FINE-SCALE MEASUREMENT OF CREEP ALONG THE SAN ANDREAS FAULT FROM REMOVAL OF DECORRELATED PIXELS IN INSAR TIME SERIES: A PROPOSED DATA FLOW FOR HIGH-VOLUME INSAR SYSTEMS

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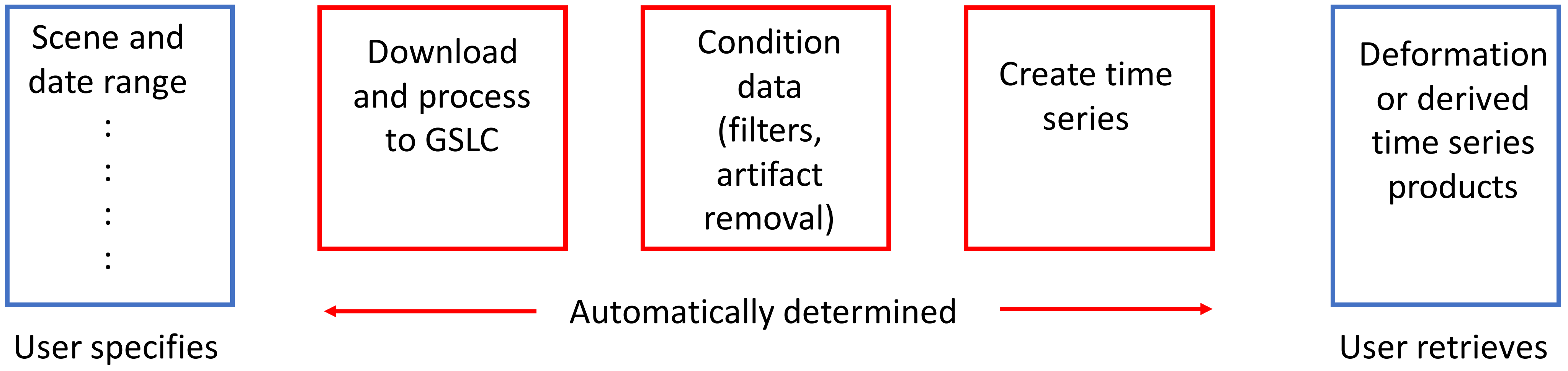
Automated production of InSAR time series

- Many sources for InSAR time series today
- Data volumes are large, scenes are many, interferograms are many•(many-1)/2
- Production from L0/L1 radar scenes can require much individual fine tuning
- Need routine generation of time series with minimal intervention
- Not quite ready for ML to solve this
    - Training sets too small
    - A good project for a future student

Goal

- Today we are solving the engineering problem, not the scientific one
- That problem:
  - How do we generate InSAR time series in ways that are routine and automatic
  - Very little human interaction
  - Results robust and reasonably optimized for quality and speed



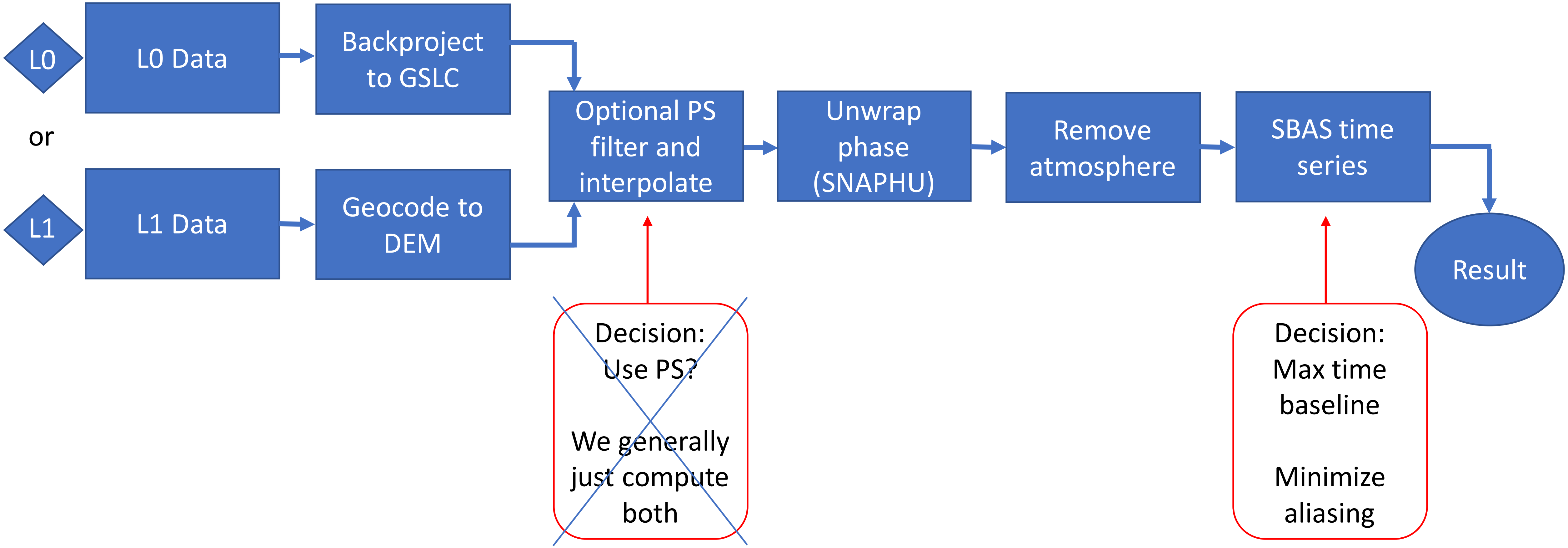
Lots of pieces exist already

- Backprojection for geocoded single look complex images (Zebker 2017)
- SBAS time series solutions (Berardino 2002)
- PS filtering for noise reduction (Hooper 2006)
  - MLE candidates (Agram 2007)
  - Cosine similarity filtering (Wang and Chen 2022)
- Robust phase unwrapping from SNAPHU (Chen 2002)
- Tropospheric artifact reduction (Zebker 2021)

- Here we combine these steps for a robust data flow that requires little to no tuning
- Now available as a standalone system, plan to integrate into ISCE software

Data flow

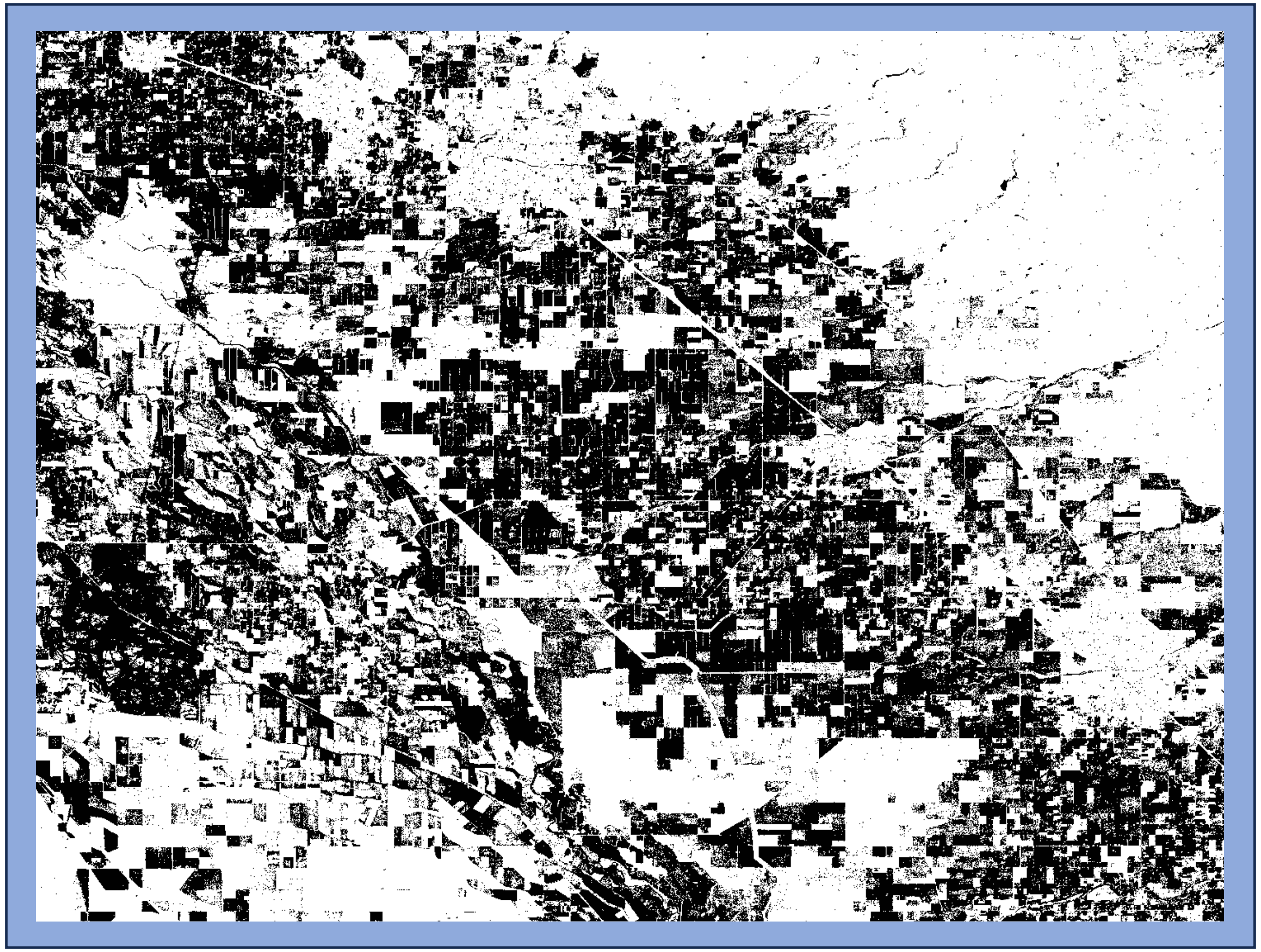
- Nearly all parameters fixed in nominal sequence



