InSAR Tropospheric Delay Modeling Based on Its Spatiotemporal Characteristics

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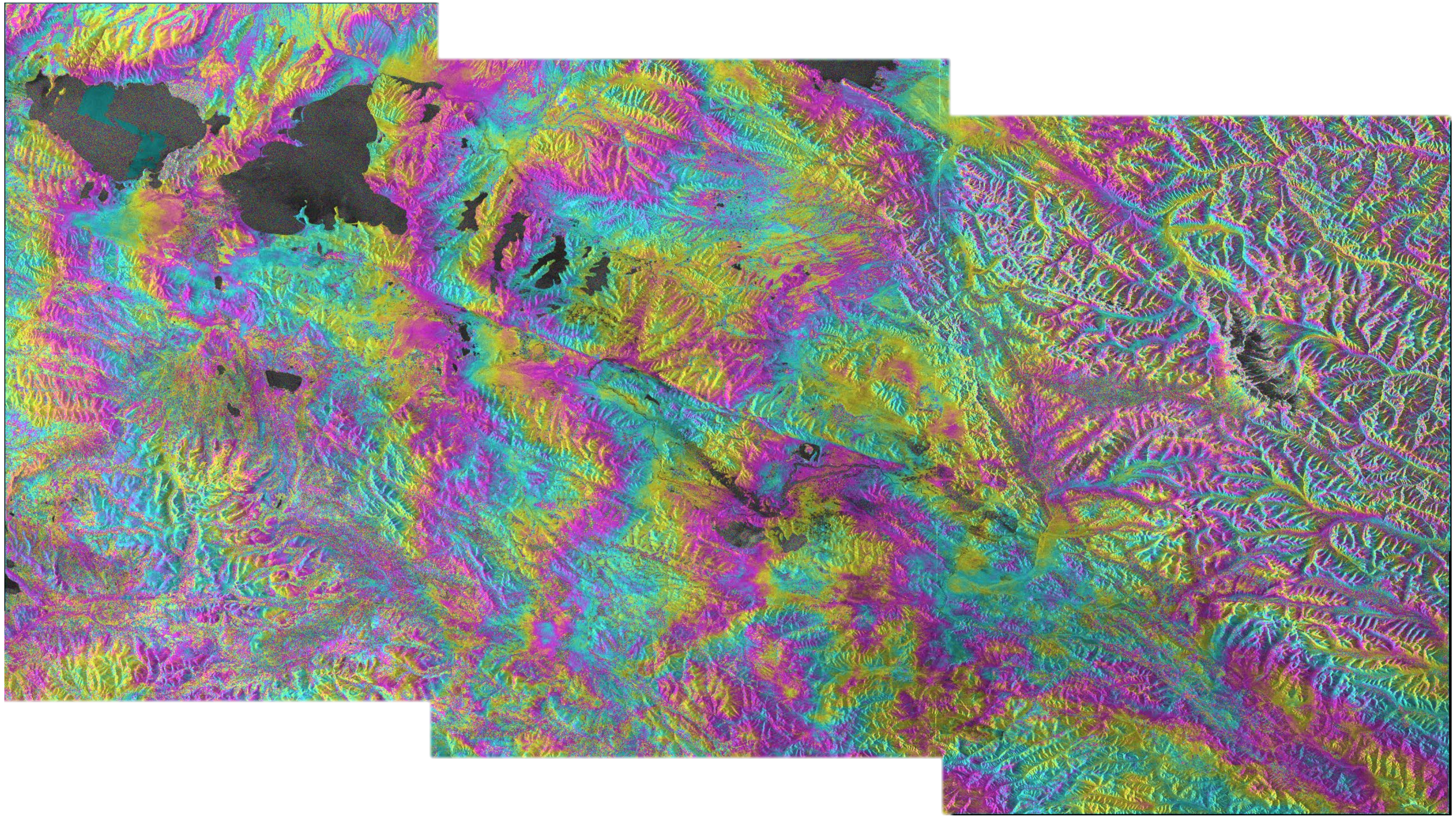
Background

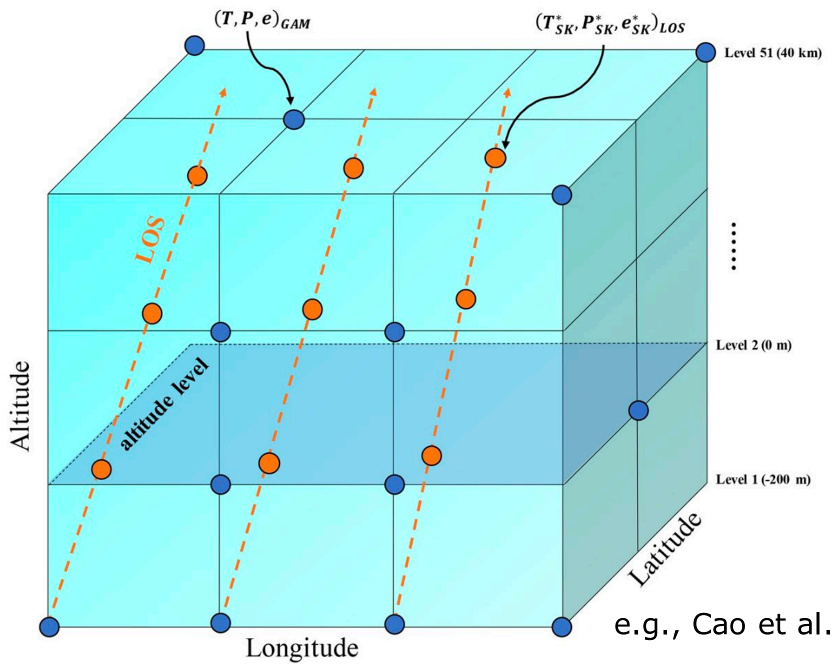
- **Signals contained in InSAR interferograms**

  - ❑ **Displacements**
  - ❑ Atmospheric delays
    - Stratified delay
    - Turbulent delay
  - ❑ Orbital errors
  - ❑ Decorrelations
  - ❑ ……



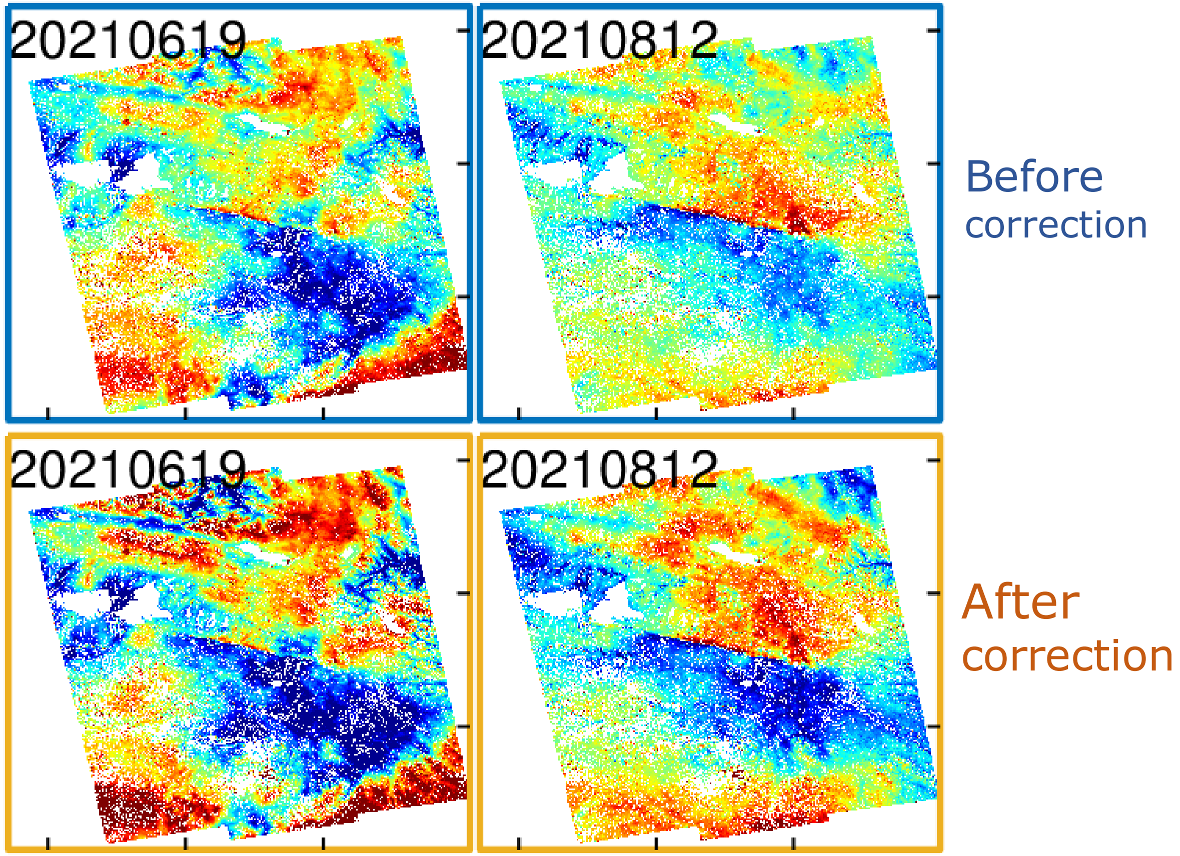
Methods to correct InSAR atmospheric delays

1、Independent datasets (e.g., weather models, GPS……)



e.g., Cao et al. (2021)

