

# A Generic Noise Model for InSAR Time Series Based on Stepwise Error Propagation

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FRINGE 2023 (Leeds)

14 September 2023



# Fringe 2021 Recommendations



## **Communicating results and their uncertainty**

the key recommendations in this regard are:

- ① Standardization of output products
- ② Error-bars and easy-to-understand statistics should accompany results and derived products for more rigorous analysis.

# Importance of Noise Model for InSAR

## ① Proper Quality Description

How precise are the InSAR products: deformation rate, timeseries, etc ? **How to estimate correct error-bars?**

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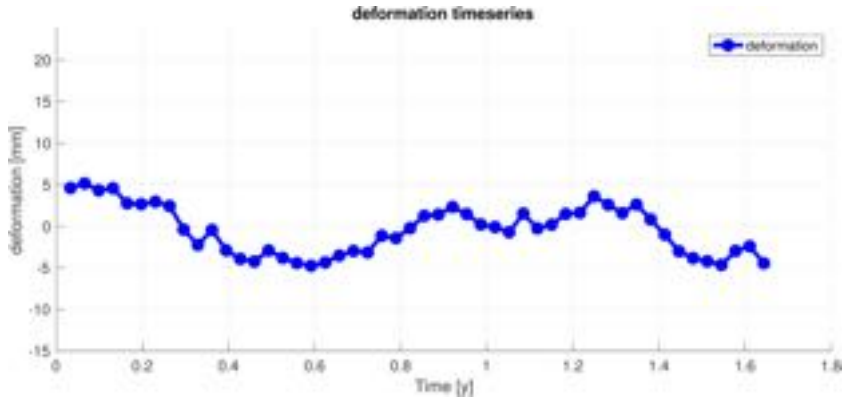
## ④ Proper interpretation

To decide whether the InSAR-based deformation estimates are significant or not? **(Difficult in case of correlated noise)**

# Importance of Noise Models for InSAR

**Interpretation: Deformation or Noise?**

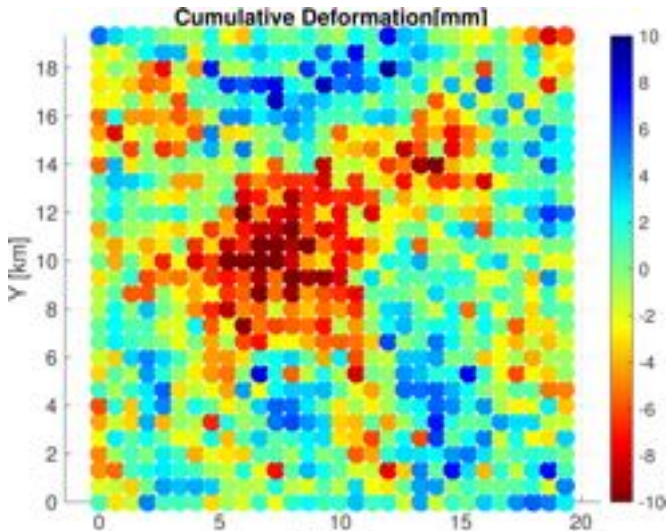
**Example 1:**



# Importance of Noise Models for InSAR

Interpretation: Deformation or Noise?

Example 2:





# Importance of Noise Models for InSAR

## Two Aspects of Quality Description

### ① Precision

What is the dispersion around the mean value? **How wide should be the error-bars?**

### ② Accuracy

How close are the measurements to their true value? **Effect of Unwarping errors!**

The main goal of this study is to describe the **precision** of InSAR timeseries in a generic form

For **Accuracy** and quality of Unwarping, see our poster No.83

# InSAR Generic Noise Model: What do we already know?

**A good body of knowledge of InSAR noise components is already exist**

## ① **Coherence\_affected Noise**

Goodman, 1976; Madsen, 1986; Bamler and Hartl, 1998, Hanssen 2001, and many other studies

## ② **Atmospheric Noise**

Hanssen 2001, Liu, 2012, and many other studies

## ③ **Coherence\_affected and atmosphere in timeseries**

Monti-Guarnieri and Tebaldini, (2007)

Hybrid Cramer-Rao bound for InSAR timeseries

Agram and Simons (2015), A noise model for InSAR time series

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**But, are these models representative for final InSAR timeseries/products delivered by different algorithms/software?**

# InSAR Generic Noise Model: What is the problem?

**Processing-induced noise?**

# InSAR Generic Noise Model: What is the problem?

## Processing-induced noise?

- ① Different spatial or temporal filtering steps reduce the noise magnitude (Noise reduction)

# InSAR Generic Noise Model: What is the problem?

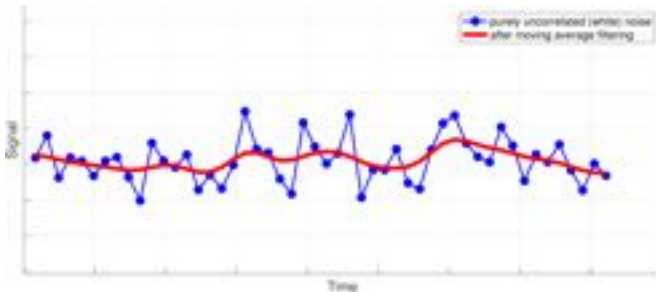
## Processing-induced noise?

- ① Different spatial or temporal filtering steps reduce the noise magnitude (**Noise reduction**)
- ② Different spatial or temporal filtering steps alters the **noise structure**

# InSAR Generic Noise Model: What is the problem?

## Processing-induced noise?

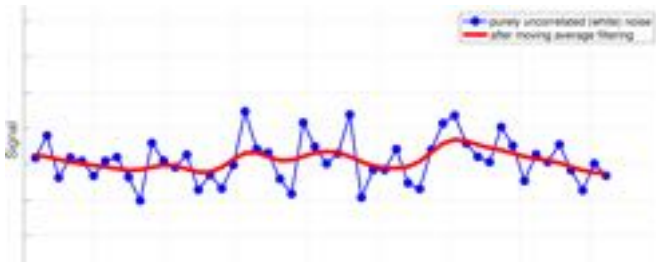
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# InSAR Generic Noise Model: What is the problem?