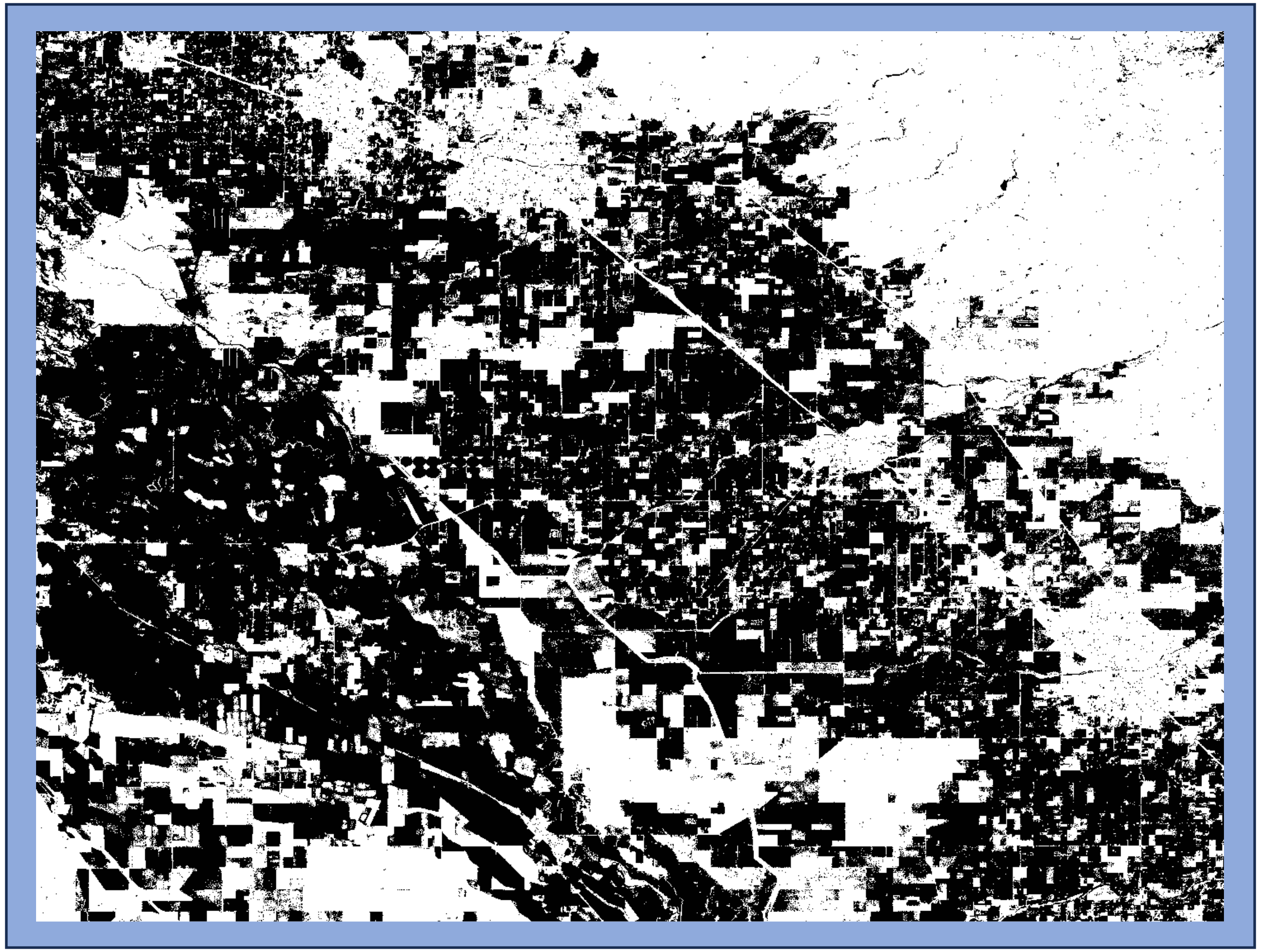
Processing details

- Prefer L0 initial products with backprojection to geocoded SLC
- PS filtering
  - First pass MLE with SCR threshold = 2
  - Downselect candidate PS thru cosine similarity (Wang and Chen, 2022)
  - Three iterations of cosine similarity, filling missing pixels
  - Spiral interpolation back to all geocoded pixel locations
- SNAPHU out of box with MCF initialization
- Atmospheric artifact removal – regression vs height
- Unweighted SBAS using maximum temporal baseline with minimal aliasing