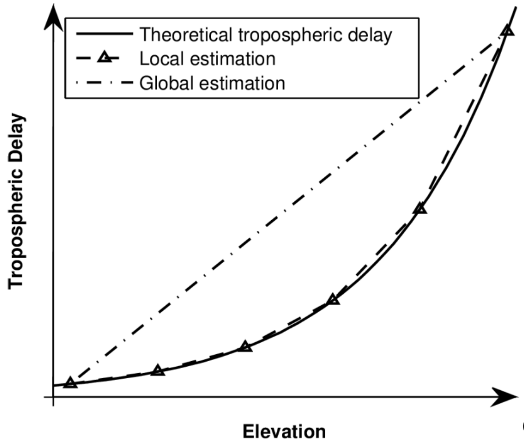
Interpolation of glabol atmopheric model
(e.g., GACOS, ICAMS)

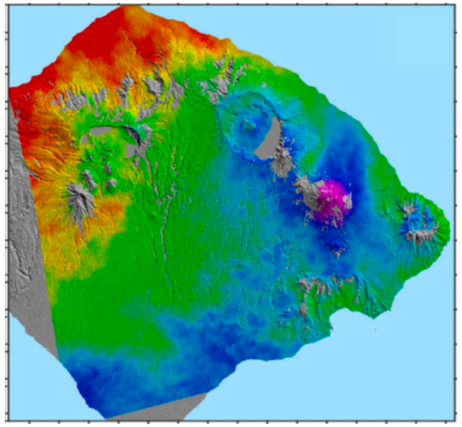


Even worse due to the inconsistence of resolution

Methods to correct InSAR atmospheric delays

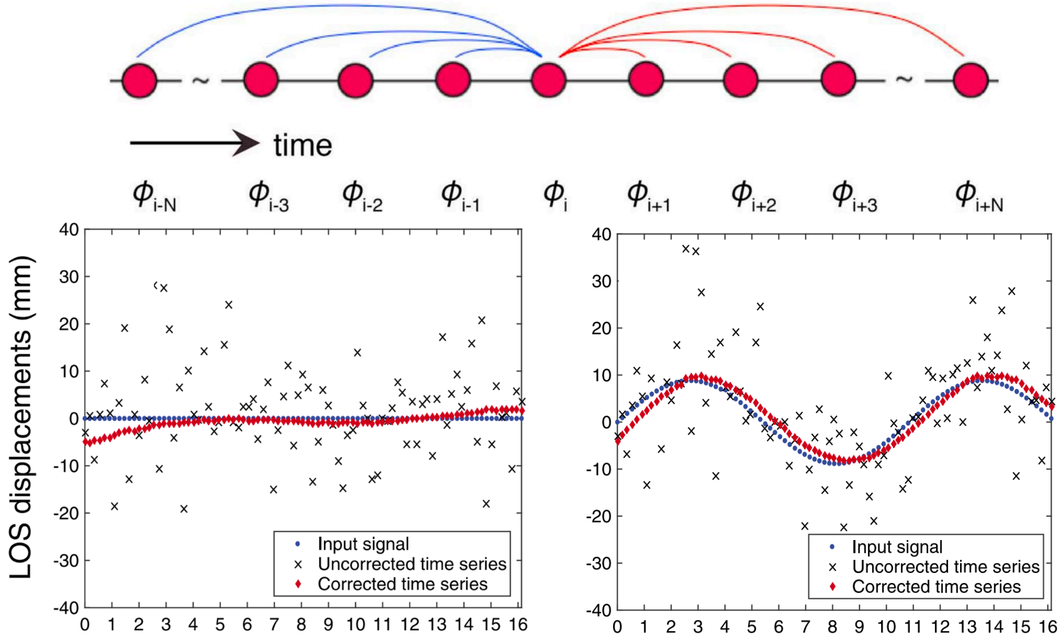
2、Data-driven methods (e.g., spatial or temporal correlation)





e.g., Liang et al. (2018, 2023)

DEM-correlated stratified delay



e.g., Tymofyeyeva & Fialko (2015)

Temporally random turbulent delay

Limitations

▲Each error components are **corrected independently**, influenced by the existence of other errors

▲There is no **mathematically models** for the atmospheric delays based only on InSAR data

Methodology

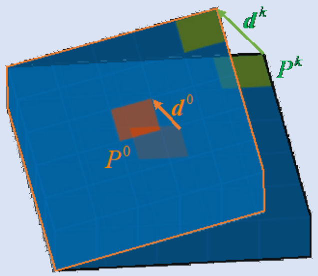
- Aim to model InSAR tropospheric delays as well as orbital errors based on their spatiotemporal characteristics

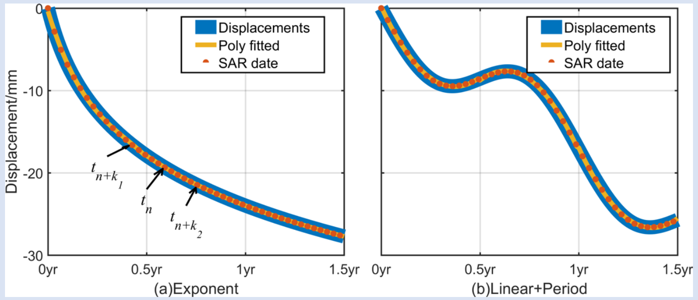
$$\phi_{insar} = \phi_{defo} + \phi_{stratified} + \phi_{turbulent} + \phi_{orb}$$

ill-posed problem ← Additional constraints

Deformation ϕ_{defo}

Correlated spatially temporally

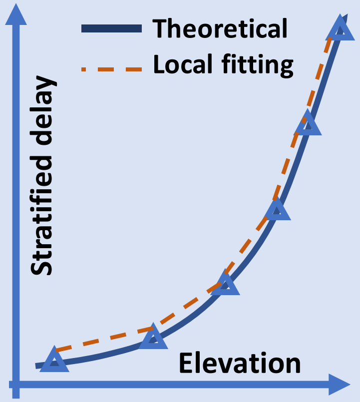


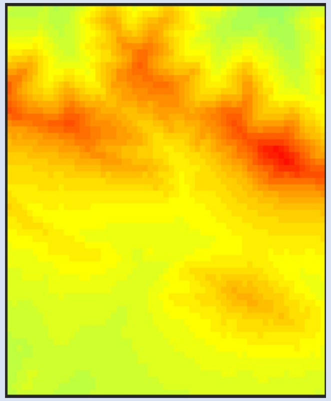


$$D = b + b_1 \boxed{t} + b_2 t^2 + b_3 t^3$$

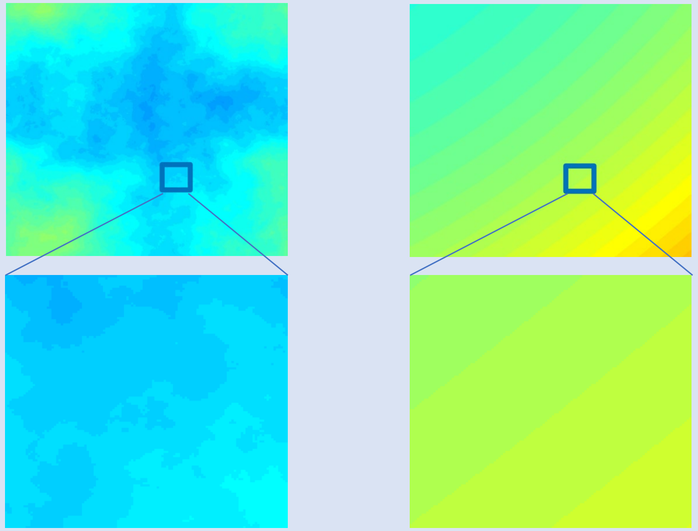
Stratified $\phi_{stratified}$ (DEM-correlated)

Spatially correlated with the local DEM $\Phi_h = k \cdot \boxed{h} + \phi_0$





Turbulent $\phi_{turbulent}$ Orbit ϕ_{orb} (Trend)



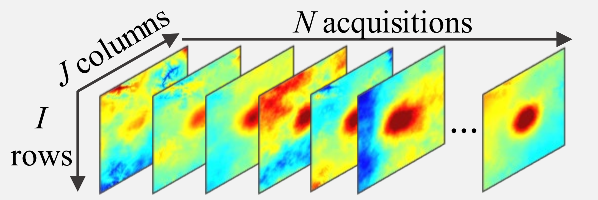
Fitted by a position-dependent ramp

$$\Phi_r = a_0 + a_1 \boxed{x} + a_2 \boxed{y}$$

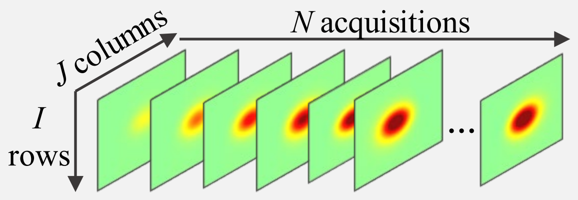
Methodology

➢ **DetrendInSAR**: to decrease both the trend and DEM-related components in InSAR time series

Input: time series with defo and errors



Output: deformation time series



DentrendInSAR

Establish equations for each pixel at each time based on the a-priori information → The DetrendInSAR model ***L=B*X*** → Solve unknowns

