Quantifying the Probability of False Alarm for Automatically Detected Features in InSAR Deformation Maps

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Abstract

The expansion in spatial coverage and data volume of Interferometric Synthetic Aperture Radar (InSAR) is prompting the need for automated InSAR processing. To be useable by stakeholders, deformation maps derived from InSAR must come with estimates of reliability. In this study, we develop a new computer vision algorithm for automatic detection of surface deformation features in InSAR deformation maps. We estimate the atmospheric noise power spectrum directly from interferograms, which we use to generate realistic synthetic noise instances. This allows us to calculate a likelihood that features in a real deformation map came from atmospheric artifacts. Because the procedure only focuses on the probability of false alarm for candidate features, it does not require any geophysical model for the signals of interest. Our method is agnostic to the computer vision algorithm used, and it can be embedded within InSAR processing frameworks to quantify the uncertainty of machine learning detection results. We demonstrate our algorithm using 80 Sentinel-1 SAR images covering 80,000 km^2 of the Permian Basin in West Texas, where oil and gas production activities have led to a rise in the number of low magnitude earthquakes. Our algorithm reliably detects millimeter-to-centimeter deformation features related with oil and gas production, groundwater pumping, wastewater injection, and the M5.0 earthquake west of Mentone, Texas. Our method provides guidance on the minimum number of Sentinel-1 acquisitions needed for interferogram stacking to confidently detect the subtle deformation. A decrease in uncertainty can be achieved by detecting and removing SAR images corrupted by tropospheric noise, which reduces the number of required acquisitions for mitigating tropospheric noise.

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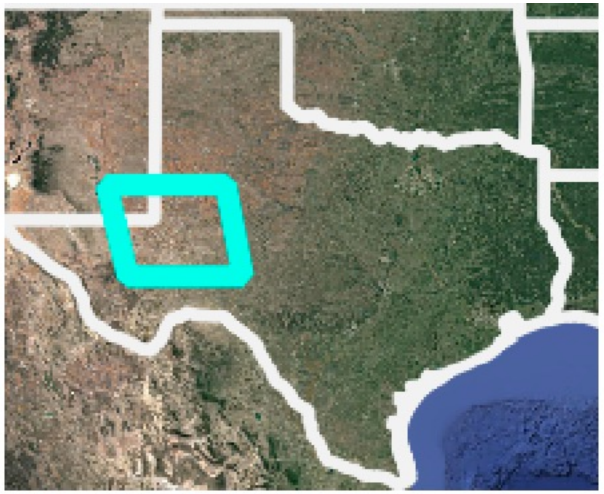
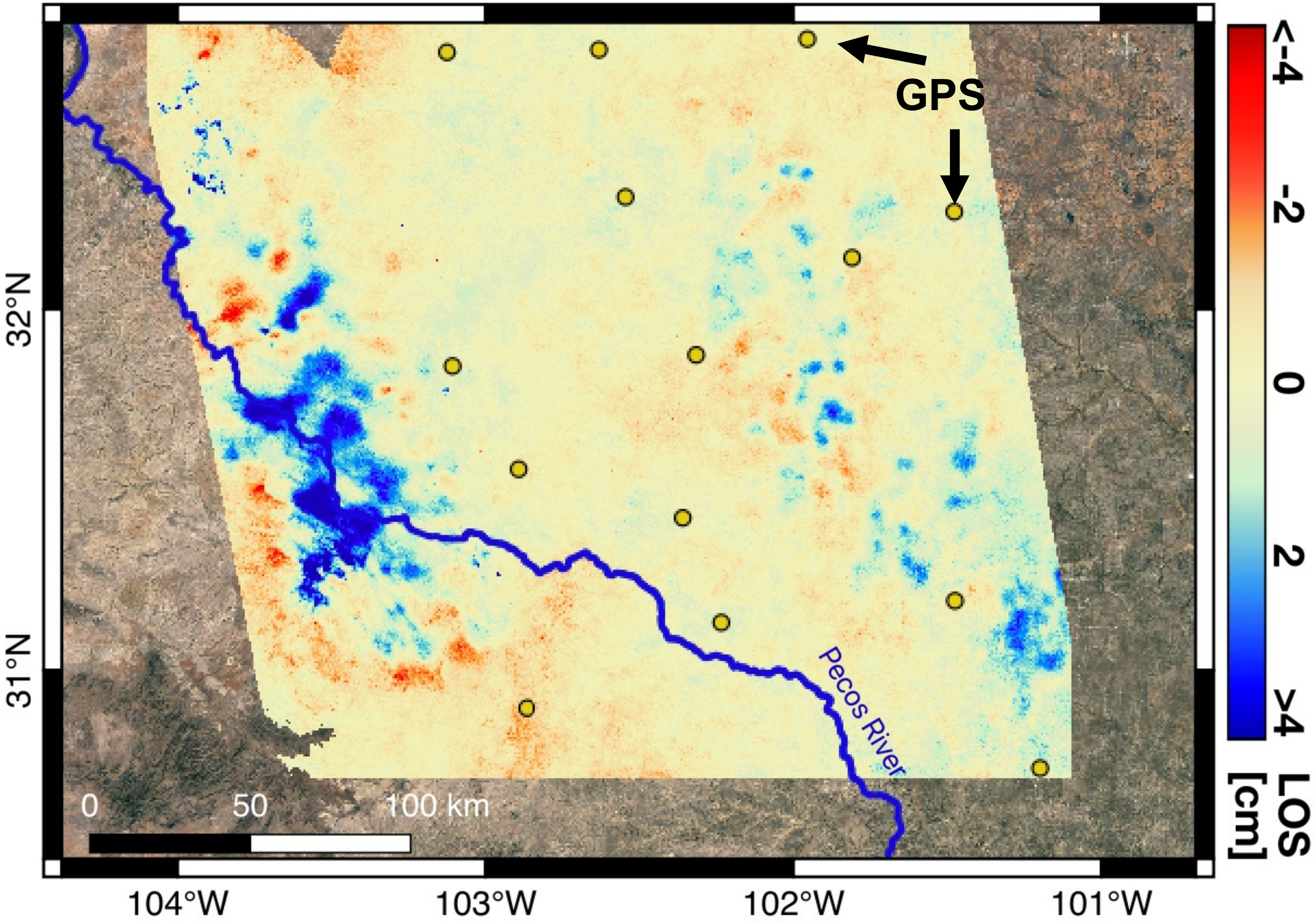
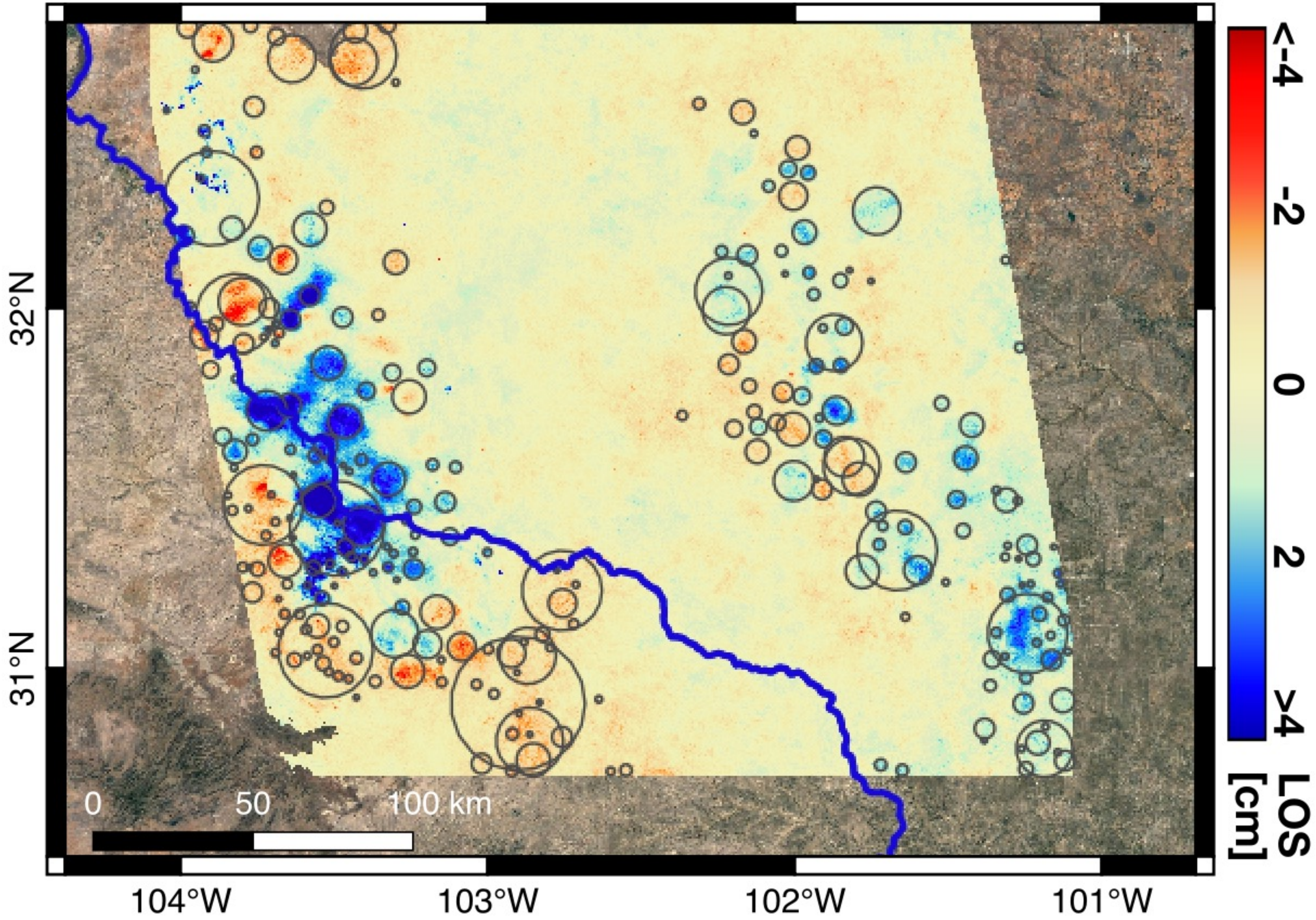
Cumulative deformation: Nov.’14 - Jan ’19