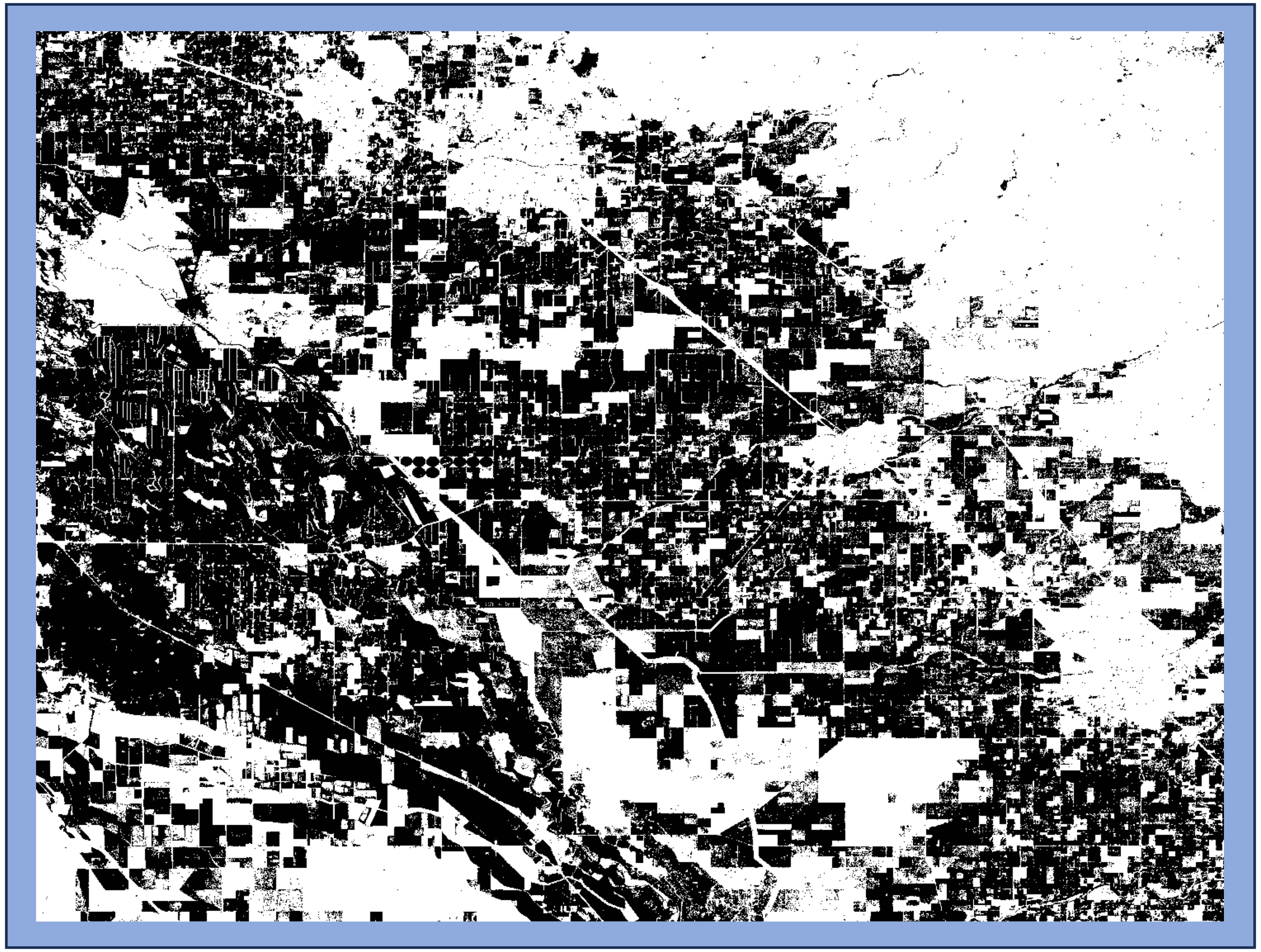
Candidate PS: use MLE, overselect here



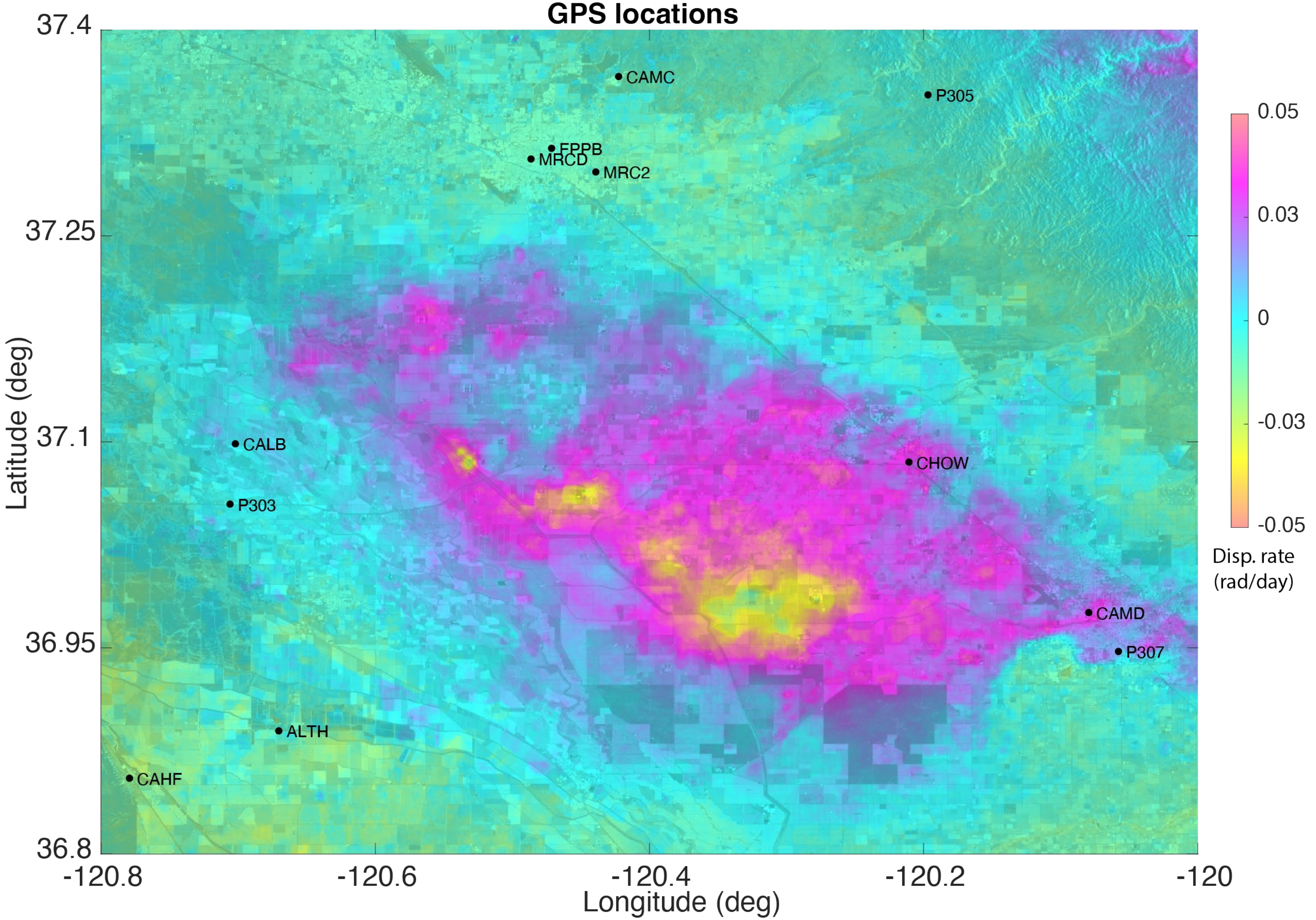
Remove false positives with cosine similarity