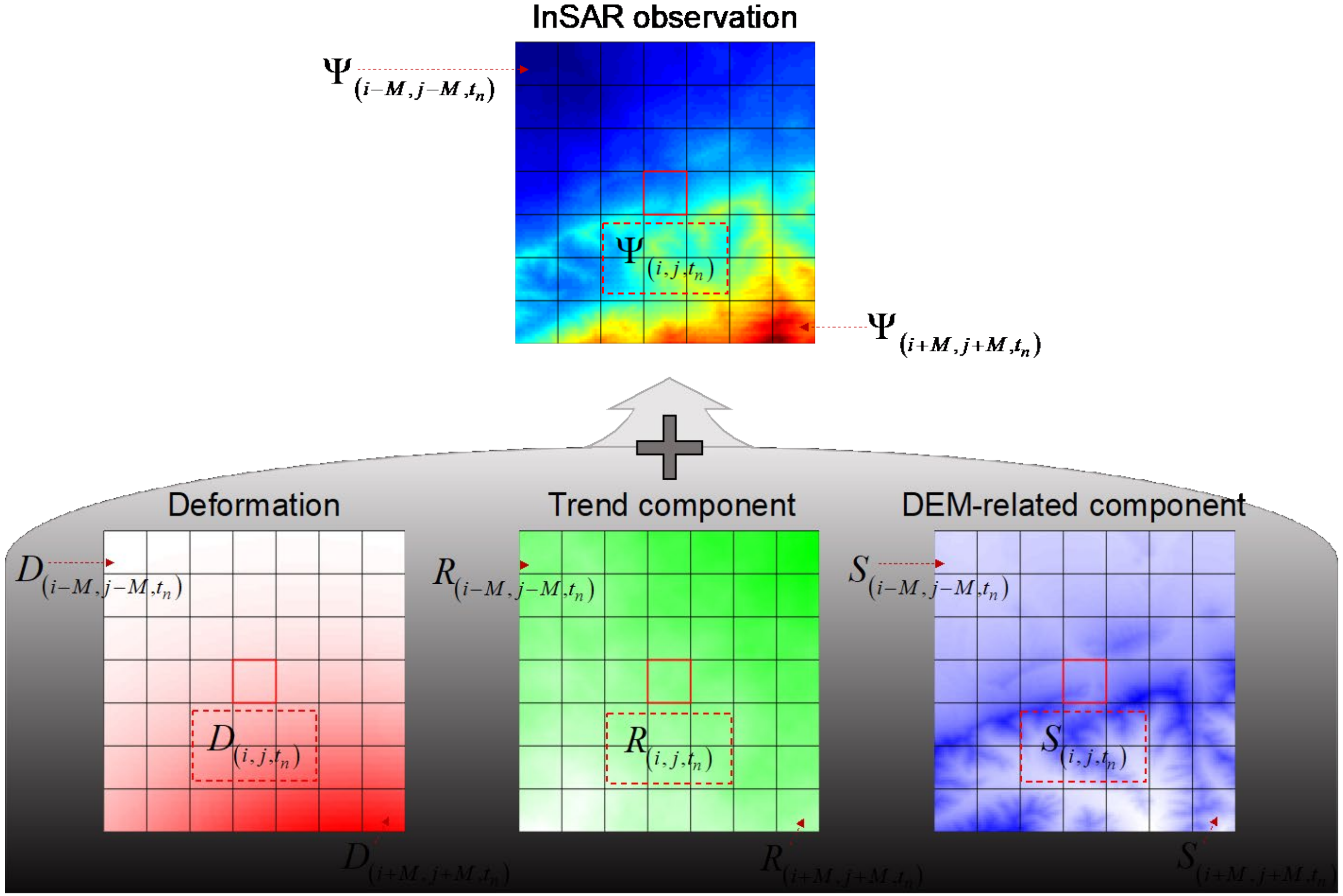
$$\begin{bmatrix} L_1 \\ L_2 \\ \vdots \\ L_m \\ \vdots \\ L_M \end{bmatrix} = \begin{bmatrix} b_{11} & b_{12} & \cdots & b_{1k} & \cdots & b_{1K} \\ b_{21} & b_{21} & \cdots & b_{2k} & \cdots & b_{2K} \\ \vdots & \vdots & \ddots & \vdots & \ddots & \vdots \\ b_{m1} & b_{m2} & \cdots & b_{mk} & \cdots & b_{mK} \\ \vdots & \vdots & \ddots & \vdots & \ddots & \vdots \\ b_{M1} & b_{M2} & \cdots & b_{Mk} & \cdots & b_{MK} \end{bmatrix} \cdot \begin{bmatrix} x_1 \\ x_2 \\ \vdots \\ x_k \\ \vdots \\ x_M \end{bmatrix}$$

The key for modeling

Unknown ***X***: **deformation**, **trend, and DEM-related** components at all pixels and all time series

Methodology

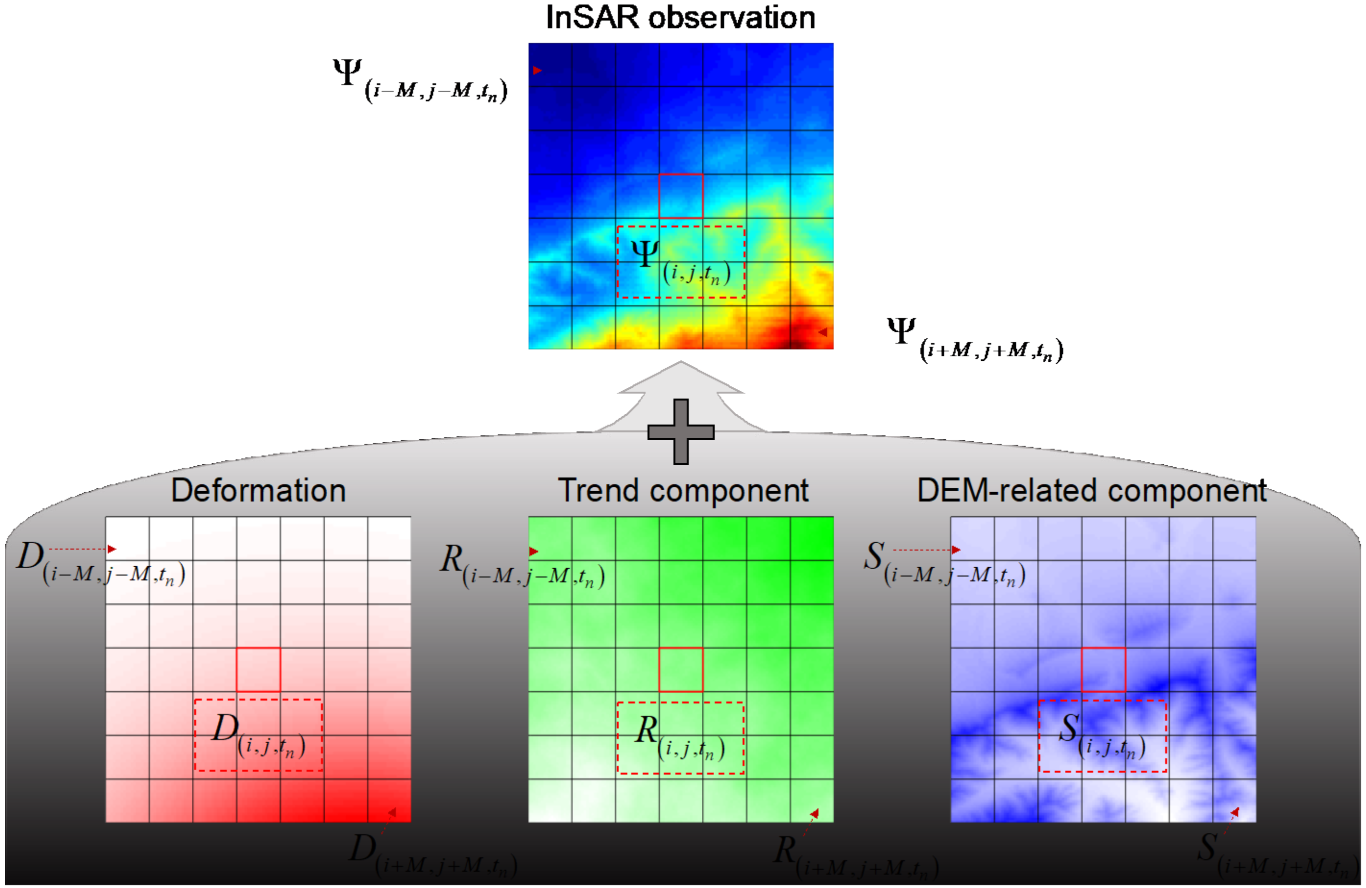
- Obtain L_m and b_{mk} at pixel (i,j) on time t_n —— **(1) based on the a-priori information of <u>trend component</u>**



For a pixel in the window: $$\Psi_{(i+x,j+y,t_n)} = \underbrace{D_{(i+x,j+y,t_n)}}_{\text{Defo}} + \underbrace{[1,x,y]\cdot\left[R_{(i,j,t_n)}, a_{(i,j,t_n),1}, a_{(i,j,t_n),2}\right]^T}_{\text{Trend}} + \underbrace{S_{(i+x,j+y,t_n)}}_{\text{DEM-related}}$$