## Processing-induced noise?

- 1 Different spatial or temporal filtering steps reduce the noise magnitude (**Noise reduction**)
- 2 Different spatial or temporal filtering steps alters the **noise structure**



Currently available noise models are not representative of true noise structure in final InSAR timeseries



# InSAR Generic Noise Model: Influencing Factors

## Noise structure of final InSAR timeseries depends on :

- ① Scattering characteristics of the targets (via coherence matrix or amplitude stability)
- ② Atmospheric delay heterogeneity (via atmospheric noise models)
- ③ Data characteristics (e.g., multilooking factor, number of acquisitions, revisit time)
- ④ Type of deformation mechanism and its spatio-temporal behavior
- ⑤ Temporal/Spatial kernels used for noise filtering
- ⑥ Distribution and location of targets used for spatial filtering of atmospheric effects

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We need a generic noise model to account for all these factors

# InSAR Generic Noise Model: Uncertainty Propagation

- **Uncertainty Propagation**

To derive or assume a noise structure for raw InSAR timeseries followed by an error propagation through all the processing steps.



## Challenges of this approach

- Complexity of the processing steps
- Incomparable strategies/algorithms among InSAR methodologies,
- Large volume of spatio-temporal InSAR observations

# InSAR Generic Noise Model: Objectives

- To develop a methodology to propagate all the noise sources
- To design an efficient error propagation scheme through all the processing steps
- The main focus on: Noise covariance matrix (not only variances)
- Large volume of data: to derive an **analytical closed-form expression** to reconstruct the variances and covariances for any given spatio-temporal deformation estimate.



# InSAR Generic Noise Model: Steps

## Steps:

- ① Exploiting the existing body of knowledge about InSAR noise sources to propagate errors through the interferogram generation steps (i.e., from statistics of SAR data to statistics of interferometric phase time series)
- ② Further error propagation in the filtering step.

# InSAR Generic Noise Model: Steps

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For the latter, we formulate the filtering step in a mathematical framework based on the prediction theory (Least-squares Collocation or Wiener Filtering). This mathematical formulation is:

- **Generic:** It can cover different existing methodologies/algorithms
- **Flexible:** It can digest deterministic/stochastic assumptions about spatiotemporal behavior of different signal/noise components
- **Simple:** It allows the application of the linear error propagation

# InSAR Generic Noise Model: Constructing the Mathematical Model

## Generic form of the prediction model:

$$y = \underbrace{Ax}_{\text{functional model}} + \underbrace{s}_{\text{Unmodeled Deformation}} + \underbrace{a}_{\text{Atmosphere}} + \underbrace{n}_{\text{Coherence\_based noise}}$$

- $y$  : timeseries of a PS/DS or timeseries of set of PS/DS or set of phase values over a single interferogram
- $Ax$  : any spatial or temporal trend in the data (e.g. linear model, planar spatial trend, etc.)
- $s$  : deformation not captured by  $Ax$  (described stochastically)
- $a$  : atmospheric signal, mainly turbulence (described stochastically)
- $n$  : scattering, thermal, coregistration/respampling noise components (described stochastically)

$$Q_y = Q_s + Q_a + Q_n$$

# InSAR Generic Noise Model: Constructing the Mathematical Model

## Generic form of the prediction model:

$$y = \underbrace{Ax}_{\text{Functional model}} + \underbrace{s}_{\text{Unmodeled Deformation}} + \underbrace{a}_{\text{Atmosphere}} + \underbrace{n}_{\text{Coherence\_based noise}}$$

$$z = \underbrace{A_z x}_{\text{Functional model}} + \underbrace{s_z}_{\text{Unmodeled Deformation}}$$

- $z$  : final filtered timeseries of a PS/DS or a set of PS/DS
- $Ax$  : any spatial or temporal deformation trend in  $z$
- $s$  : deformation not captured by  $A_z x$



# InSAR Generic Noise Model: Constructing the Mathematical Model

$$y = Ax + s + a + n \quad z = A_z x + s_z$$

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## Generic solution for $z$

$$\text{step 1 : } \hat{x} = \underbrace{(A^T W A)^T A^T W}_{R} y \quad (\text{Least Squares Estimate of } x)$$

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$$\text{step 2 : } \hat{z} = A_z \hat{x} + K(y - A \hat{x}) \quad (\text{Prediction of } z)$$

$$\hat{z} = A_z R y + K(y - A R y) = \underbrace{(A_z R + K - A R)}_F y$$

# InSAR Generic Noise Model: Constructing the Mathematical Model

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Having  $F$  and  $Q_y$  then we can obtain the covariance matrix of  $\hat{z}$  :

$$Q_{\hat{z}} = F Q_y F^T$$

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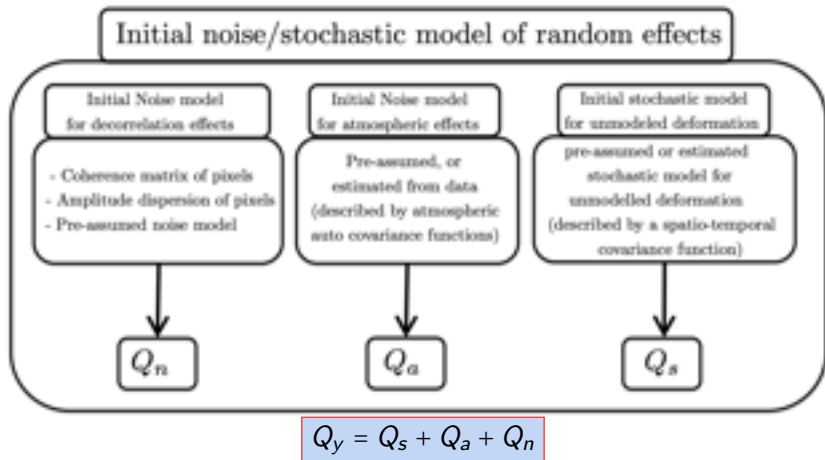
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How to get  $Q_y$  ?