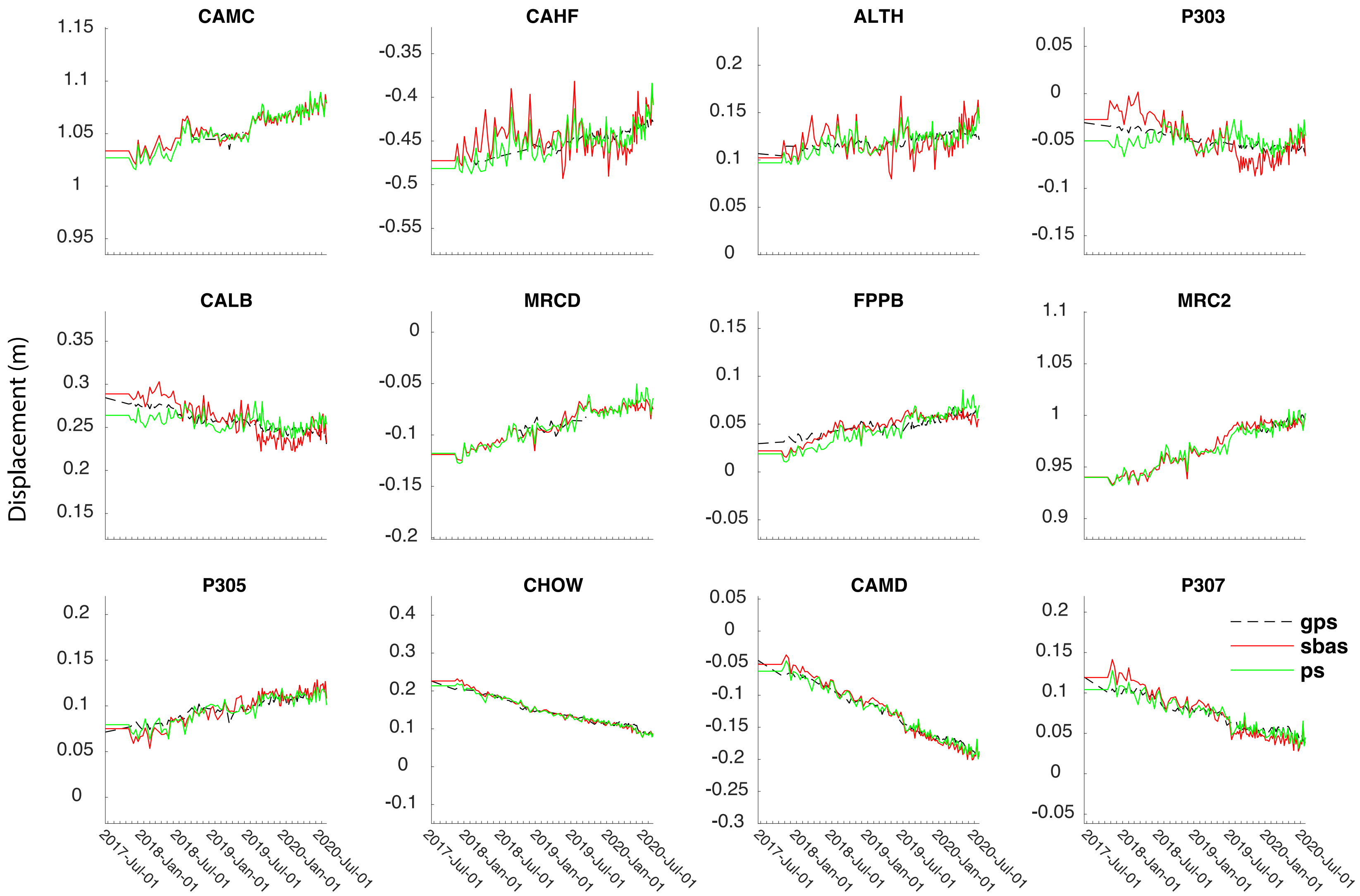
Fill in misses with cosine similarity



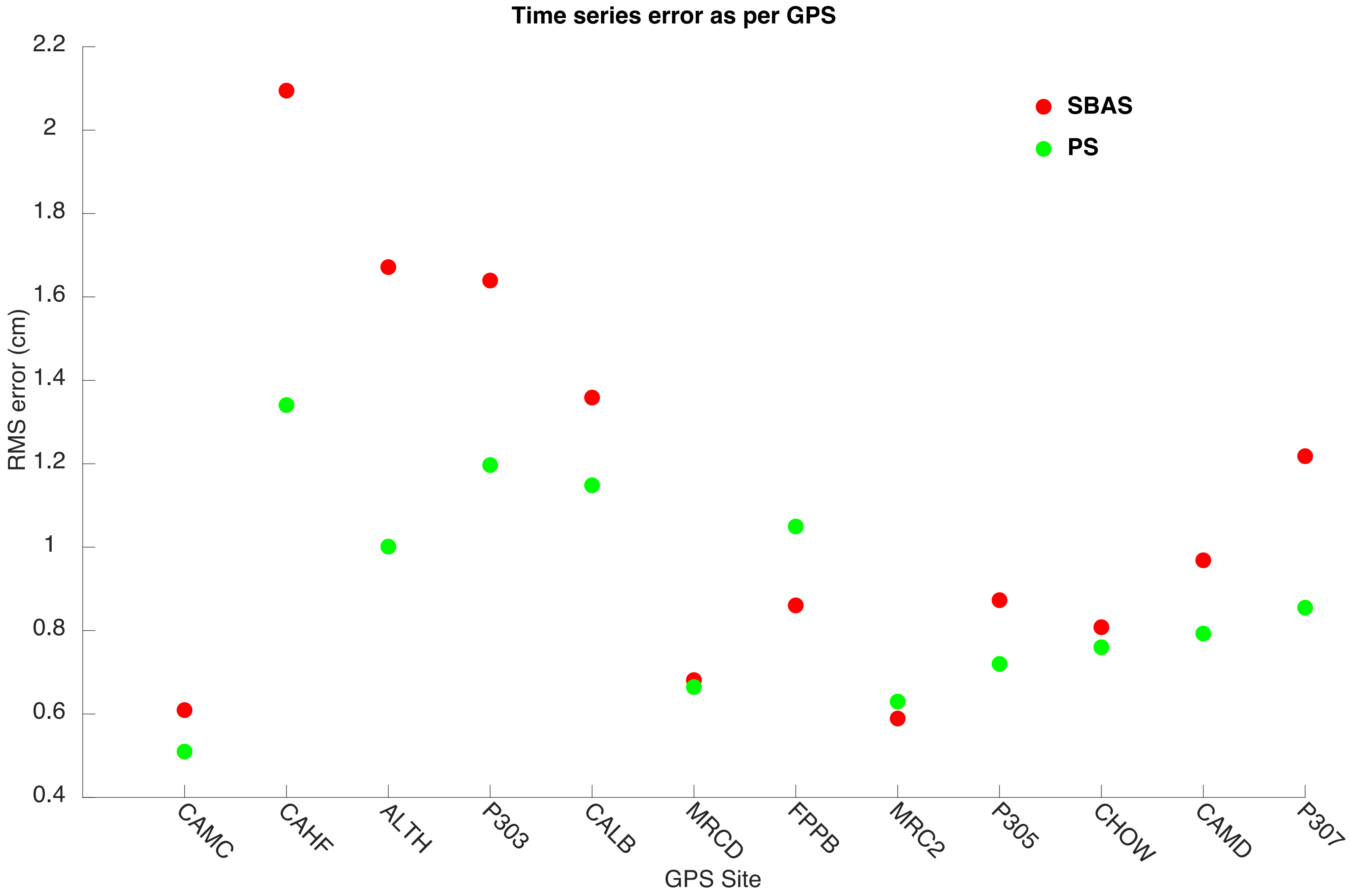
Interpolate holes and apply SBAS



Accuracy: Check vs GPS

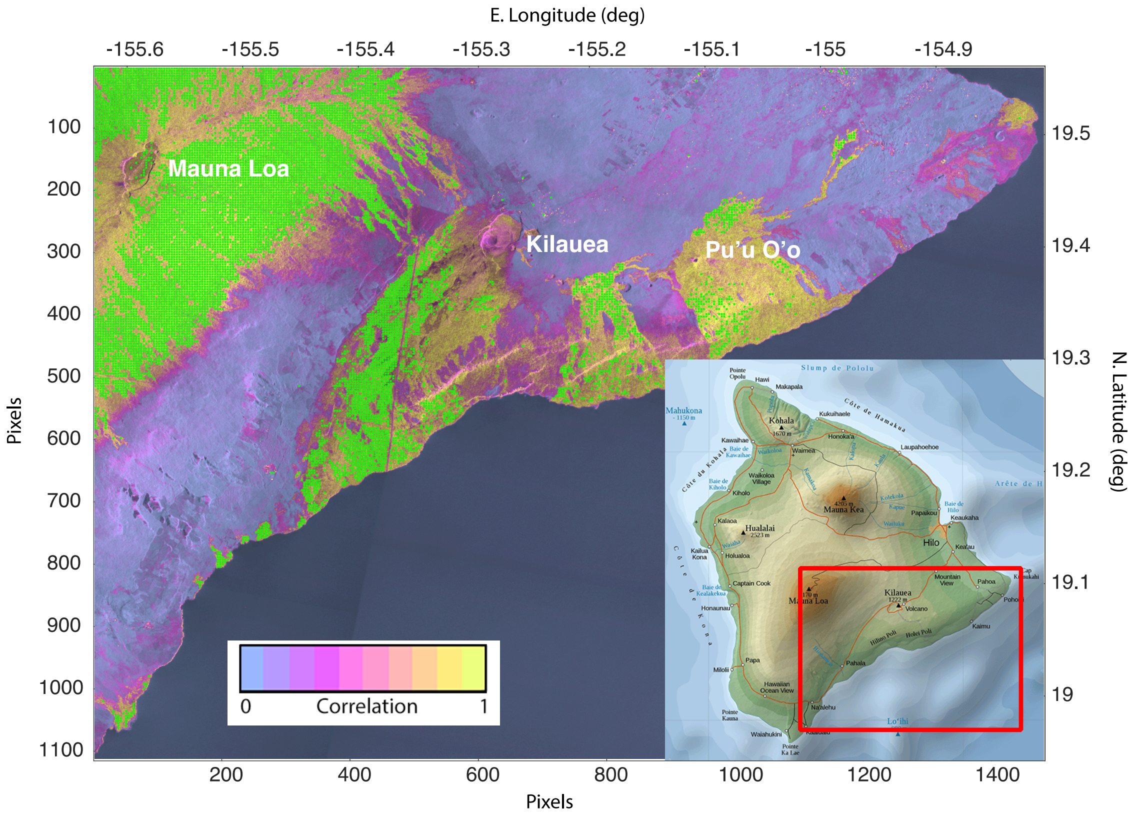


Errors: SBAS-only vs PS

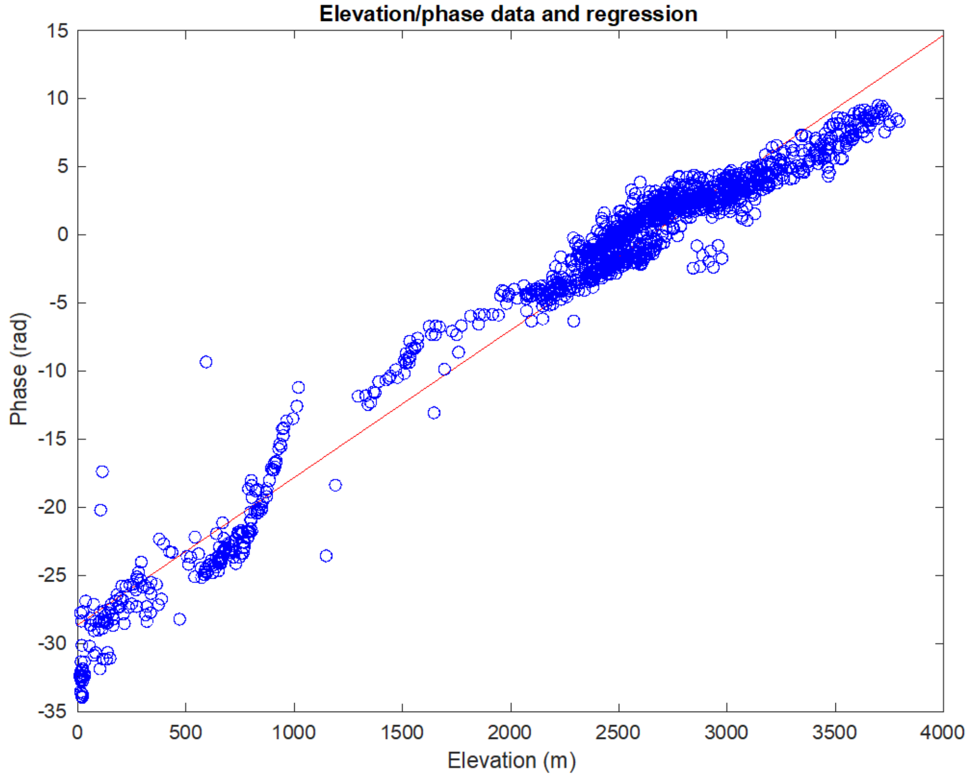


Remove troposphere via elevation regression

