# Getting to the point: Rapid, high quality point selection and variable point time series for deformation monitoring

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# Why Sentinel-1 is a game changer?

- Systematic acquisitions, high duty cycle
- Large image footprints: ~250 x 250-1000 km
- Designed for InSAR
- 20 year operational program
- Free, full and open data policy

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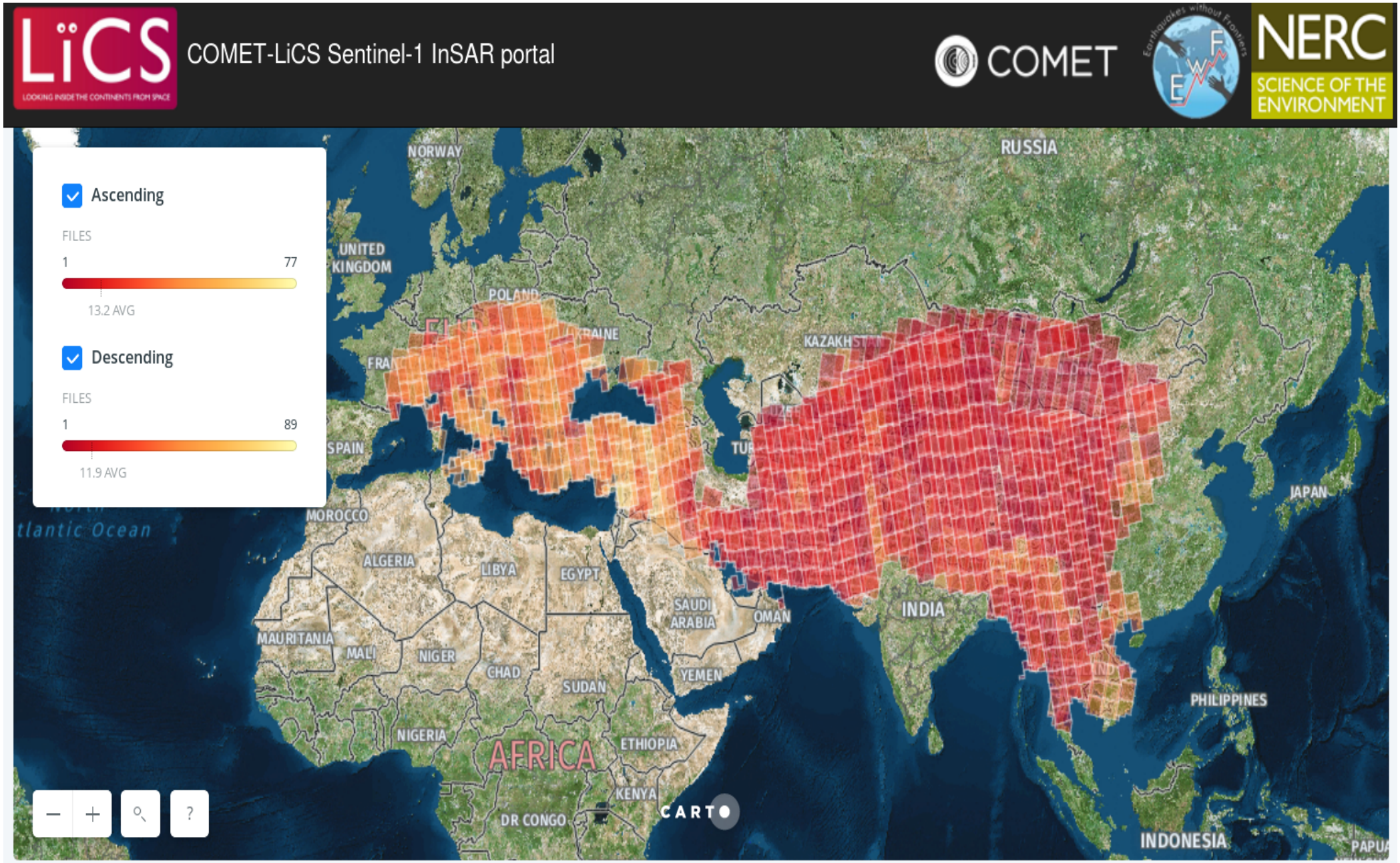
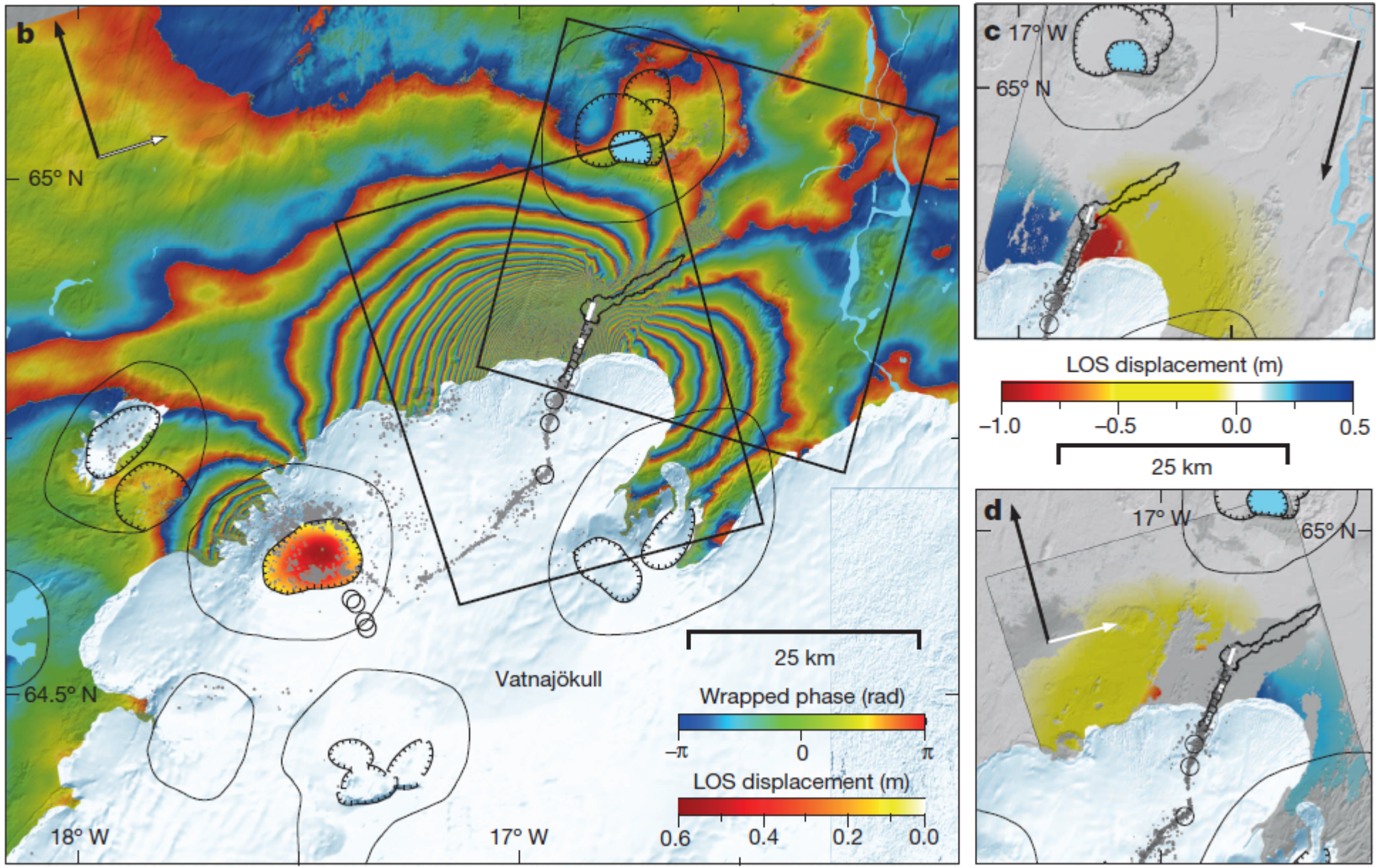
# Sentinel-1 data volumes



# Volcanic deformation monitoring




Sigmundsson et al., Nature [2015]

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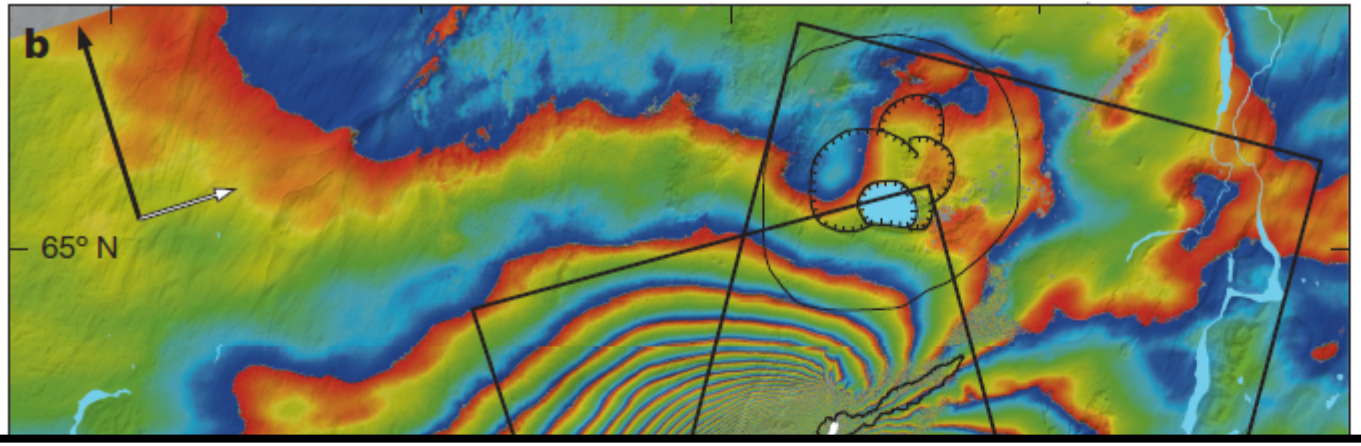
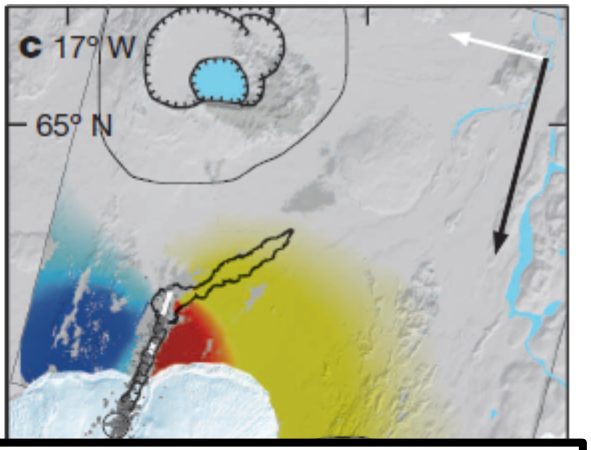
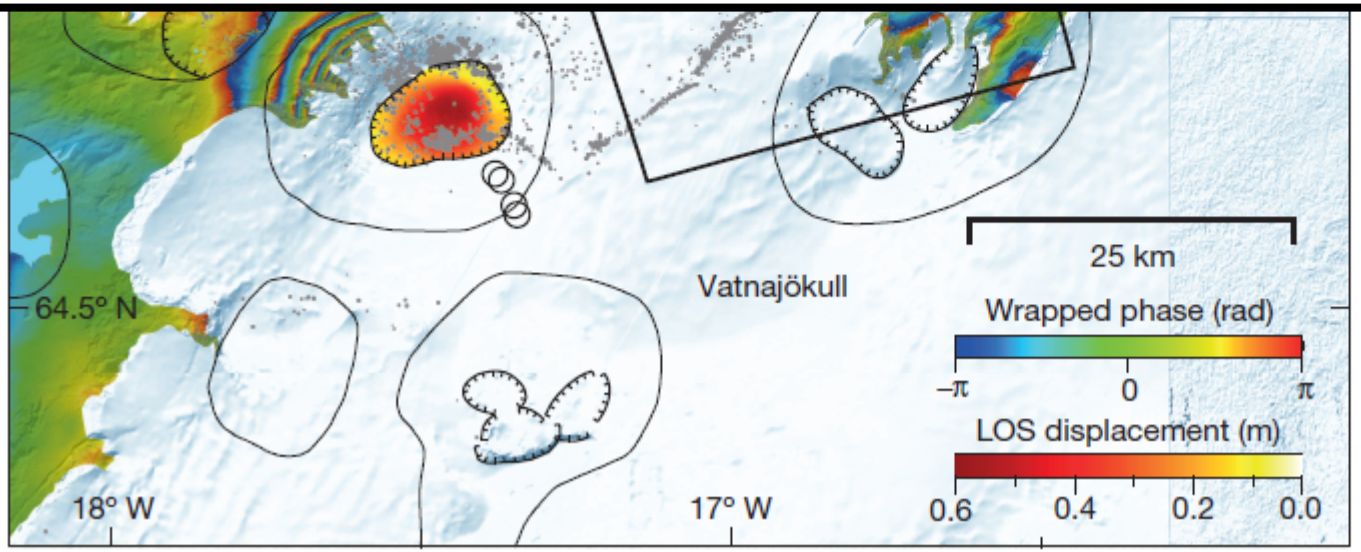
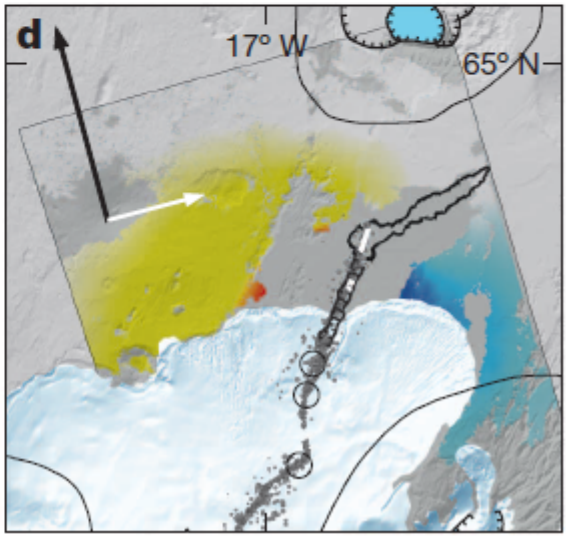



**Differential interferogram unwrapping relies on coherence estimate**

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# Strain mapping

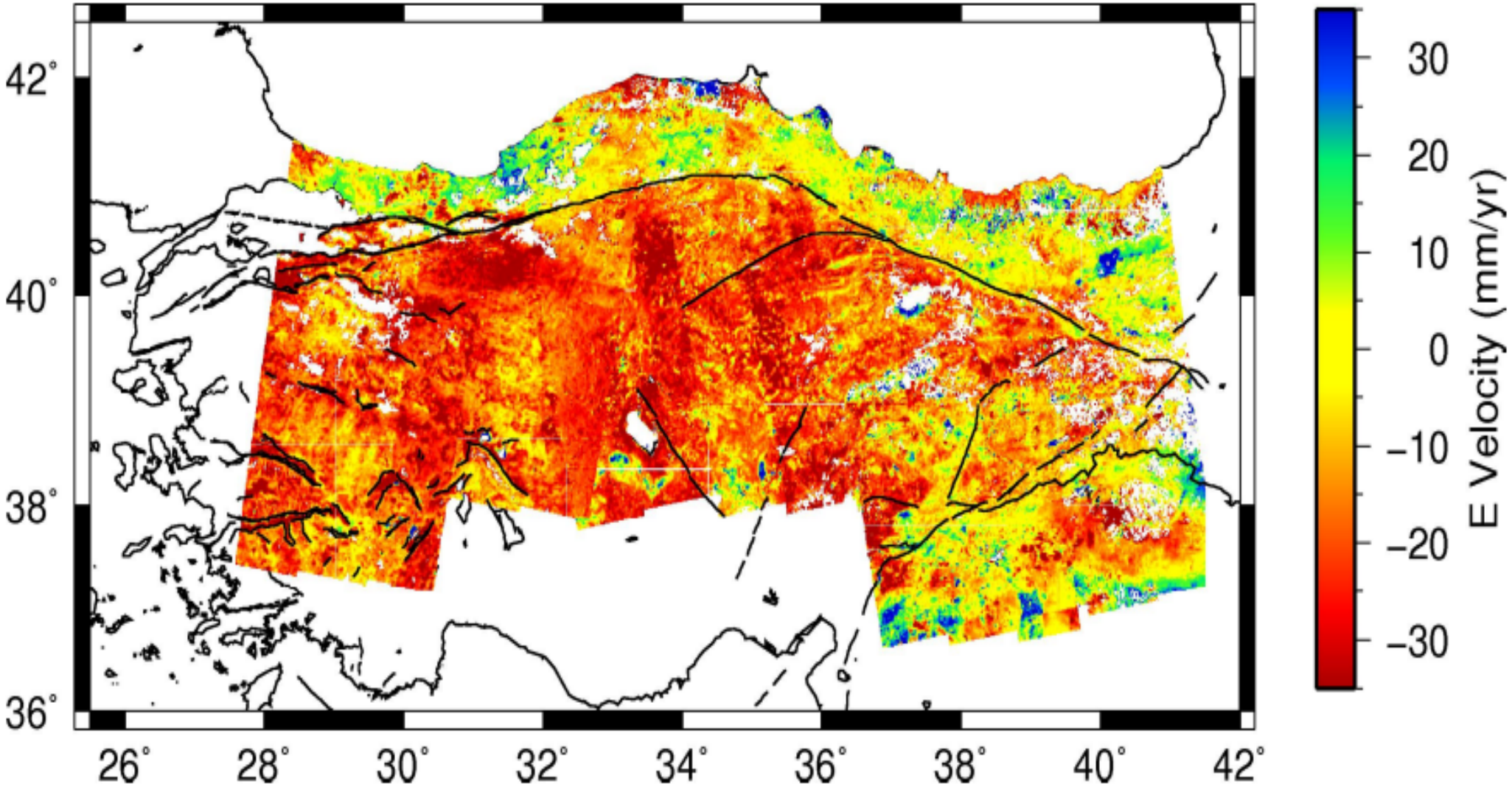
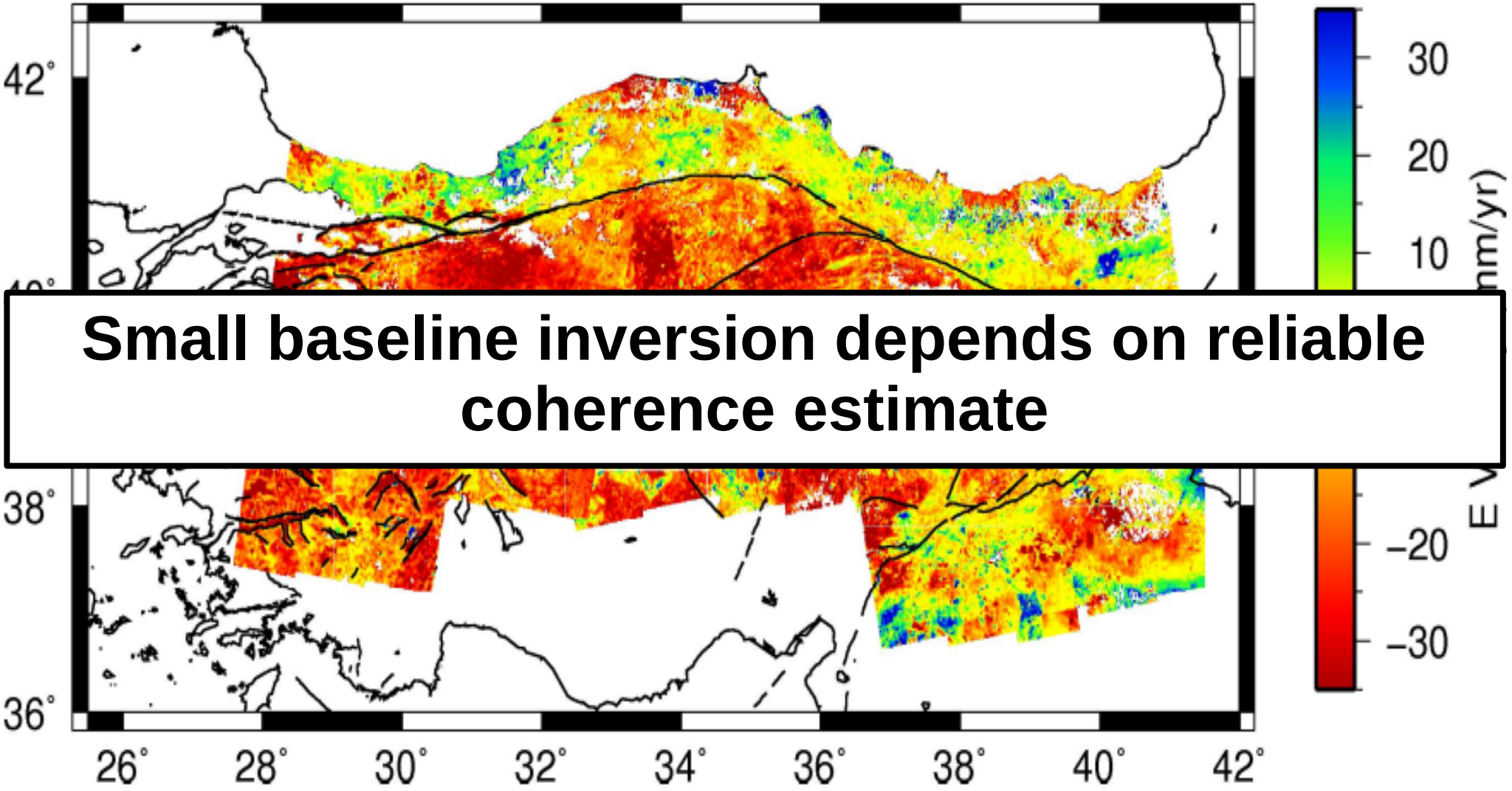