# InSAR Generic Noise Model: Constructing $Q_y$

## Steps:

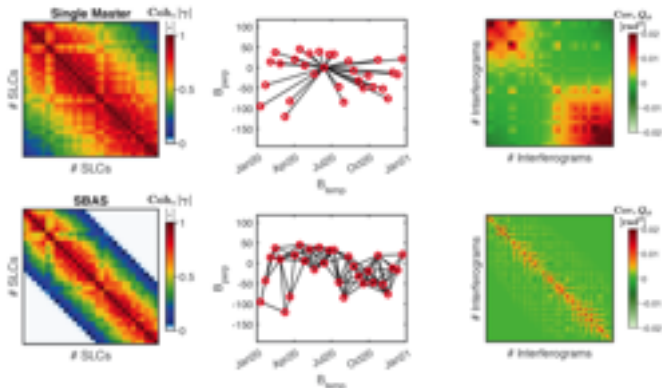
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# InSAR Generic Noise Model: Constructing $Q_y$

## Steps:

- 1 Exploiting the existing body of knowledge of InSAR noise sources



Samie-Esfahny and Hanssen, 2017, On the evaluation of second order phase statistics in SAR interferogram stacks

# InSAR Generic Noise Model: Challenges

**Challenges of the full error propagation:**  $Q_{\hat{z}} = FQ_y F^T$

- ① There are some filtering steps applied in the space domain and some in the time domain
- ② The error propagation should be capable to join the spatial and the temporal operations



# InSAR Generic Noise Model: Challenges

## Challenges of the full error propagation: $Q_{\hat{z}} = FQ_y F^T$

- 1 There are some filtering steps applied in the space domain and some in the time domain
- 2 The error propagation should be capable to join the spatial and the temporal operations

## Solution:

- 1 Applying a step-wise error propagation, first in time then in space
- 2 Merging the temporal and spatial models together by a simple transformation between the time domain and the space domain

# InSAR Generic Noise Model: Time+Space Filtering

## Steps:

- 1 Apply a high-pass filter in the time domain on timeseries of set of initial points (we call it set N) to separate deformation from atmosphere/noise
- 2 Apply a low-pass filter on the set N in each interferogram to estimate the spatially low frequency noise (mainly atmospheric noise)
- 3 Interpolate the estimated noise on other set of points (we call it set P) to get the correction
- 4 Apply the correction on the phases of set P

# InSAR Generic Noise Model: Time Domain Propagation

**Mathematical model for pixel  $i$  :**

$$[y_i]_{N \times 1} = A_i x_i + \underbrace{s_i + a_i + n_i}_{e_i}$$

$y_i$	$N \times 1$ phase vector of pixel $i$
$A_i x_i$	Temporal trend in timeseries of pixel $i$
$s_i$	$N \times 1$ phase vector of unmodeled defo
$e_i$	$N \times 1$ phase vector of noise components

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Solution for  $e_i$  (high-pass filter) :

$$\begin{cases} \hat{x}_i = (A_i^T W_i A_i)^{-1} A_i^T W_i y_i \\ \hat{e}_i = K_i (y_i - A_i \hat{x}_i) = \\ \quad K_i \underbrace{(I_N - A_i A_i^T W_i A_i)^{-1} A_i^T W_i}_{R_i} y_i \end{cases} \begin{cases} W_i & N \times N \text{ weight matrix } i \\ K_i & N \times N \text{ high-pass kernel} \end{cases}$$

$$\hat{e}_i = K_i R_i y_i$$

# InSAR Generic Noise Model: Time Domain Propagation

**Mathematical model for pixel  $i$  :**

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**Mathematical model for ...**

**set of  $M$  pixels in an initial Network (denotes by  $N$ ) :**

$$\underbrace{\begin{bmatrix} \hat{e}_1 \\ \hat{e}_2 \\ \vdots \\ \hat{e}_M \end{bmatrix}}_{\hat{e}_N} = \underbrace{\begin{bmatrix} K_1 & & & \\ & K_2 & & \\ & & \ddots & \\ & & & K_M \end{bmatrix}}_K \underbrace{\begin{bmatrix} R_1 & & & \\ & R_2 & & \\ & & \ddots & \\ & & & R_M \end{bmatrix}}_R \underbrace{\begin{bmatrix} y_1 \\ y_2 \\ \vdots \\ y_M \end{bmatrix}}_{y_N}$$

$$\hat{e}_N = KR y_N$$

# InSAR Generic Noise Model: Space Domain Propagation

**Mathematical model for the network points in  $k$ th interferogram :**

$$\underbrace{\begin{bmatrix} \hat{e}_1^k \\ \hat{e}_2^k \\ \vdots \\ \hat{e}_M^k \end{bmatrix}}_{\hat{e}_N^k} = B_N^k z^k + a^k + n^k \quad \left\{ \begin{array}{l} \hat{e}_N^k \quad \text{vector of estimated ecomponents} \\ B_N^k \quad \text{Spatial trend in } k\text{th ifg} \\ a^k \quad M \times 1 \text{ vector of atmospheric noise } k\text{th ifg} \\ n^k \quad M \times 1 \text{ coh\_based noise } k\text{th ifg} \end{array} \right.$$

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**Solution for  $a_k$  for set of  $p$  pixels in  $P$  in  $k$ th interferogram (low pass filter):**

$$\begin{cases} \hat{z}^k = (B_N^k T W^k B_N^k)^{-1} B_N^k T W^k \hat{e}_N^k \\ \hat{a}_P^k = B_P^k \hat{z}^k + L^k (\hat{e}_N^k - B_N^k \hat{z}^k) = H^k \hat{e}_N^k \end{cases} \quad \left\{ \begin{array}{ll} W^k & M \times M \text{ weight matrix } i \\ L^k & p \times M \text{ high-pass kernel} \end{array} \right.$$

$$\hat{a}_P^k = H^k \hat{e}_N^k$$

# InSAR Generic Noise Model: Space-Time Connection

$$\hat{e}_N = KR y_N$$

Time Domain Propagation

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Space Domain Propagation



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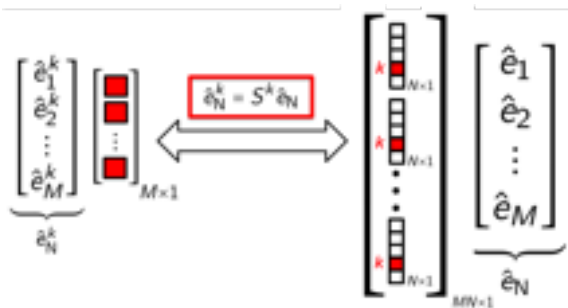
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Time Domain Propagation

