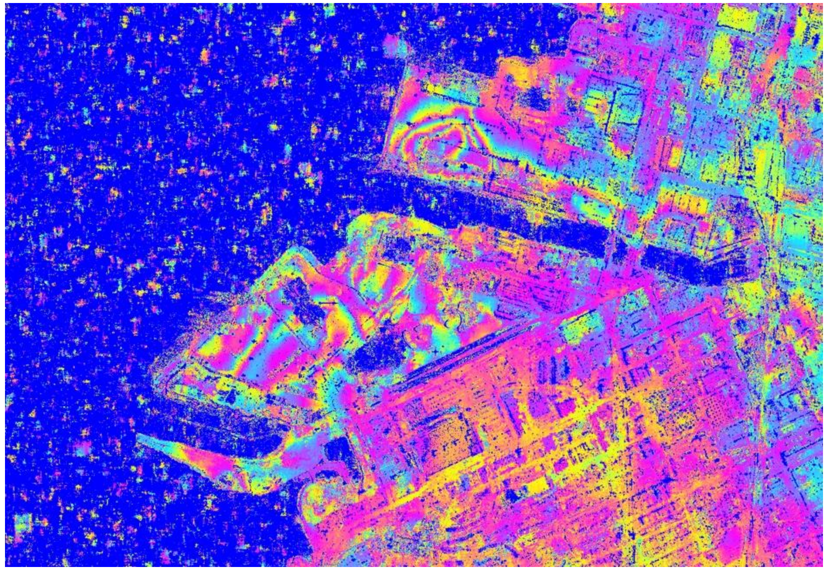
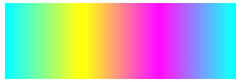


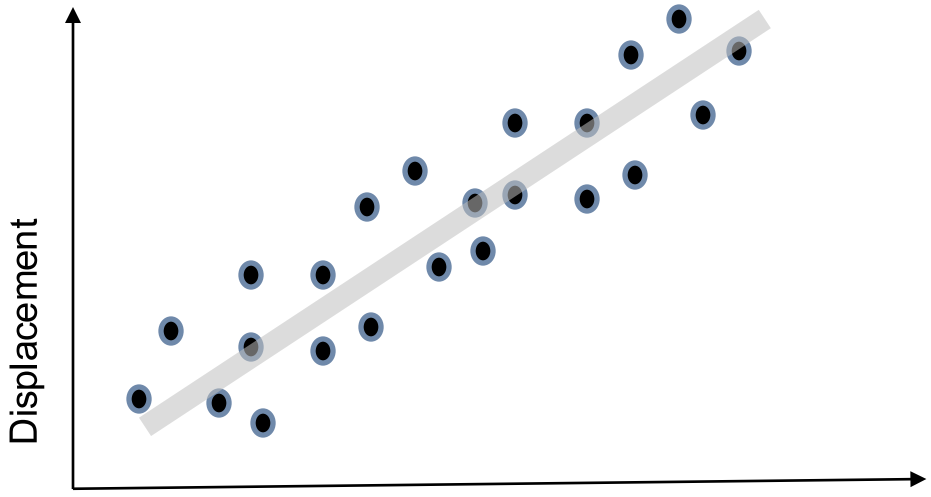
Image from Fattahi, et al (JPL)

$-\pi$  π

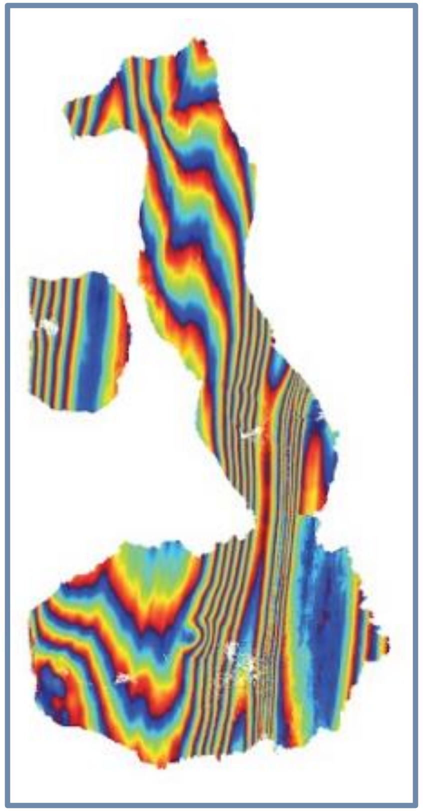
(Left) Conventional 2-pass interferometry between 2 CSK SAR scenes acquired on 2011-06-24 and 2013-10-11 over the Central Waterfront in San Francisco, CA. Subsidence features are not clear due to the large time separation between the 2 images. (Right) The same interferogram generated from timeseries analysis.