Image from Rich Walters

# Strain mapping

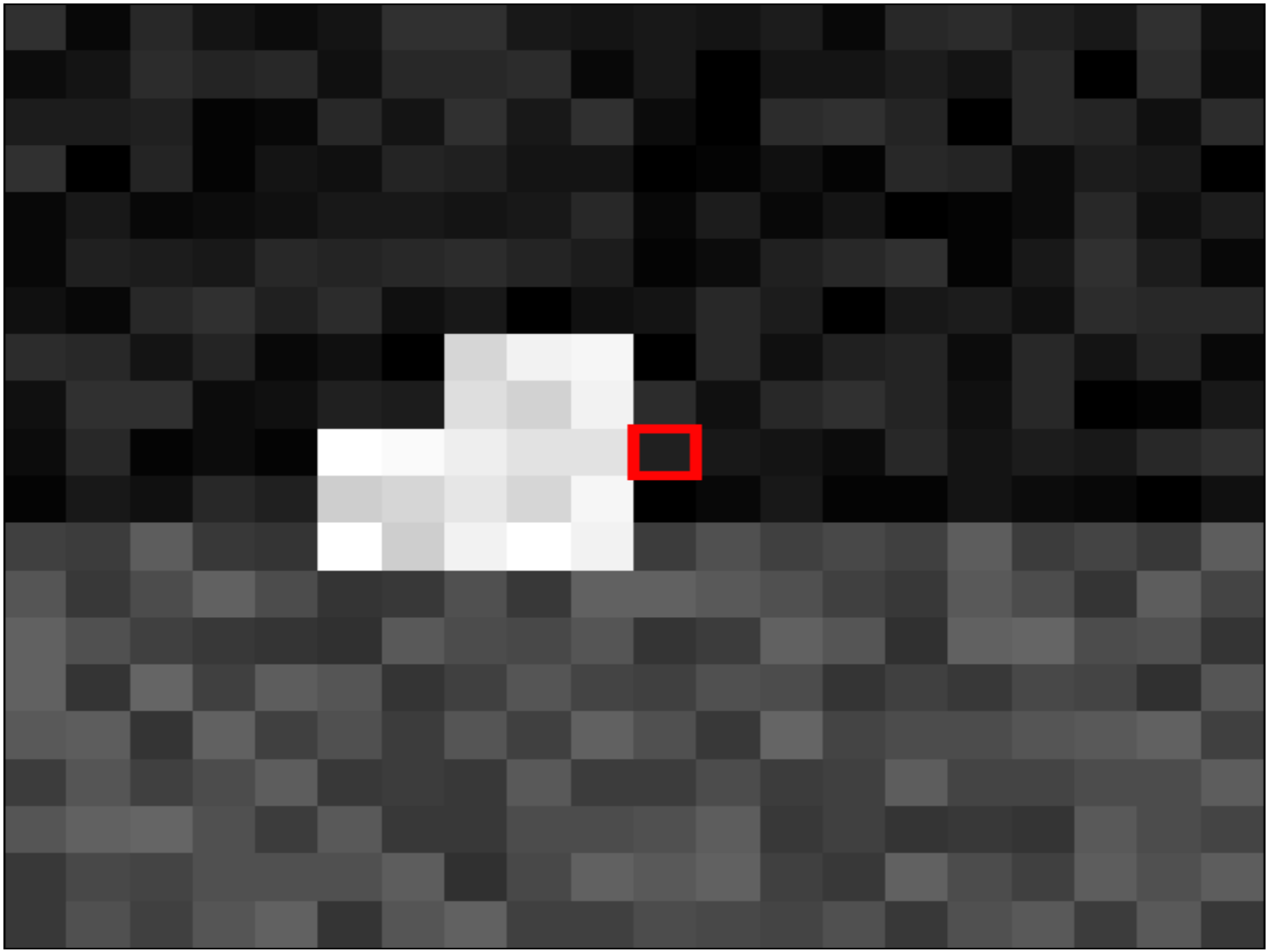



**Small baseline inversion depends on reliable coherence estimate**

Image from Rich Walters

# Boxcar coherence

- Traditional
- Fast
- Flexible



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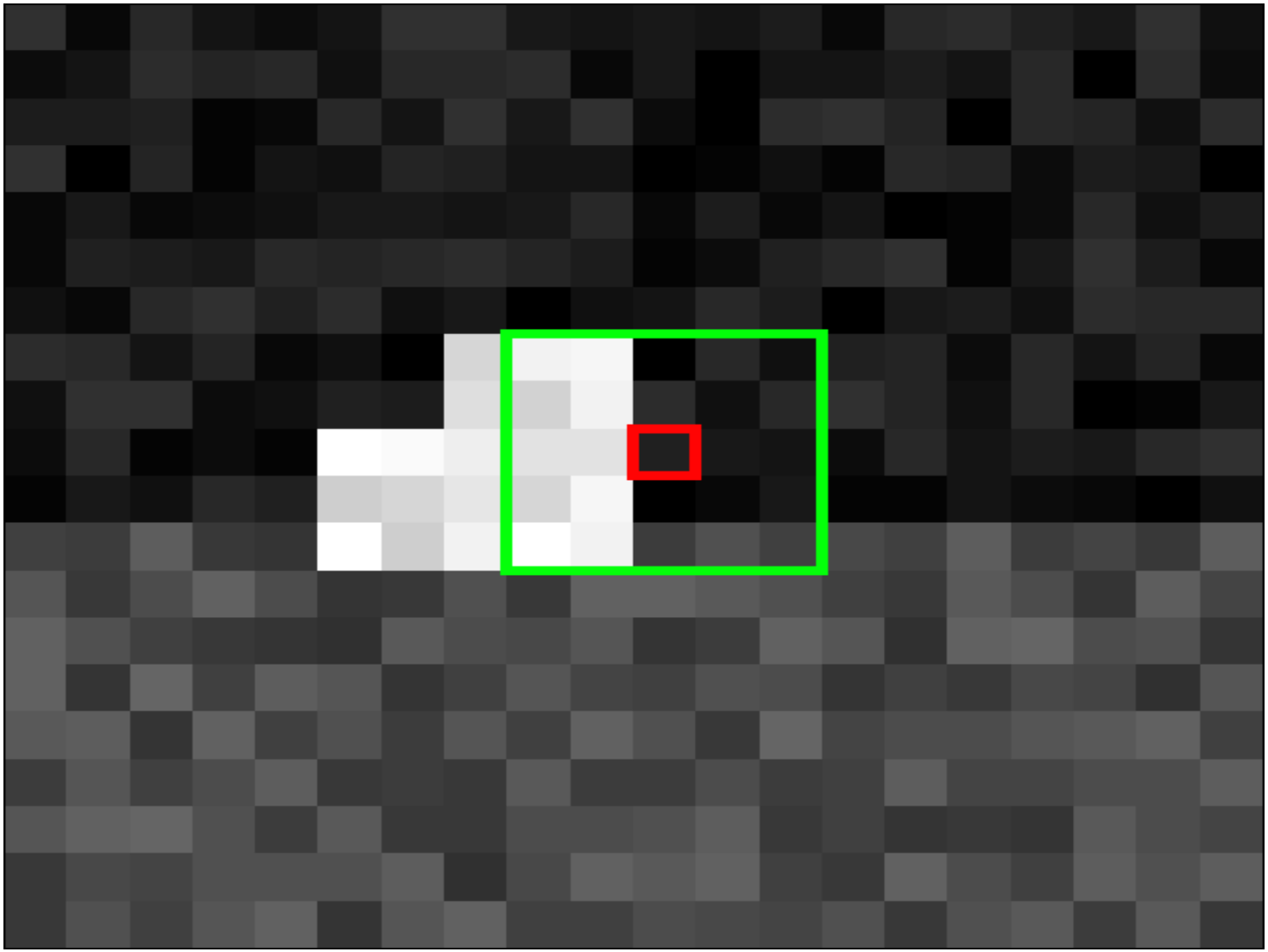
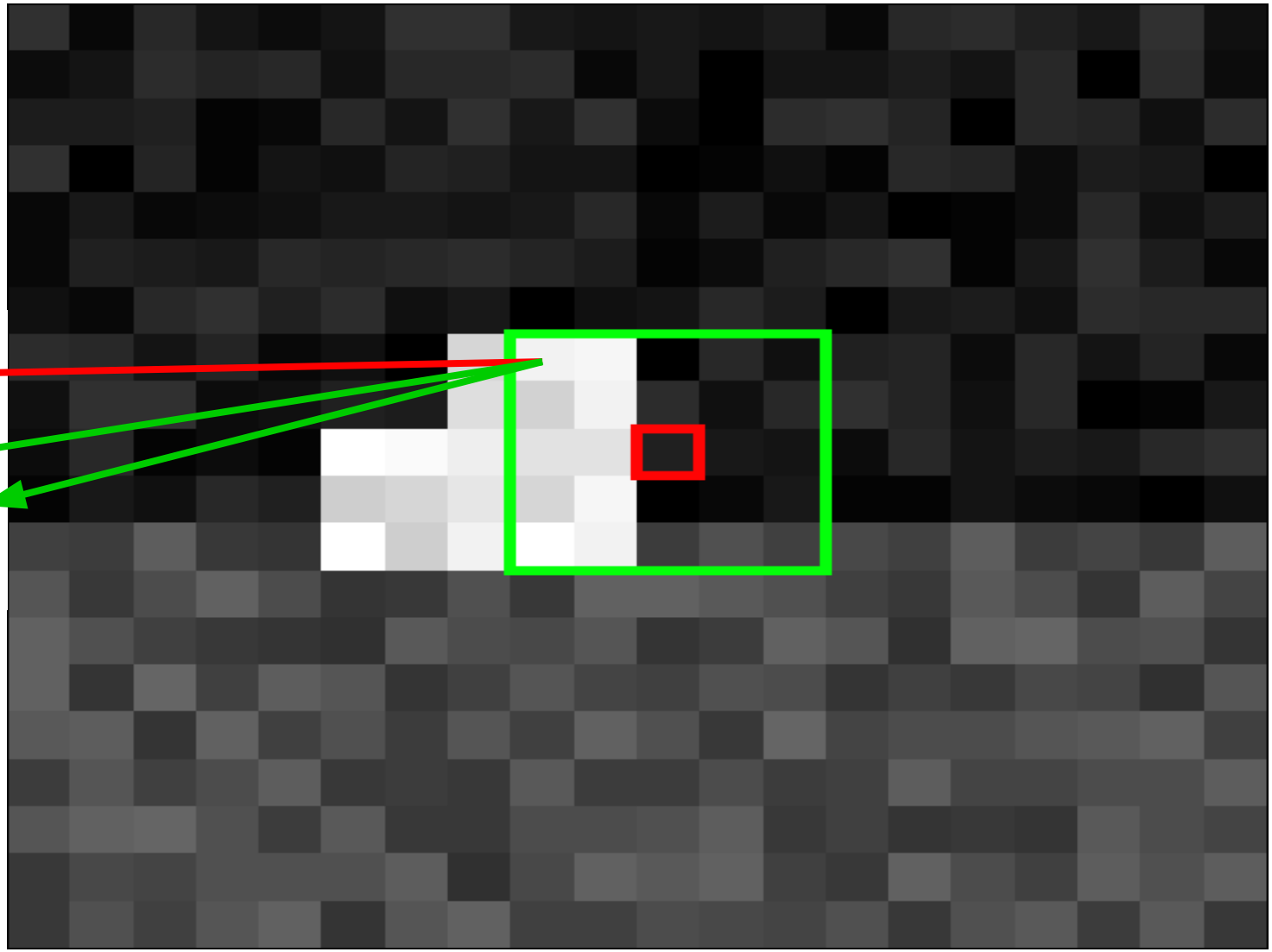


# Boxcar coherence

**Interferometric signal for each pixel (phase + amplitude!)**

$$\delta_L = \frac{\sum_{i=1}^{L} z_1^{(i)} z_2^{*(i)}}{\sqrt{\sum_{i=1}^{L} |z_1^{(i)}|^2 \sum_{i=1}^{L} |z_2^{(i)}|^2}}$$

**Amplitude for each pixel**



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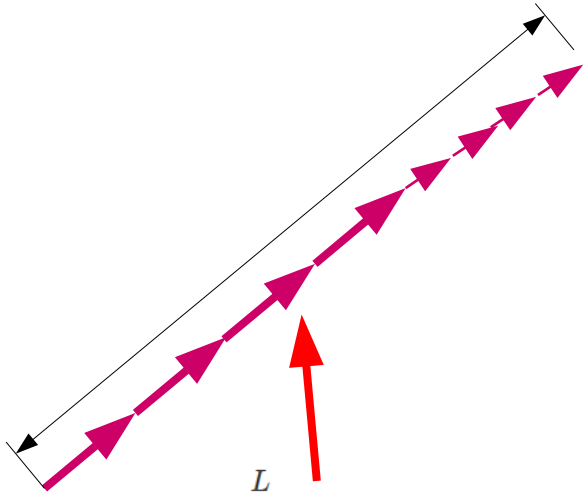

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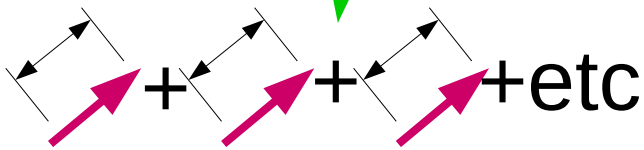


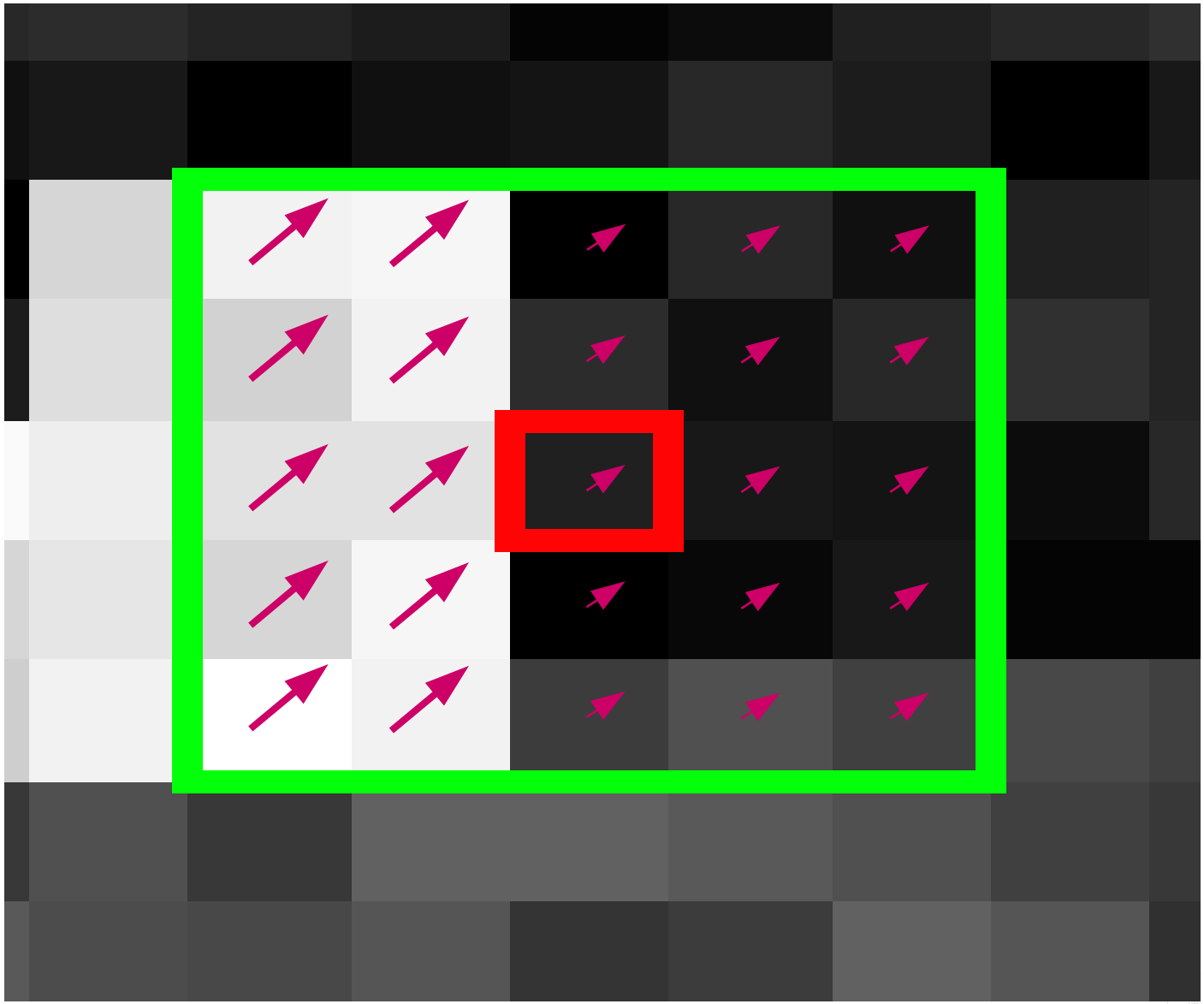

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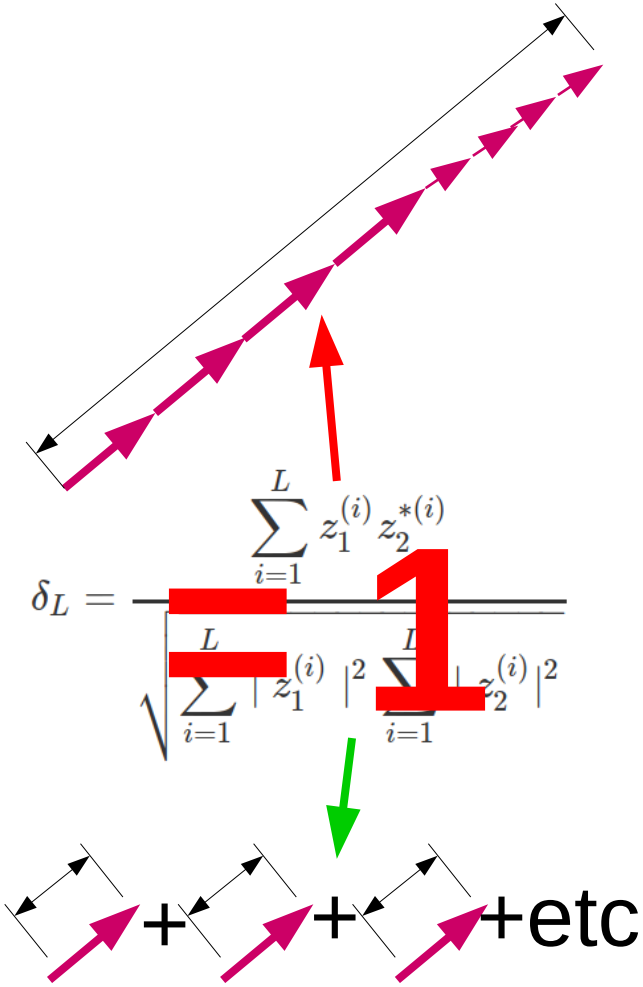


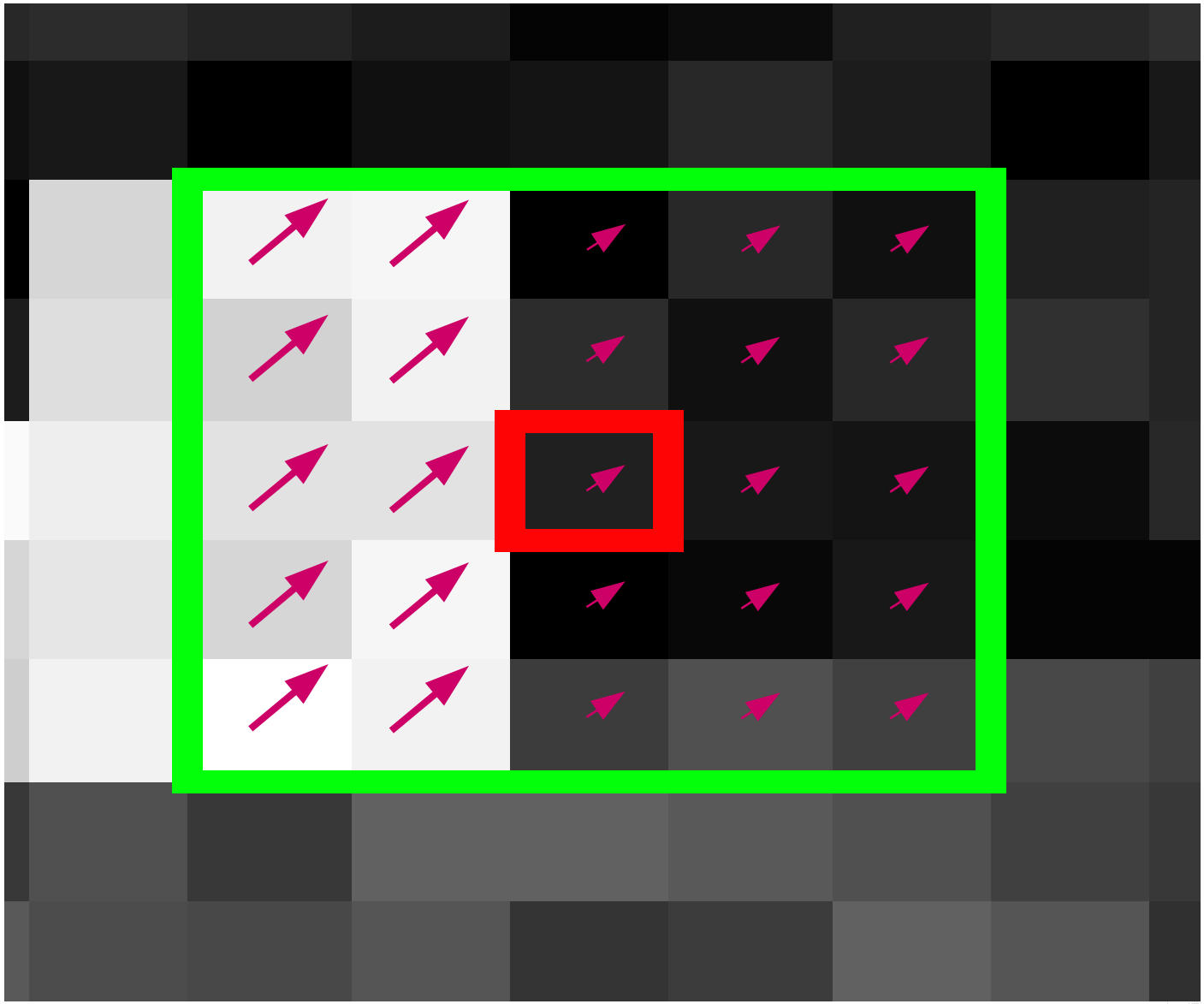

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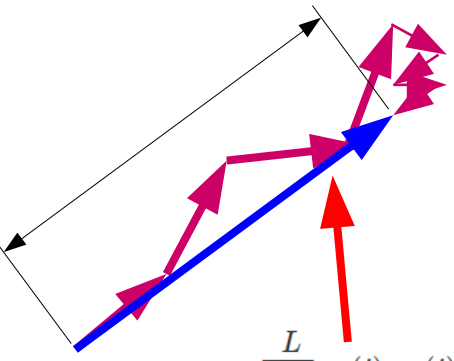

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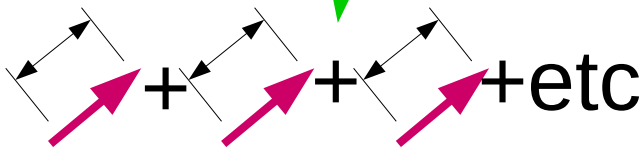