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To merge these two equations, we should write  $\hat{e}_N^k$  as a function of  $\hat{e}_N$



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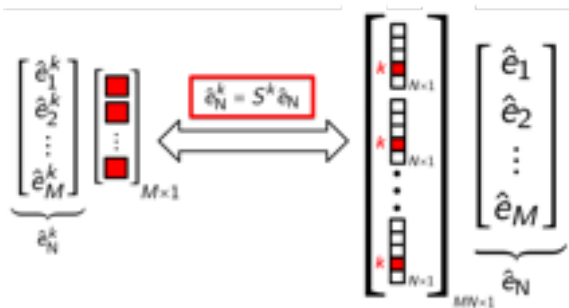
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Merging all equations above, we get:

$$\hat{a}_p^k = H^k S^k KR y_N$$

## InSAR Generic Noise Model: Final filtered phases

$$\hat{a}_P^k = \underbrace{H^k S^k K R}_{F^k} y_N$$

Above equation is the correction that should be applied on phase values of set P in the  $k$ th interferogram.

So the filtered phases of points in P in the  $k$ th and  $f$ th interferograms are:

$$\begin{aligned} \hat{y}_{P^k} &= y_P^k - F^k y_N \\ \hat{y}_{P^f} &= y_P^f - F^f y_N \end{aligned} \implies \begin{bmatrix} \hat{y}_{P^k} \\ \hat{y}_{P^f} \end{bmatrix} = \begin{bmatrix} I_p & 0 & F^k \\ 0 & I_f & F^f \end{bmatrix} \begin{bmatrix} y_{P^k} \\ y_{P^f} \\ y_N \end{bmatrix}$$

The final filtered phases were written  
as a linear function of original timeseries

## InSAR Generic Noise Model: precision of filtered phases

Precision of filtered phases is described by the dispersion of the remaining noise sources in the filtered data:

$$\begin{aligned} \epsilon_P^k &= e_P^k - F^k y_N \\ \epsilon_P^f &= e_P^f - F^f y_N \end{aligned} \implies \begin{bmatrix} \epsilon_{P^k} \\ \epsilon_{P^f} \end{bmatrix} = \underbrace{\begin{bmatrix} I & 0 & F^k \\ 0 & I & F^f \end{bmatrix}}_F \begin{bmatrix} e_P^k \\ e_P^f \\ y_N \end{bmatrix}$$

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Applying linear (co)variance propagation law:

$$\begin{bmatrix} Q_{\epsilon_P^k} & Q_{\epsilon_P^k \epsilon_P^f} \\ Q_{\epsilon_P^f \epsilon_P^k} & Q_{\epsilon_P^f} \end{bmatrix} = F \begin{bmatrix} Q_{e_P^k} & Q_{e_P^k e_P^f} & Q_{e_P^k y_N} \\ Q_{e_P^f e_P^k} & Q_{e_P^f} & Q_{e_P^f y_N} \\ Q_{e_N y_P^k} & Q_{e_N y_P^f} & Q_{y_N} \end{bmatrix} F^T$$

## InSAR Generic Noise Model: precision of filtered phases

**(Co)variance matrix of phase values of points P in  $k$ th ifg:**

$$Q_{\epsilon_P^k} = Q_{e_P^k} - F^k Q_{y_N e_P^k} - Q_{e_P^k y_N} F^{kT} + F^k Q_{y_N} F^{kT}$$

**Cross (co)variance between  $k$ th and  $f$ th ifg:**

$$Q_{\epsilon_P^k \epsilon_P^f} = Q_{e_P^k e_P^f} - F^k Q_{y_N e_P^f} - Q_{e_P^k y_N} F^{fT} + F^k Q_{y_N} F^{fT}$$

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- 2 With the second equation, we can compute the covariance between any two phase values in the time/space domains



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- 1 With the first equation we can compute the variance of any target in any interferogram
- 2 With the second equation, we can compute the covariance between any two phase values in the time/space domains
- 3 F matrices captures all the filtering settings (e.g., type of the kernels, location of points, functional models, etc)

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**(Co)variance matrix of phase values of points P in  $k$ th ifg:**

$$Q_{\epsilon_P^k} = Q_{e_P^k} - F^k Q_{Y_N e_P^k} - Q_{e_P^k Y_N} F^{kT} + F^k Q_{Y_N} F^{kT}$$

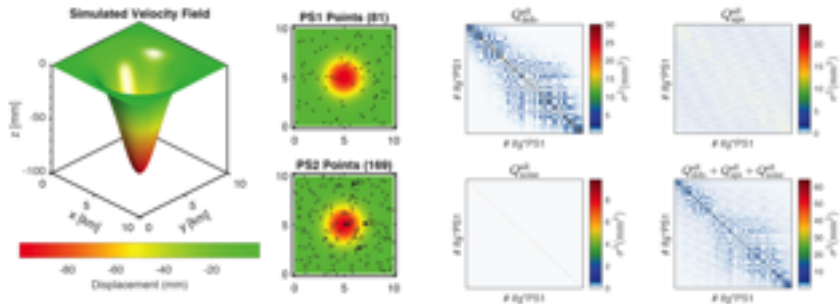
**Cross (co)variance between  $k$ th and  $f$ th ifg:**

$$Q_{\epsilon_P^k \epsilon_P^f} = Q_{e_P^k e_P^f} - F^k Q_{Y_N e_P^f} - Q_{e_P^k Y_N} F^{fT} + F^k Q_{Y_N} F^{fT}$$