Permian Basin,
West Texas

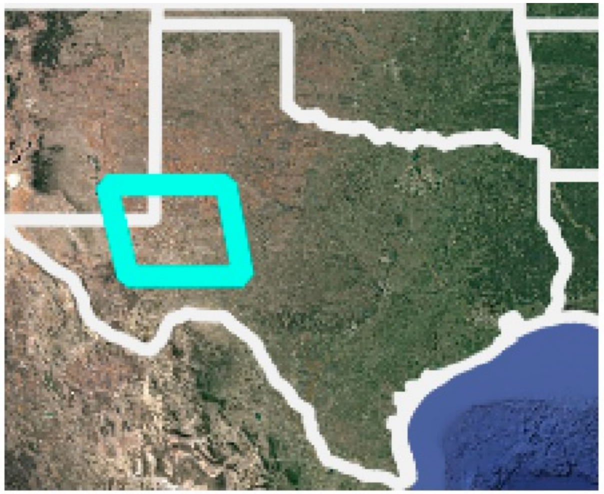




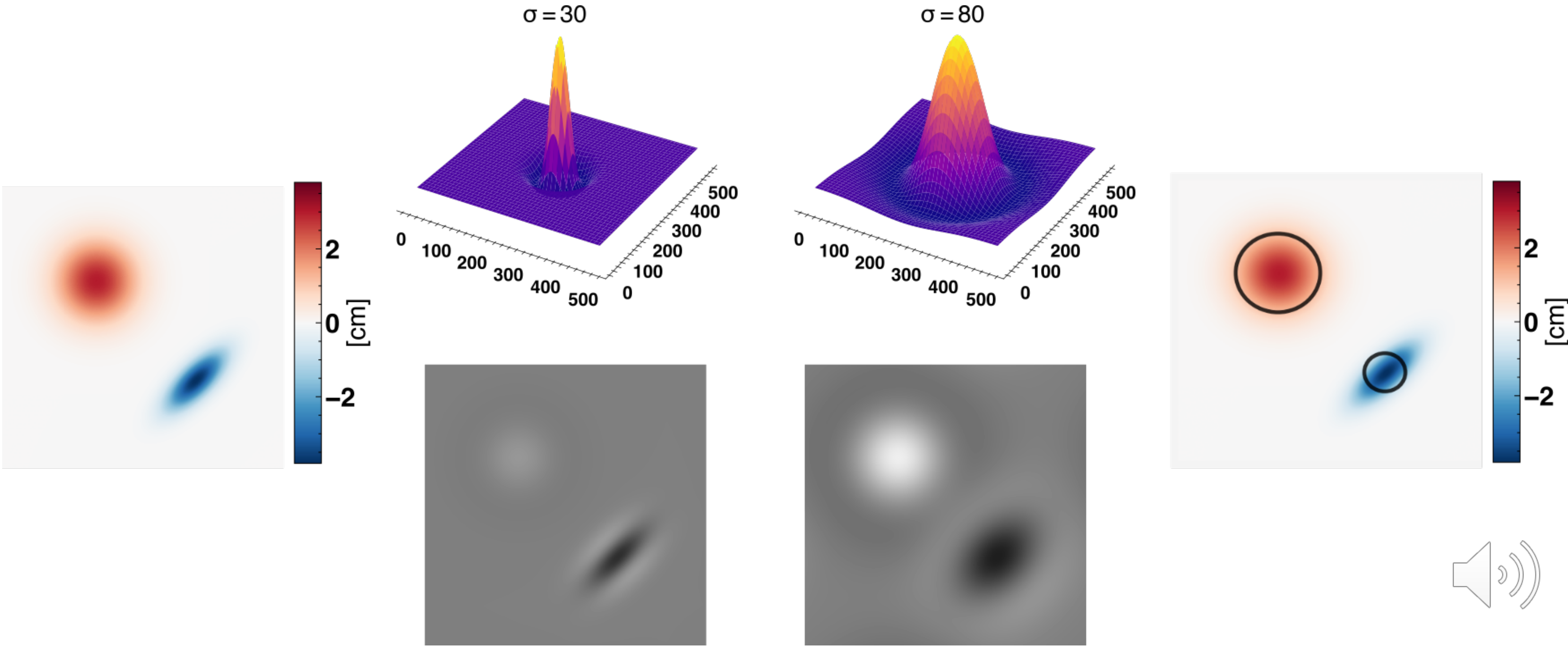
Automatic detections: $p < 0.01$



Permian Basin,
West Texas

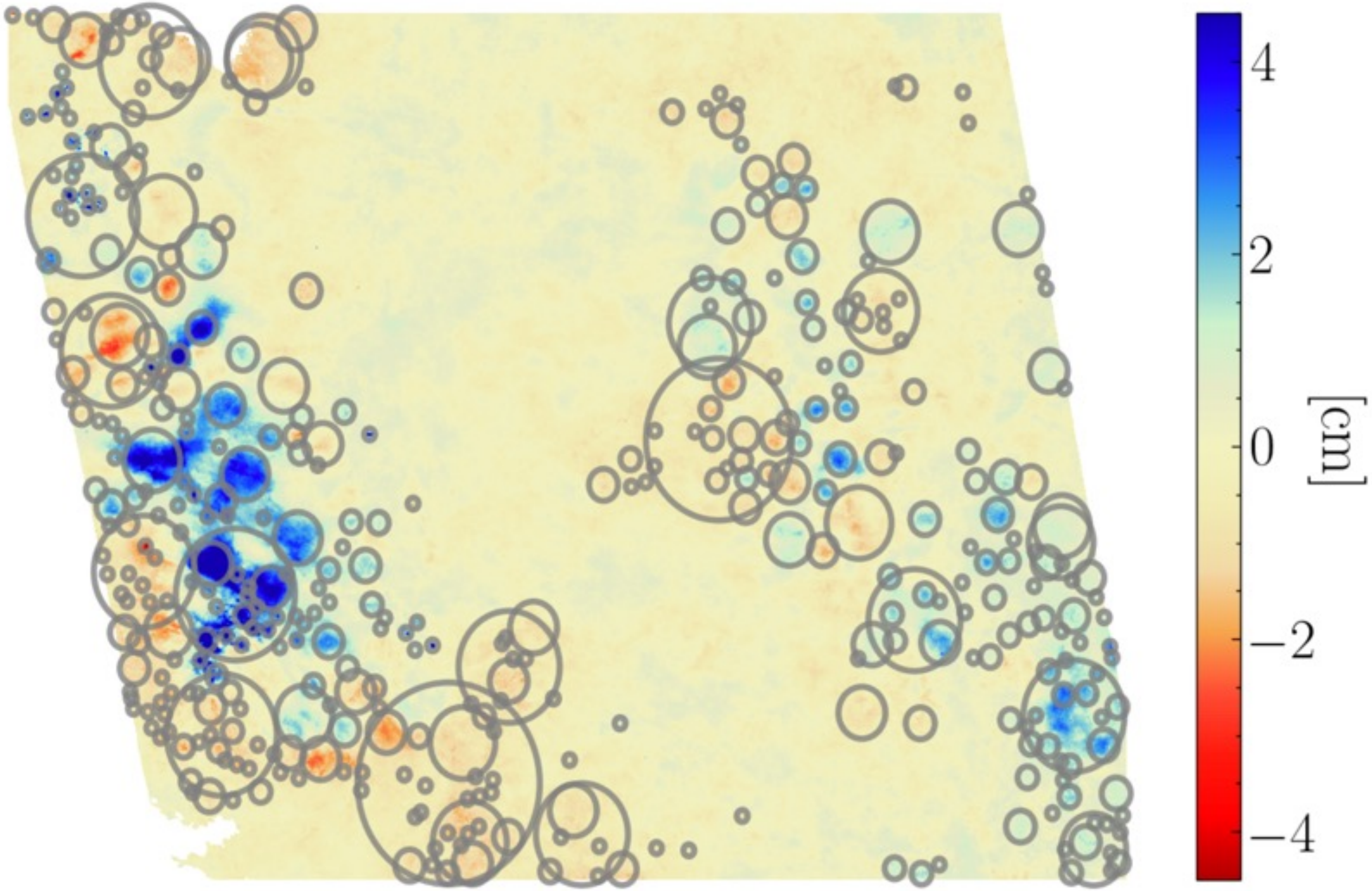


LoG filtering for blob detection



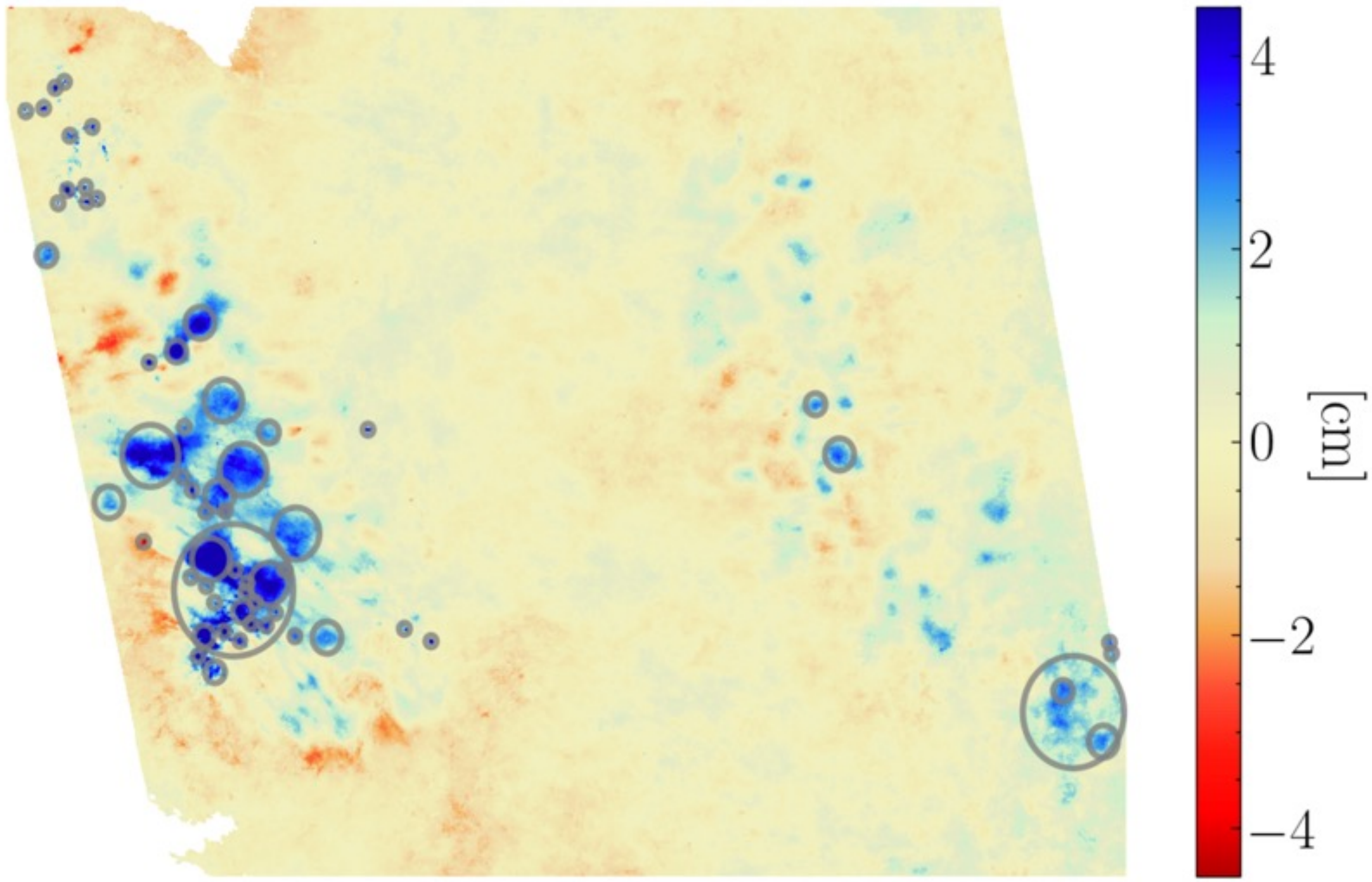
Detection Threshold?