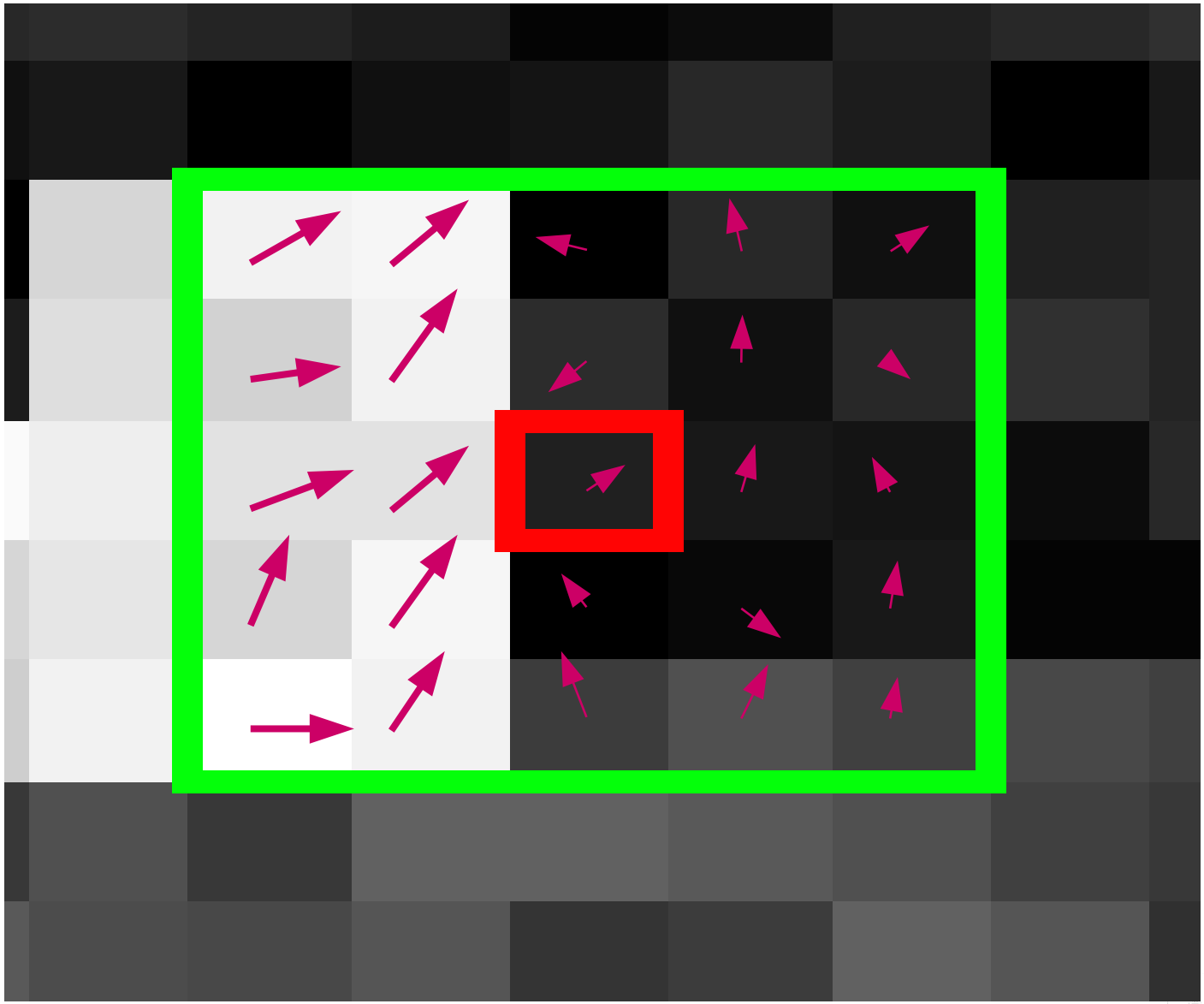

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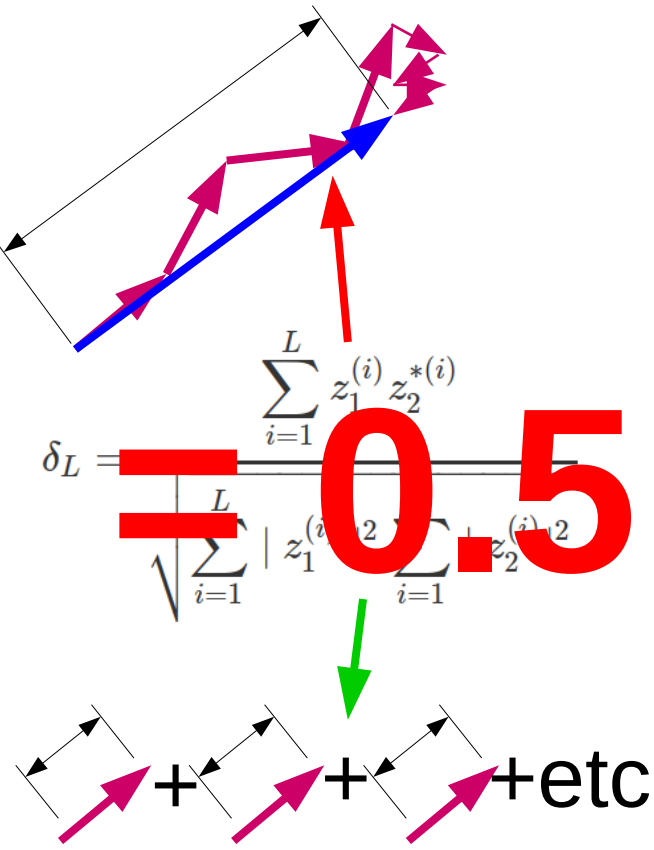


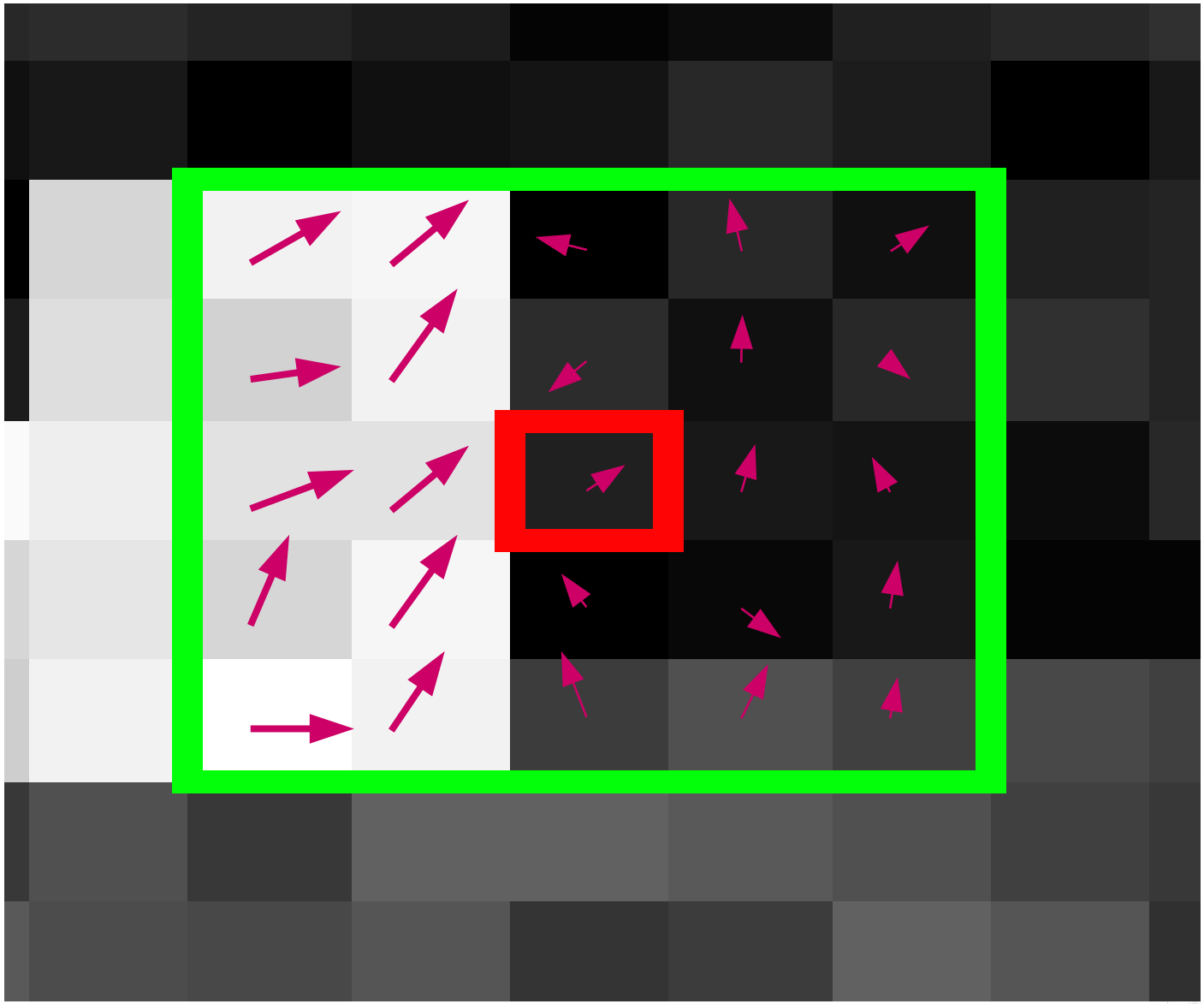

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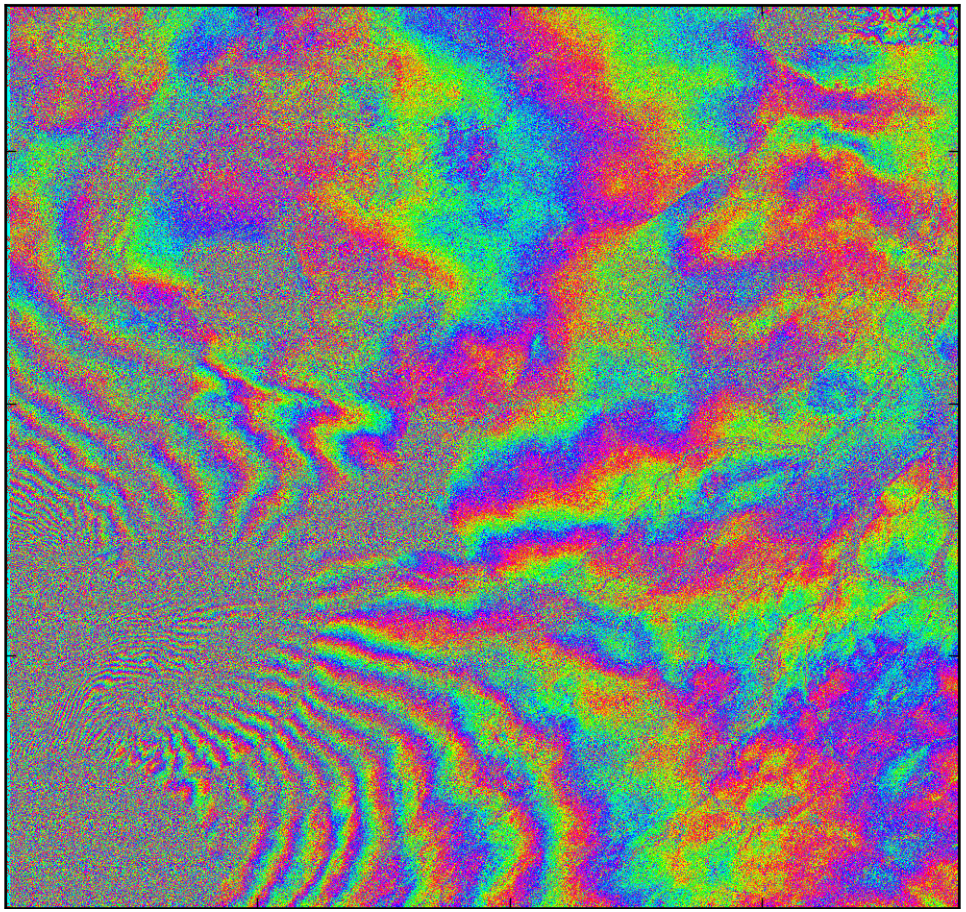
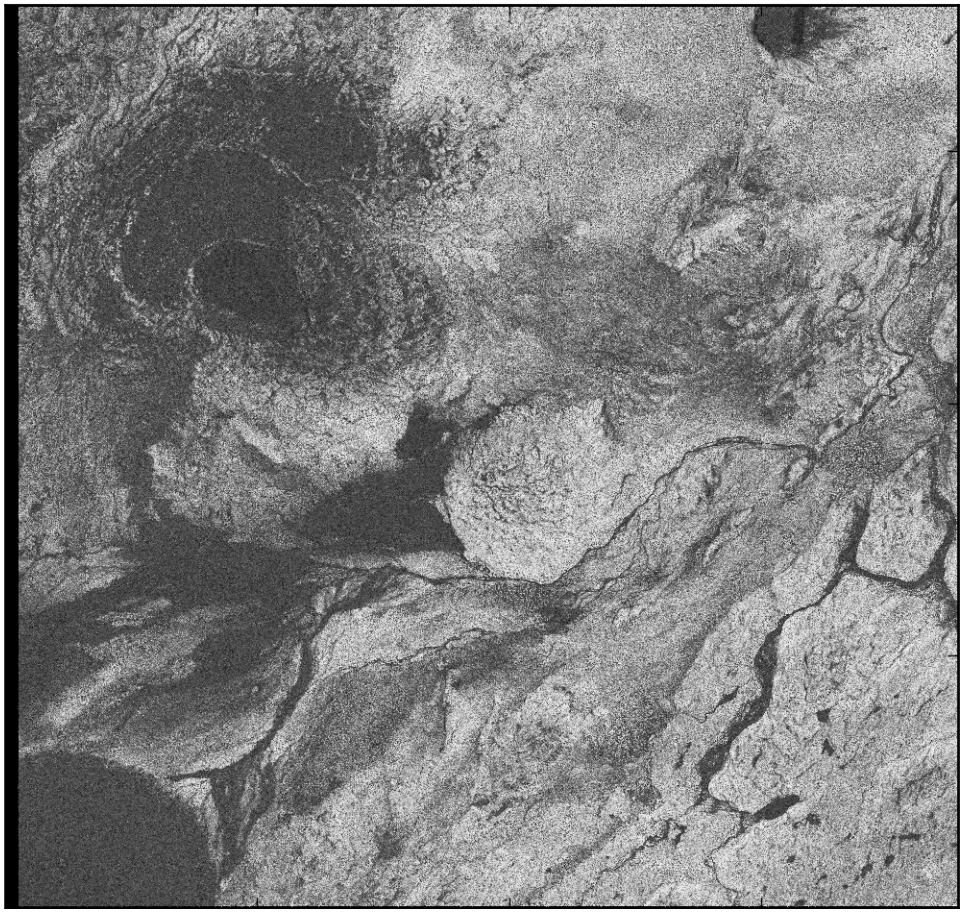
# Boxcar coherence example: Bardarbunga rifting





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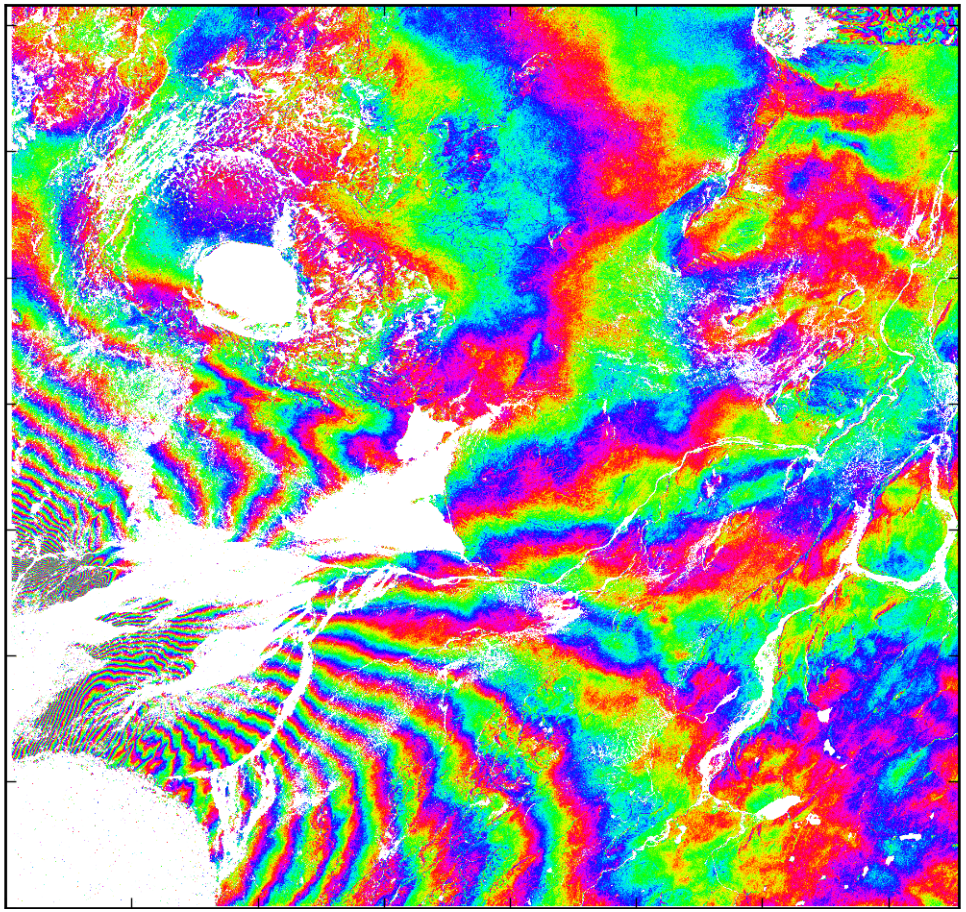

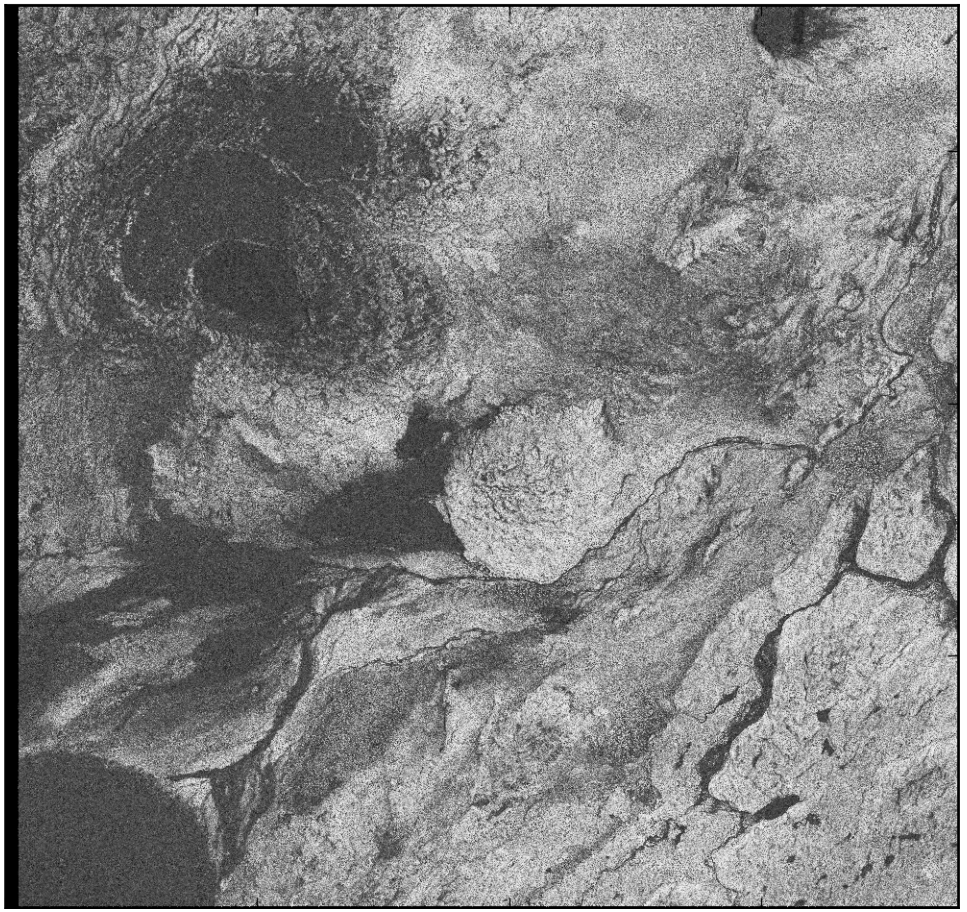

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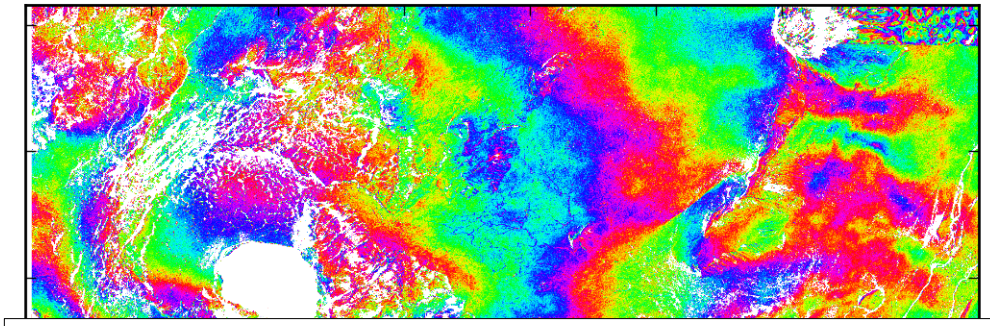
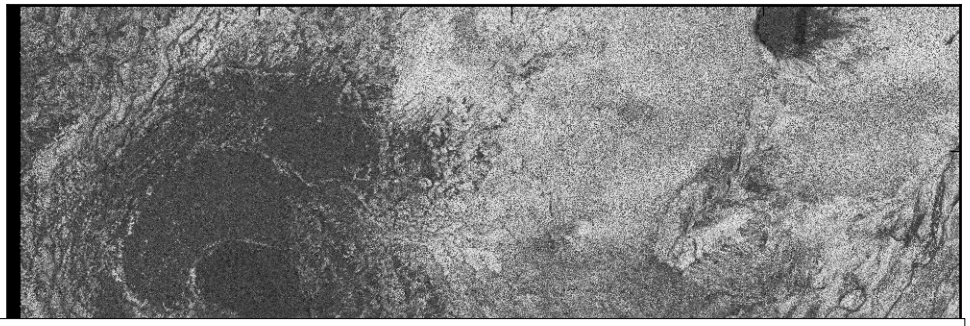
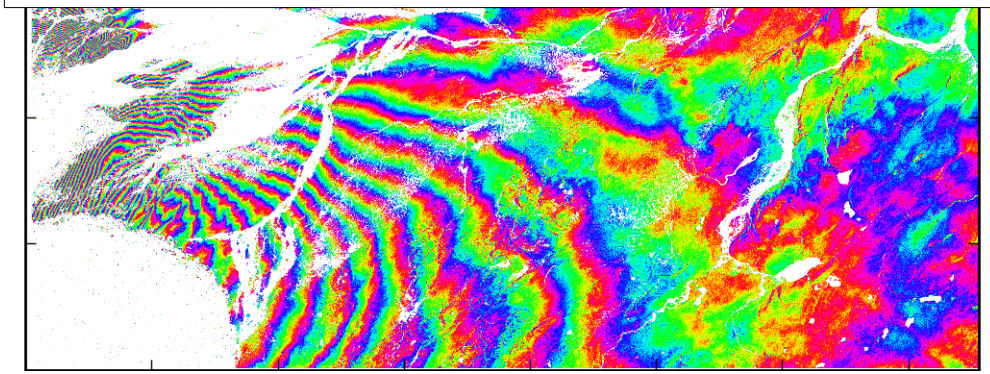
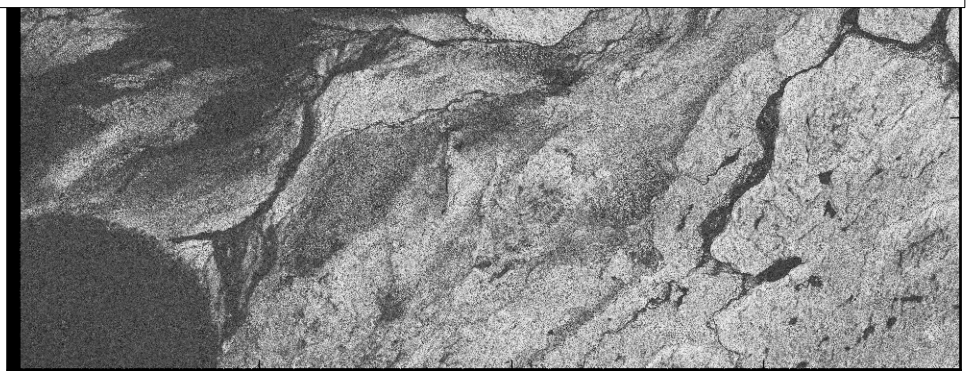