- 1 With the first equation we can compute the variance of any target in any interferogram
- 2 With the second equation, we can compute the covariance between any two phase values in the time/space domains
- 3 F matrices captures all the filtering settings (e.g., type of the kernels, location of points, functional models, etc)
- 4 Q matrices captures all the initial noise structure and effects of pre-processing (e.g., phase linking, multilooking, etc)

# Synthetic data validation

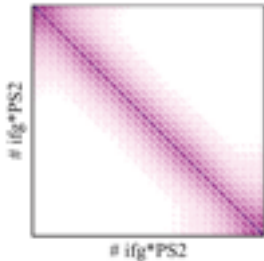
To check the validity of the deriviations



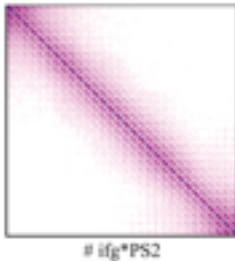
# Synthetic data validation

To check the validity of the deriviations

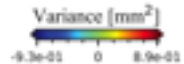
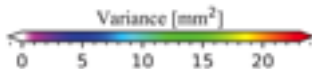
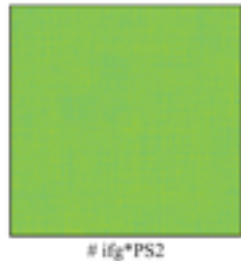
A: Proposed model



B: Empirical Cov Matrix

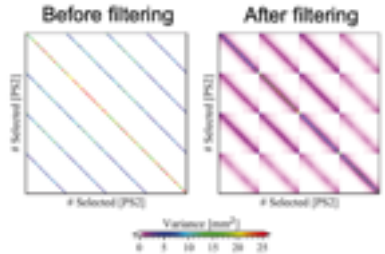
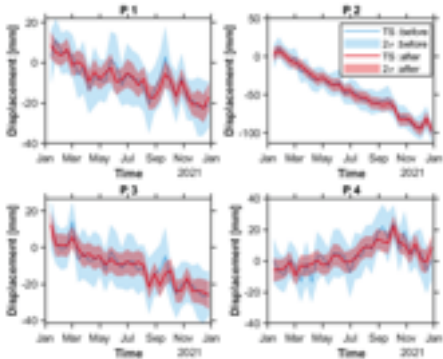


Difference  $A - B$



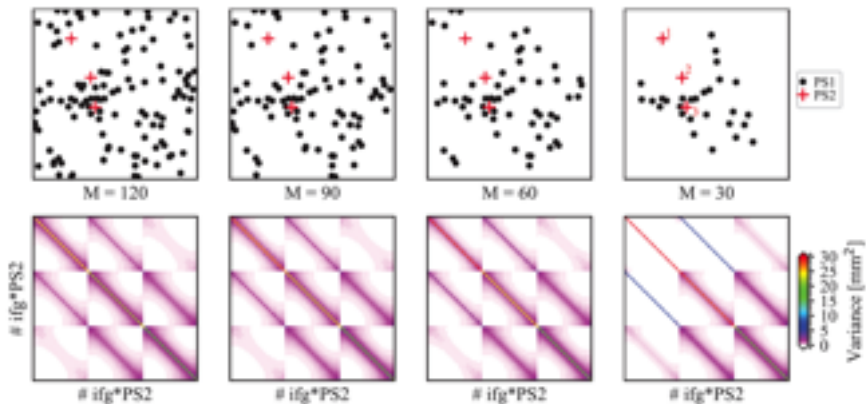
# InSAR Generic Noise Model: Synthetic Data Example

## Effect of filtering



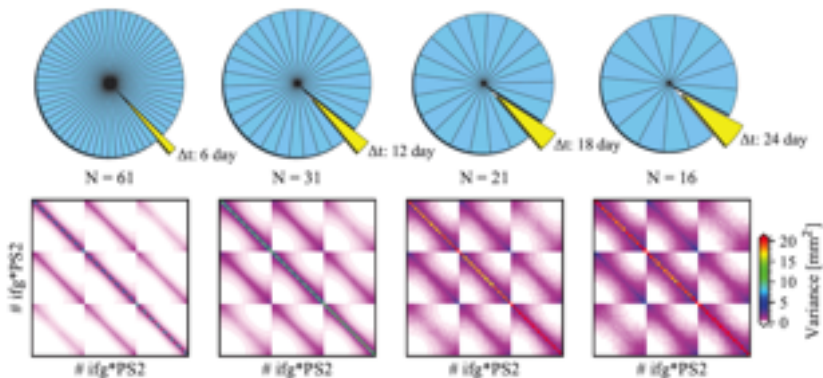
# InSAR Generic Noise Model: Synthetic Data Example

## Effect of point density of the initial network N



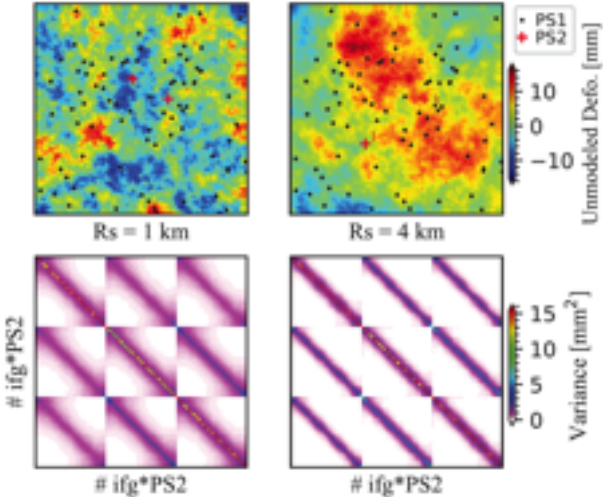
# InSAR Generic Noise Model: Synthetic Data Example