Methodology

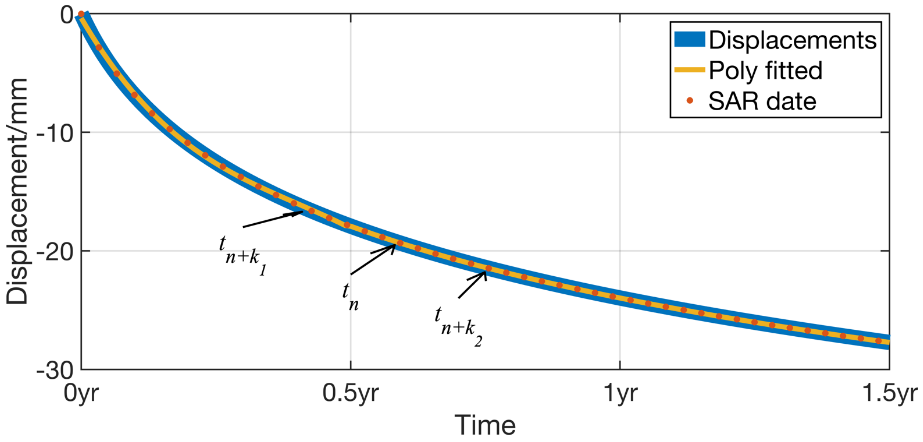
➢ Obtain L_m and b_{mk} at pixel (i,j) on time t_n —— **(2) based on the a-priori of DEM-correlated component**



For a pixel in the window: $$\Psi_{(i+x^*,j+y^*,t_n)} = \underbrace{D_{(i+x^*,j+y^*,t_n)}}_{\text{Defo}} + \underbrace{R_{(i+x^*,j+y^*,t_n)}}_{\text{Trend}} + \underbrace{\left[1, \Delta h_{(x^*,y^*)}\right] \cdot \left[S_{(i,j,t_n)}, b_{(i,j,t_n)}\right]^T}_{\text{DEM-related}}$$

Methodology

➢ Obtain L_m and b_{mk} at pixel (i,j) on time t_n —— **(3) based on the a-priori information of temporal deformation**



Deformations during a time window satisfy:

$$D = b + b_1 t + b_2 t^2 + b_3 \boxed{t^3}$$

time

Formula of the constraint: $\boxed{0 = \boldsymbol{C} \cdot \boldsymbol{X}}$ ⇨ 0 = (the fitted defo at t_n) — (the original defo at t_n)

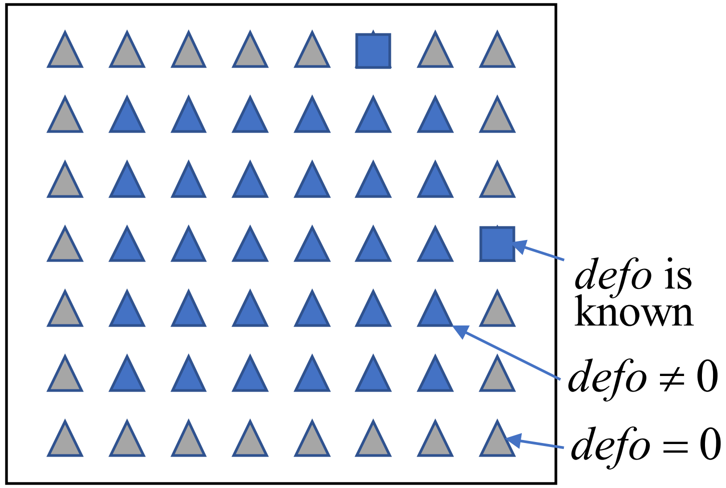
$\boldsymbol{X}$: the deformation time series

$= f(\boldsymbol{X}) - x_{t_n}$

$\boldsymbol{C}$: the coefficient

Methodology

- Obtain L_m and b_{mk} at pixel (i,j) on time t_n —— **(4) based on the a-priori information of <u>known-defo pixels</u>**



Similar formula of the constraint:

$$0 = 1 \cdot D_{(i,j,t_n)} \quad \text{OR} \quad \text{Value} = 1 \cdot D_{(i,j,tn)}$$

Methodology

- Combining the a-priori information at all pixel and all time series

(1) based on the a-priori information of trend component

$$\Psi_{(i+x,j+y,t_n)} = D_{(i+x,j+y,t_n)} + [1,x,y]\cdot\left[R_{(i,j,t_n)}, a_{(i,j,t_n),1}, a_{(i,j,t_n),2}\right]^T + S_{(i+x,j+y,t_n)}$$

(2) based on the a-priori information of DEM-related component

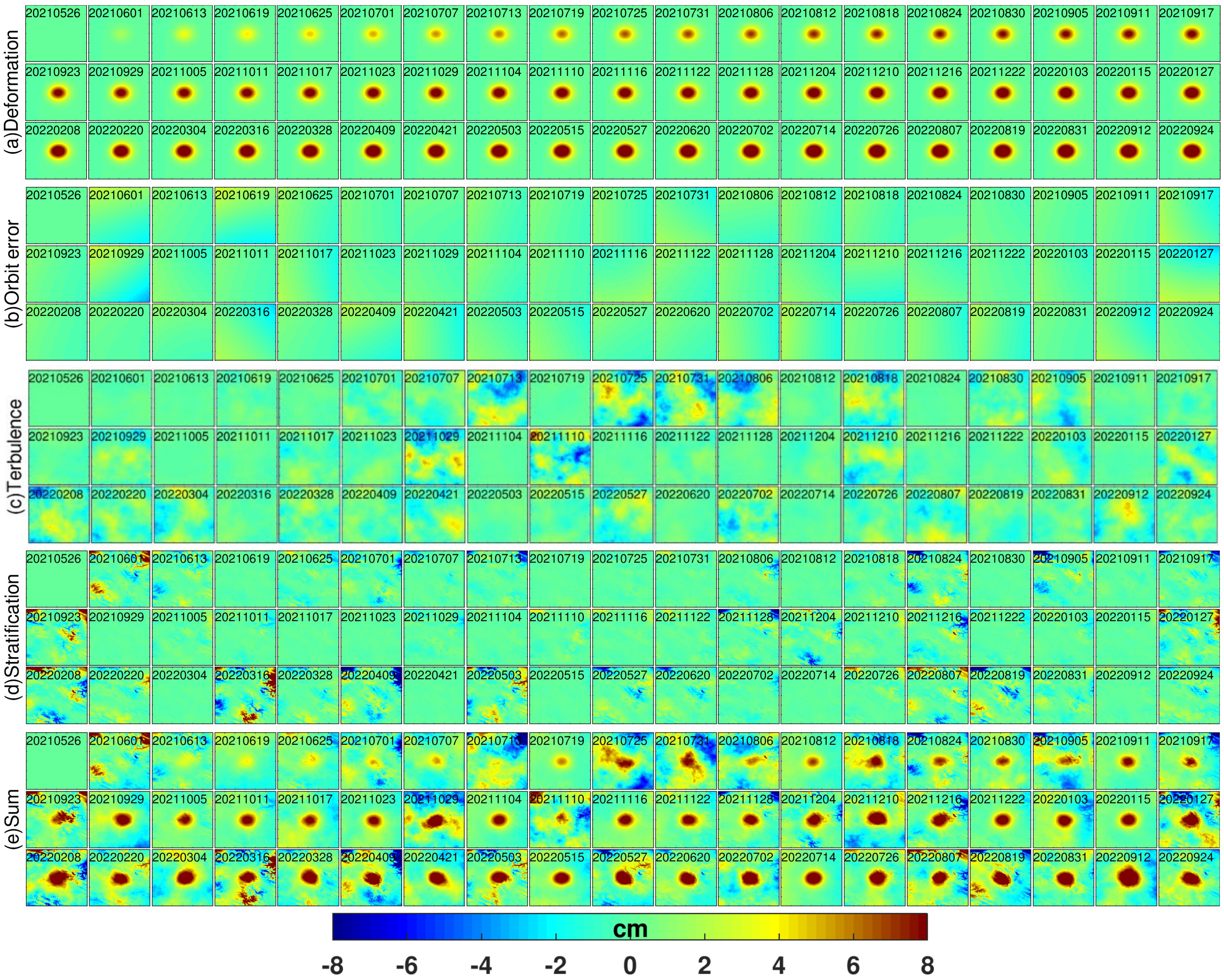
$$\Psi_{(i+x^*,j+y^*,t_n)} = D_{(i+x^*,j+y^*,t_n)} + R_{(i+x^*,j+y^*,t_n)} + \left[1, \Delta h_{(x^*,y^*)}\right]\cdot\left[S_{(i,j,t_n)}, b_{(i,j,t_n)}\right]^T$$

(3) based on the a-priori information of temporal deformation $0 = C \cdot X$

(4) based on the a-priori information of known-defo pixels $0 = 1\cdot D_{(i,j,t_n)}$ OR $D_0 = 1\cdot D_{(i,j,tn)}$

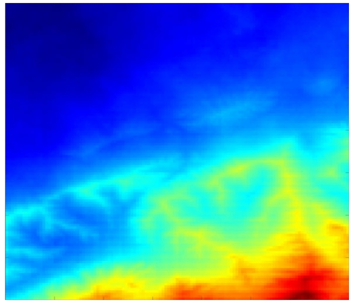
$L=B*X$ $\xrightarrow{\text{Least square method}}$ Trend and DEM-related components $\Rightarrow$ Displacements

Simulation Data

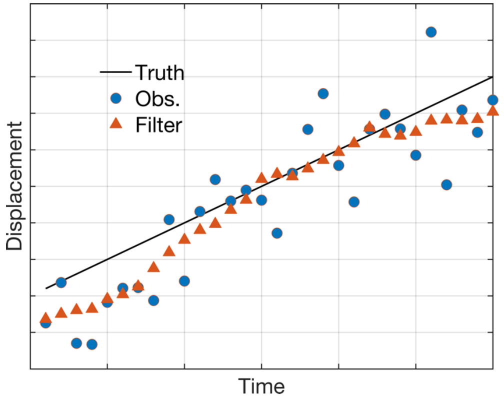


Benchmark methods

FitFilter: Fit a ramp and a DEM-correlated component, followed by a temporal filter