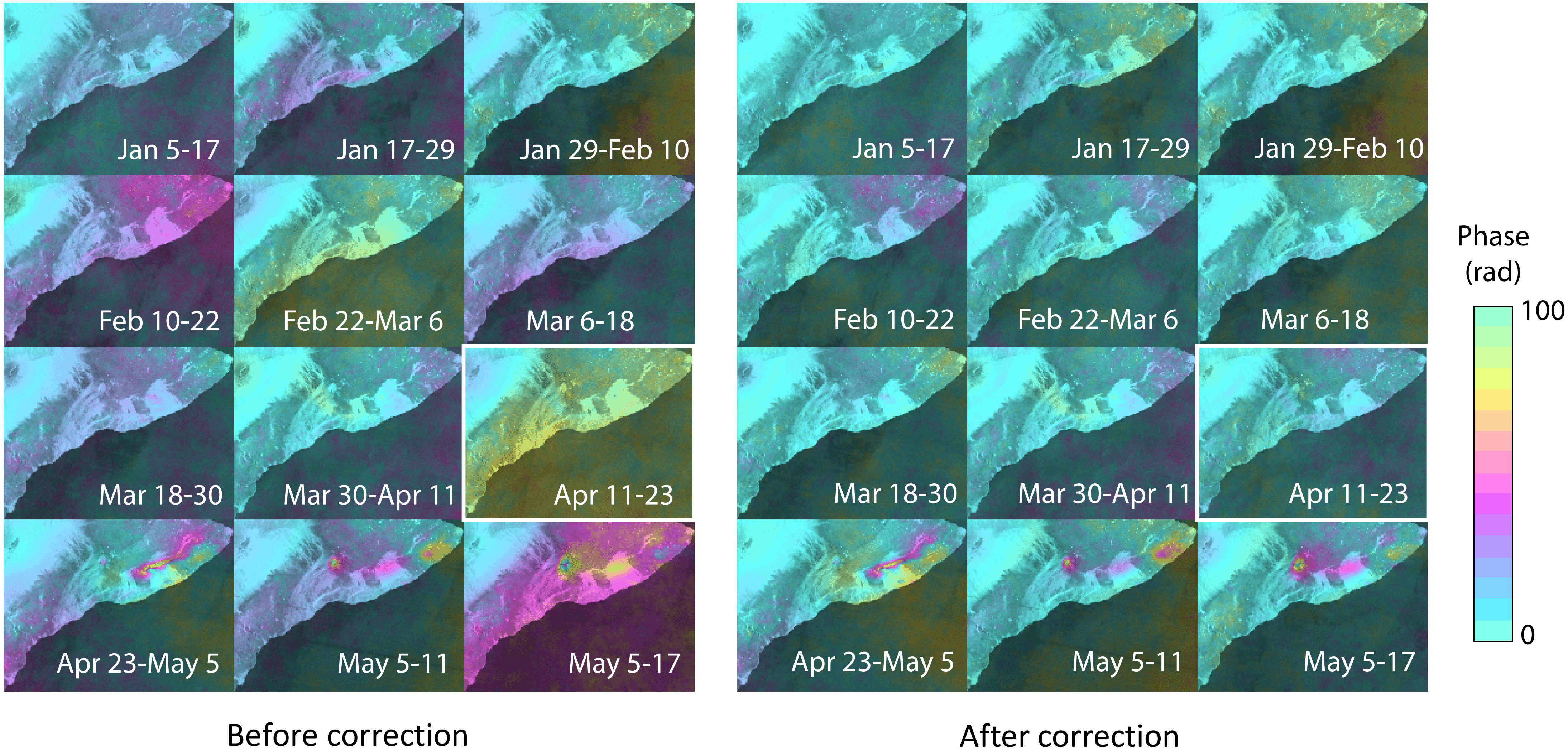
Select coherent points



Remove height dependence



Correction applied to each interferogram



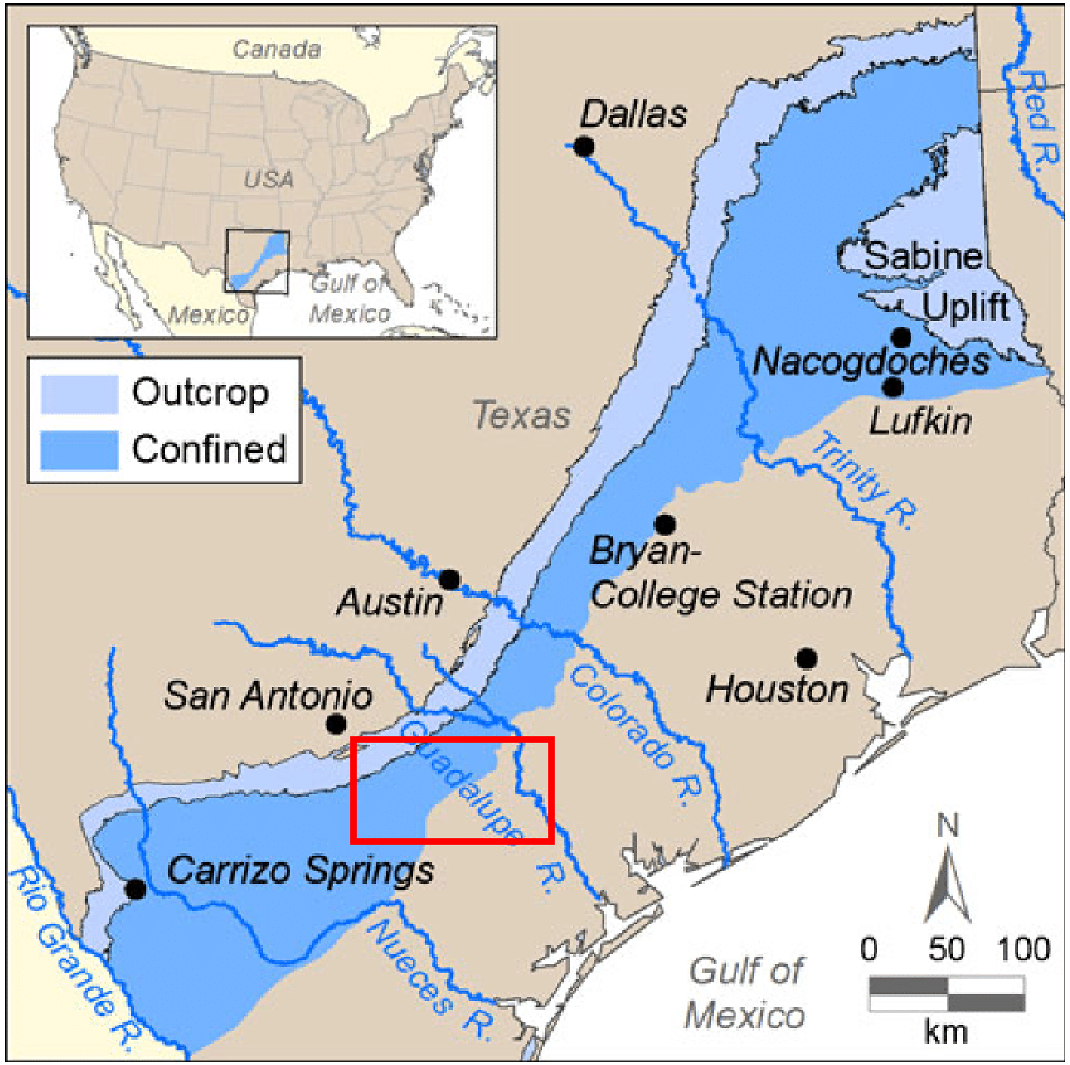
Two application examples

- Creep rate along San Andreas Fault (SAF) creeping section
  - Goal: finer spatial scale than is available from current GPS