Too low threshold -> False Alarms

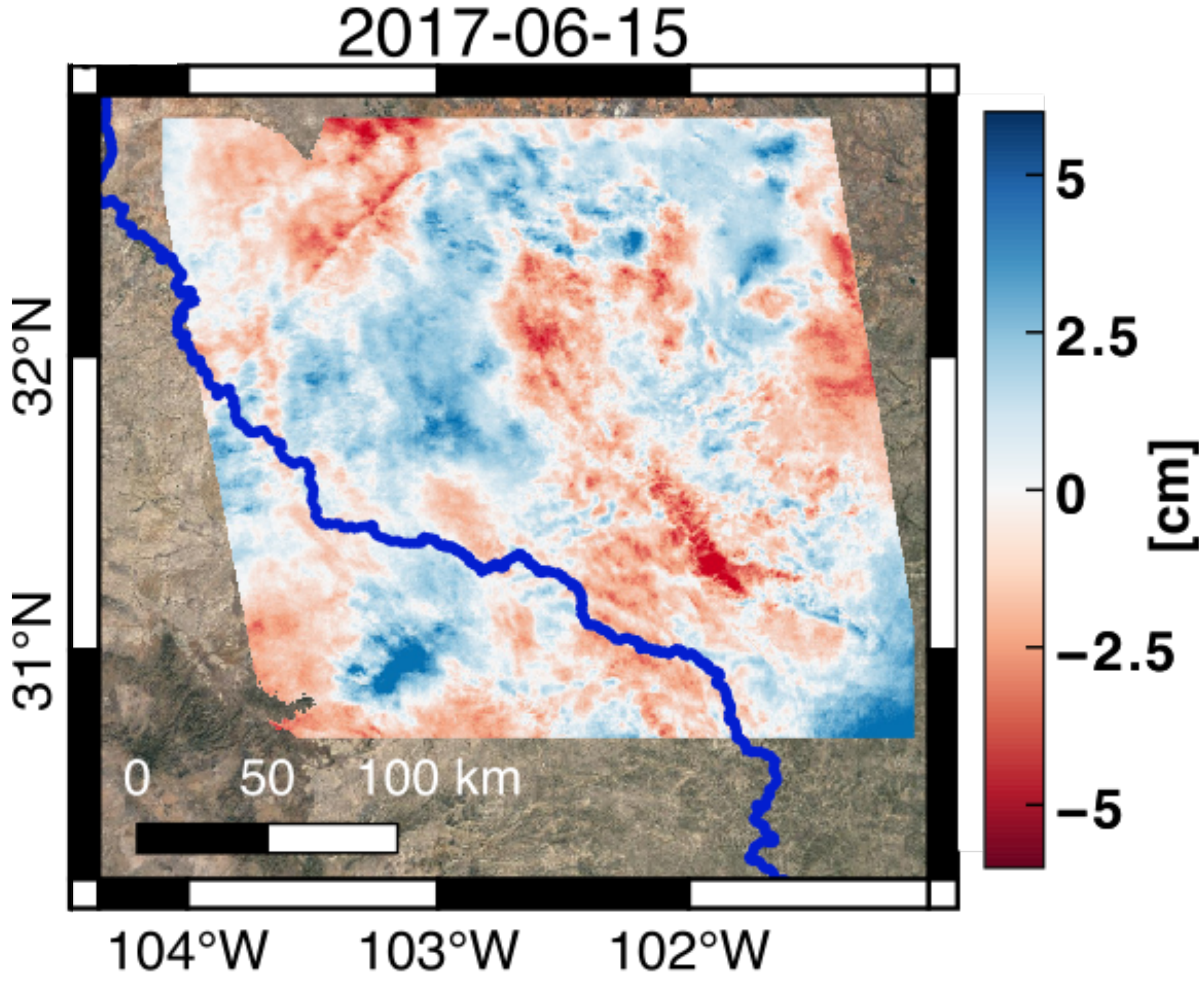


Detection Threshold?