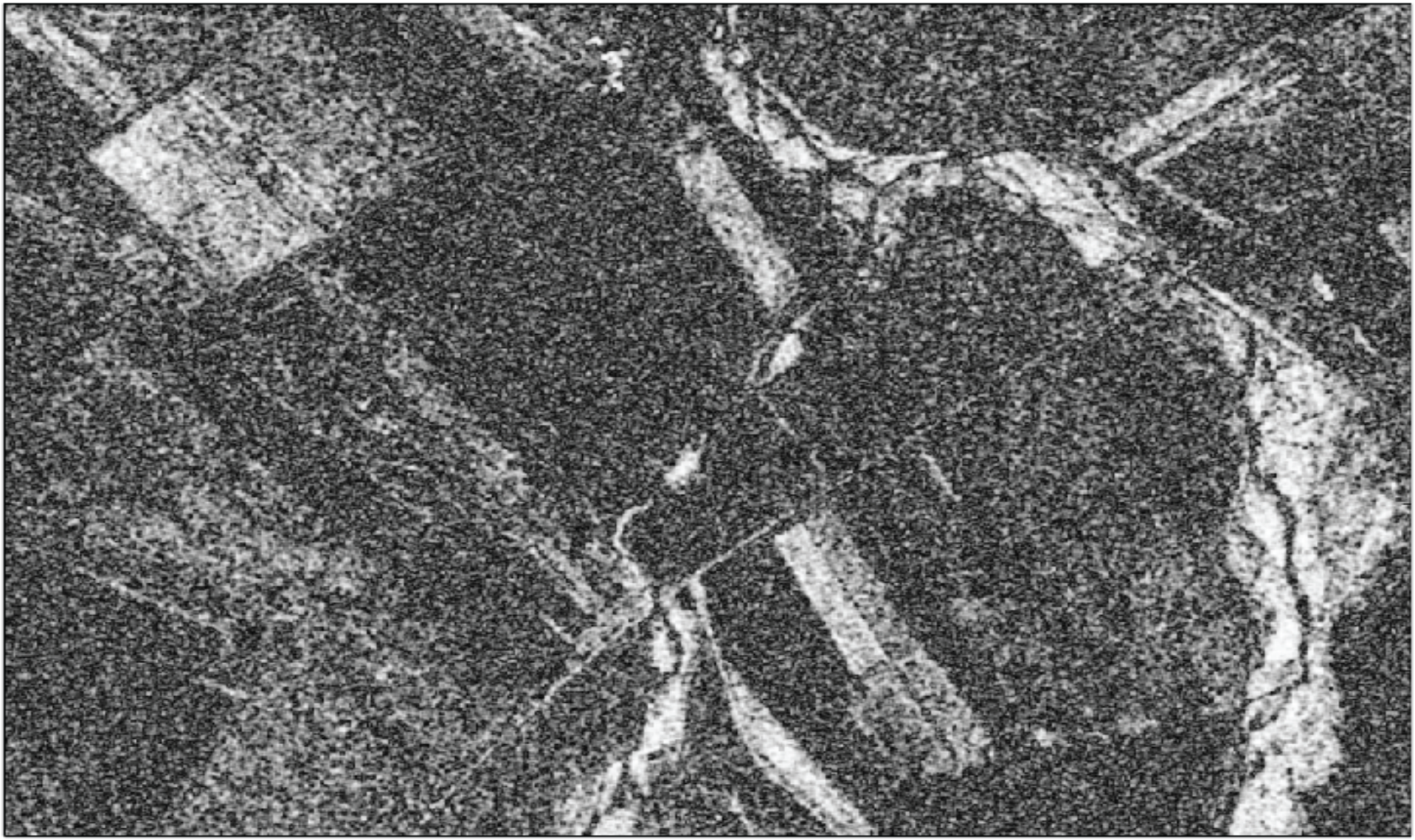


**Boxcar coherence can work well as a quick and flexible selection mechanism, but...**





# Boxcar coherence issues



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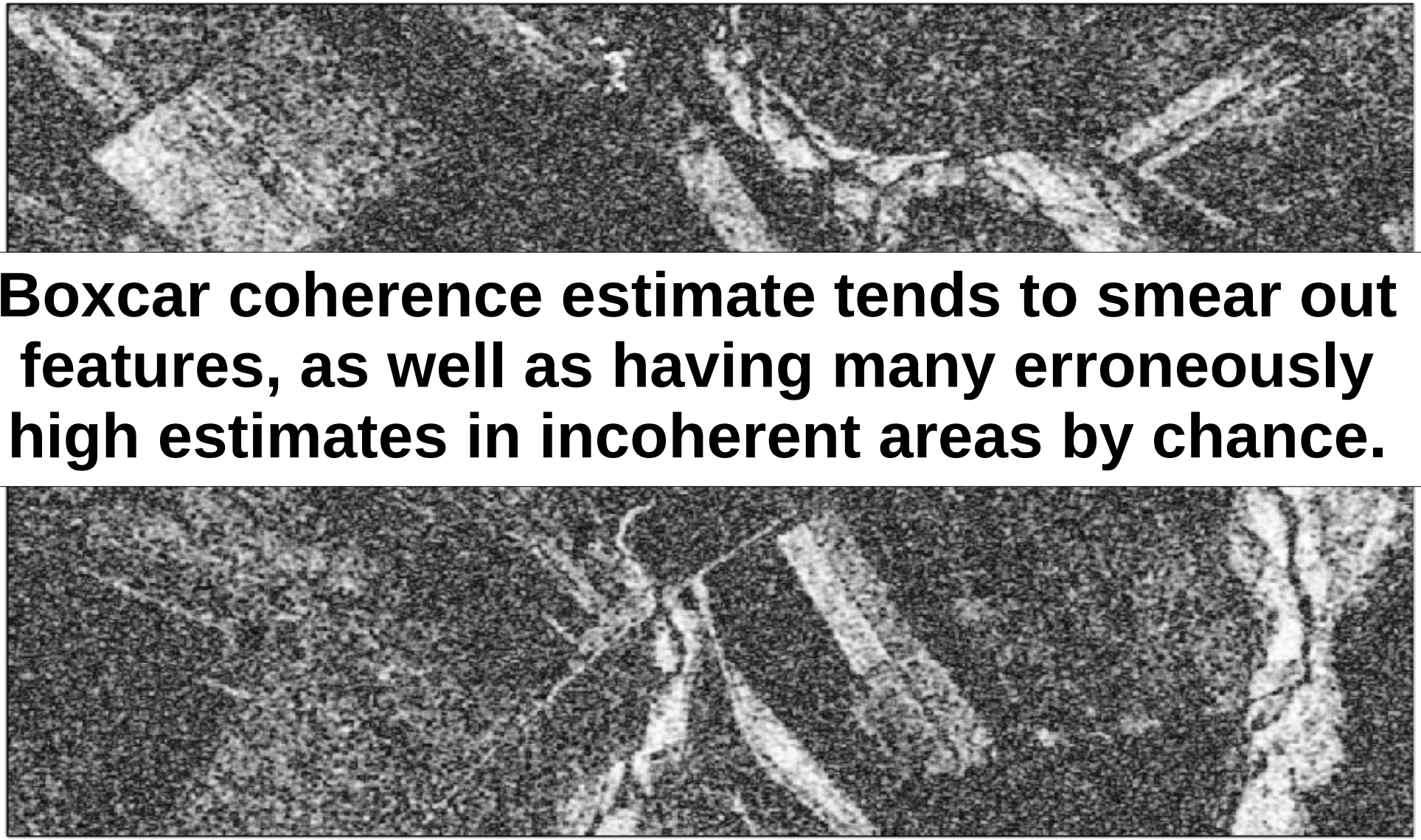

**Boxcar coherence estimate tends to smear out features, as well as having many erroneously high estimates in incoherent areas by chance.**

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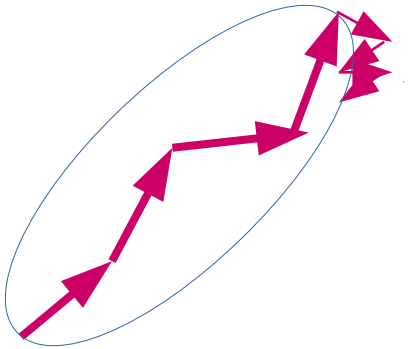
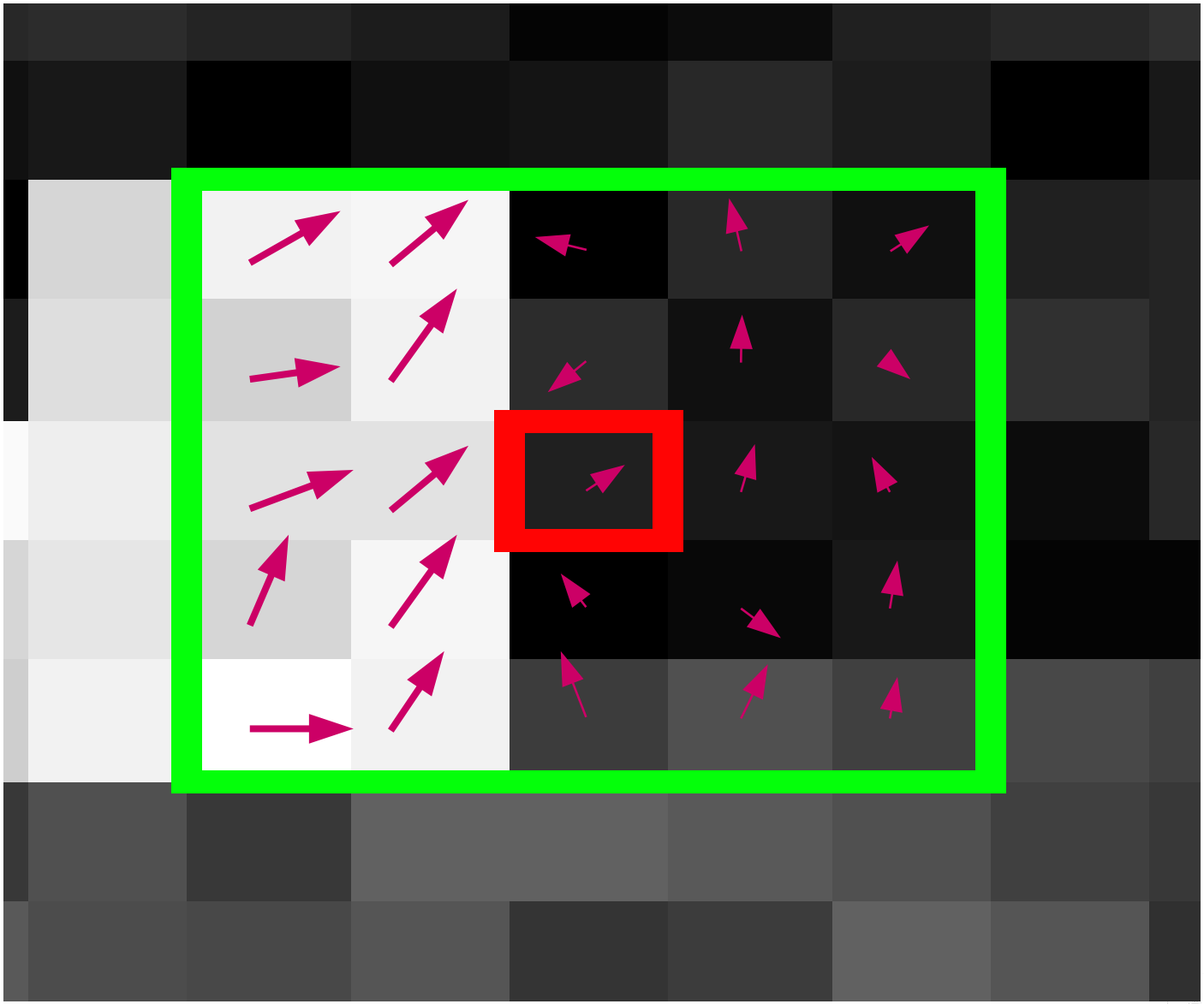
# Boxcar coherence smearing

Bright targets dominate the ensemble!





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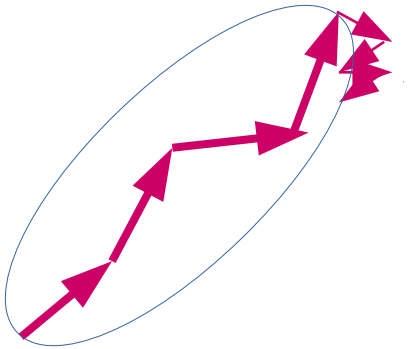
# Boxcar coherence smearing

Bright targets dominate

**Small windows have less smearing, but more sensitive to false positives. Large windows result in more smearing.**



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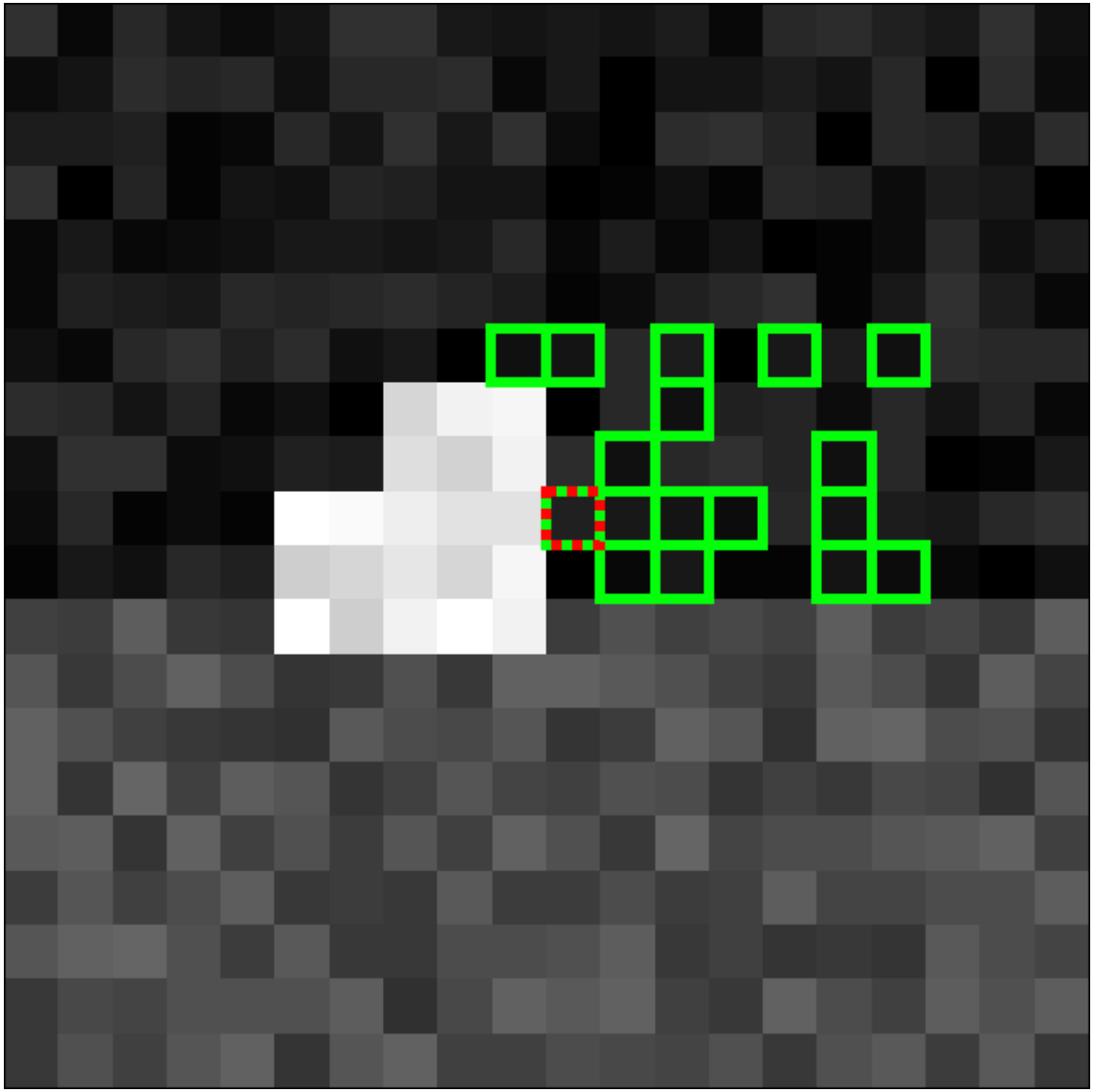
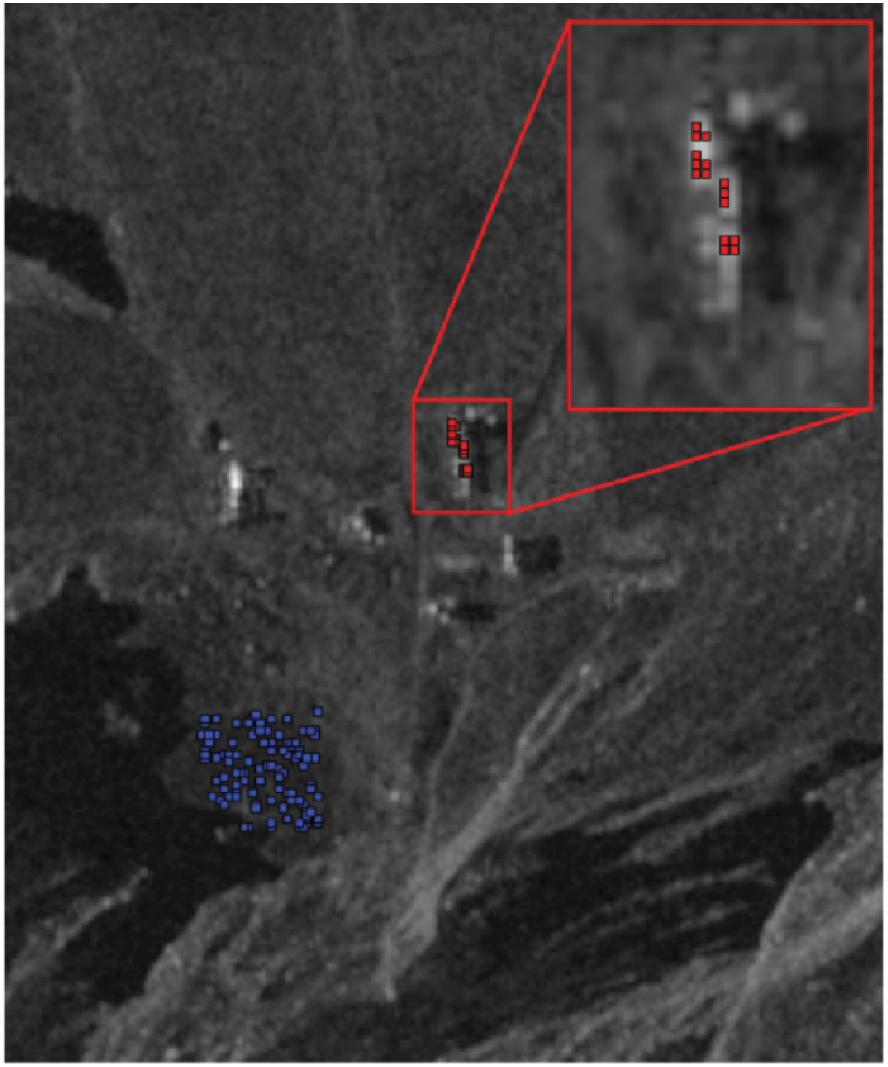
# Sibling based coherence

- Use only nearby pixels with similar behaviour through time (“siblings”)
- We use amplitude statistics through time as an indicator



# Sibling identification

- Tendency to select fewer, closely grouped siblings for strong scatterers, many spread out siblings for poorer scatterers