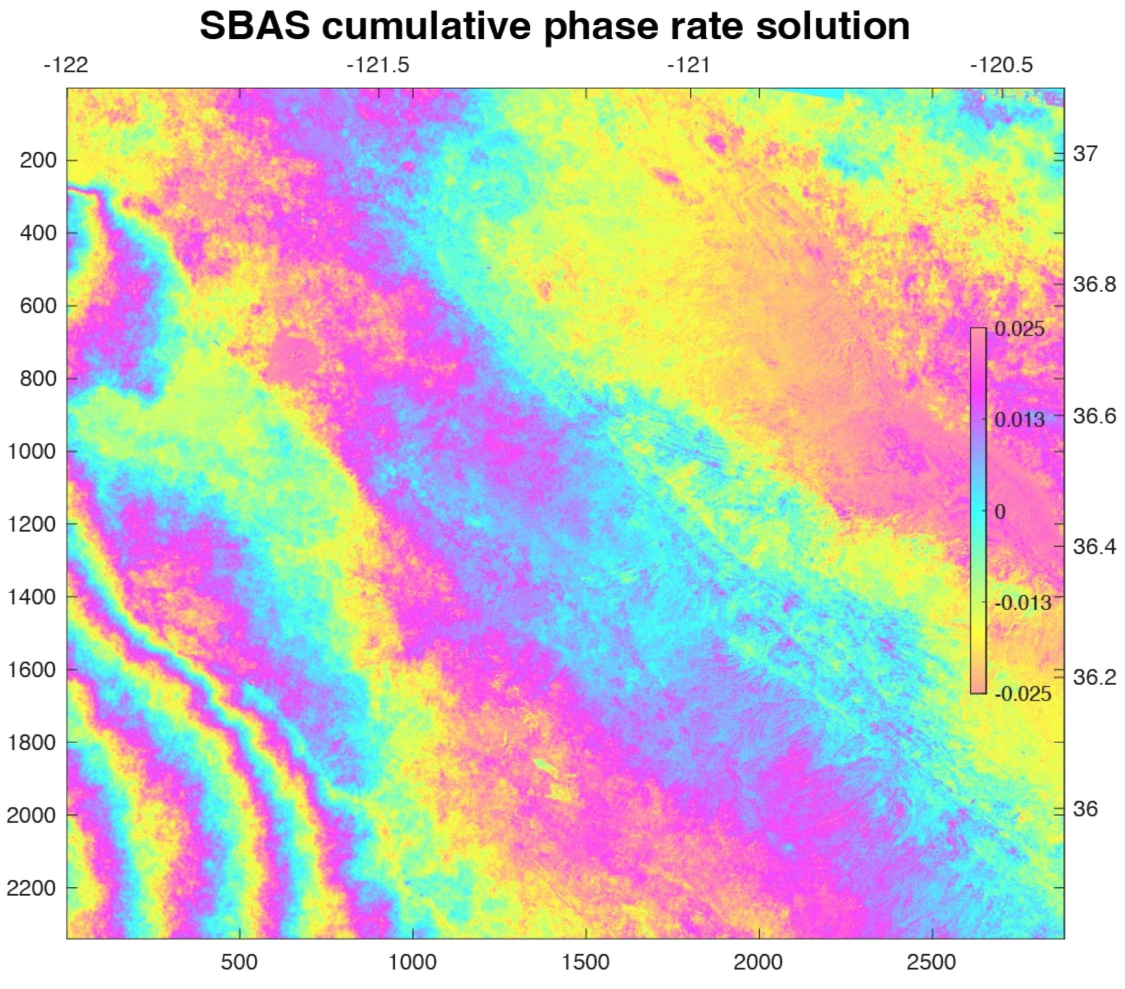
- Subsidence due to water withdrawal from Carrizo-Wilcox aquifer near San Antonio, TX
  - Goal: observation in highly vegetated area

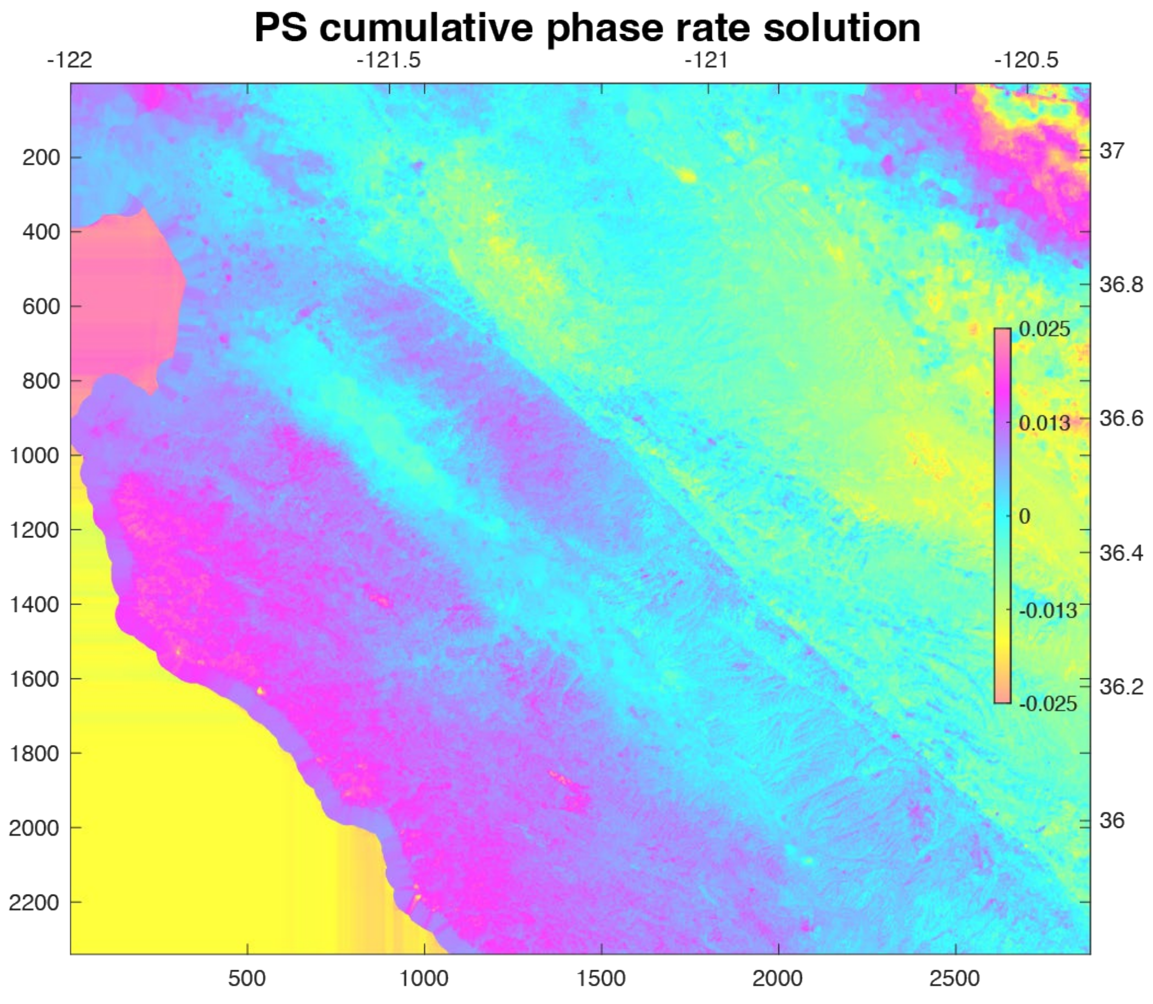
SAF creeping section may accommodate strain and lessen risk