Why InSAR Time-series analysis?
b) to improve the accuracy of estimated displacement

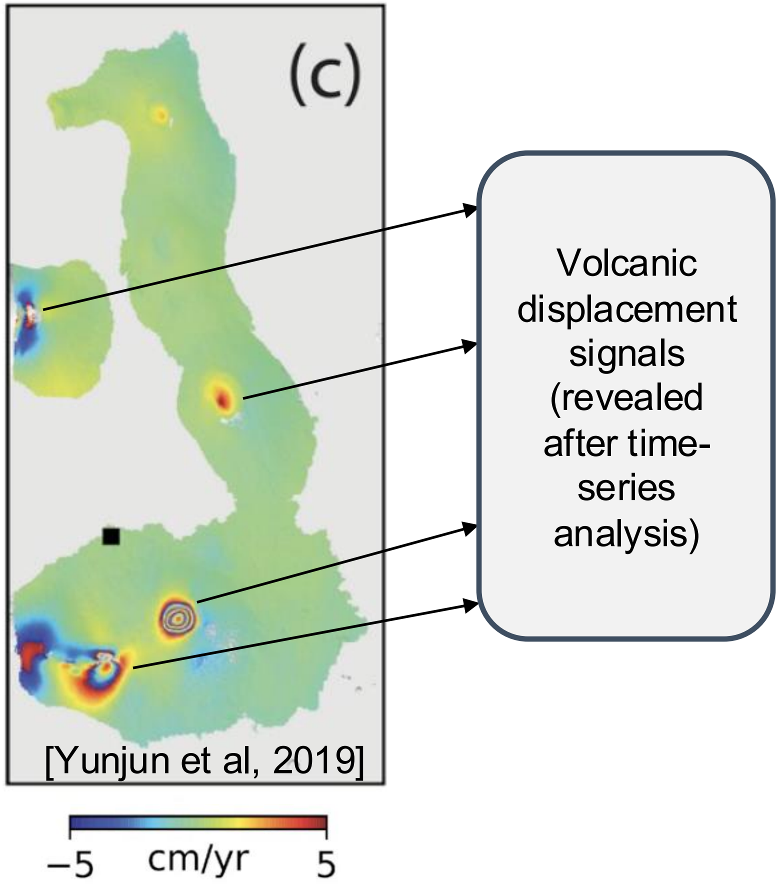
- Different sources of noise (such as tropospheric and ionospheric delay) are spatially coherent but mostly random in time
- Time-series analysis allows to reduce the impact of noise and improve accuracy of estimated displacement



One interferogram heavily dominated by atmosphere



A velocity map derived from time-series analysis



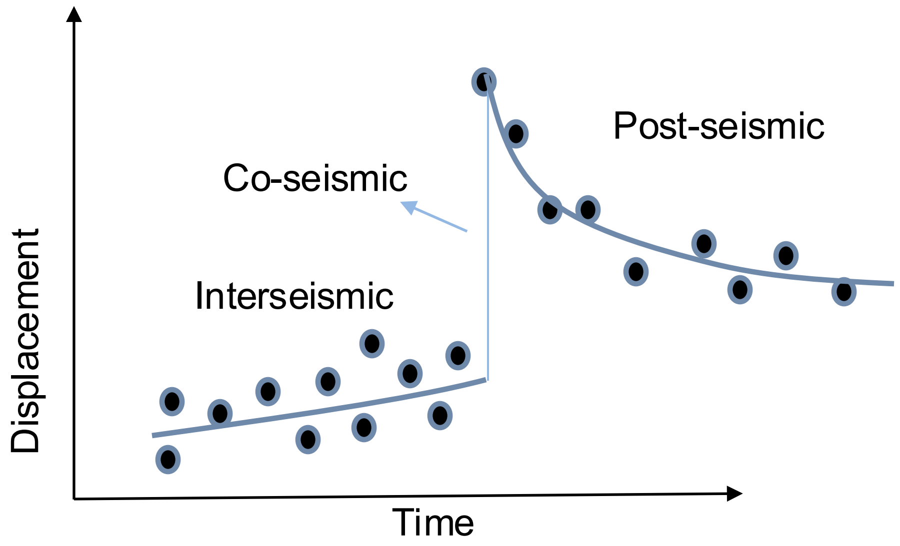
Why InSAR Time-series analysis?
c) to understand the temporal evolution of the ground displacement

- The displacement of the ground surface may evolve through time leading to non-linear change of the displacement time-series