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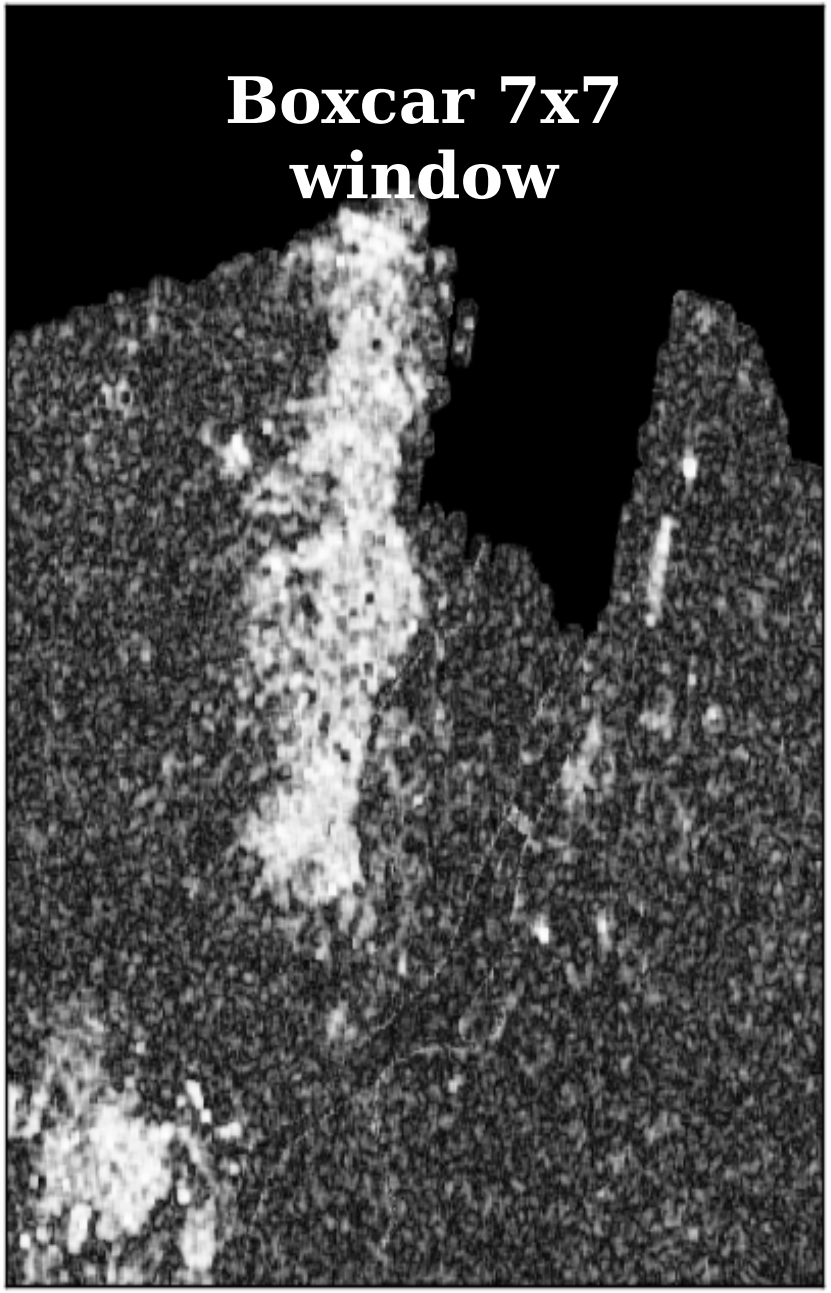
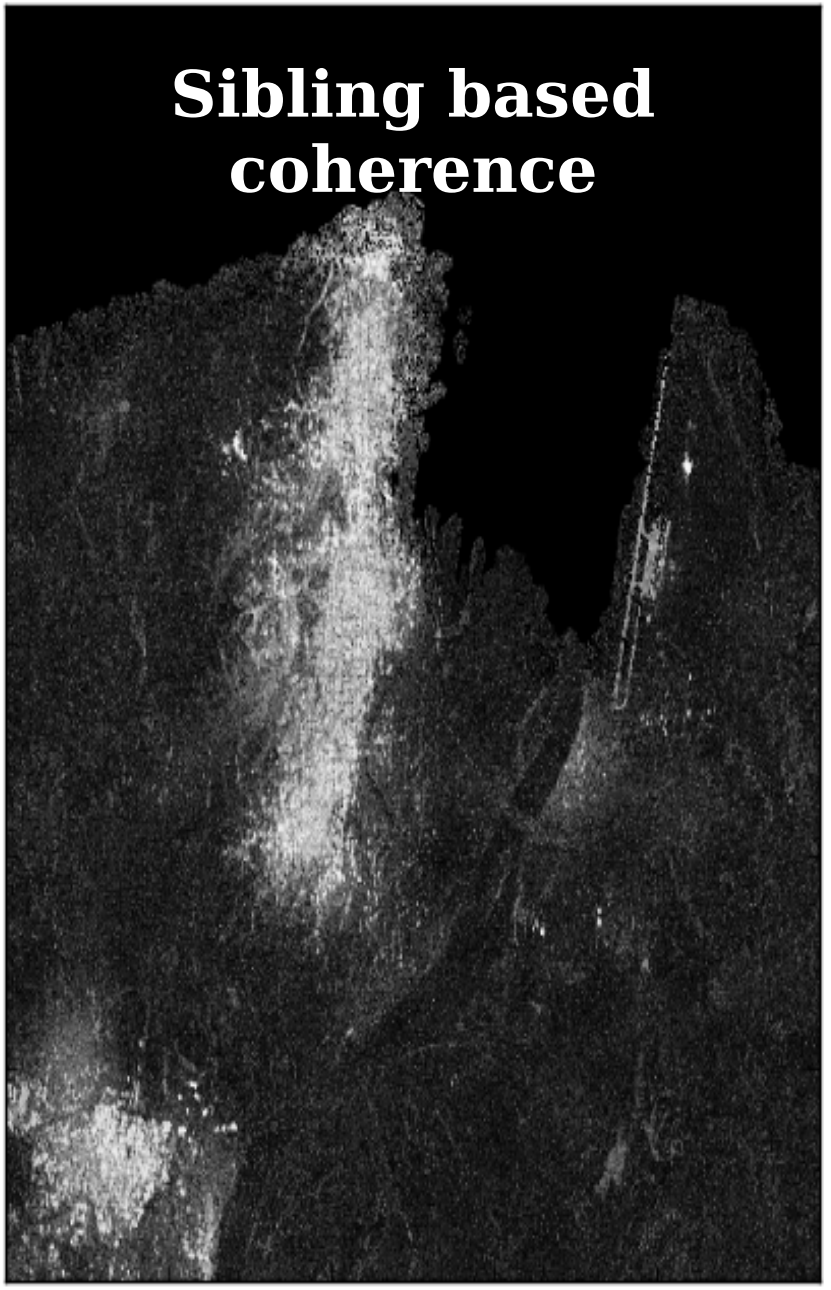
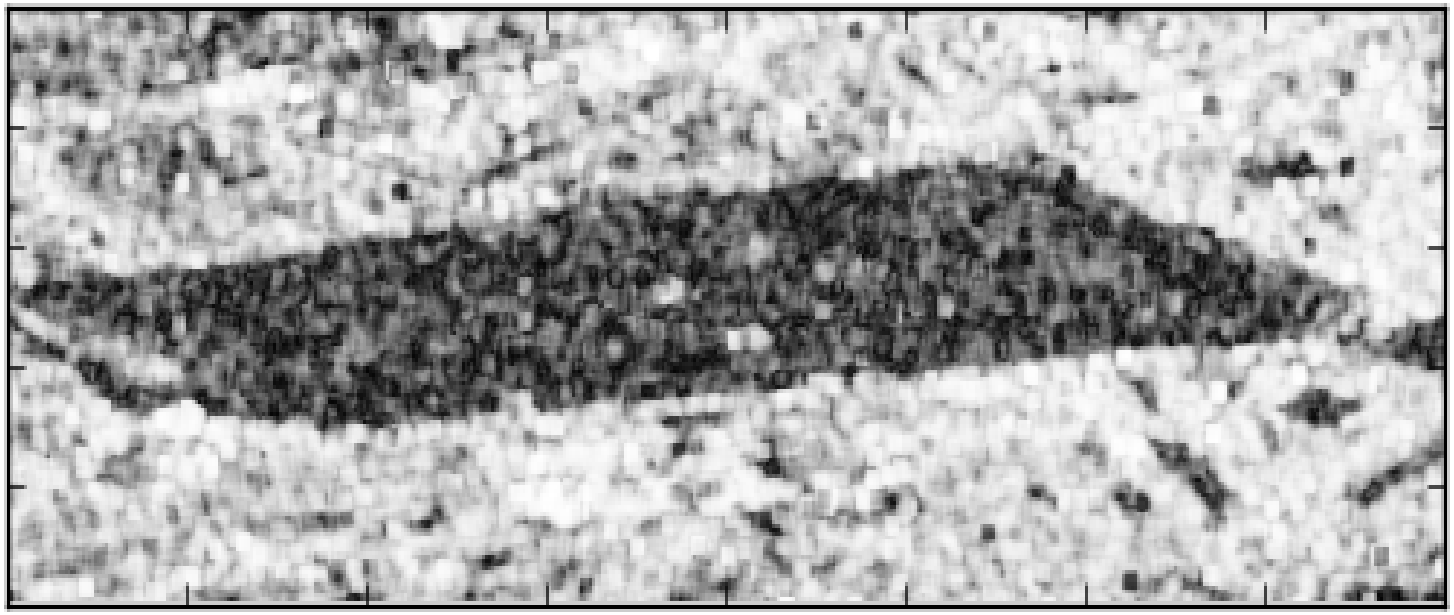
# Coherence comparison



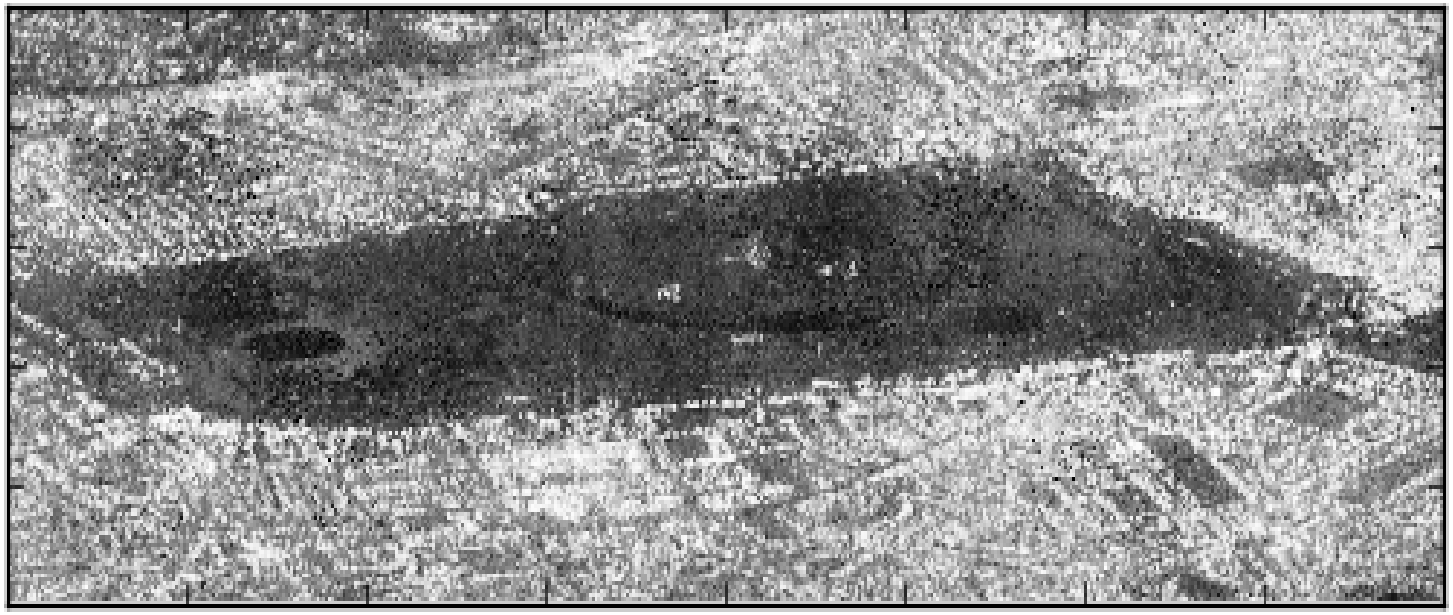



# Coherence comparison

**Boxcar 7x7 window**



**Sibling based coherence**



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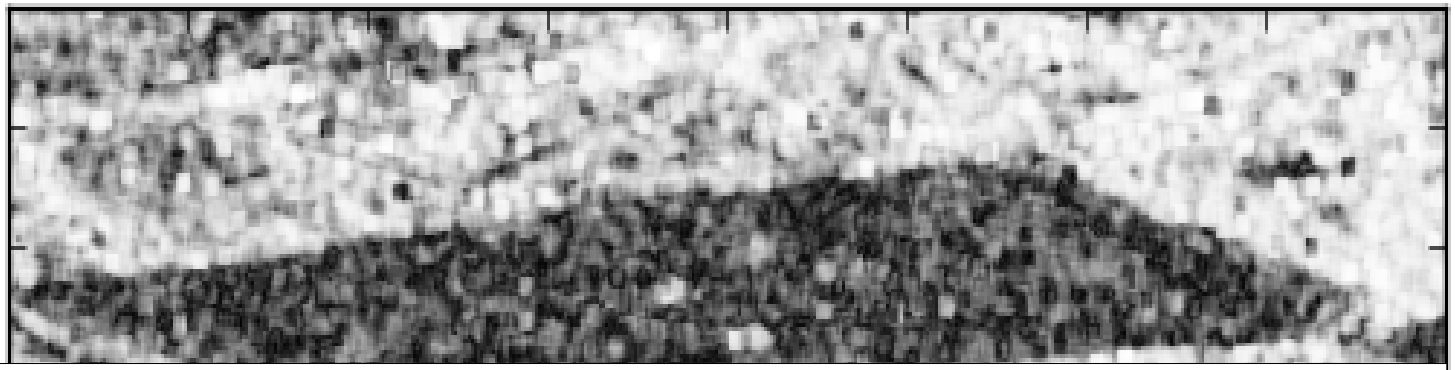
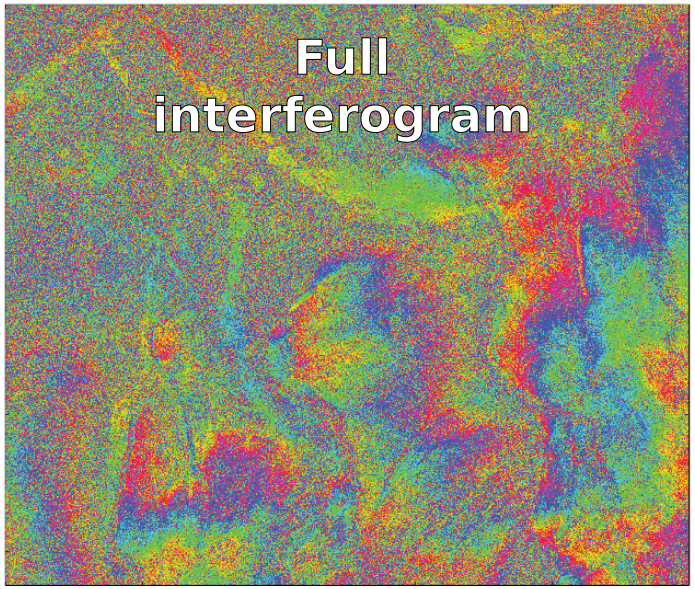
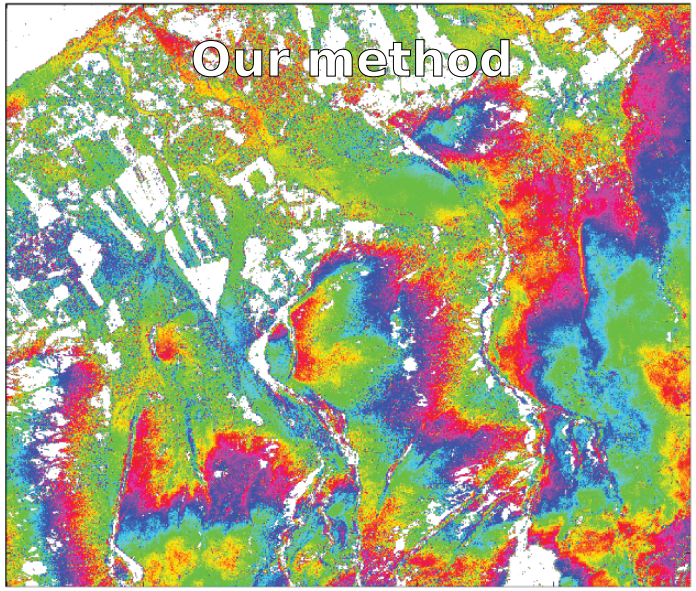


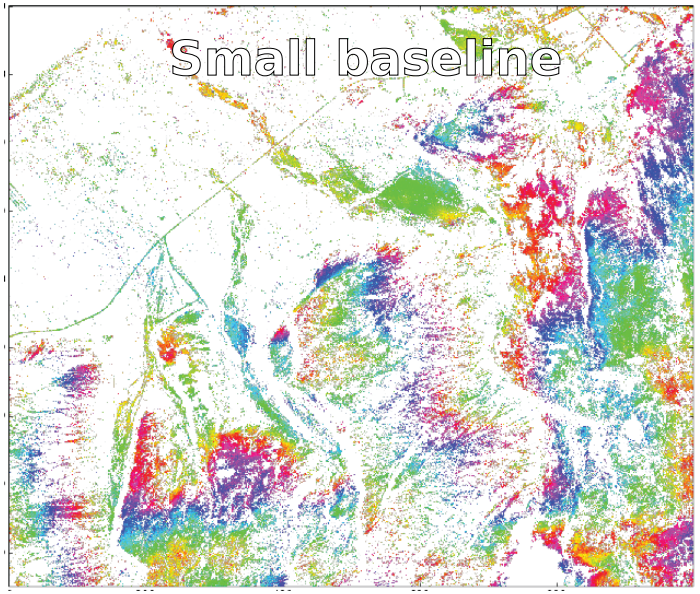
**Using sibling based ensembles in coherence estimates result in high resolution, sharp coherence images.**

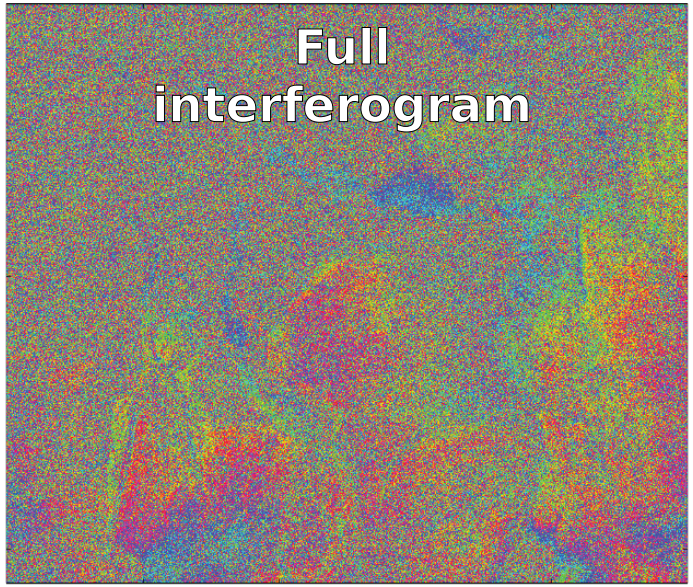
**Sibling based coherence**

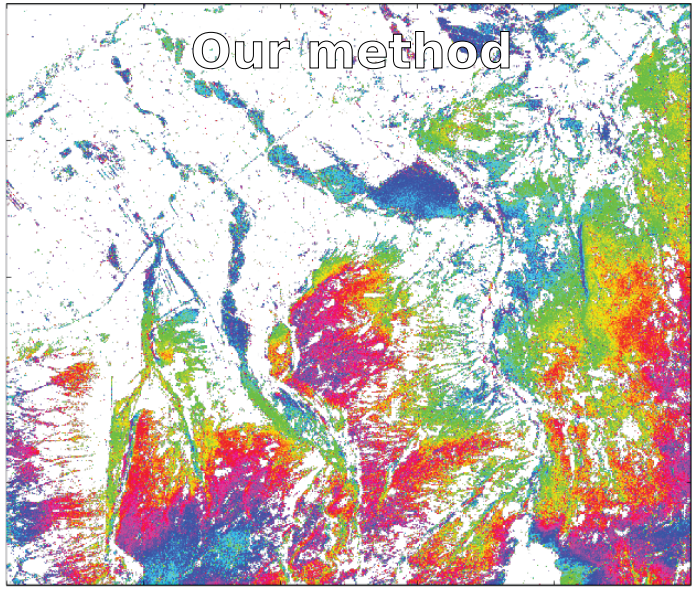
# Point selection comparison

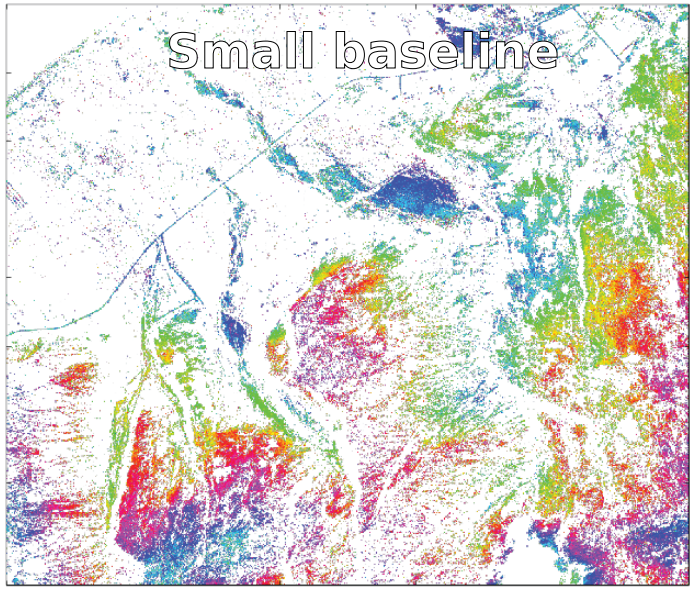
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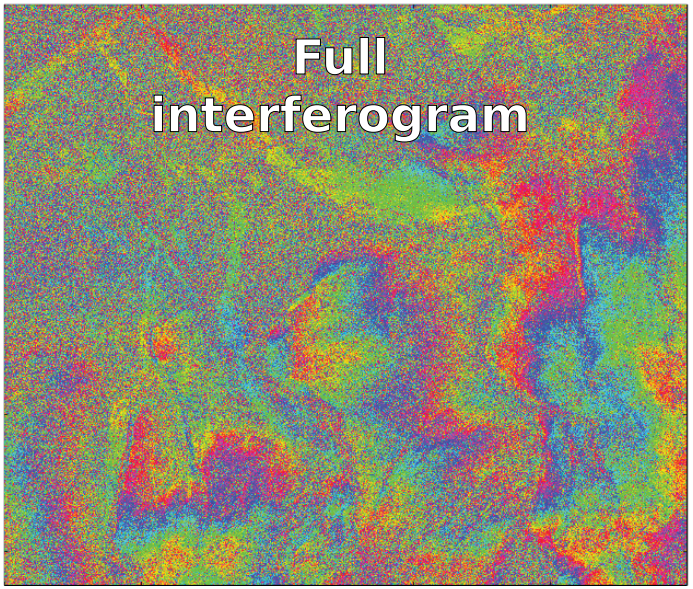