<u>Too high threshold -> Misses</u>

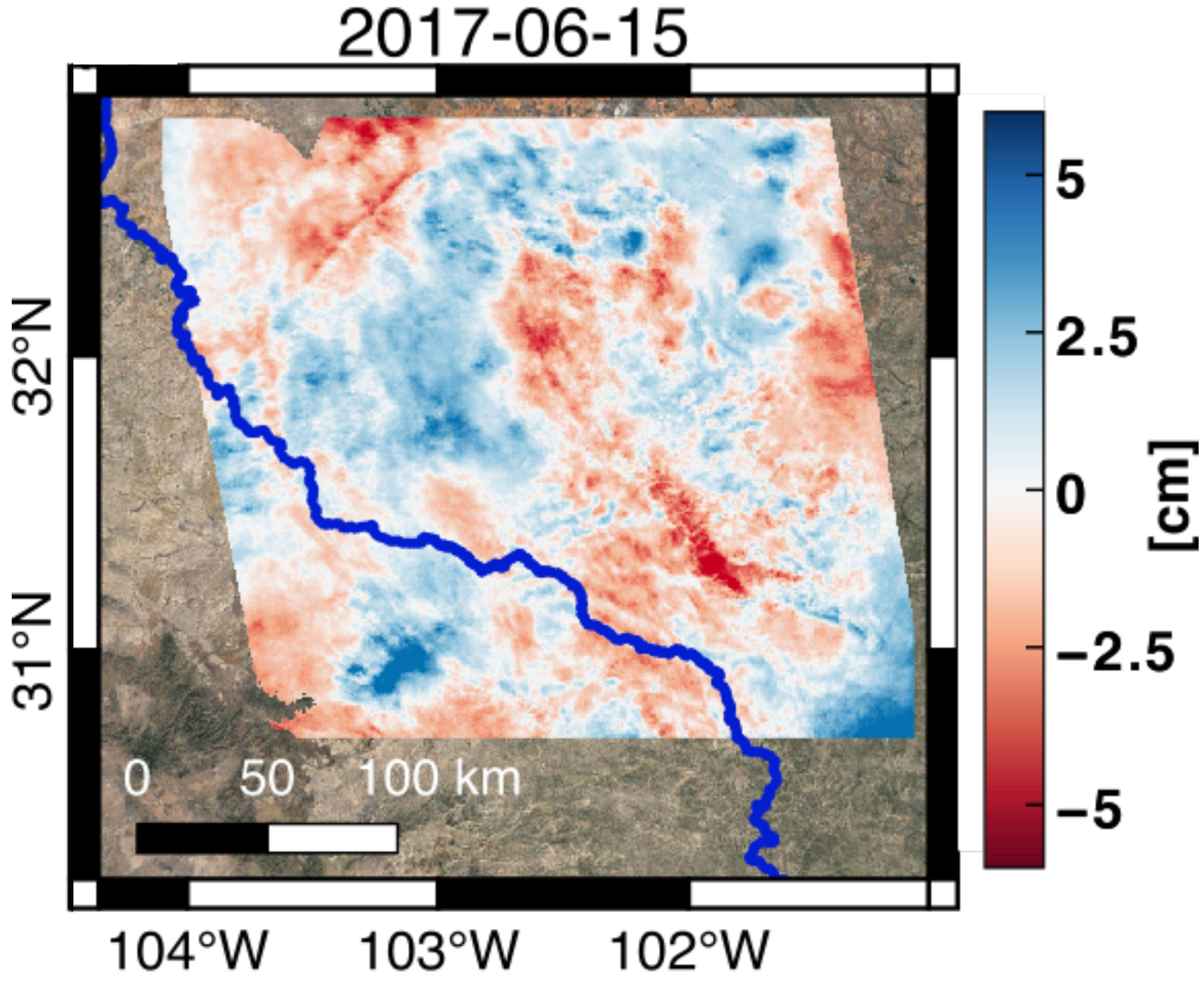


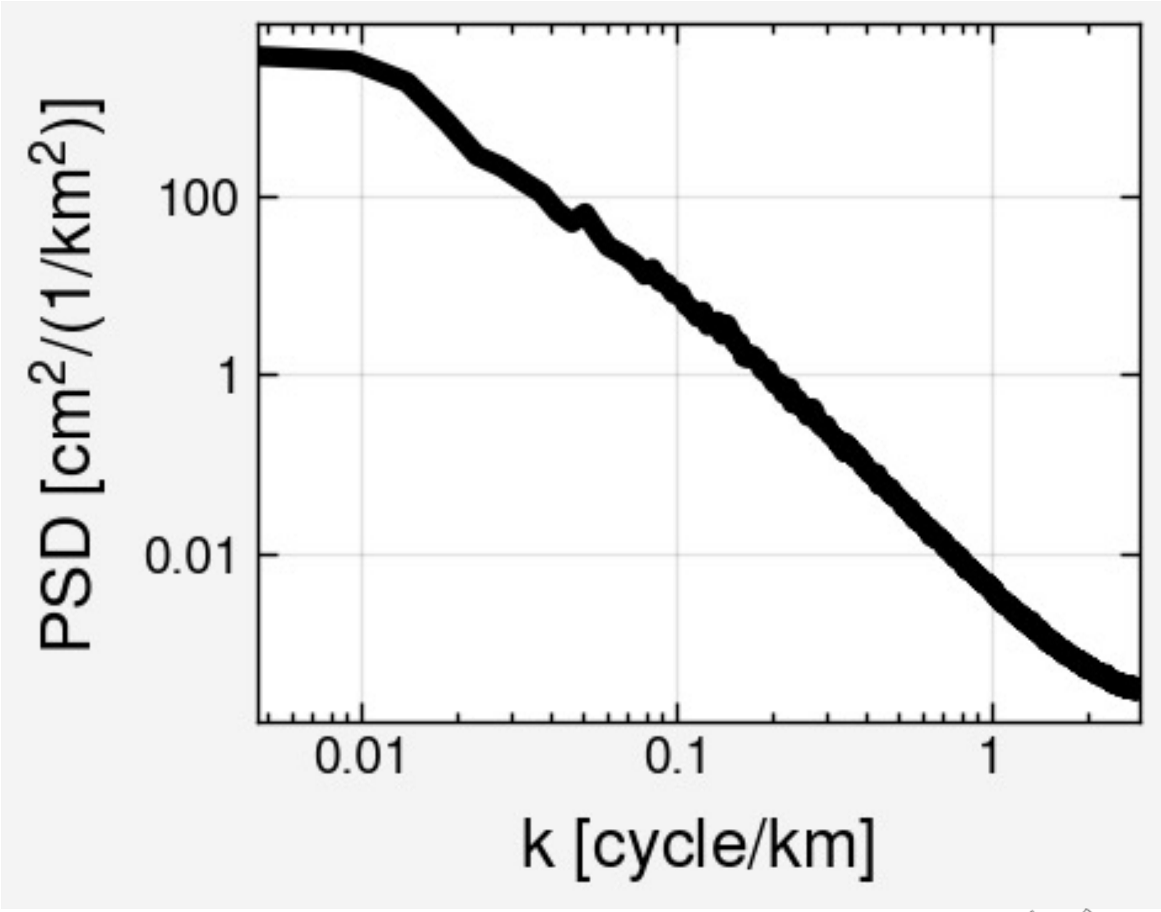
Characterize tropospheric turbulence



$$\bar{\alpha}_n = \frac{\lambda}{4\pi} \frac{1}{N-1} \left(\sum_{k=1, k \neq n}^{N} \phi_{n,k} \right)$$