## Effect of revisit time



# InSAR Generic Noise Model: Synthetic Data Example

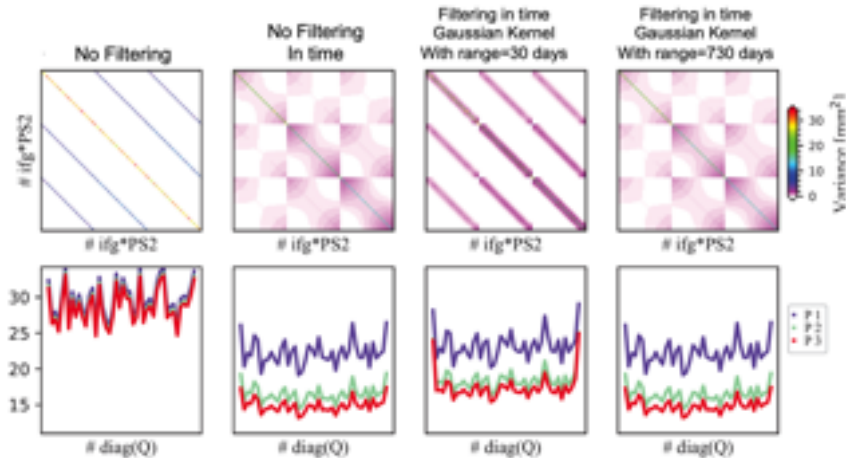
## Effect of unmodeled deformation





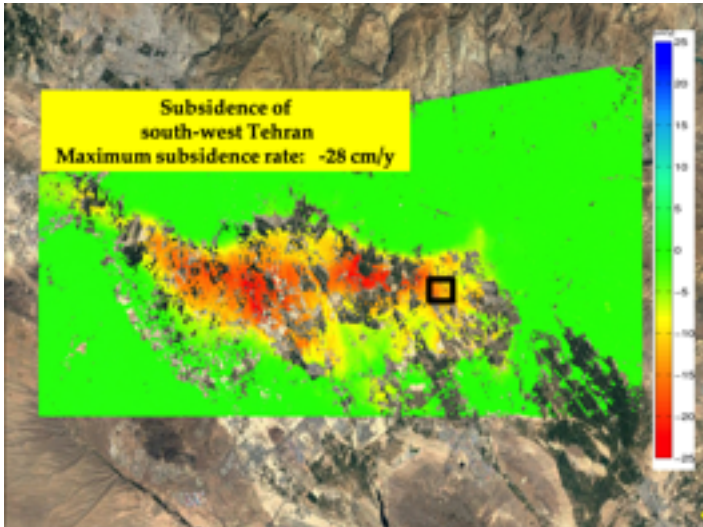
# InSAR Generic Noise Model: Synthetic Data Example

## Effect of Kernel type used for filtering in the time domain



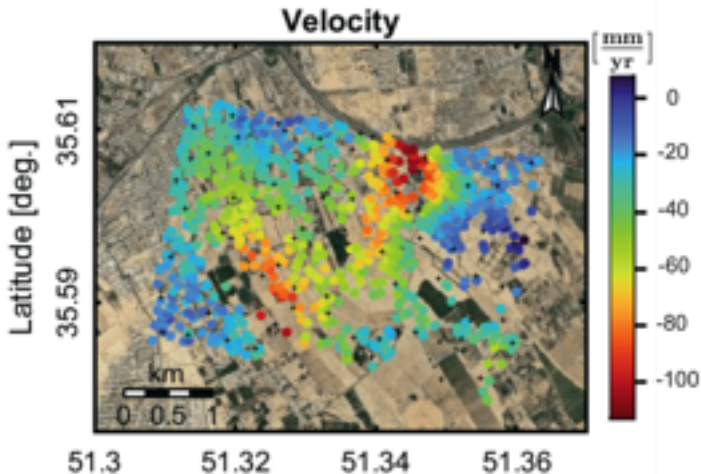
# InSAR Generic Noise Model: Real Data

30 SLC images, Sentinel-1A, one year of data 2021



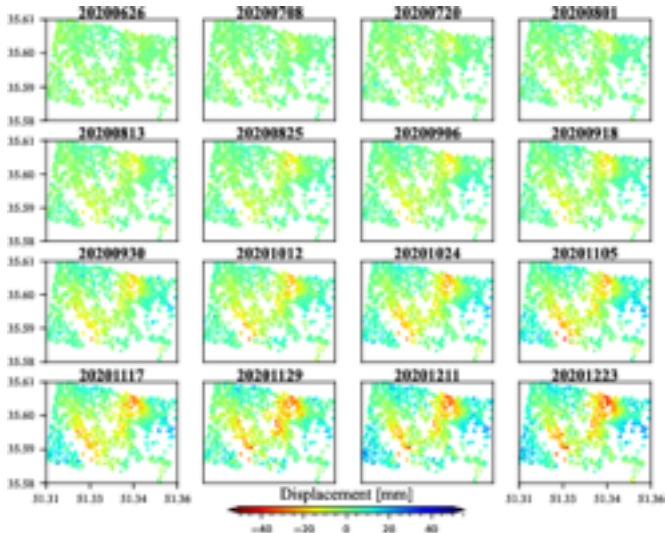
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30 SLC images, Sentinel-1A, one year of data 2021