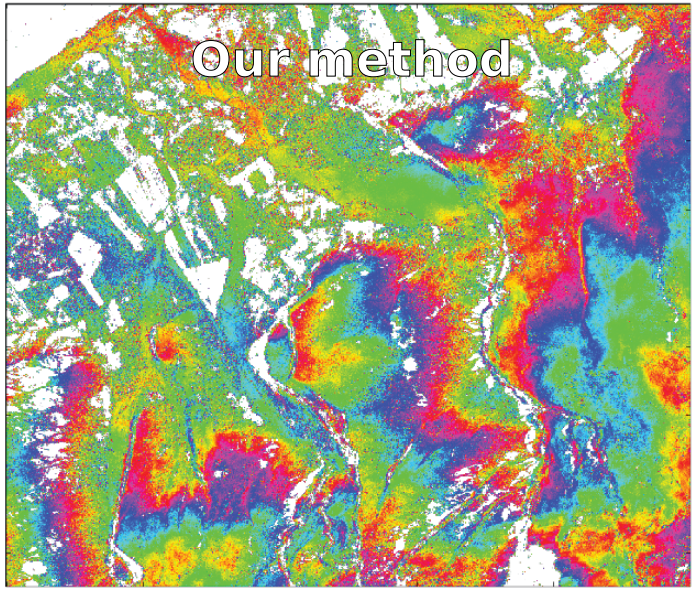


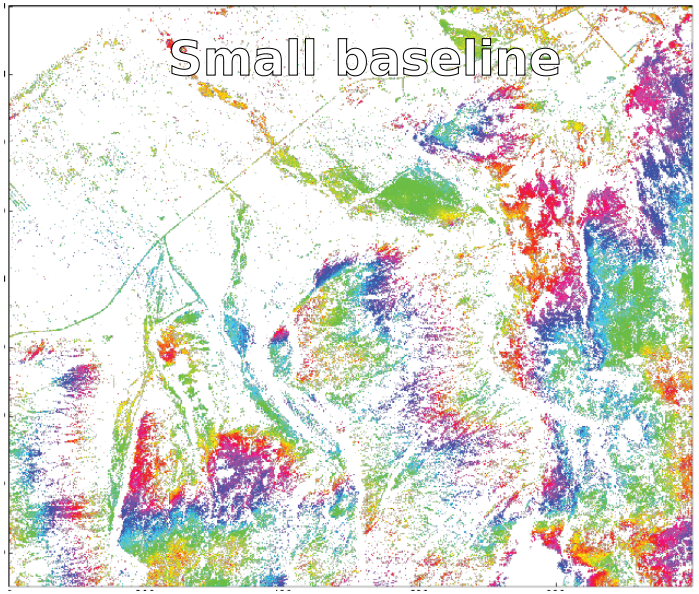


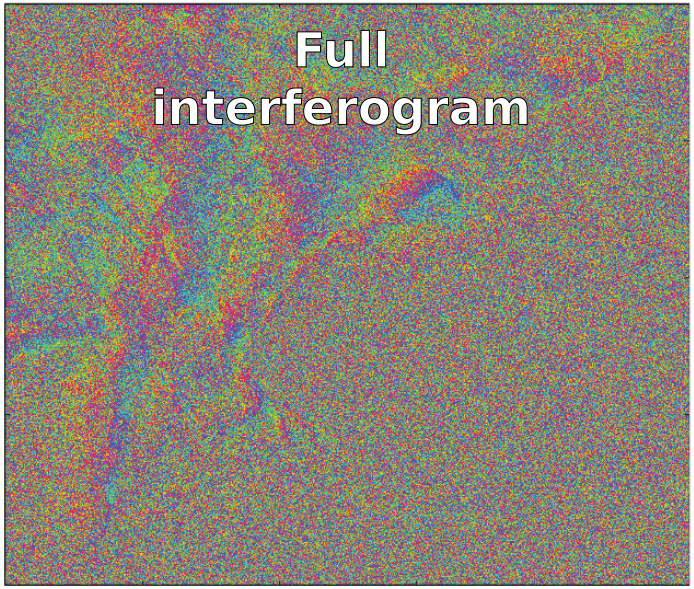


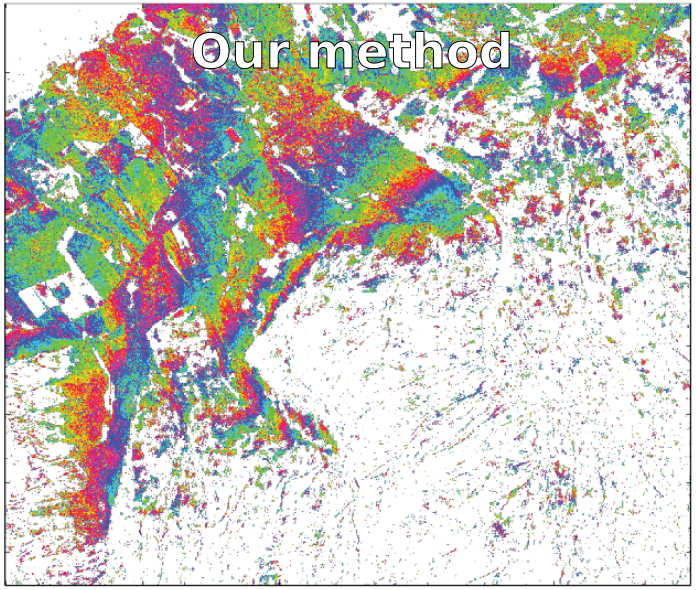


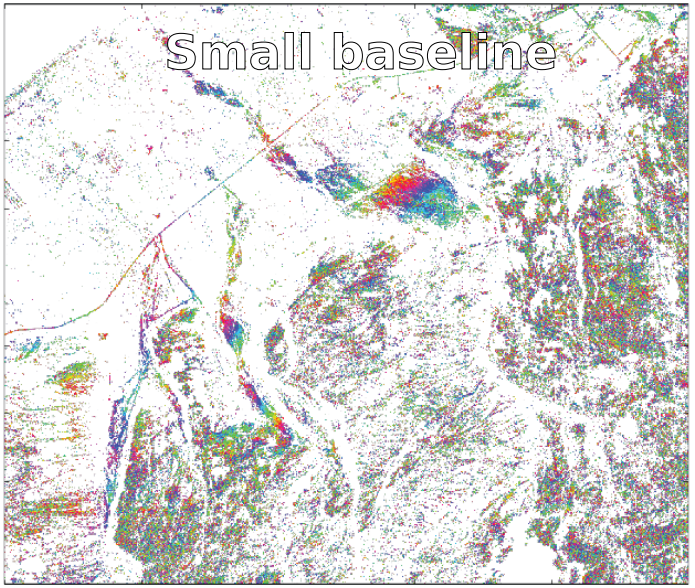


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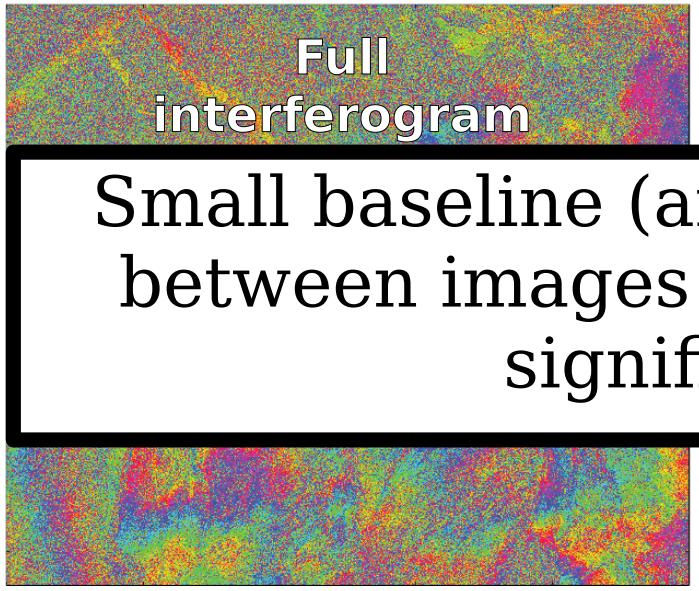
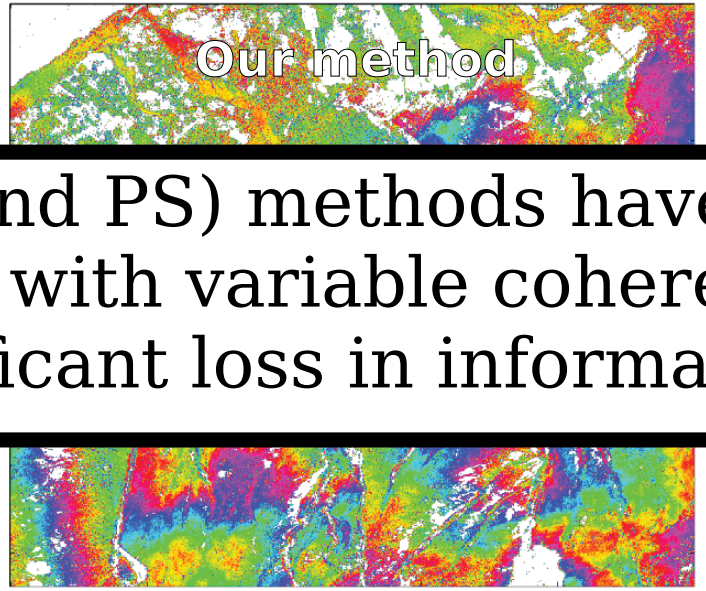
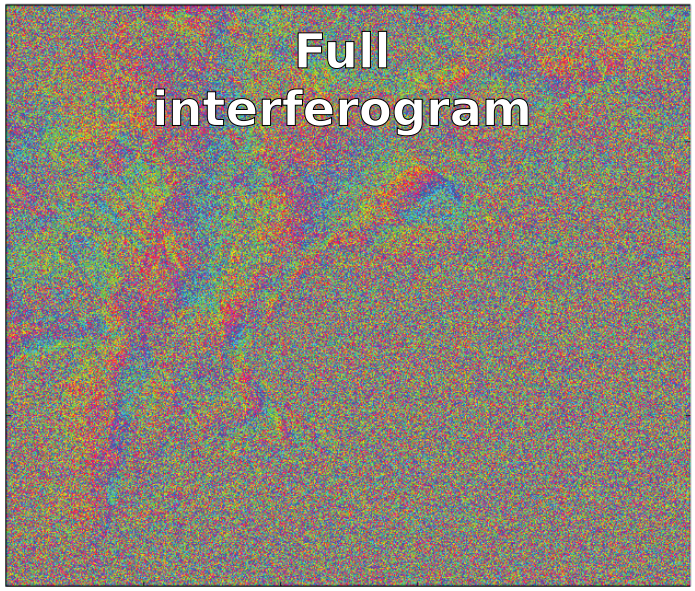
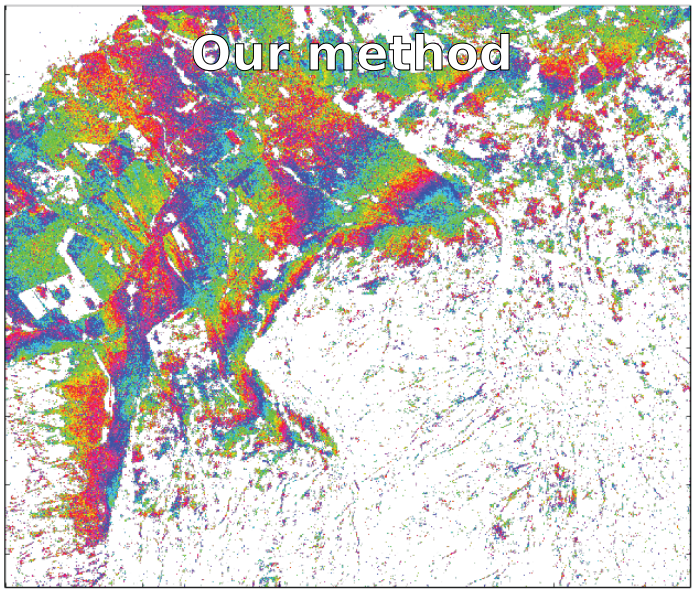
# Point selection comparison

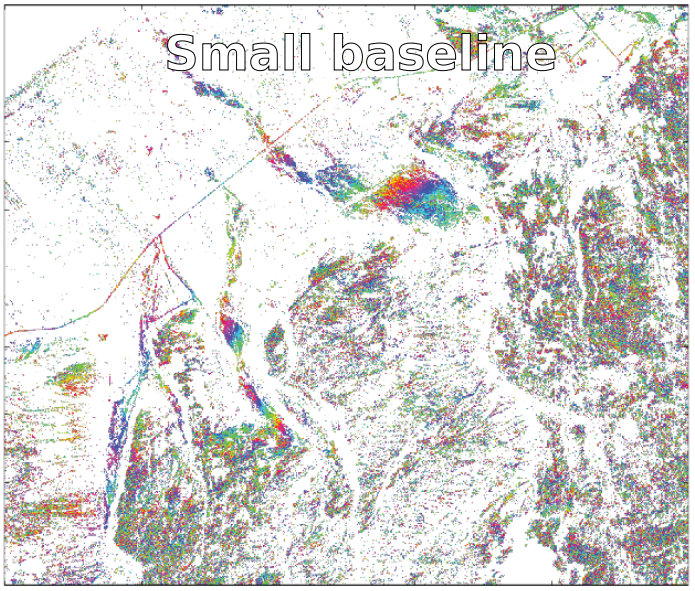


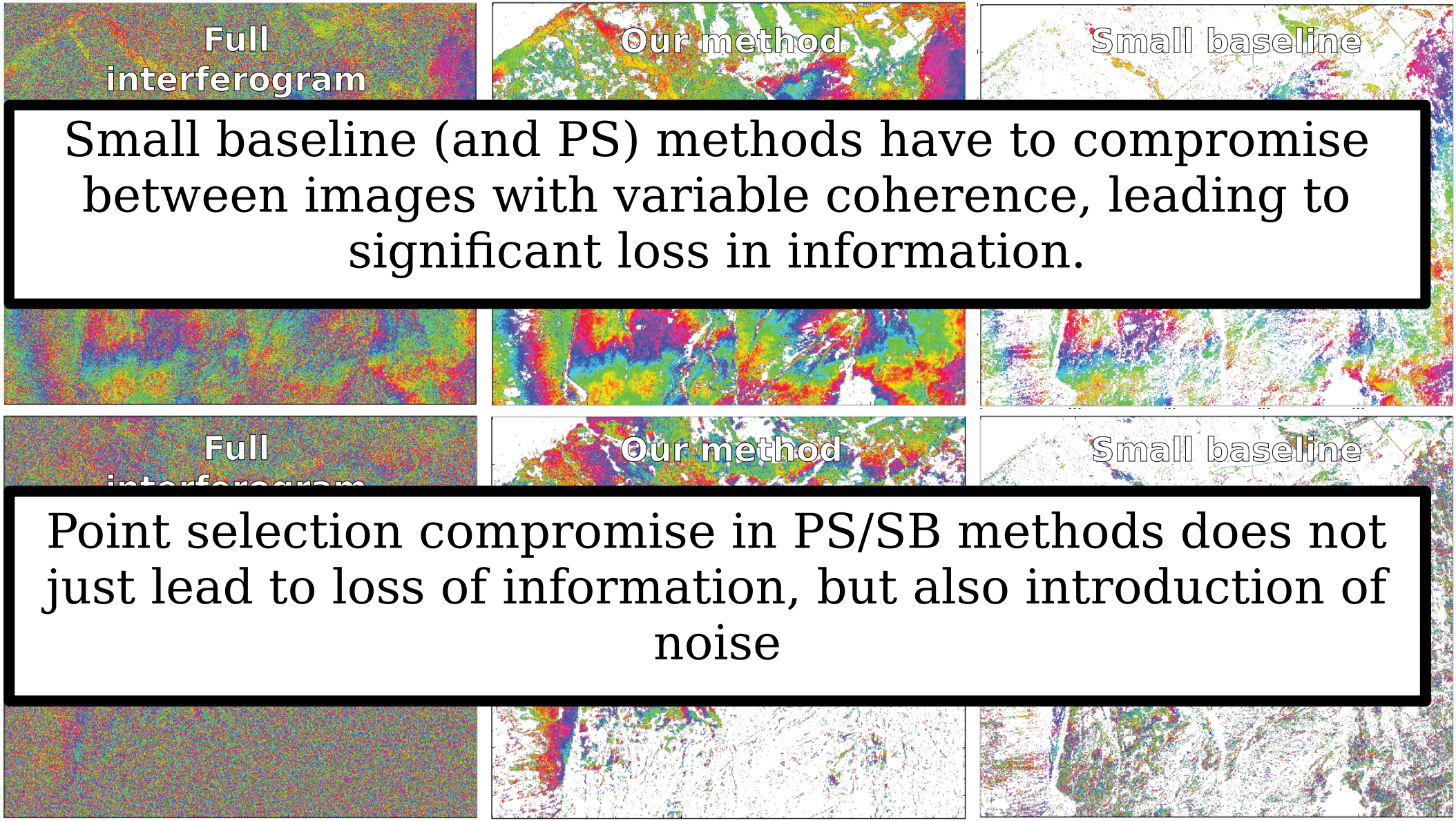
Small baseline (and PS) methods have to compromise between images with variable coherence, leading to significant loss in information.



# Point selection comparison

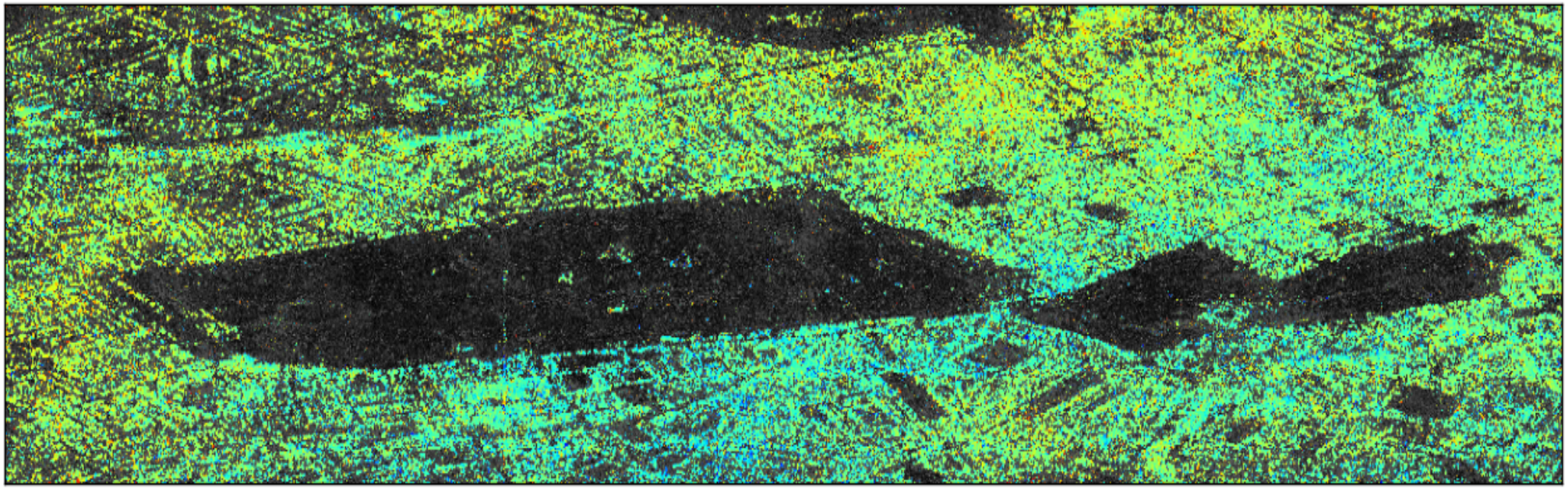



Small baseline (and PS) methods have to compromise between images with variable coherence, leading to significant loss in information.

Point selection compromise in PS/SB methods does not just lead to loss of information, but also introduction of noise

# Point selection

**20150515-20150527**



-20 0 20

[mm]

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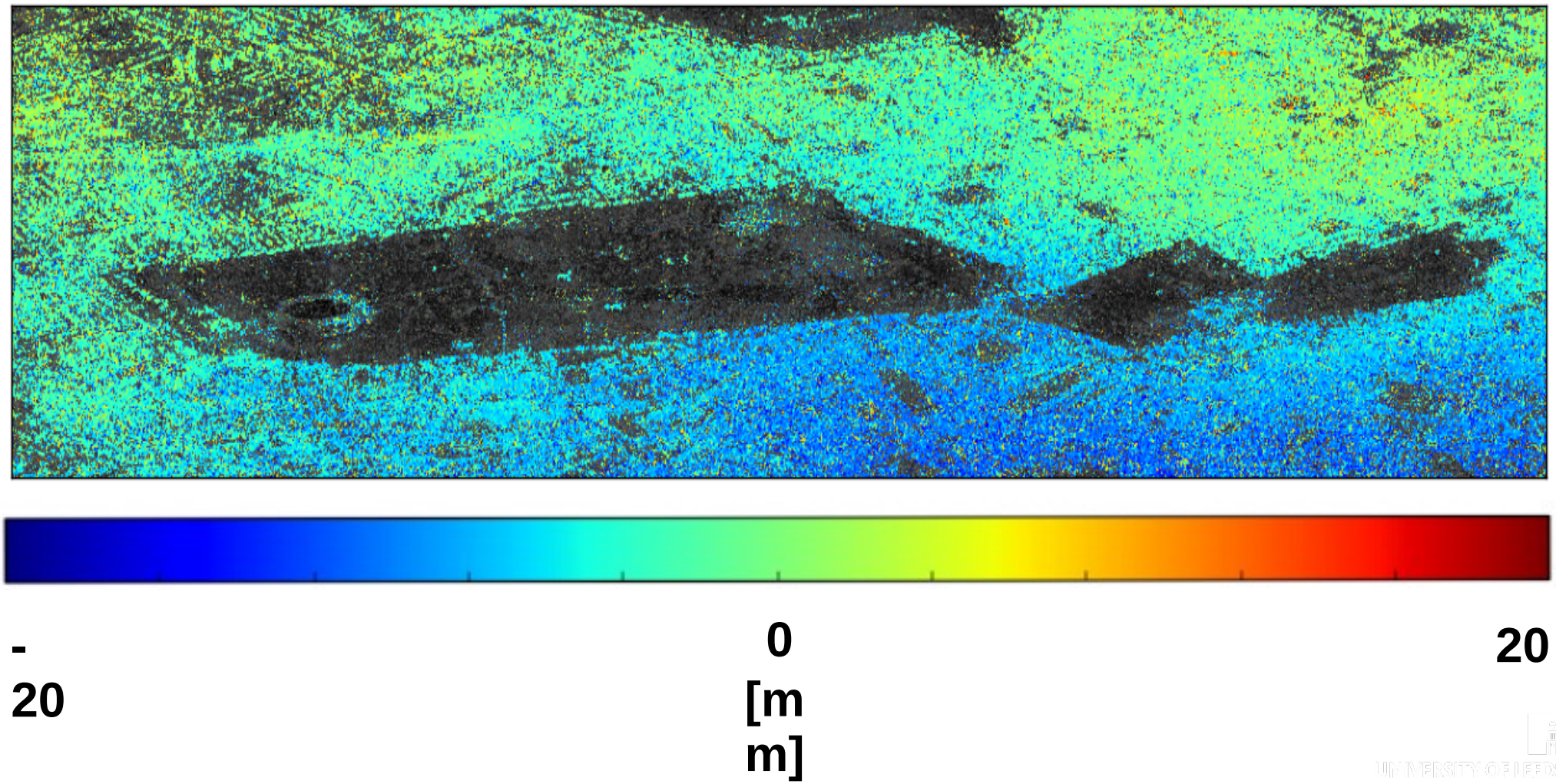
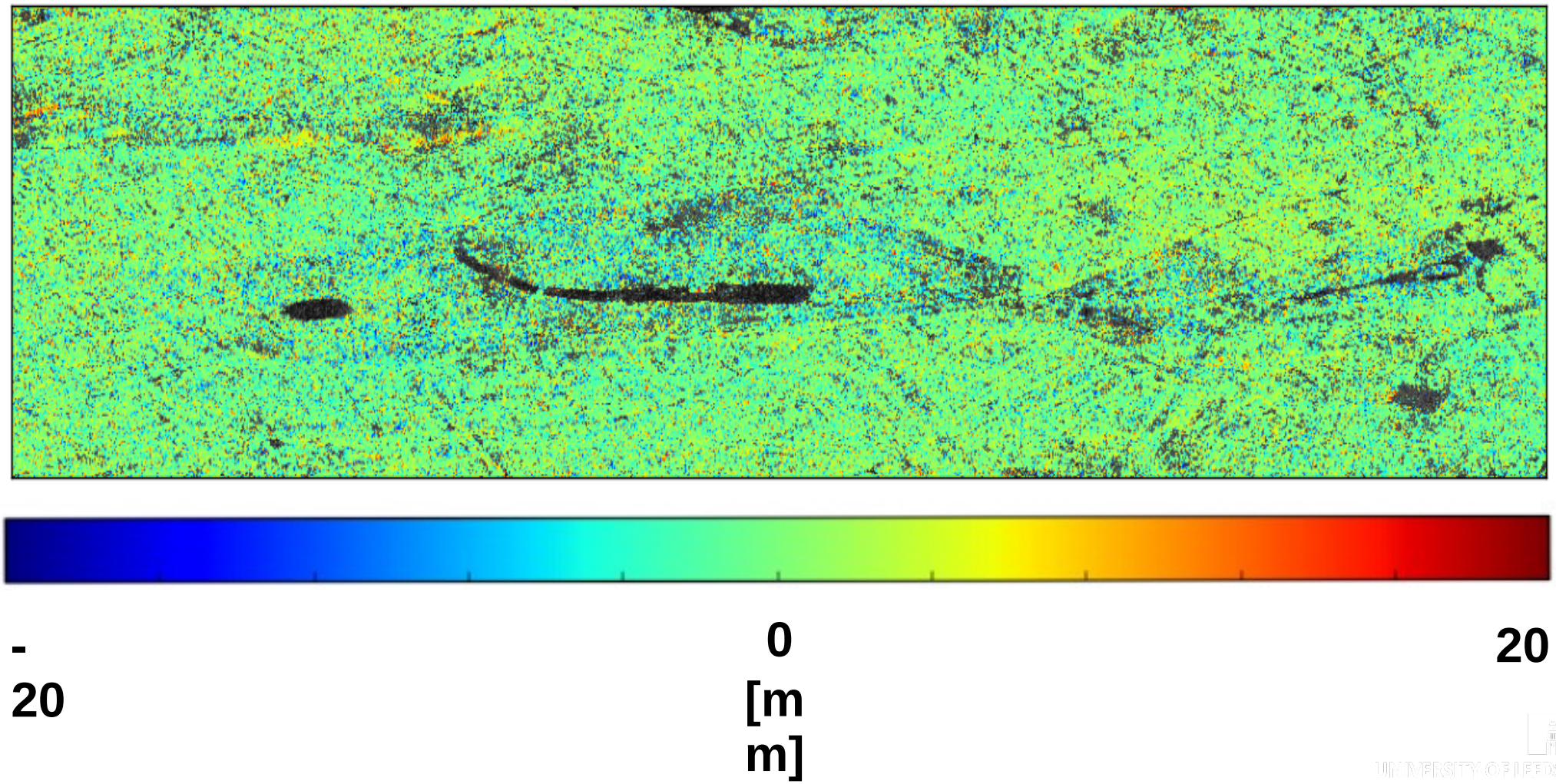
# Variable point selection