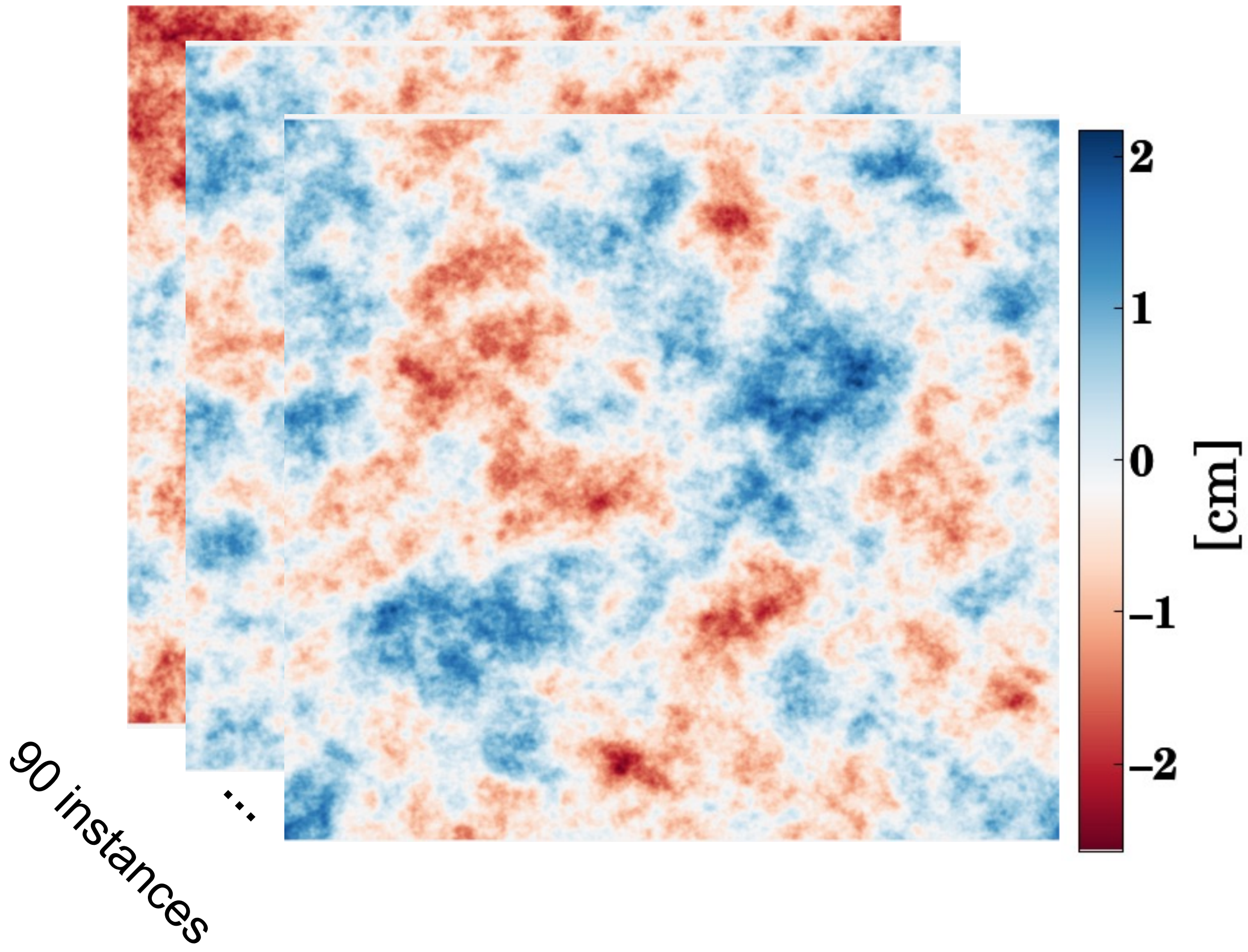
Characterize tropospheric turbulence





Noise simulations to create PDF of turbulence artifacts

Noise simulated from spectrum

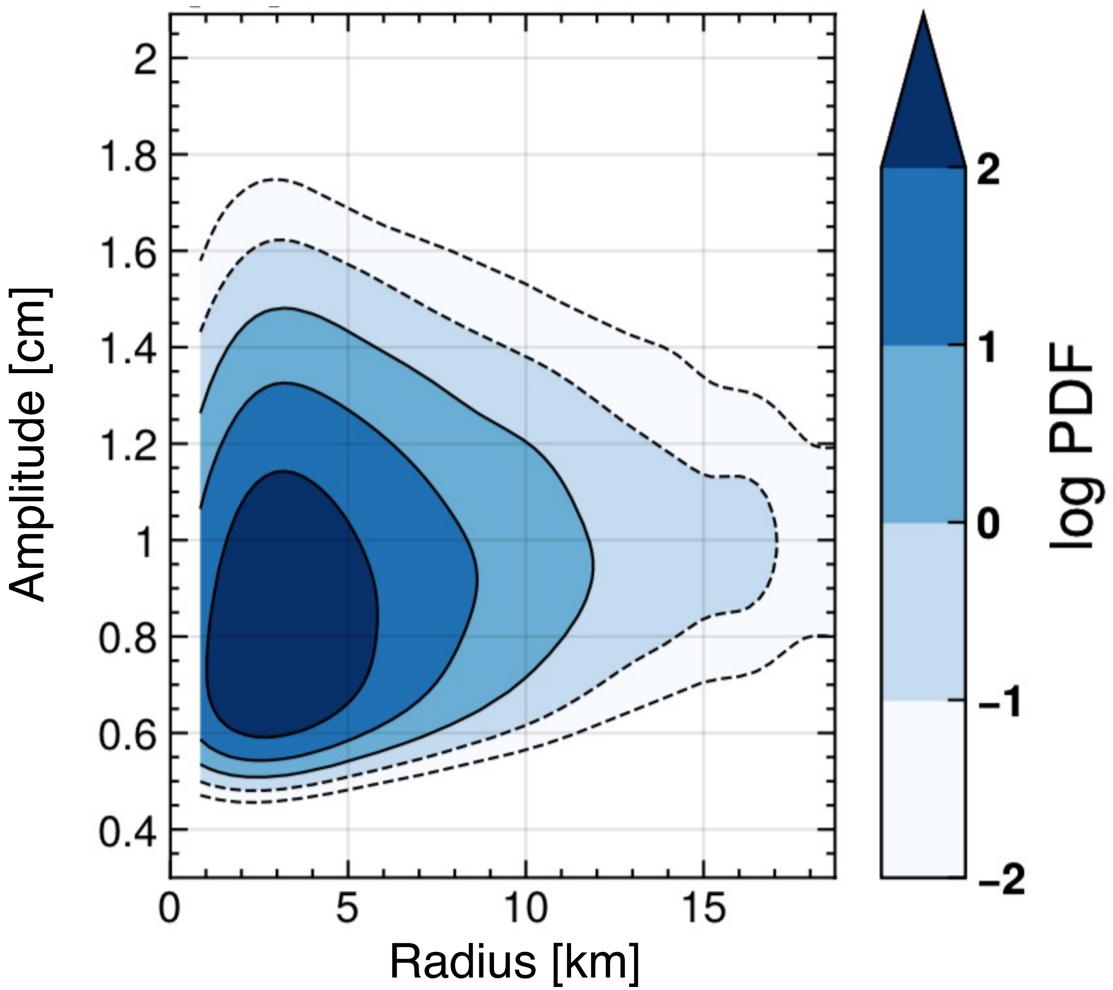


Time series (e.g. SBAS, stacking) for “noise only” deformation map