- Examples of non-linear evolution of ground displacement:
  - Earthquake cycle (interseismic + coseismic + postseismic)
  - Volcanic unrest
  - Seasonal ground water change

- Understanding the temporal pattern of the ground displacement is crucial to better understand the driving mechanisms

- Measuring the displacement and its variation in time is only possible by time-series analysis



Distributed Scatterer (DS) time-series analysis algorithms

National Aeronautics and Space Administration

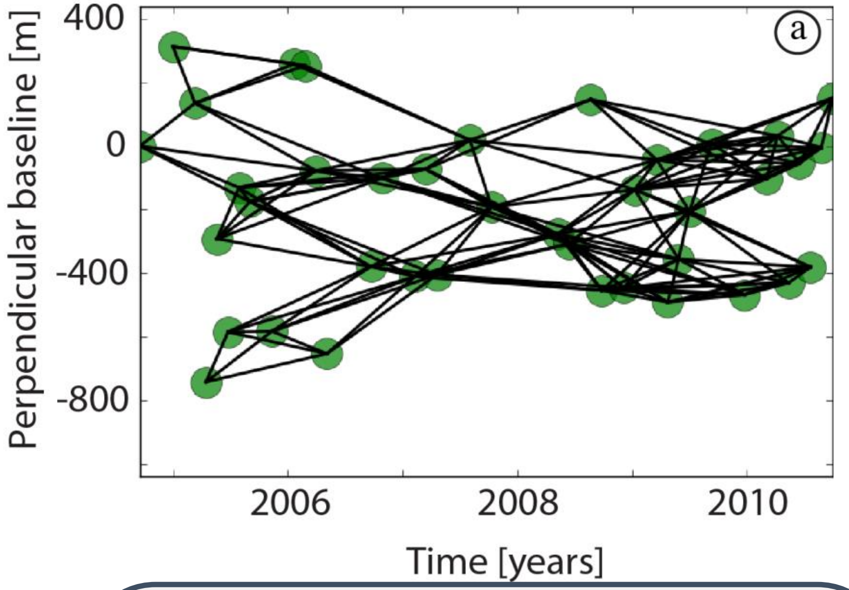
- The interferometric phase of Distributed Scatterers (DS pixels) are noisier than PS pixels and therefore the DS analysis algorithms generally involve multi-looking/averaging to reduce noise

- In theory one could create a single reference network of DS interferograms (similar to PS algorithm), unwrap and estimate displacement time-series

- In practice, DS pixels decorrelate rapidly in time and therefore a redundant network of interferograms are used to invert for a single reference interferometric phase time-series

- Depending on the network of interferograms we have two main category of DS analysis algorithms
    - **Small Baseline algorithms (SBAS)**
    - **Full covariance based algorithms**

A network of small baseline interferograms



- Each green circle in this plot represents one SAR image
- Each line represents one interferogram
- Generally interferograms made with short temporal and short perpendicular baselines are more coherent

Repeat pass InSAR phase components

$$\delta\phi = \underbrace{\delta\phi_{displacement}}_{\text{signal}} + \underbrace{\delta\phi_{atmosphere} + \delta\phi_{geometry} + \delta\phi_{scattering} + \delta\phi_{noise}}_{\text{noise}}$$

- **mm to cm** (tectonics, hydrological induced subsidence and uplift, tides, volcanic unrest, etc)
- 10s of cm (e.g., earthquakes, volcanic events)

Few cm to 10s or 100s of cm

Few cm for modern sensors with small orbital tubes

mm level contributions from changes to scattering properties of the targets

- Decorrelation (few degrees due to thermal noise up to random numbers between -π and π for total decorrelation)
- Processing errors

- When the goal is to estimate ground displacement, the displacement component is **signal** and the rest are **noise**
- Most InSAR noise components are spatially correlated but mostly random in time
- The goal of InSAR time-series analysis is to enhance the signal to noise ratio

DS time-series analysis - Full covariance algorithms

- Simulations show that MLE estimates of wrapped phase time-series are more precise than the CED estimates

- However, MLE estimators require computing the inverse of the Coherence matrix. Computing the inverse requires the coherence matrix to be positive-definite

- Ignoring an estimate when coherence is not positive definite will lead to loosing an estimate for many coherent pixels

4- Combined phase-linking algorithm [Mirzaee, Amelung, Fattahi, 2023]**:**
1- Compute Covariance and Coherence matrices
2- Check if Coherence is positive
3- If Coherence is positive-definite, Estimate MLE
    else:
        Regularize Coherence
        if regularized coherence positive-definite, estimate MLE
        else estimate CED