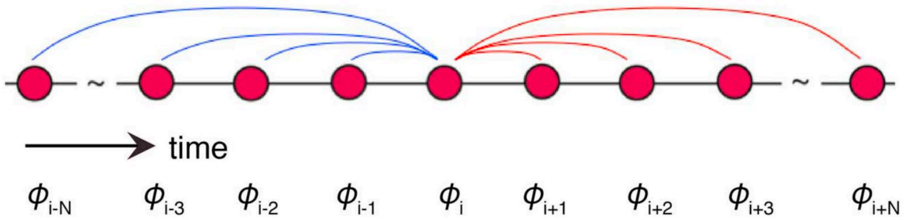


$$\varphi = a_0 + \underbrace{a_1 \cdot x + a_2 \cdot y}_{\text{ramp}} + \underbrace{k \cdot h}_{\text{DEM-correlated}}$$



$$\varphi_i = \frac{1}{2N+1} \sum_{n=-N}^{N} \varphi_{i+n}$$

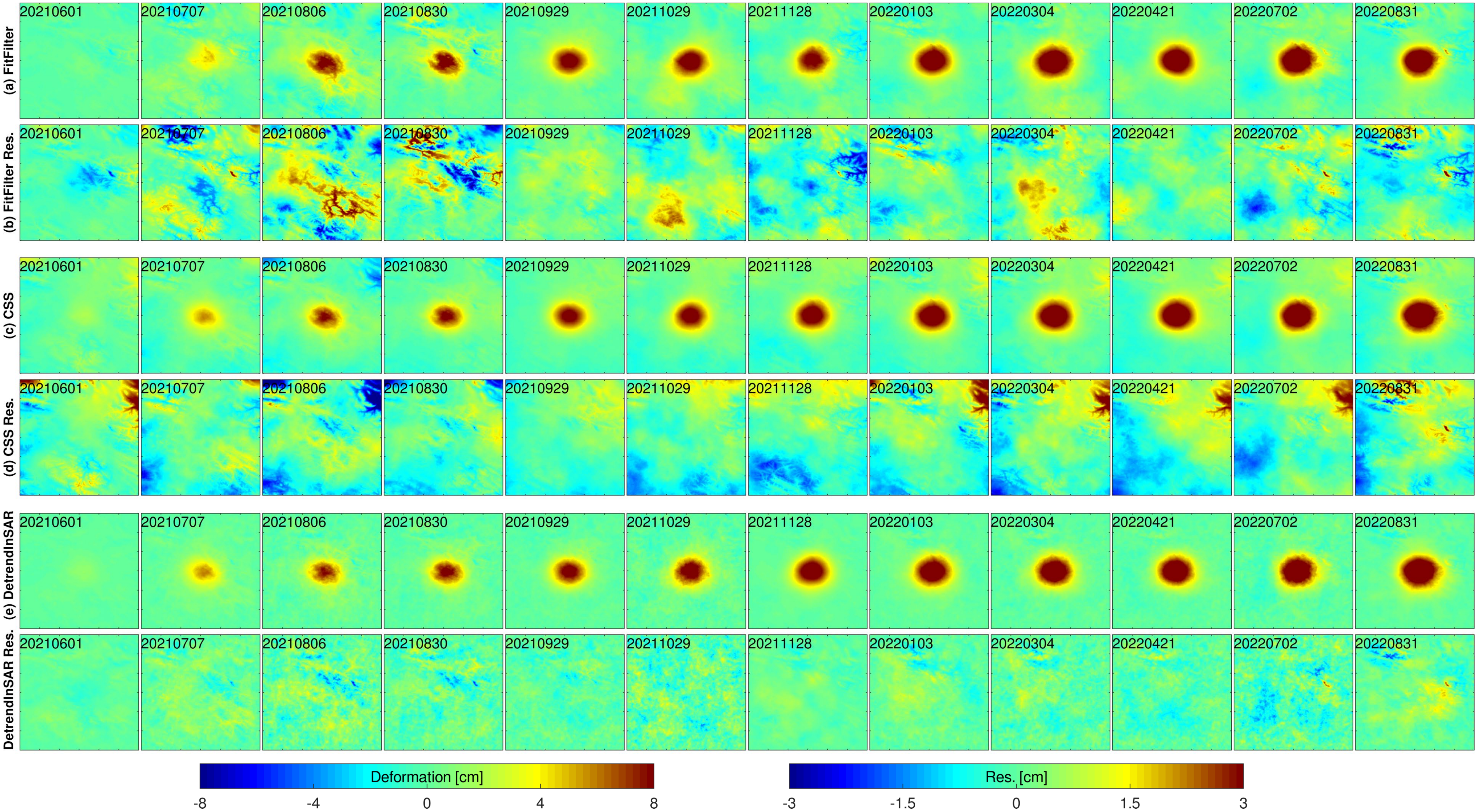
CSS: Common Scene Stacking



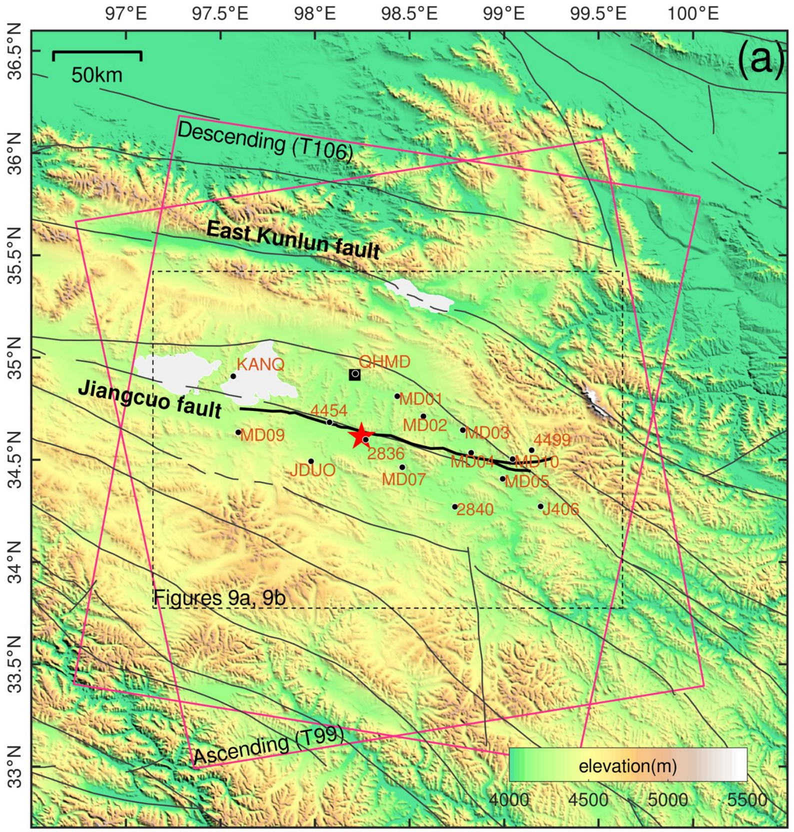
e.g., Tymofyeyeva & Fialko (2015)

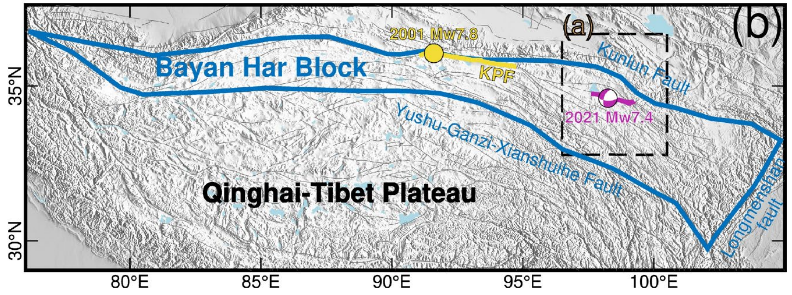
$$a_i = \lim_{N \to \infty} \frac{1}{2N} \sum_{j=1}^{N} \Delta\phi_{i(i-j)} - \Delta\phi_{(i+j)i}$$