**20150714-20150726**



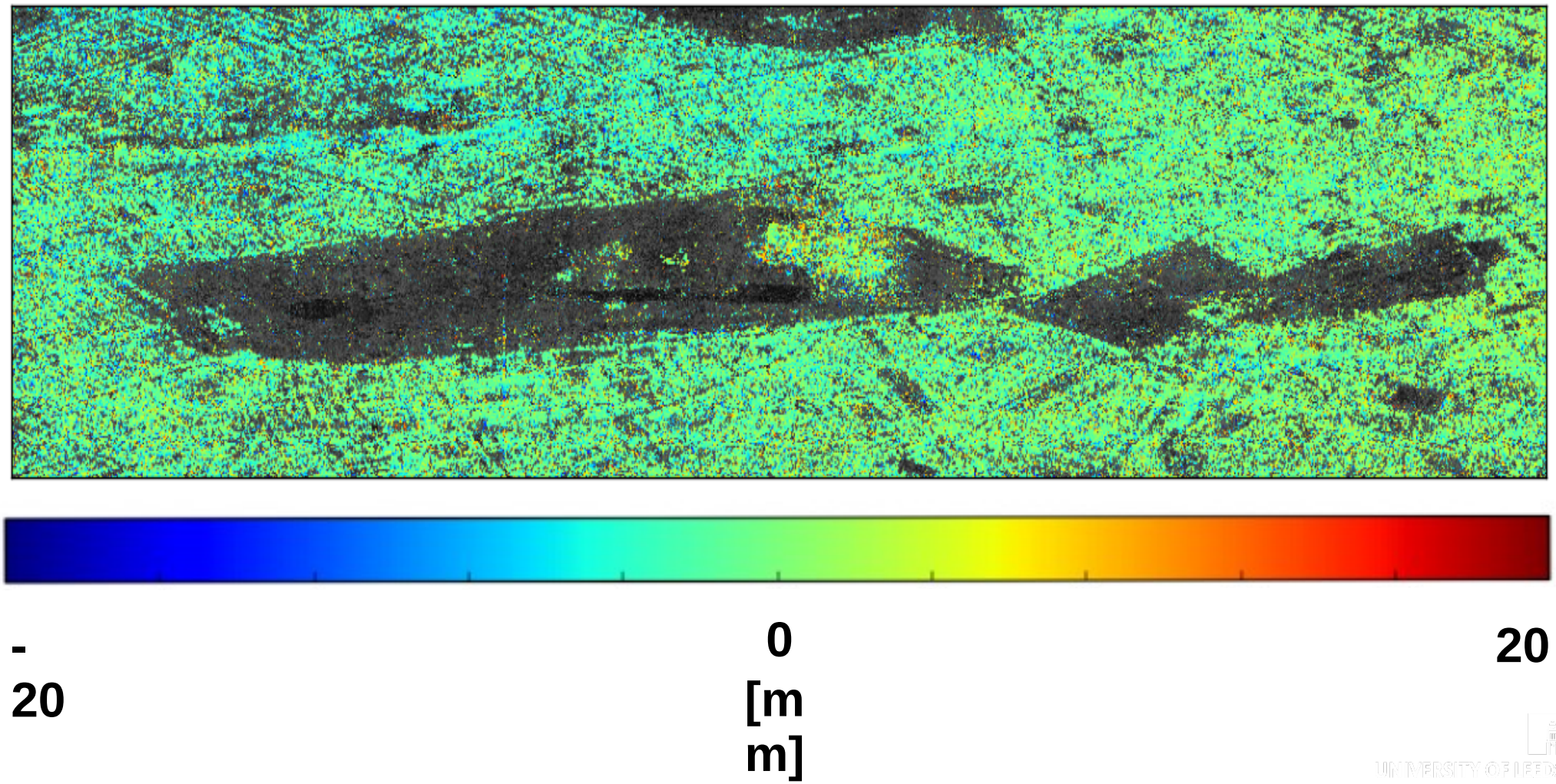
# Variable point selection

**20161129-20161205**



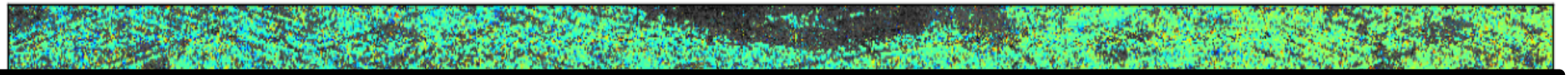
# Variable point selection

**20161205-20161211**



# Variable point selection

**20161205-20161211**



**Point selection on an interferogram-by-interferogram basis removes the selection compromise inherent in many time series techniques.**

-20 0 20

[mm]

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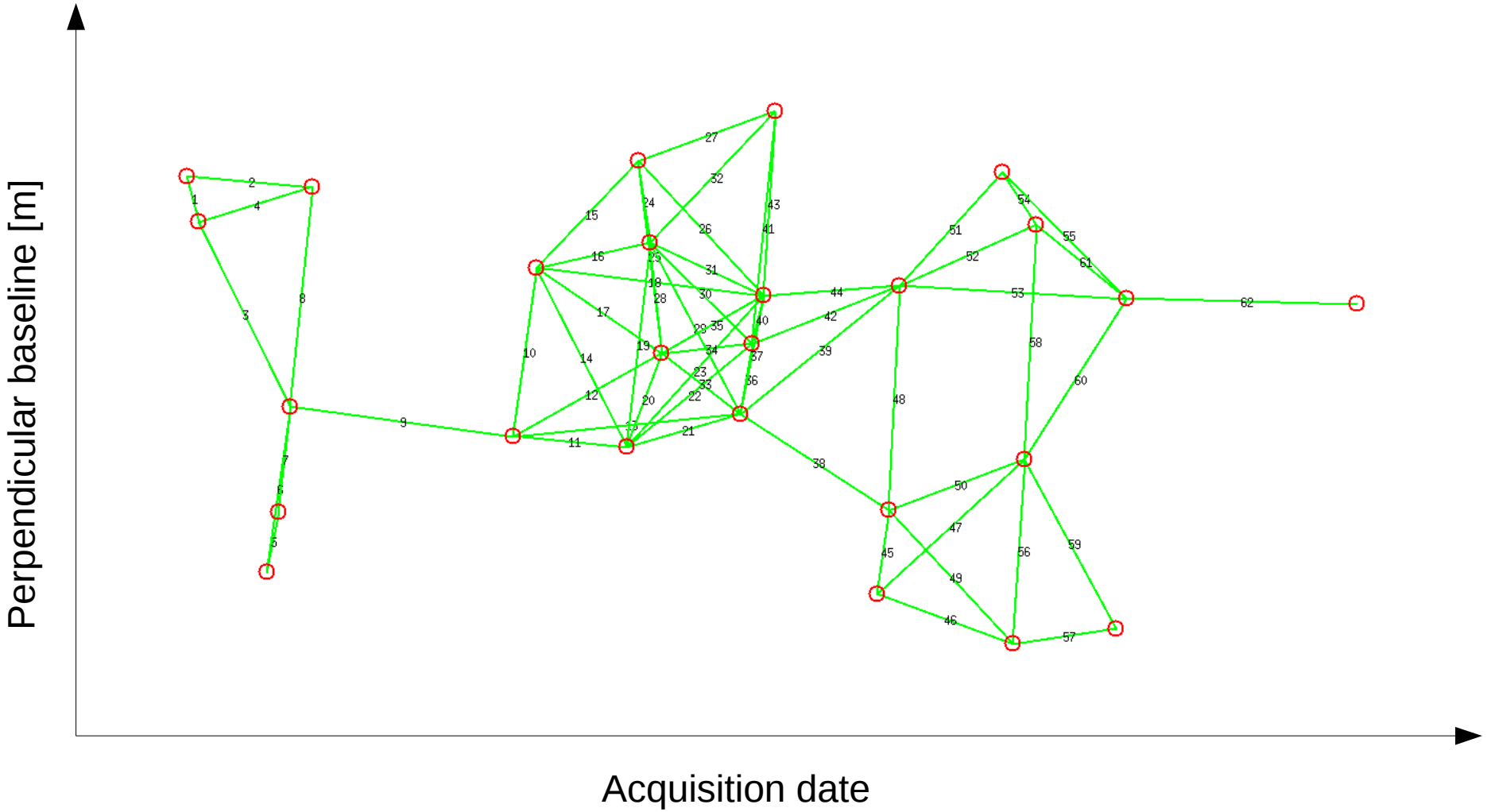
# Timeseries inversion

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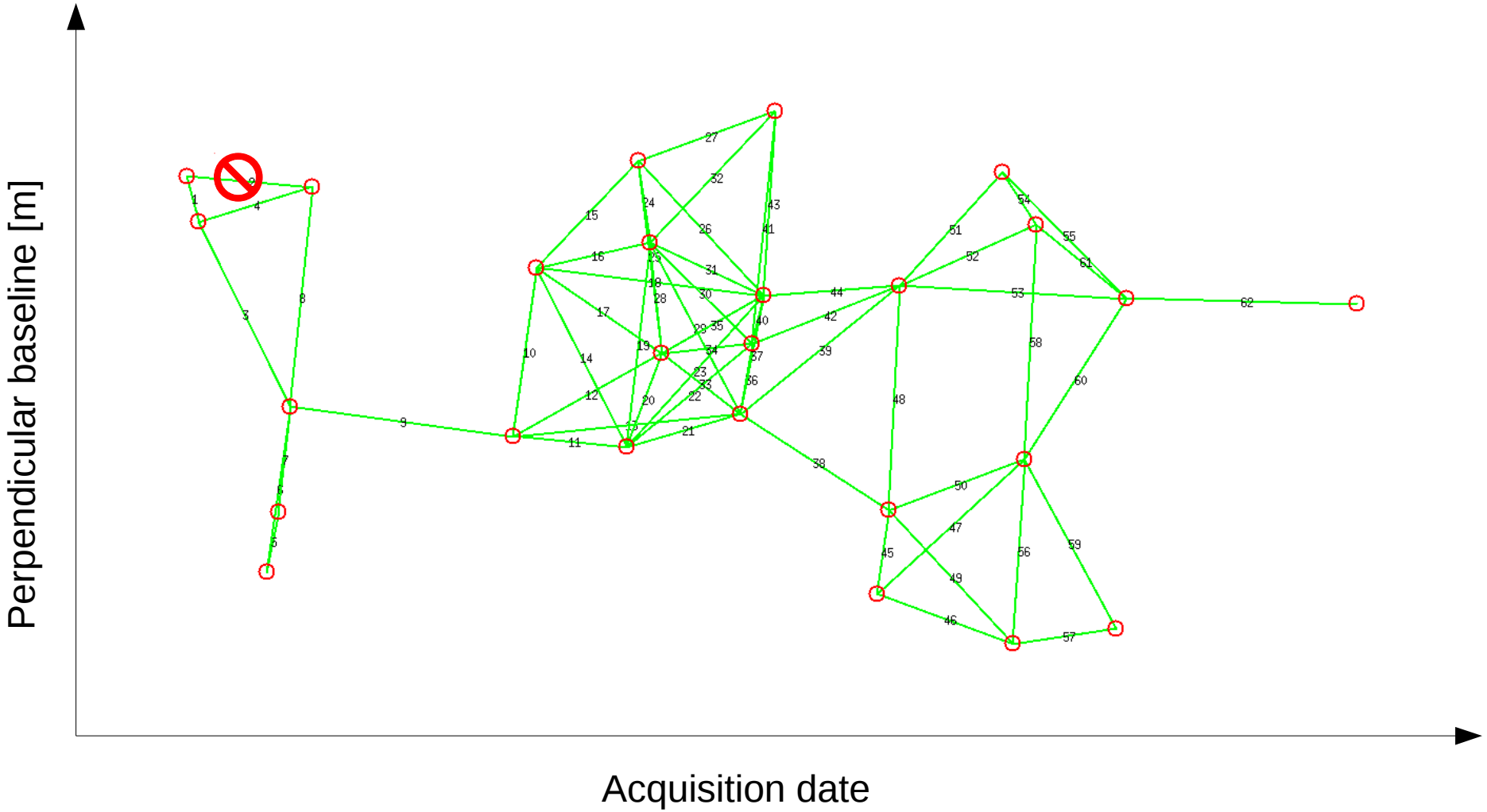
# Timeseries inversion

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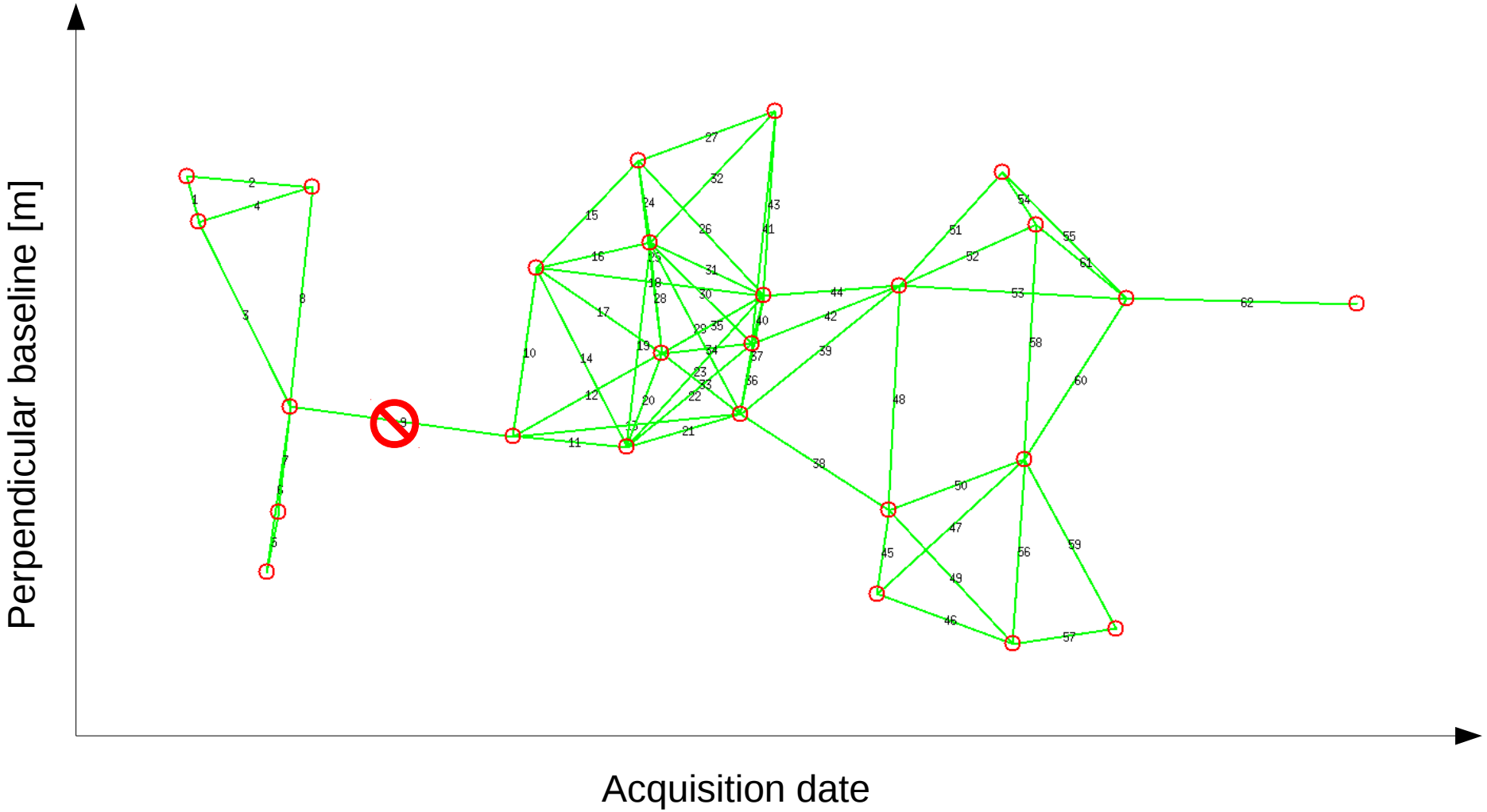
# Timeseries inversion

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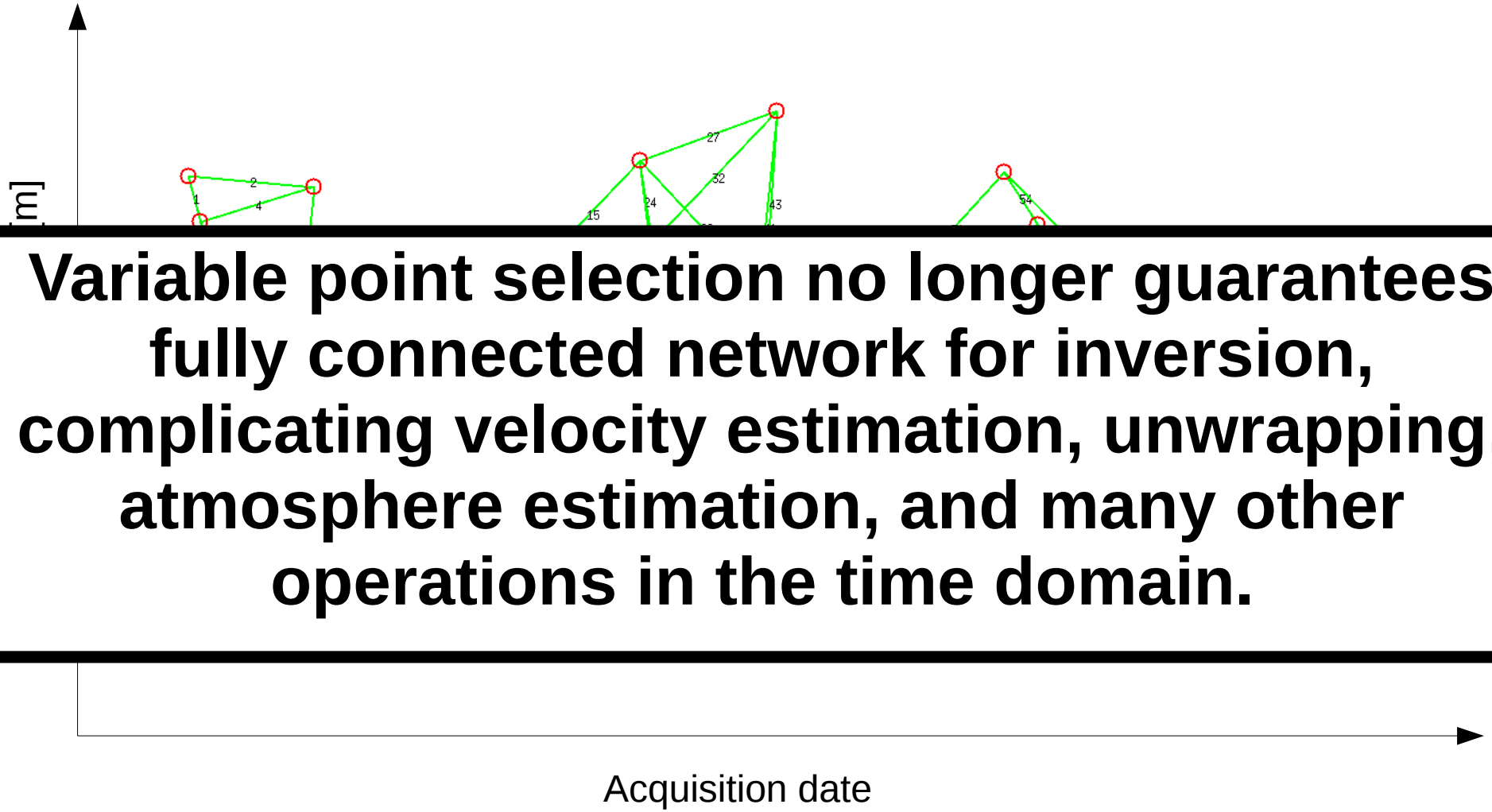
# Timeseries inversion




**Variable point selection no longer guarantees fully connected network for inversion, complicating velocity estimation, unwrapping, atmosphere estimation, and many other operations in the time domain.**

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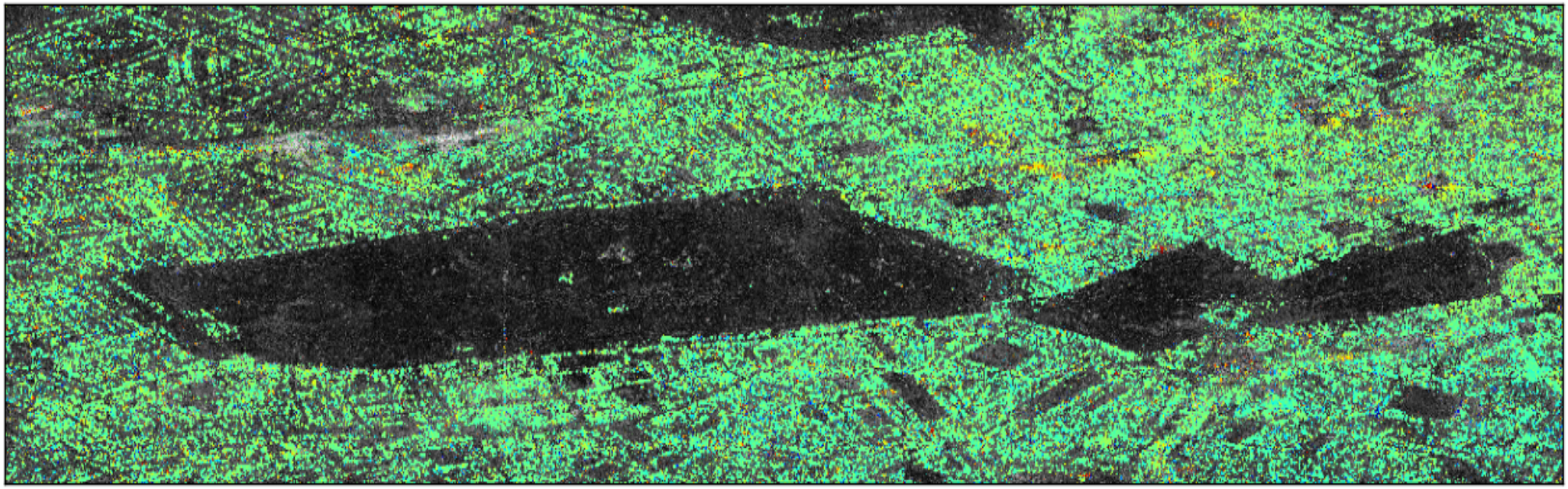
# Timeseries inversion

## Linear velocity estimate
### (only points for which there is a fully connected SB network)



-20 0 20

[mm/yr]