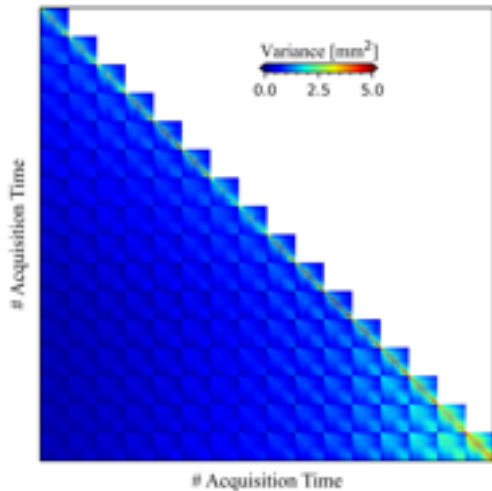
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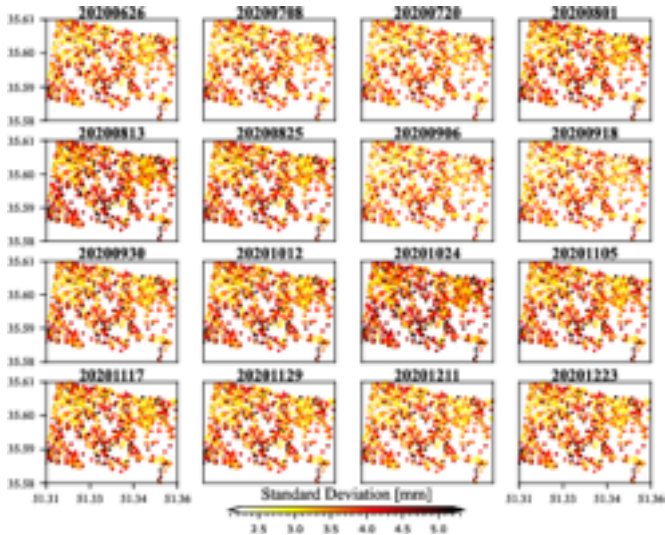
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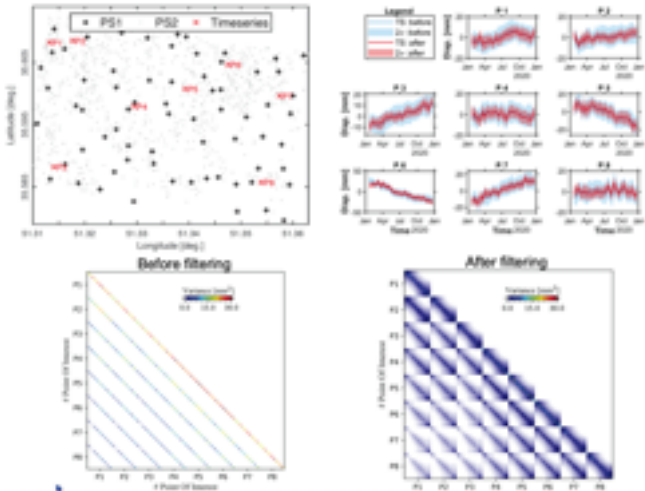
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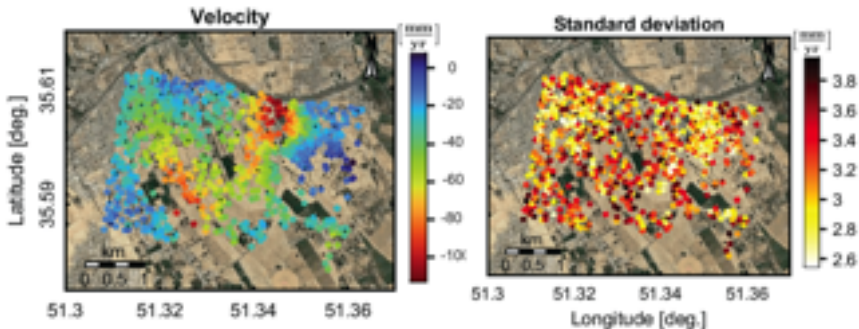
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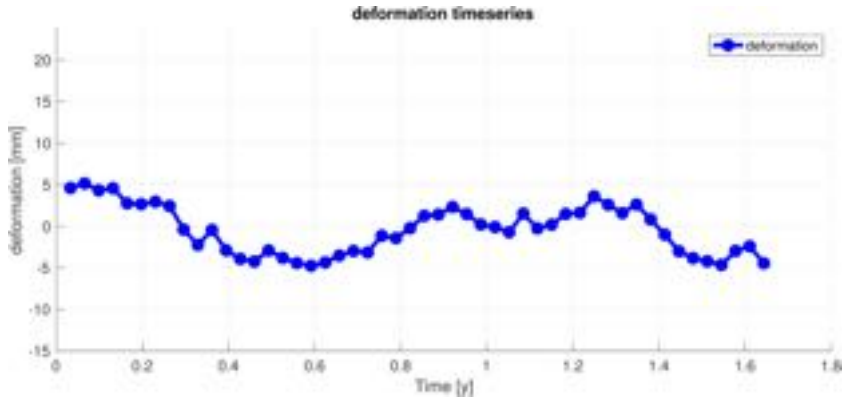




# Importance of Noise Models for InSAR

**Interpretation: Deformation or Noise?**

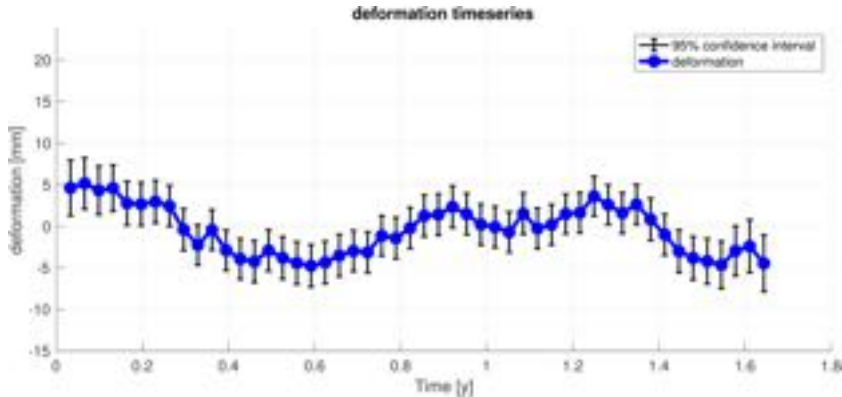
**Example 1:**



# Importance of Noise Models for InSAR

Interpretation: Deformation or Noise?