Simulated Comparison

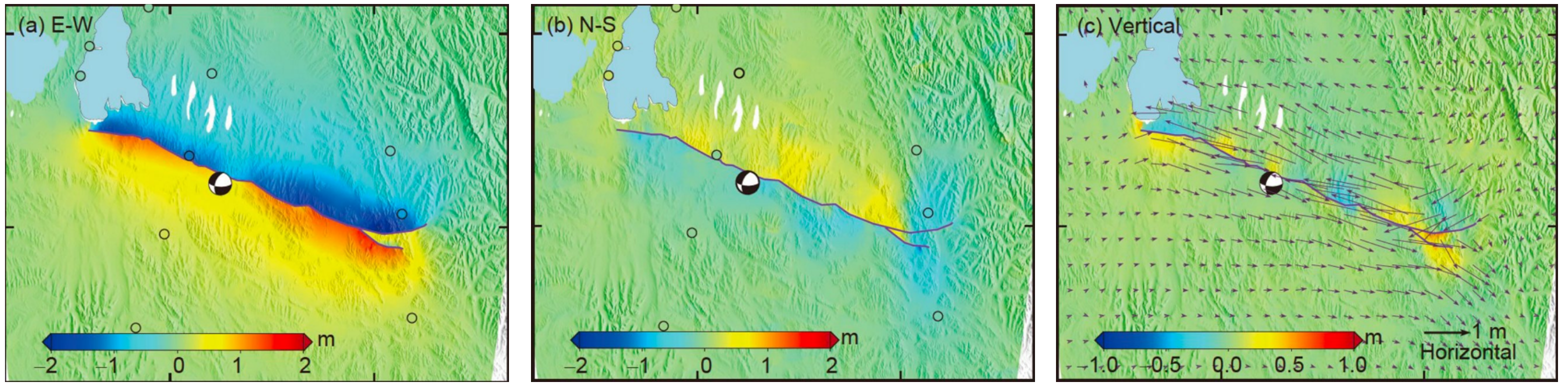


The 2021 Mw7.4 Maduo earthquake

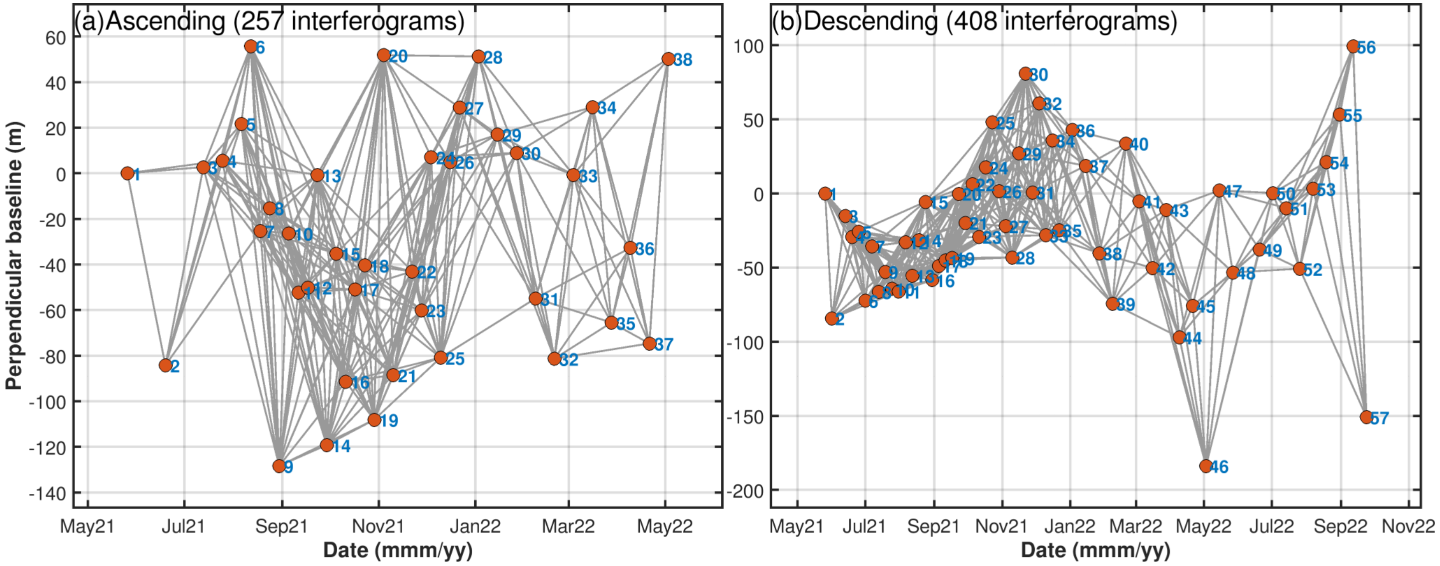




Coseismic displacements

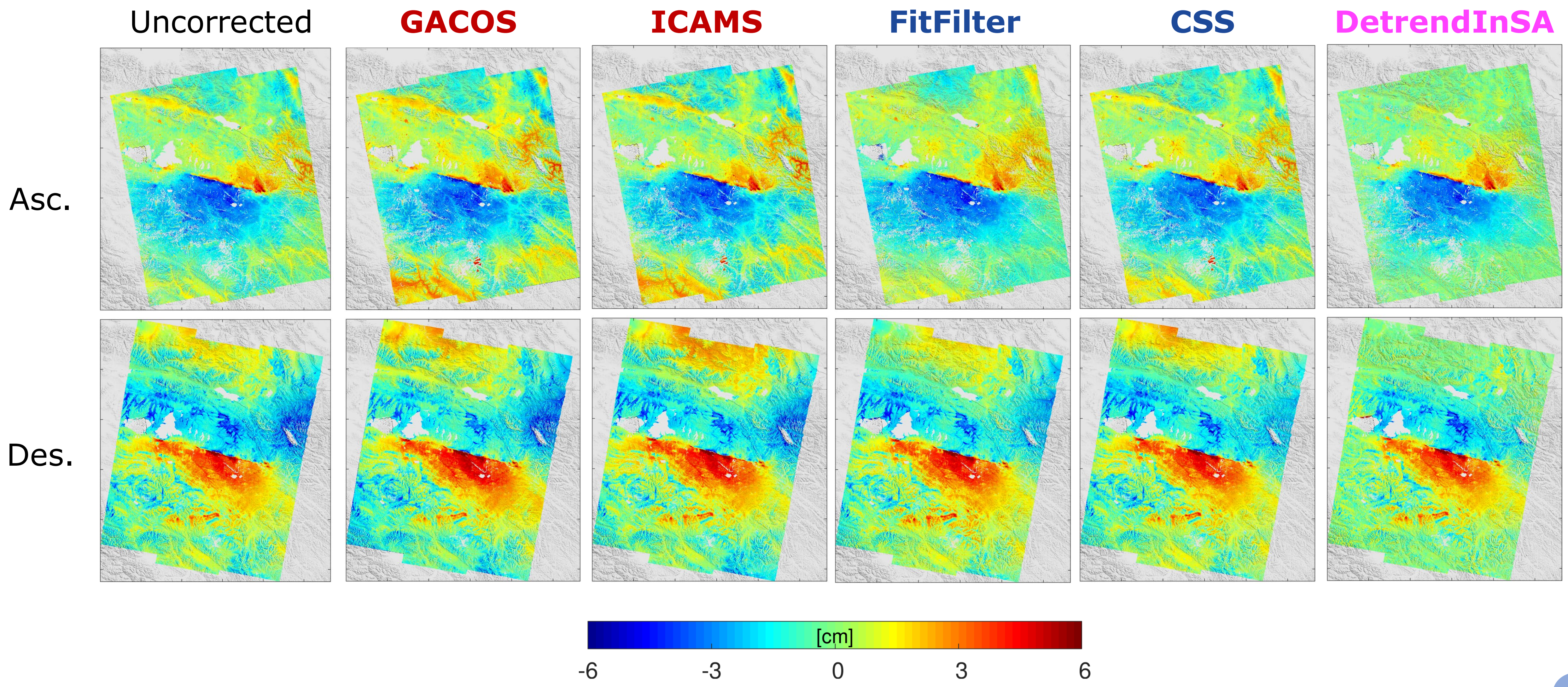


16 months of postseismic Sentinel-1 images



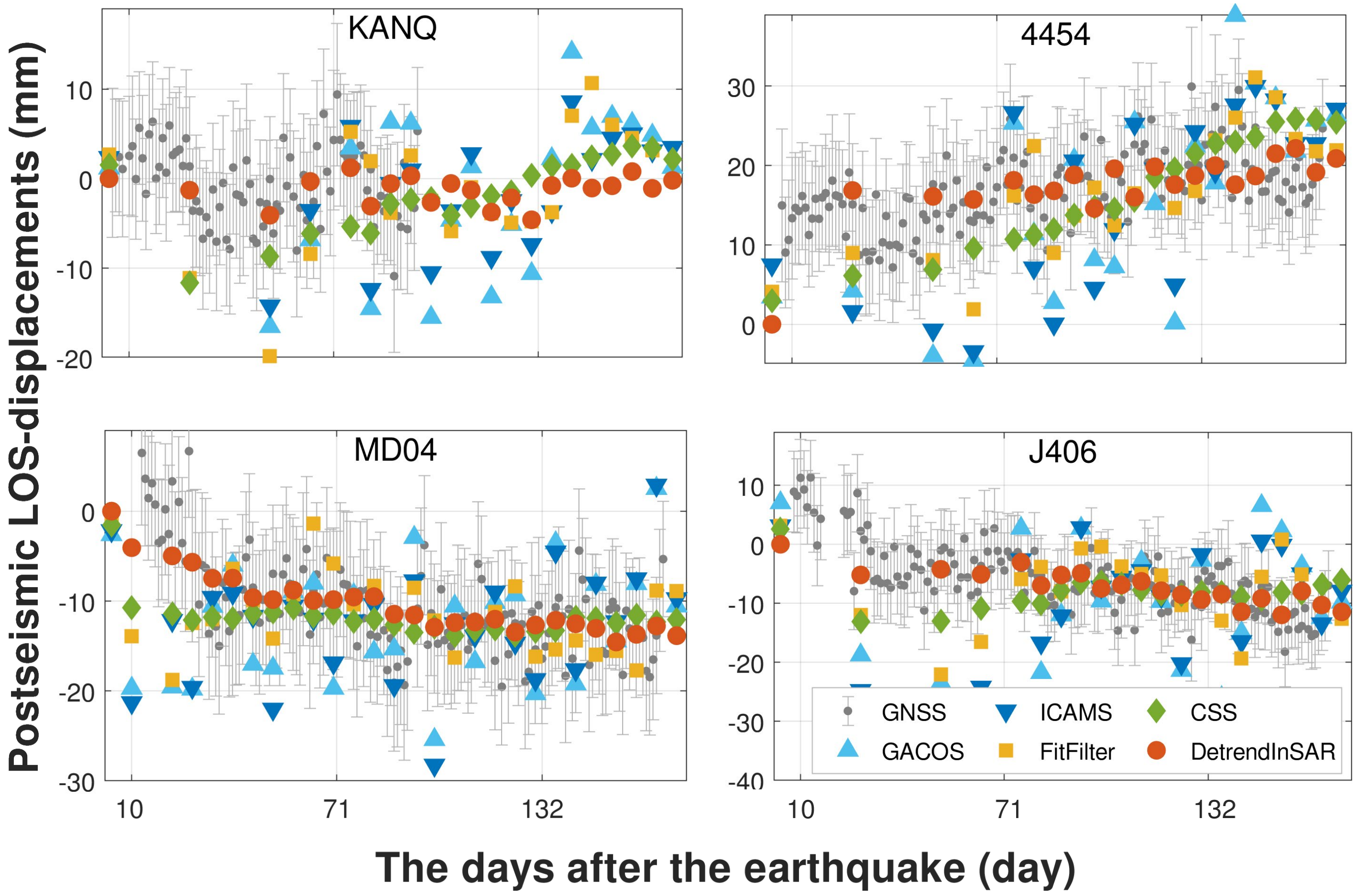