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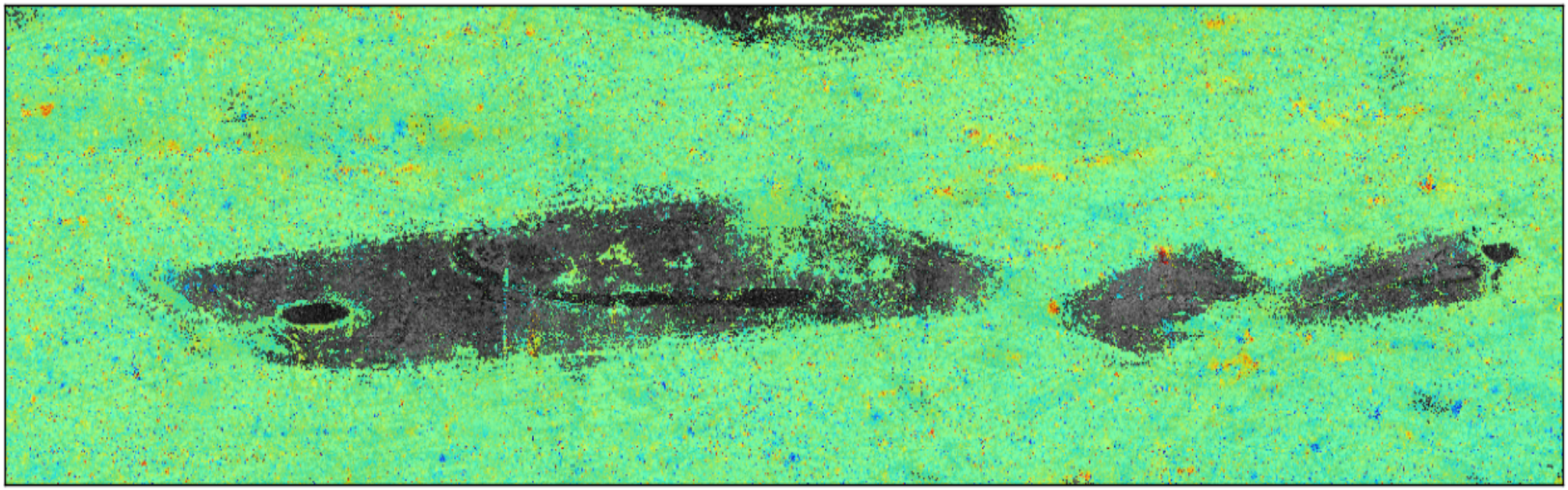
# Timeseries inversion

**Linear velocity estimate**
**(Points present in at least 15 epochs)**



**-20** **0** **20**

**[mm/yr]**

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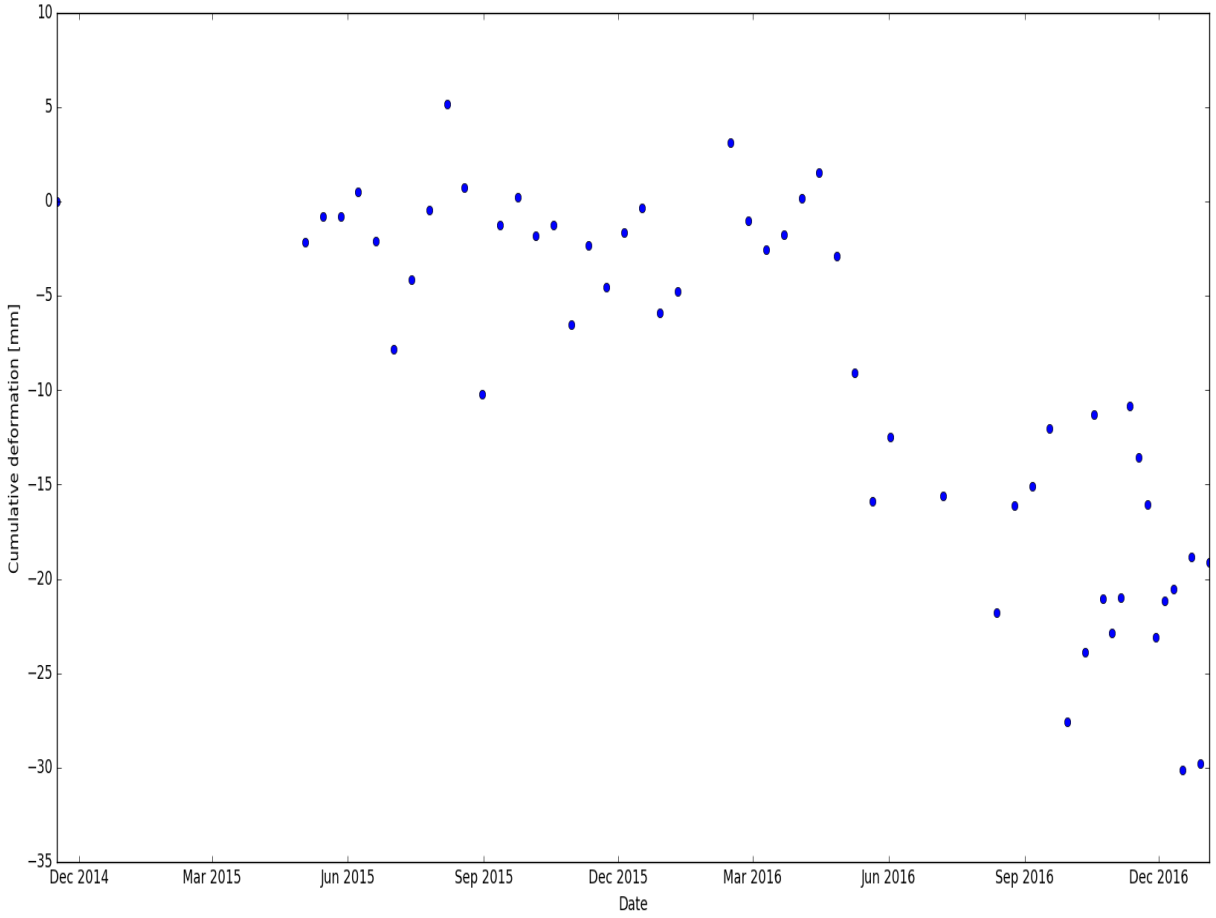
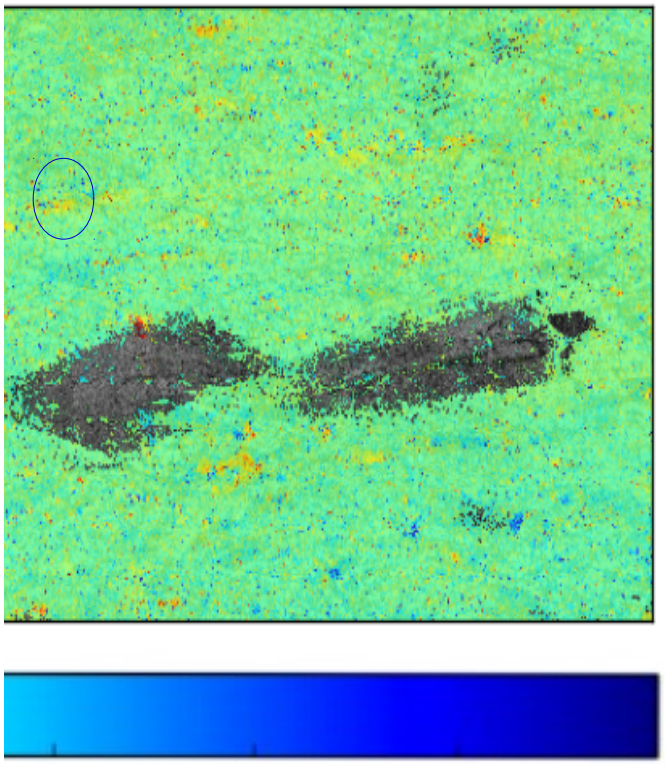
# Timeseries inversion

te



20

[mm/yr]

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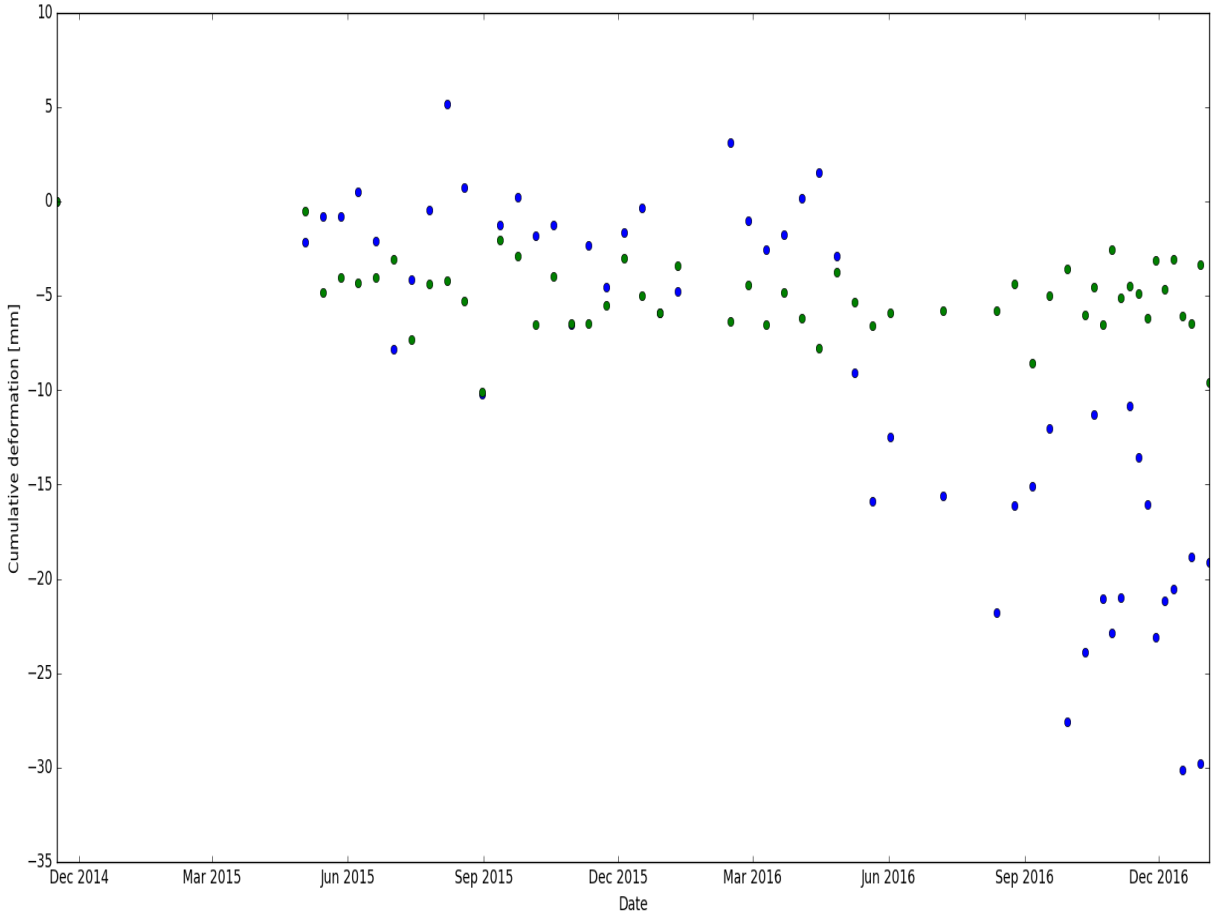
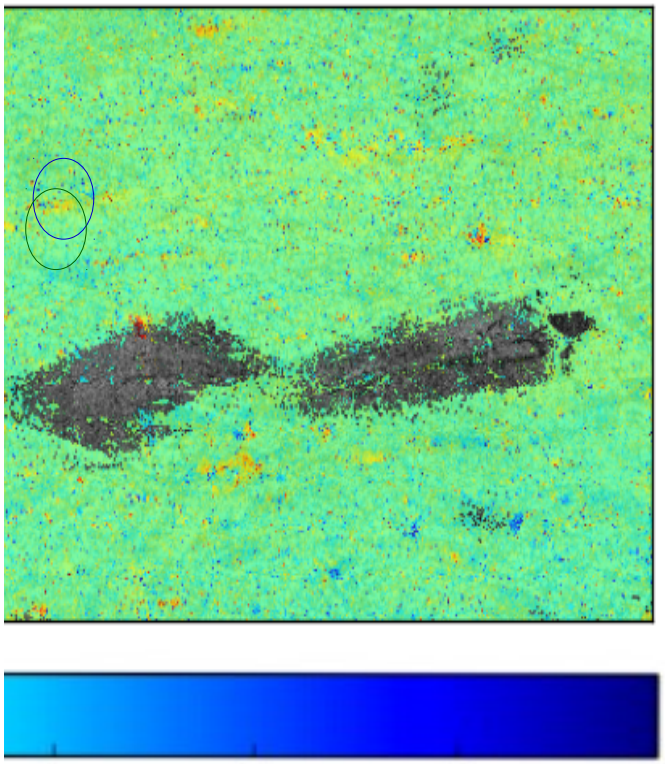
# Timeseries inversion

te



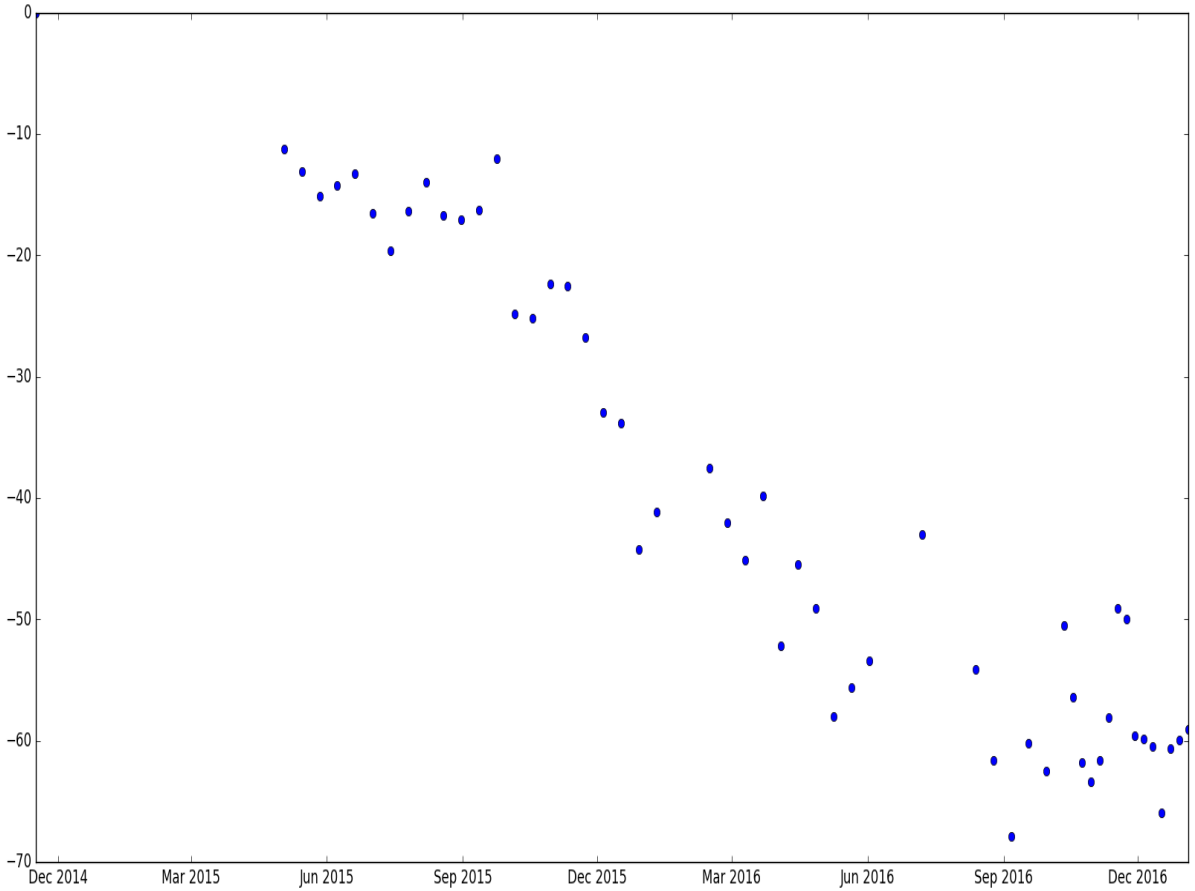



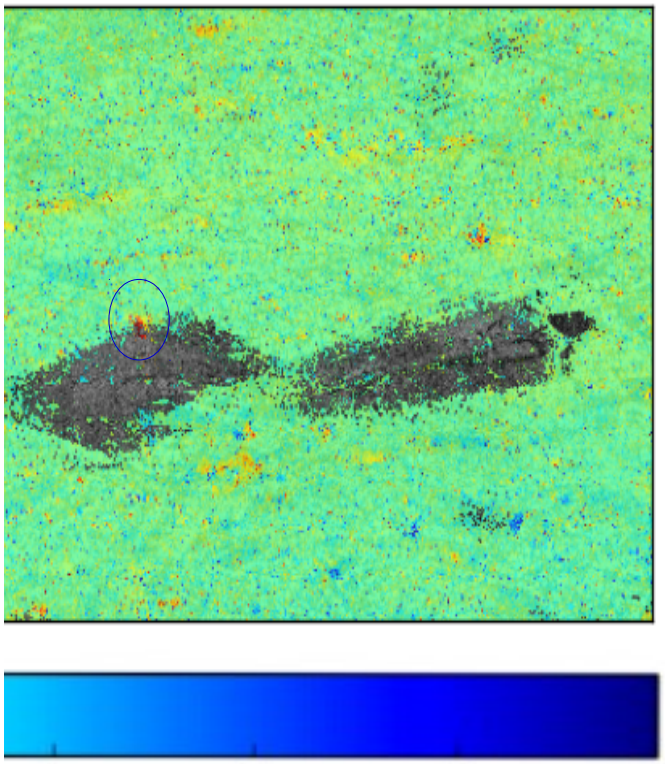
20

[mm/yr]

# Timeseries inversion

te



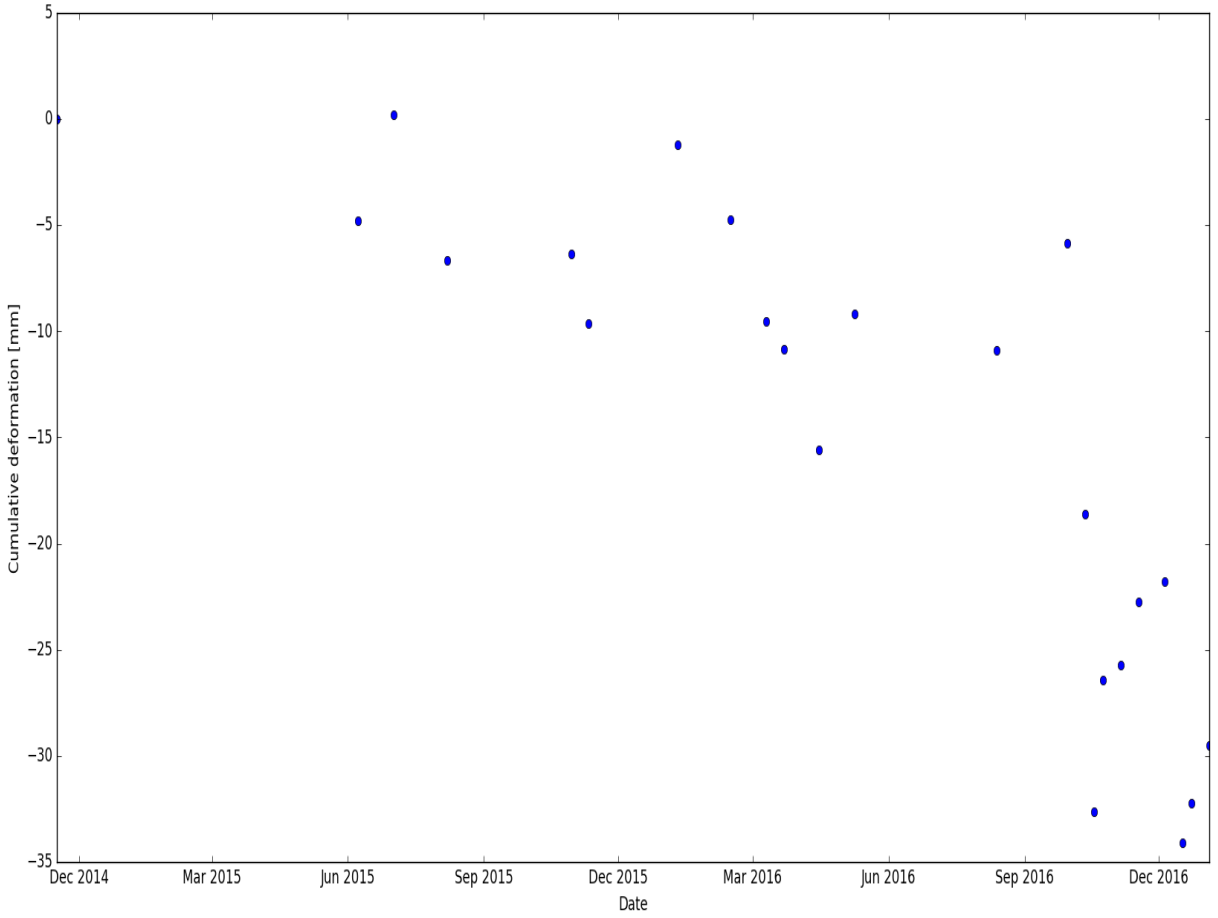



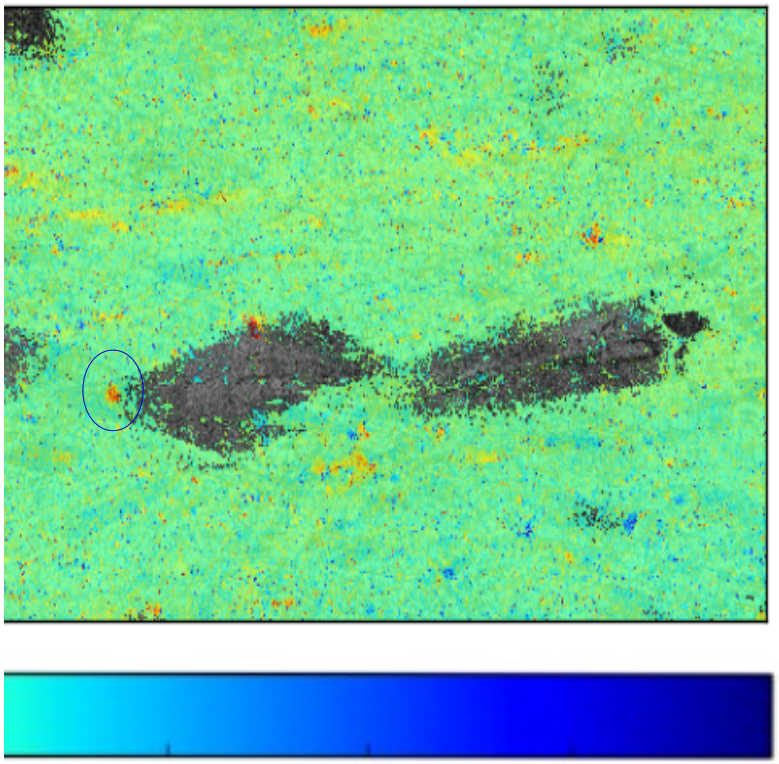
20

[mm/yr]

# Timeseries inversion

imate



20

[mm/yr]

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# Take home messages

- Effective monitoring requires efficient processing methods
- Sibling based ensembles result in high resolution, sharp coherence images
- Individual point selection avoids the selection compromise inherent in many time series methods
- Variable point selection complicates operations in time, like unwrapping and certain atmospheric corrections.

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@KarstenSpaans

LiCS
LOOKING INSIDE THE CONTINENTS FROM SPACE

COMET

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