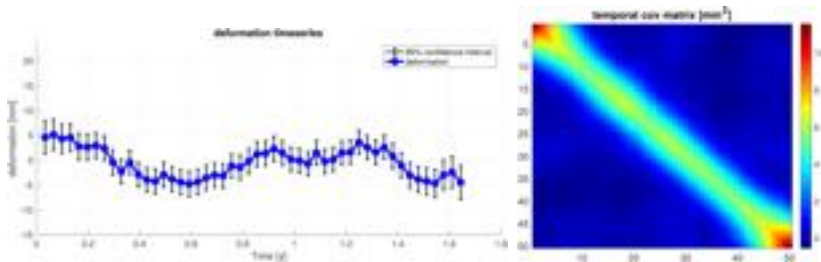
Example 1:



# Importance of Noise Models for InSAR

## Interpretation: Deformation or Noise?

### Example 1:



If we have the full  $Q$ , We can test whether this is a signal or noise:

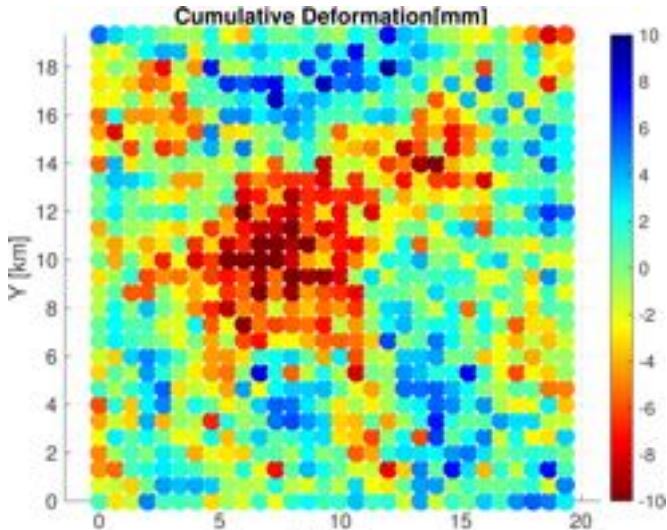
$$y^T Q^{-1} y \sim \chi^2(N) \quad N: \text{ number of images}$$

$$y^T Q^{-1} y = 54 \leq \chi_{0.05}^2(50) = 67$$

# Importance of Noise Models for InSAR

Interpretation: Deformation or Noise?

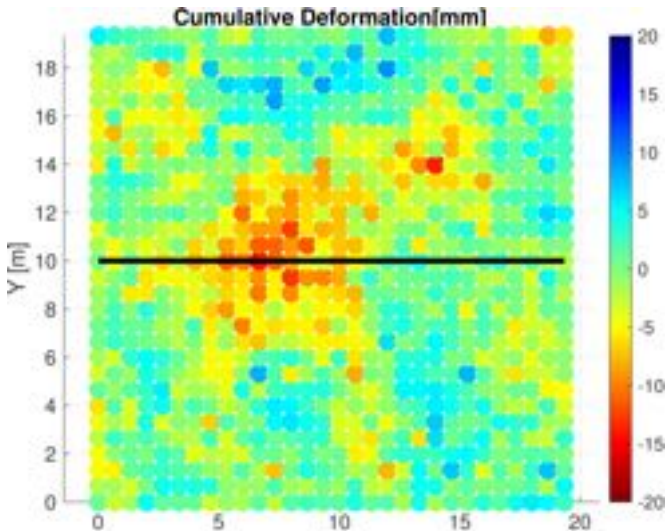
Example 2:



# Importance of Noise Models for InSAR

Interpretation: Deformation or Noise?

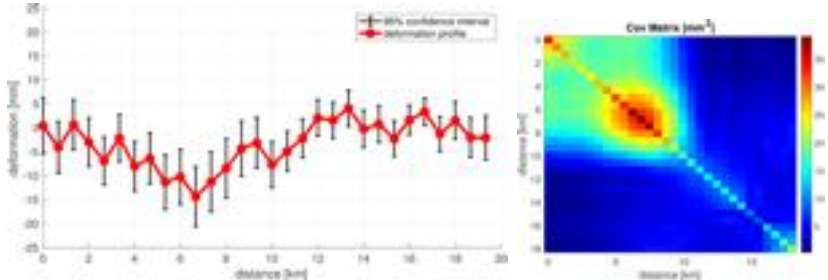
Example 2:



# Importance of Noise Models for InSAR

Interpretation: Deformation or Noise?

Example 2:



If we have the full  $Q$ , We can test whether this is a signal or noise:

$$y^T Q^{-1} y \sim \chi^2(N) \quad N: \text{ number of points on the profile}$$

$$y^T Q^{-1} y = 34 \leq \chi_{0.05}^2(30) = 44$$

# Conclusions

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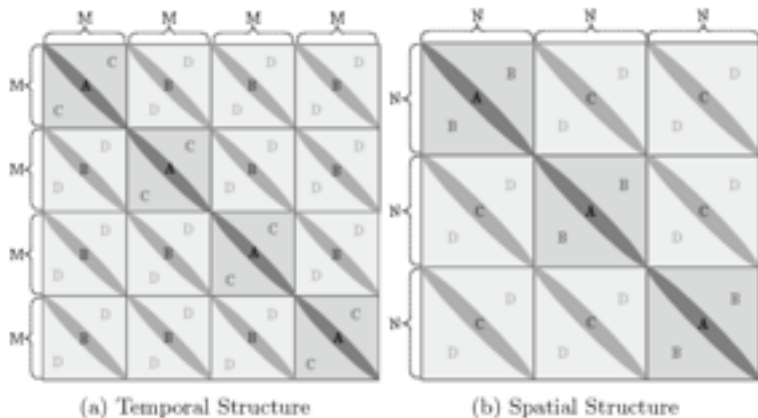
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- The proposed formulation can be easily **extended** to cover other processing steps
- In TInSAR results we usually have spatio-temporally **correlated/smooth** noise
- **Error-bars are not enough**, we need to address the covariances!



# Temporal vs Spatial Structure



**Fig. 4:** The schematic presentation of the spatial-temporal structure of the covariance matrix for 4 points and 3 interferograms. The variance and covariance values can be classified into four different groups A: variances, B: spatial covariances, C: temporal covariances, and D: spatio-temporal covariances. a) Temporal structure b) Spatial structure.