The 2021 Mw7.4 Maduo earthquake

- **Comparison of different methods**



The 2021 Mw7.4 Maduo earthquake

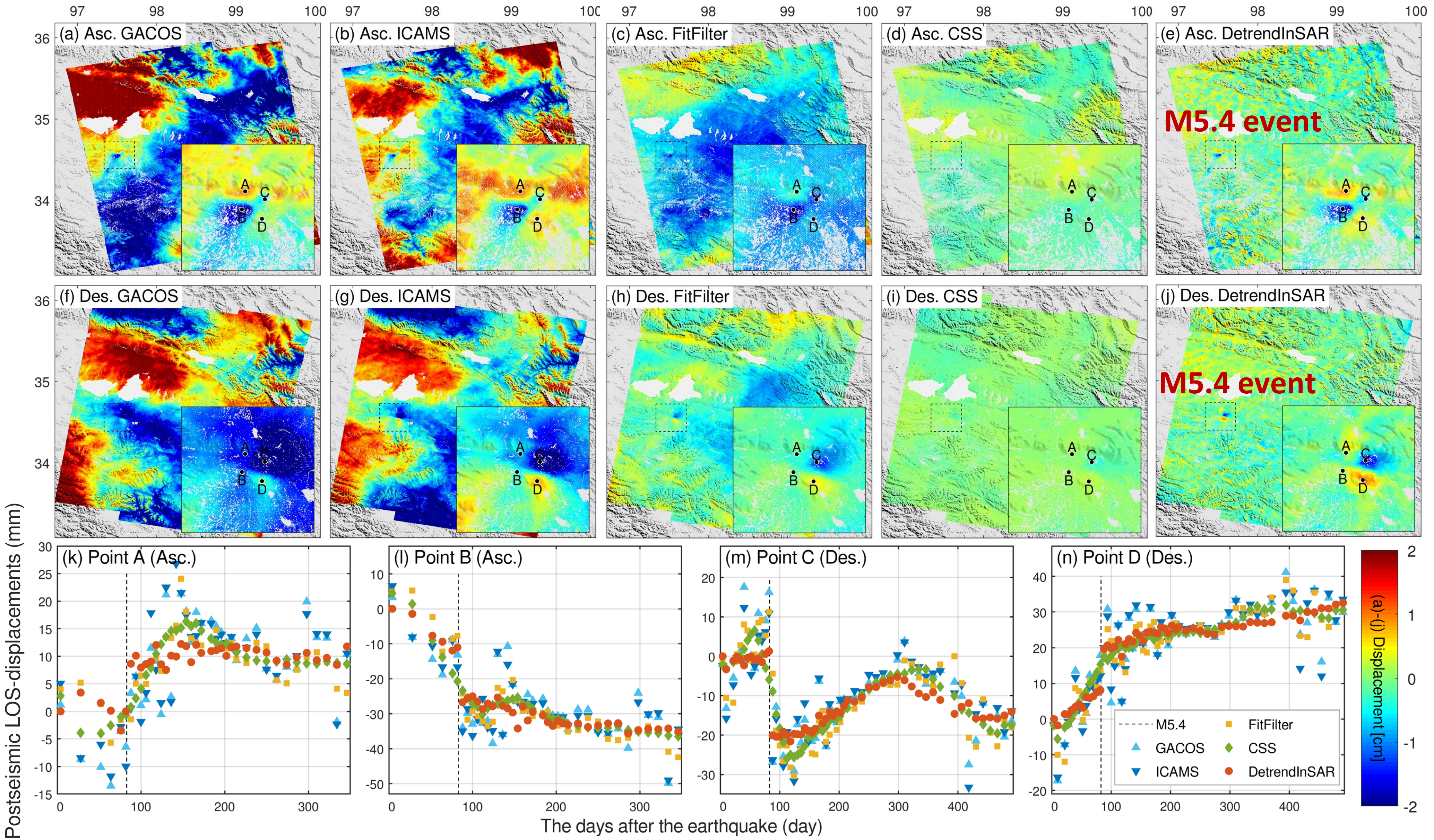
➢ **Comparison with 160-day GNSS**



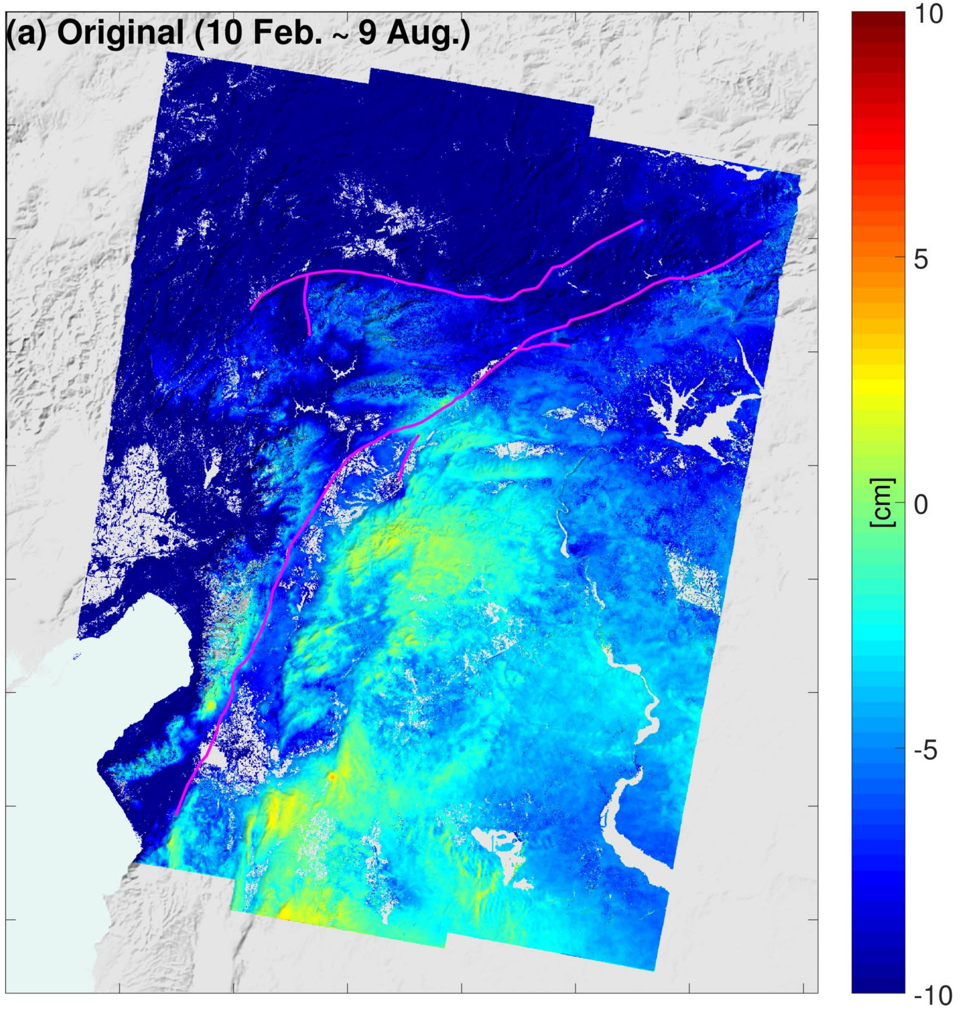
RMSEs by comparing with GNSS (mm)