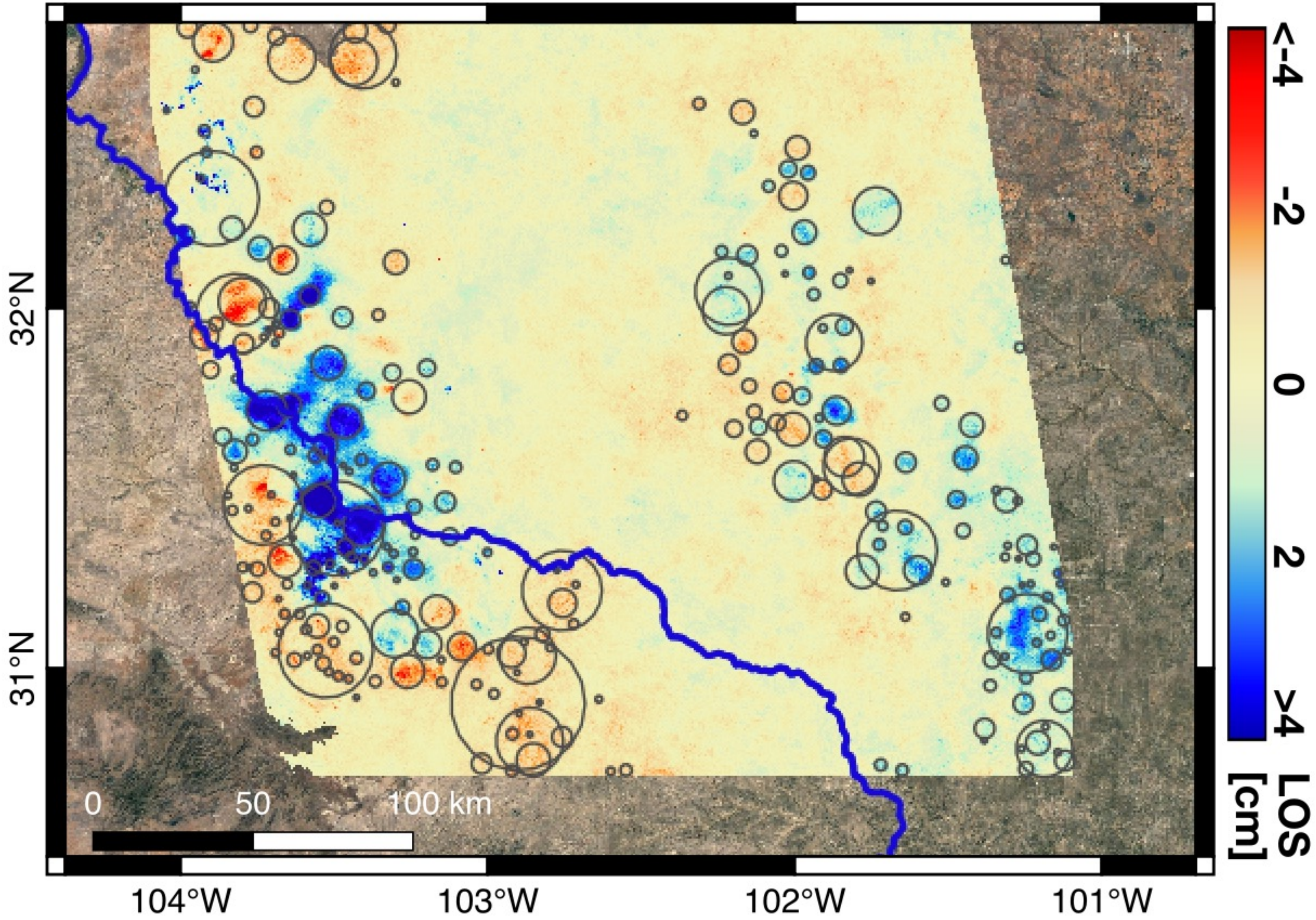
Blob detection on “noise only” deformation map

Noise simulations to create PDF of turbulence artifacts

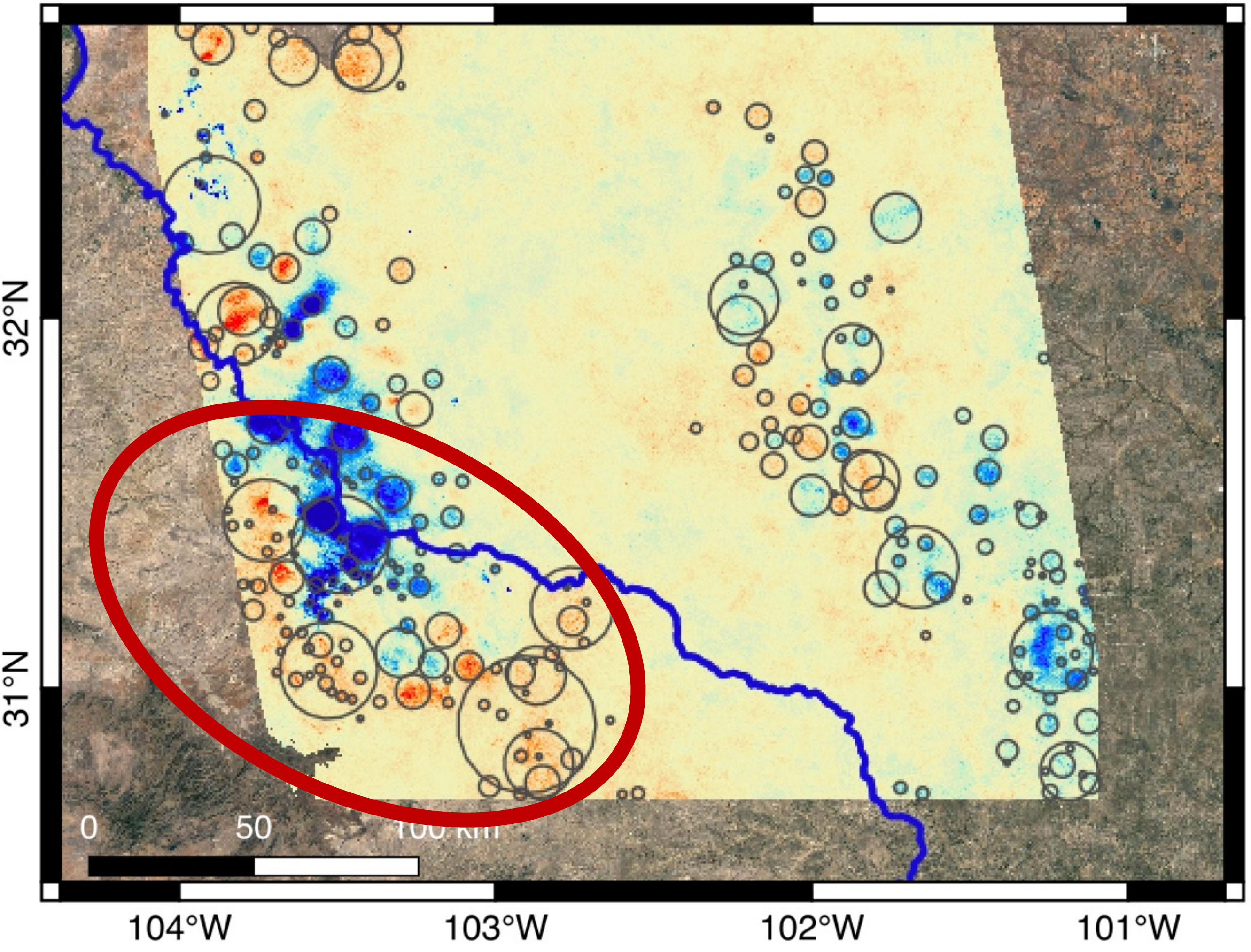
PDF of noise artifacts in deformation maps