Carrizo-Wilcox aquifer – a vegetated terrain

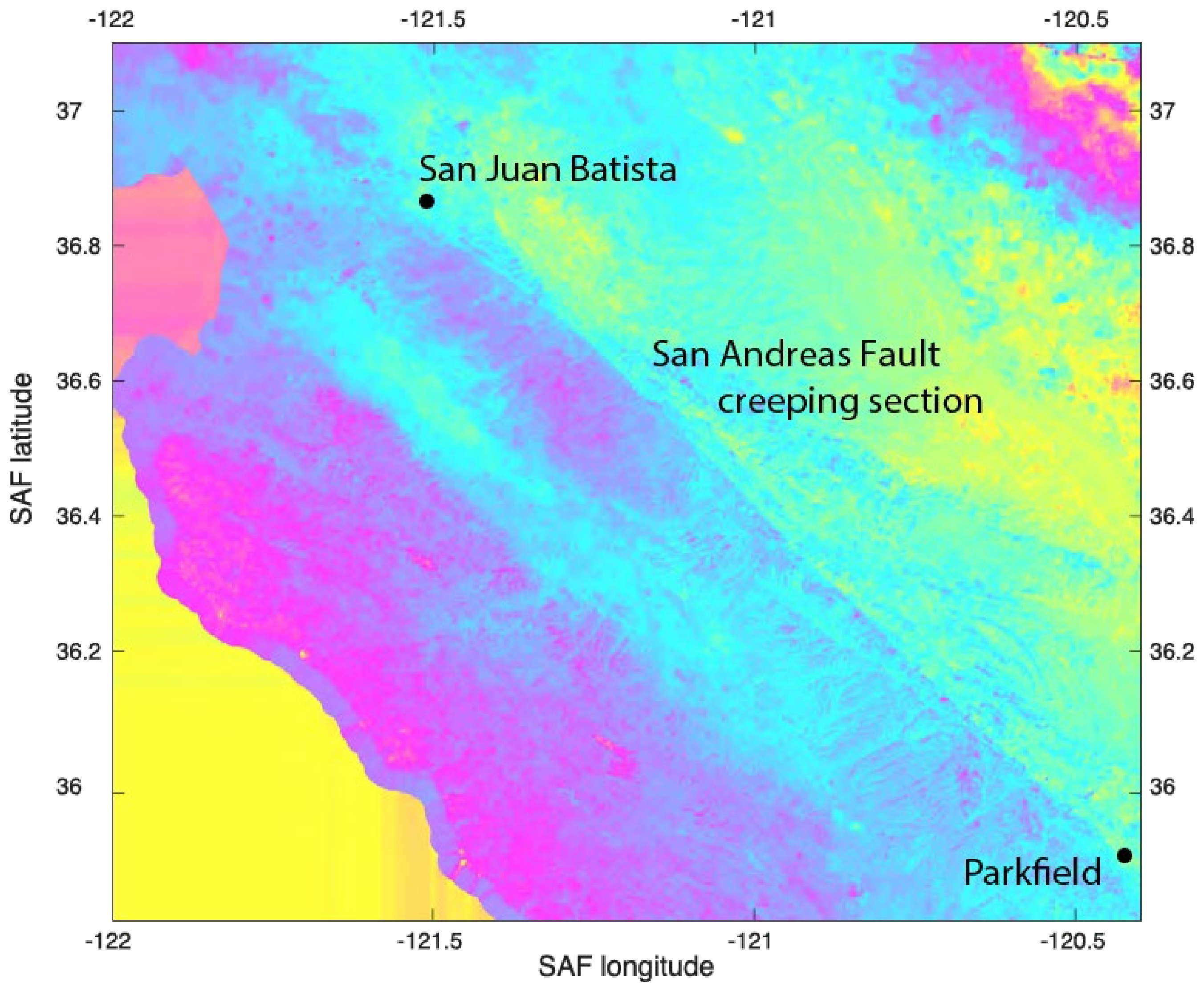


SBAS/PS SAF creep rate solutions

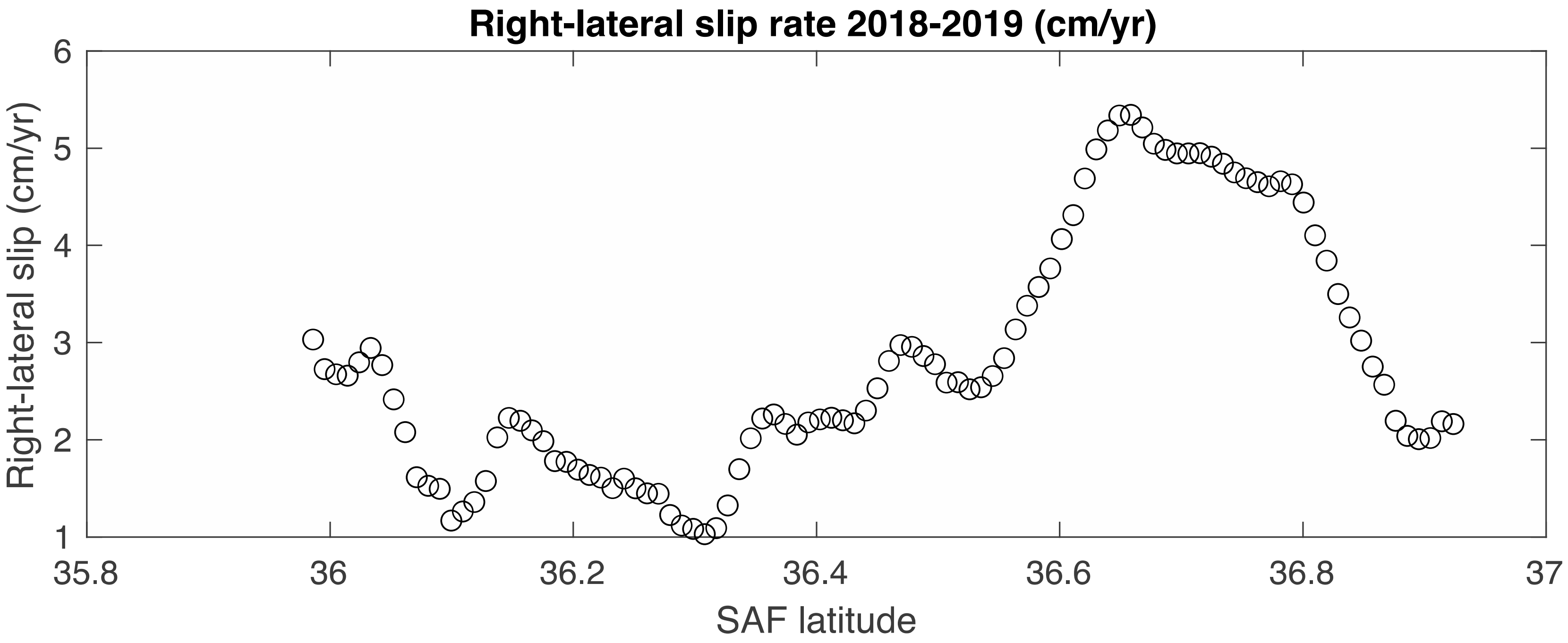




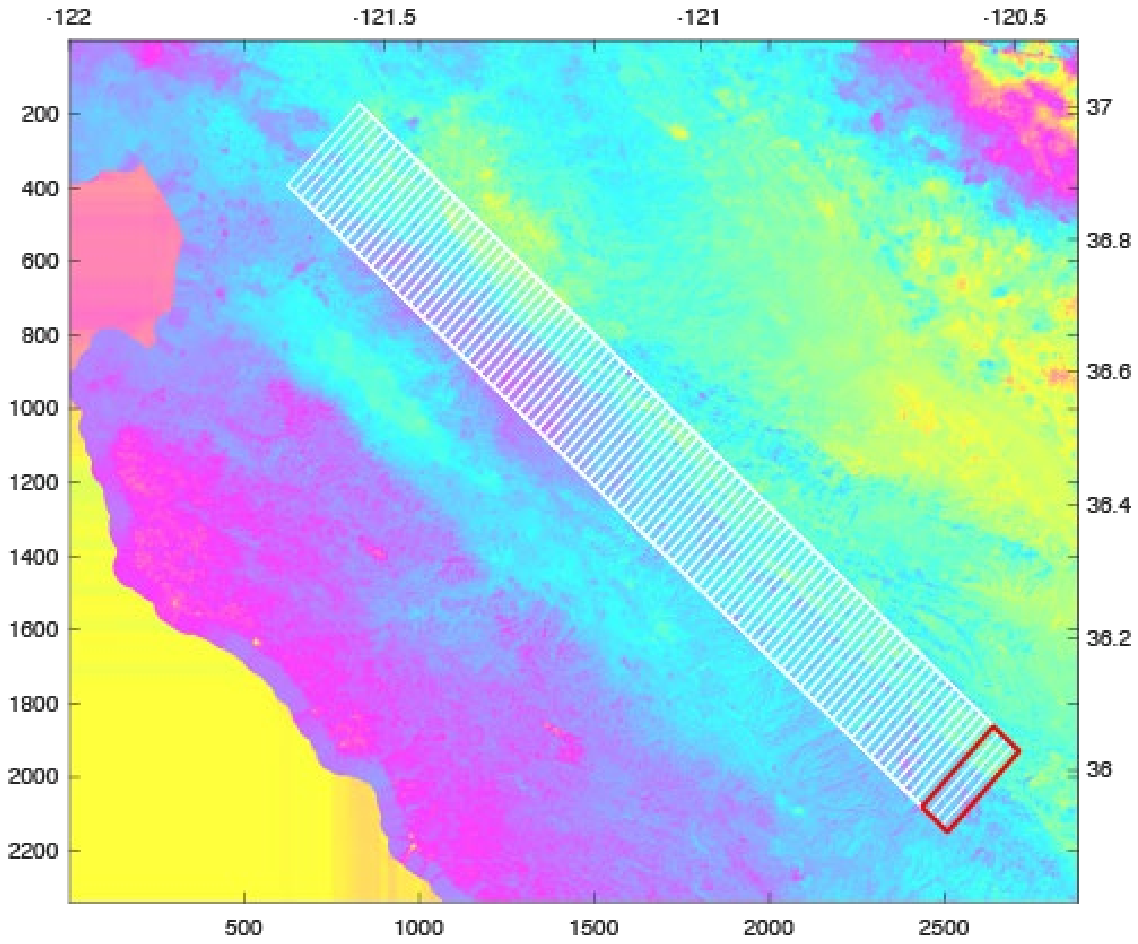
Fine resolution solution for creep rate 2018-19