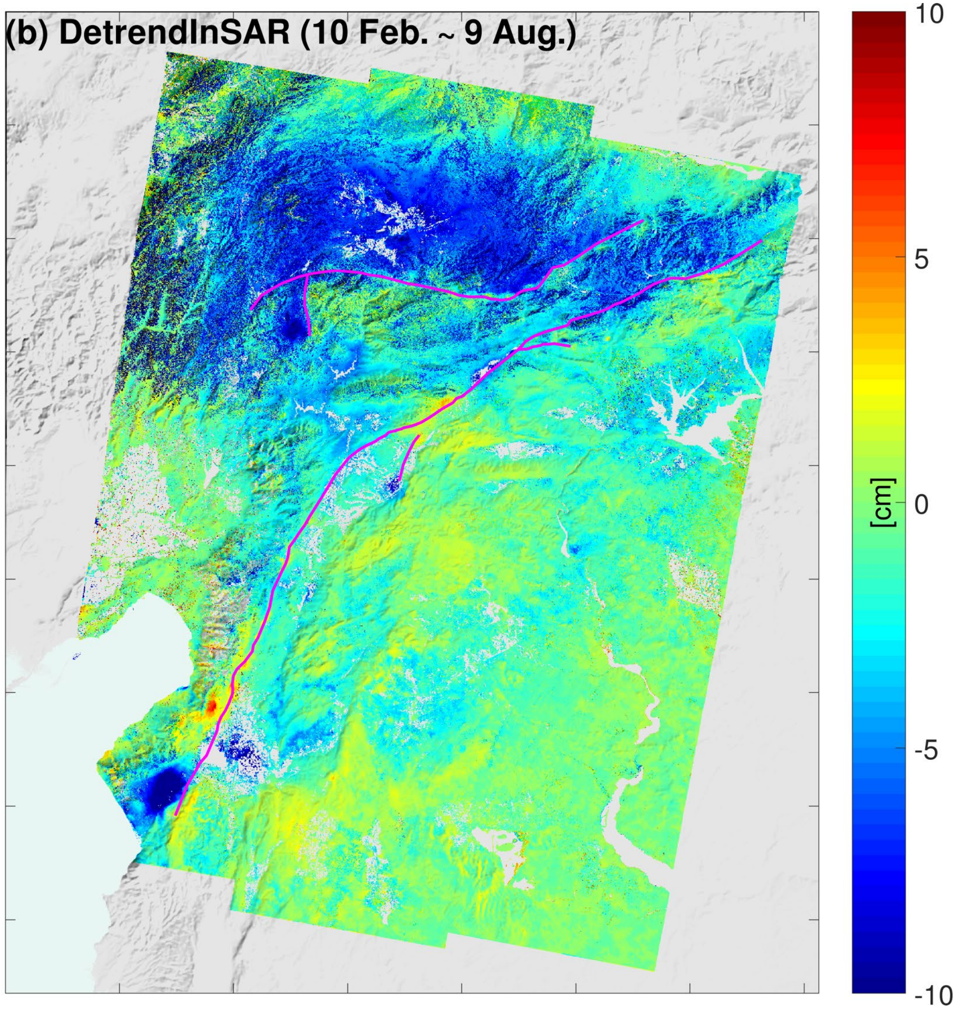
Method	Asc.	Des.
GACOS	11.1	8.7
ICAMS	10.9	8.0
FitFilter	6.7	6.8
CSS	3.9	4.5
DetrendInSAR	3.1	3.6

Displacement example of an M5.4 post-earthquake



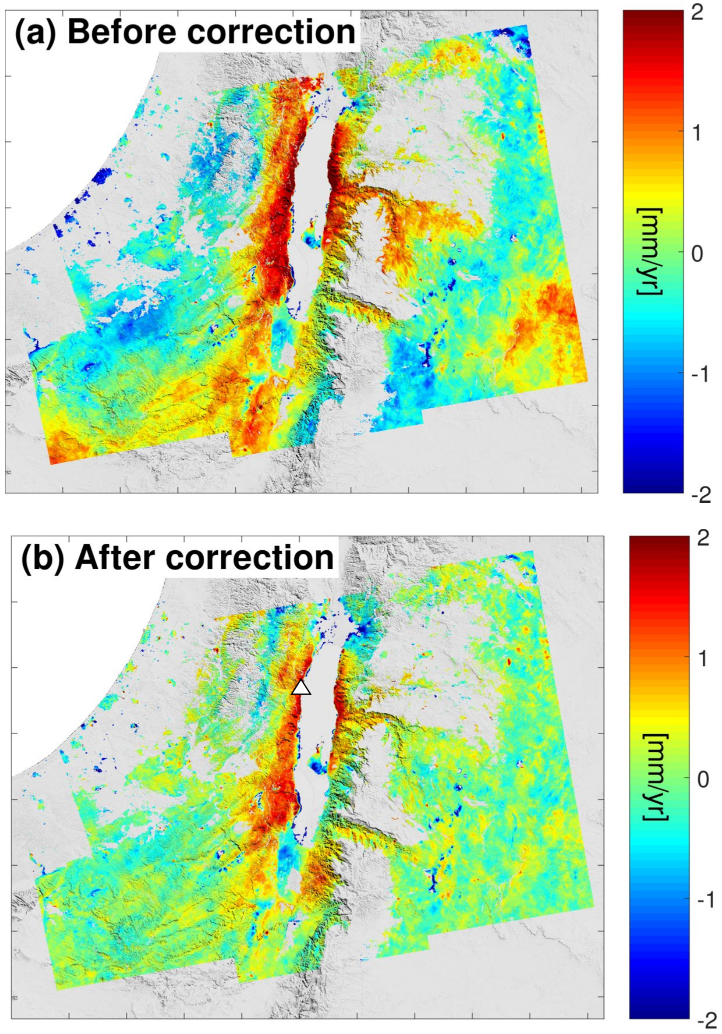
The 2023 Türkiye earthquake sequence



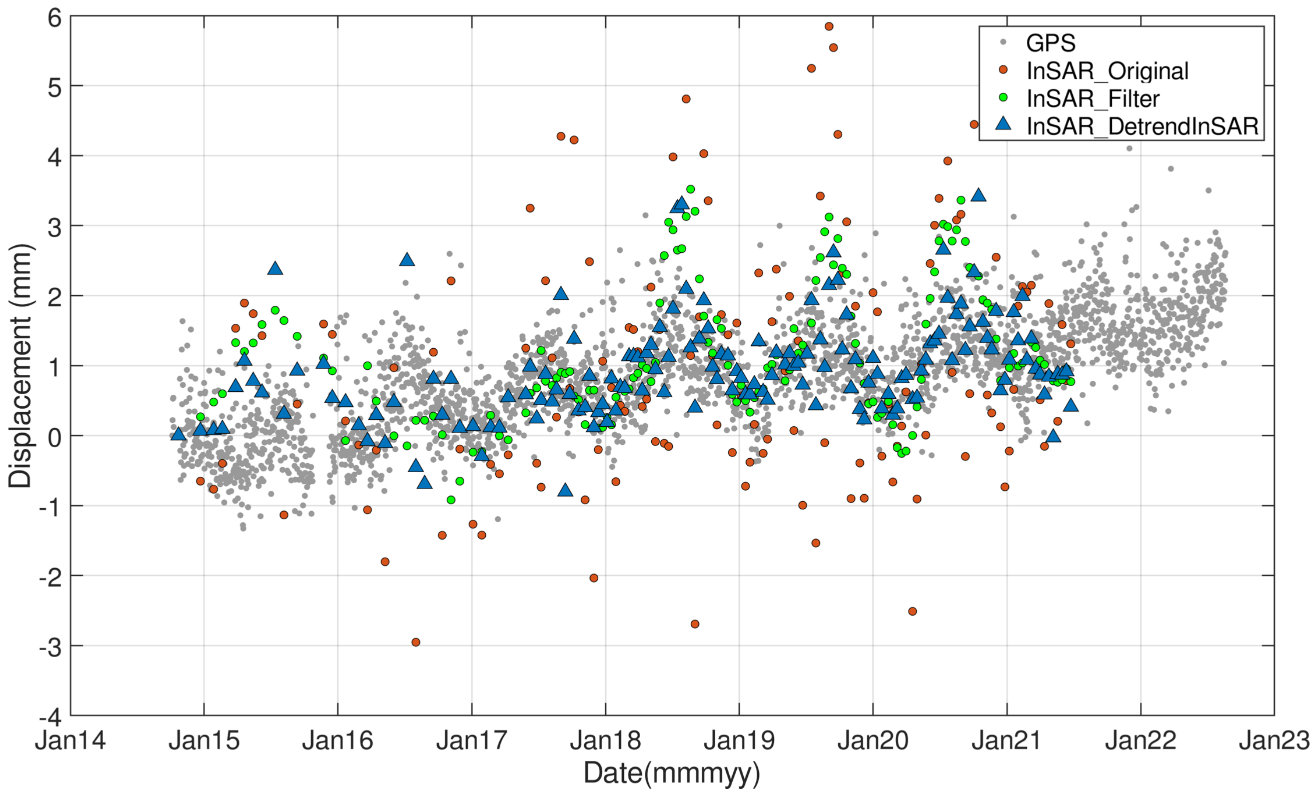


From *Kang Wang* at UC, Berkeley

The water-level decrease-induced rebound of Dead Sea



From *CDI*, KAUST



open DetrendInSAR code

- **Input**: `displacement time series, Date list, dem`
- **Key parameters**: `"defo=0" region, window size, weight`
- **Output**: `corrected data`

- **Advantages**
  - `Simple input`
  - `Feasiblity to adjust parameters`

DetrendInSAR
10.5281/zenodo.8241402

- **Why not have a try**

Conclusions

- We propose a new InSAR time-series method (**DetrendInSAR**) for reducing atmospheric delays;
- Simulation and real data analysis over the 2021 Maduo earthquake **validate** DetrendInSAR method;
- DetrendInSAR **open code**
  - Not the best but **worth a try**
  - InSAR atmospheric delays correction is still **a challenging topic**
- Welcome to “**4.01c The 2023 Türkiye earthquake sequence**”
  - **Off-fault damage** of the 2023 Kahramanmaraş earthquakes estimated from **3D displacements** of satellite radar images

DetrendInSAR
10.5281/zenodo.8241402

Thanks for your attention!
Welcome comments and suggestions……