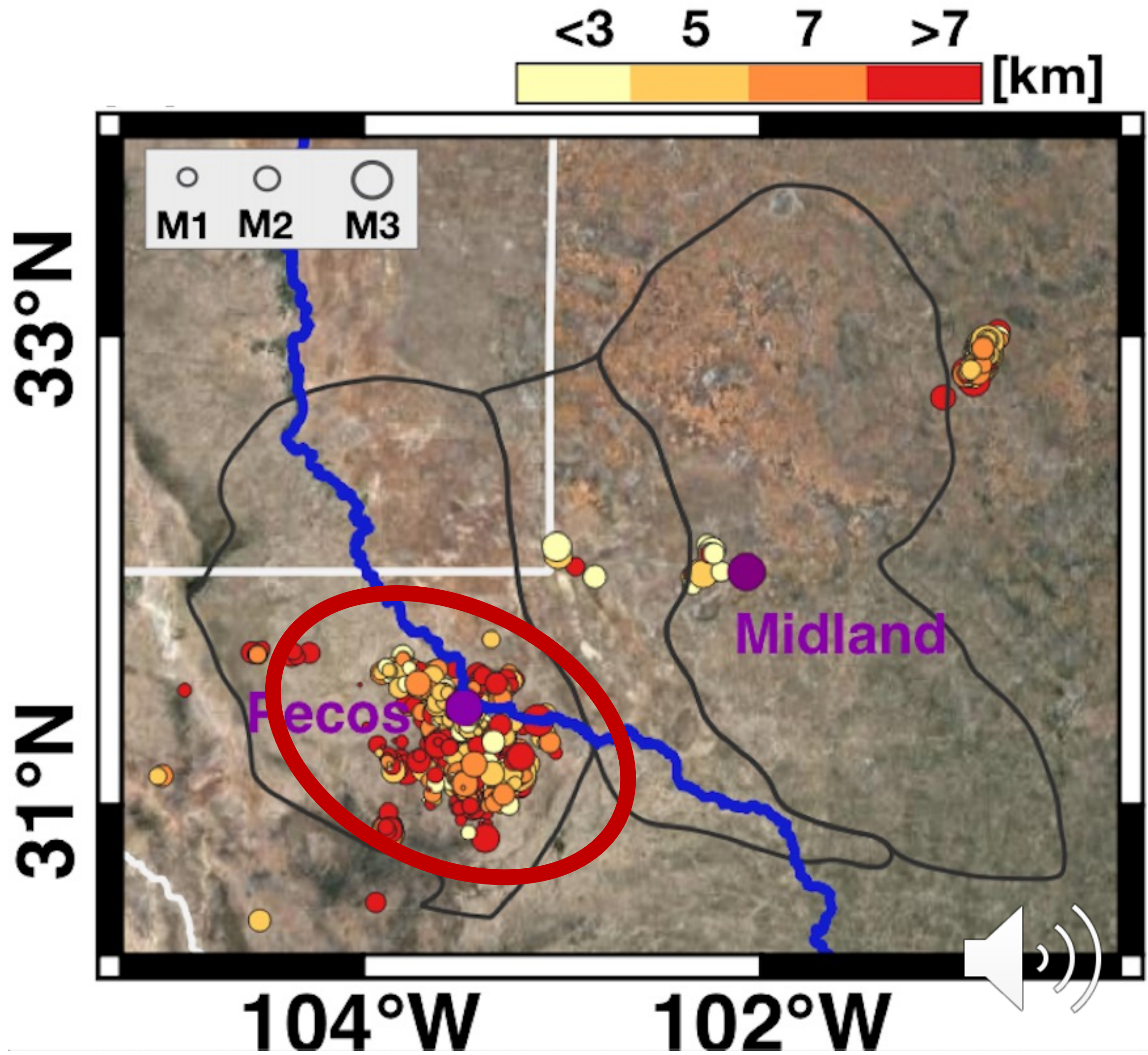


Low p-value detections: $p < 0.01$

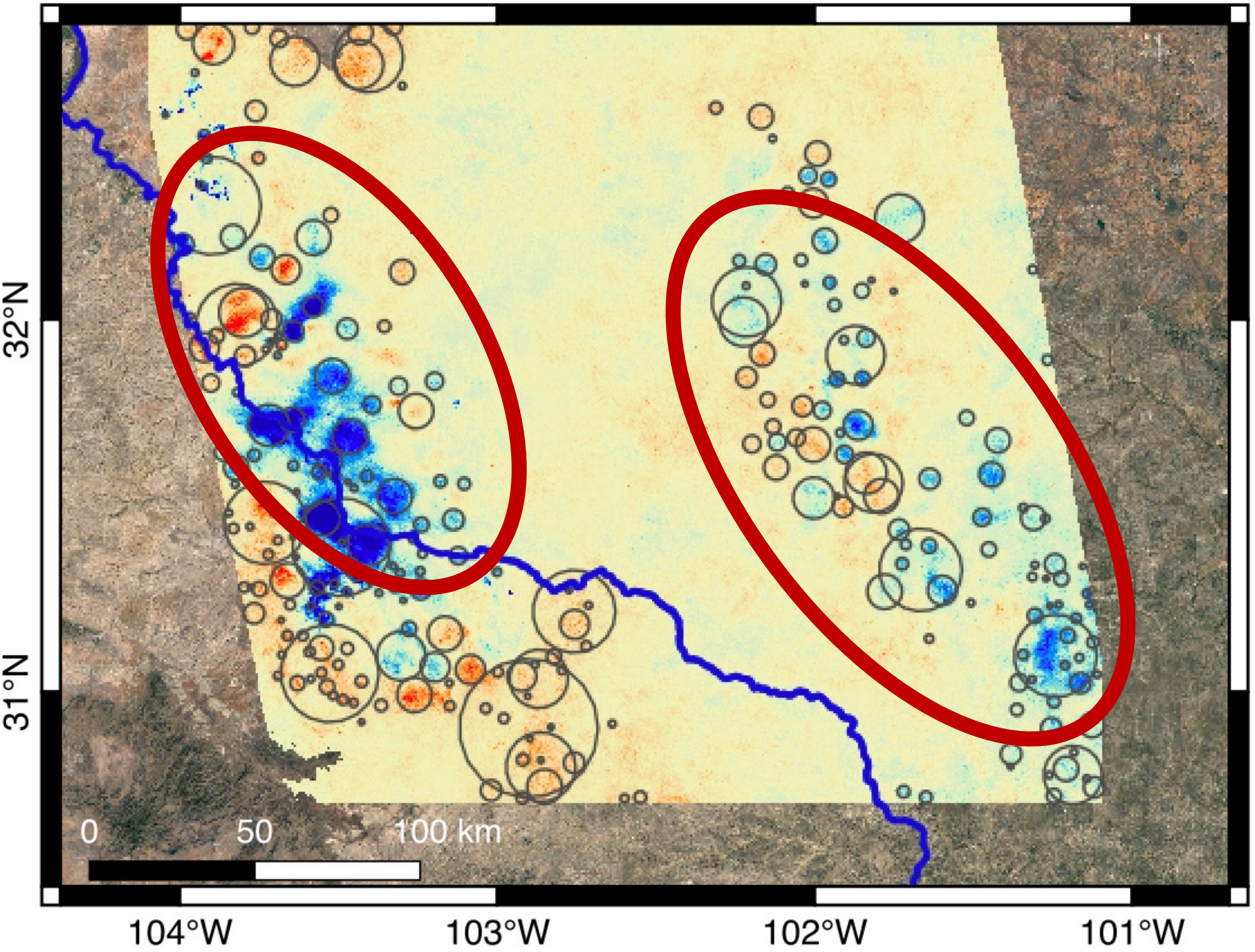


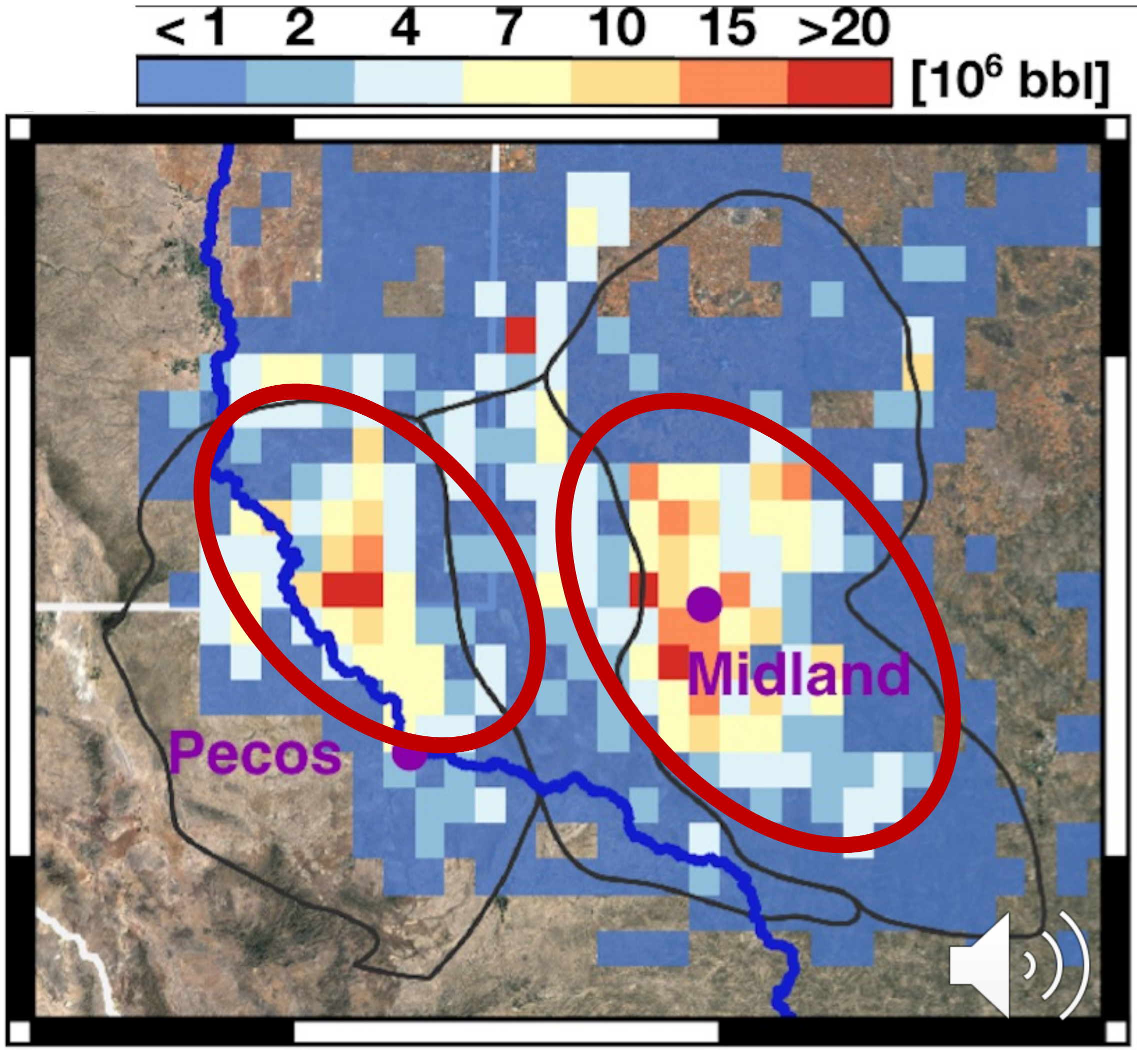