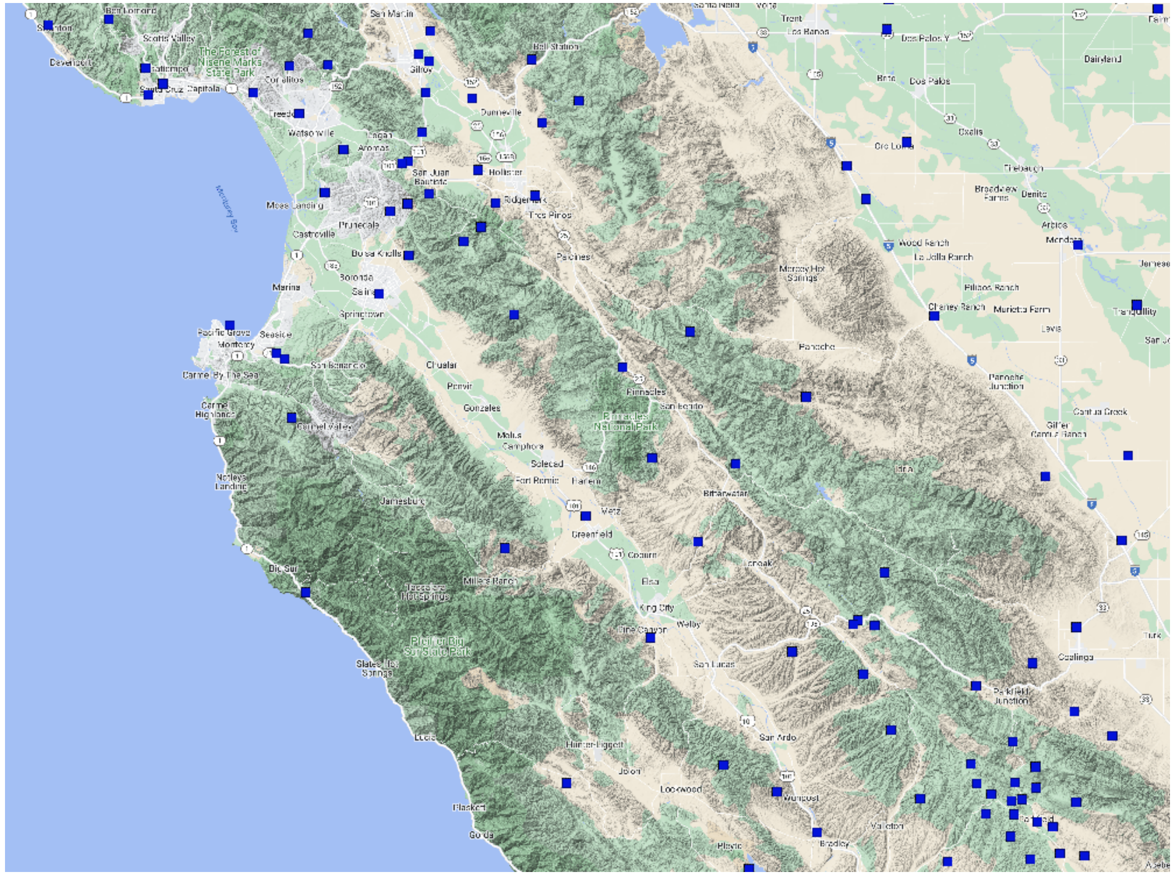
Right lateral slip rate along creeping section



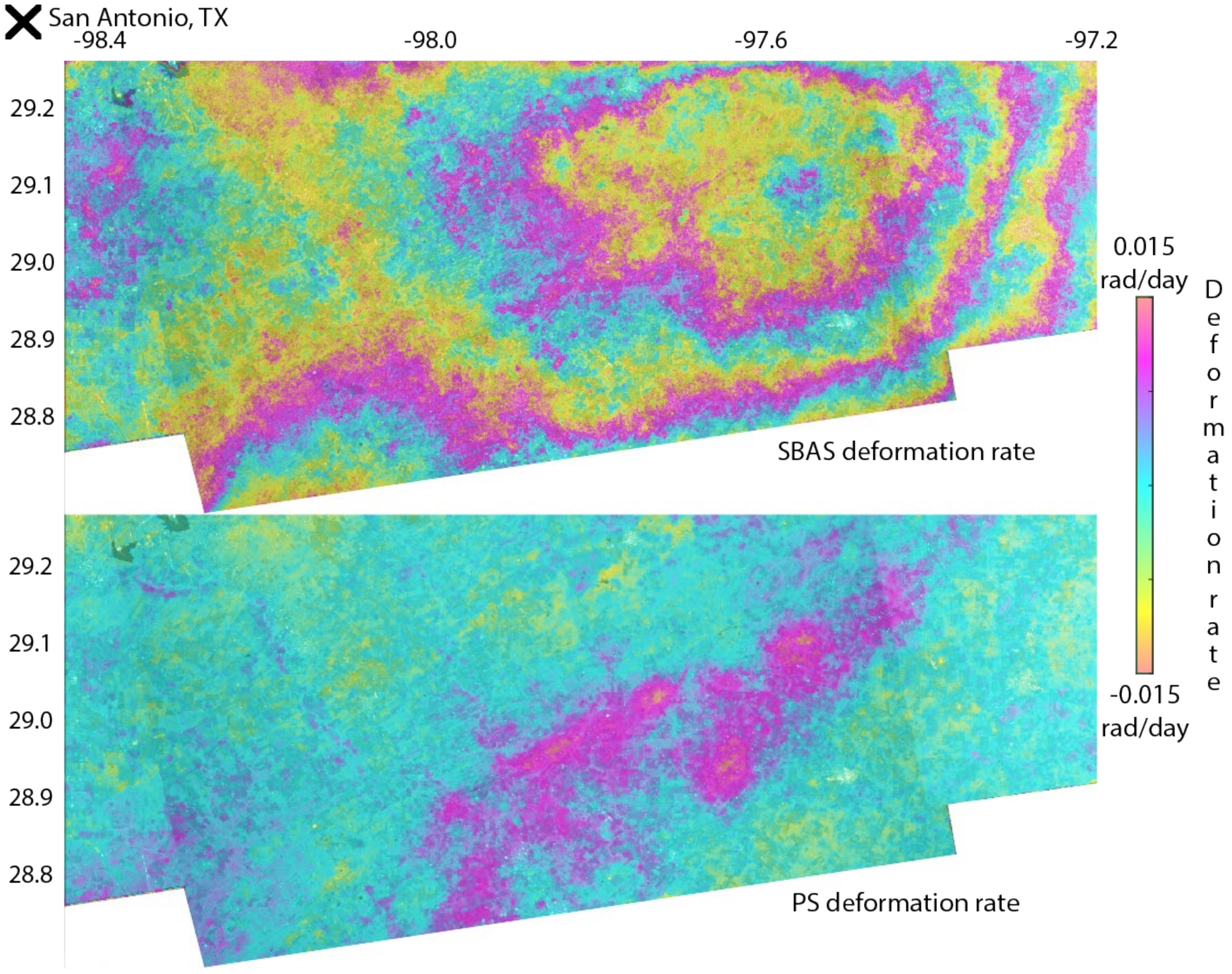
Averaging boxes for InSAR rate measurement



GPS coverage along creeping section



Aquifer subsidence, SE of San Antonio, TX



SBAS-only solution exhibits false signature from multiple phase unwrapping errors

PS filter solution shows clear aquifer subsidence signal

Conclusions

- Developed a robust and accurate software architecture
  - Use as standalone soup to nuts package
  - Plan to integrate within ISCE (3? 4?)
- Standardized parameter selection for consistency – could be edited
- Performance (untuned) yields finer spatial result than GPS at cm- to mm-level
- Routine application reveals deformation in highly decorrelating areas
- Future work could develop context-sensitive parameters
- With a large enough data set might enable ML parameter selection and data interpretation