Low p-value detections: $p < 0.01$



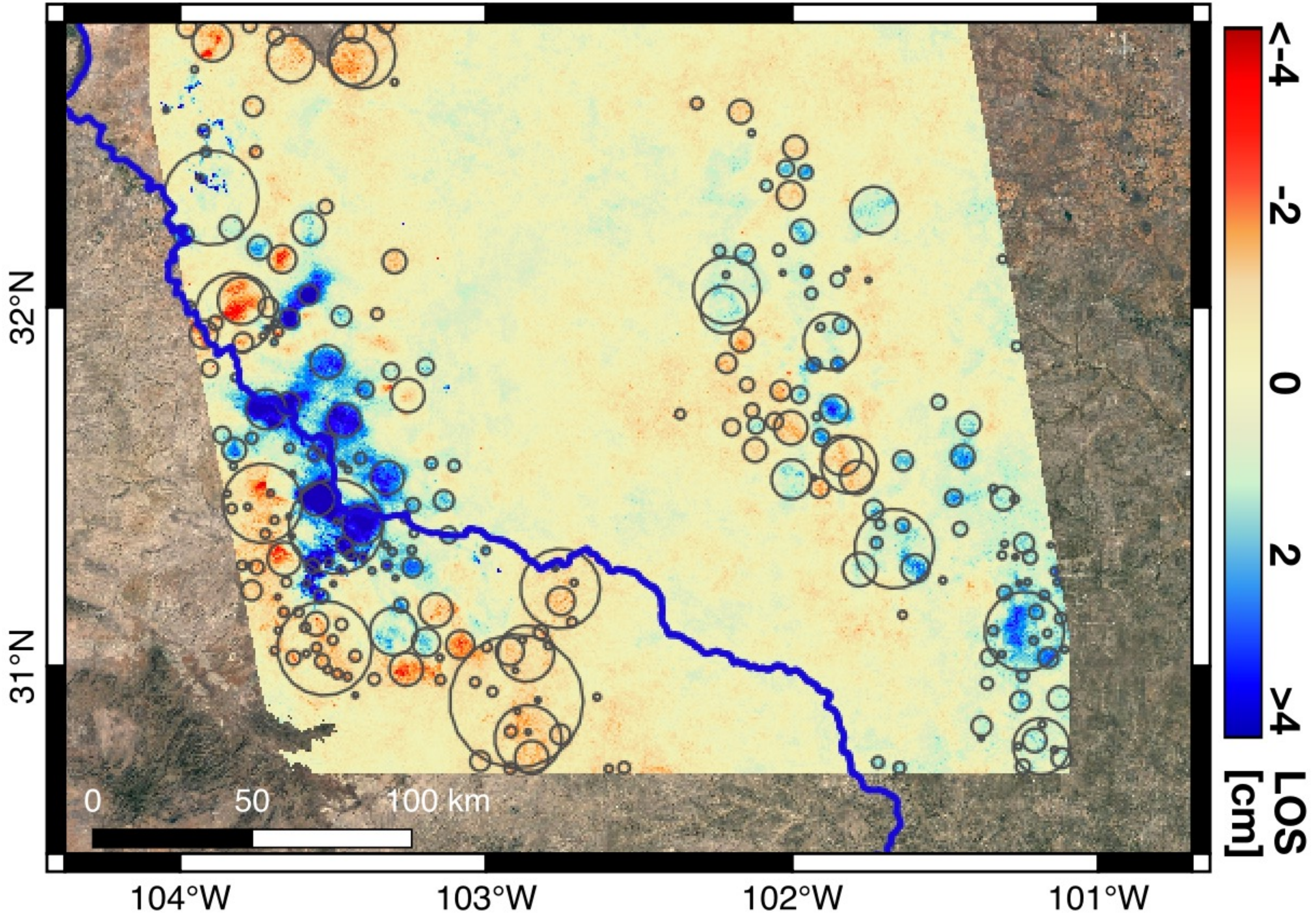


Low p-value detections: $p < 0.01$





Low p-value detections: $p < 0.01$



Low p-value detections: **p < 0.05**