Automated Processing, Streaming, and Integration of InSAR Time Series and GNSS Data; as part of the Collaborative GeoSciFramework Research Project

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What is GeoSciFramework?

The **main goal** of the GeoSciFramework project is to improve intermediate-to-short term forecasts of catastrophic natural hazard events, allowing researchers to instantly detect when an event has occurred and reveal the more suppressed, long-term motions of Earth's surface at unprecedented scales.

Data: Seismic, GNSS, tide gauge, and satellite SAR data are all effective tools used to characterize earthquakes, tsunamis, and volcanic eruptions. However, the size and complexity of the data, combined with models and the required processing steps makes evaluating hazards for early warning a Big Data problem.

Framework: Geoscientists and computer scientists are working together to build a real-time processing system capable of streaming multiple large data sets while employing machine learning algorithms designed to recognize signals produced by geophysical events.

Using DInSAR to Measure Short-to-Long Term Hazard Events:

Automated processing of differential interferometric synthetic aperture radar (DInSAR) over Yellowstone National Park and the Big Island of Hawaii will be streamed into the GeoSciFramework to measure ground deformation and associated time series. Time series will be integrated with other data sets, including in situ seismic, strain, GNSS, gas and thermal sensors. Machine learning will be performed on all data sets to detect geophysical hazards.

We have successfully automated InSAR time series using traditional methods (See figures 1 and 2) on GMT5SAR and GIAnT. We are currently comparing results from the recently proposed method by Zebker & Zheng (2017), by rewriting C code on GMT5SAR. The method utilizes only the phase component of the radar signal to obtain time series (See Figure 1).

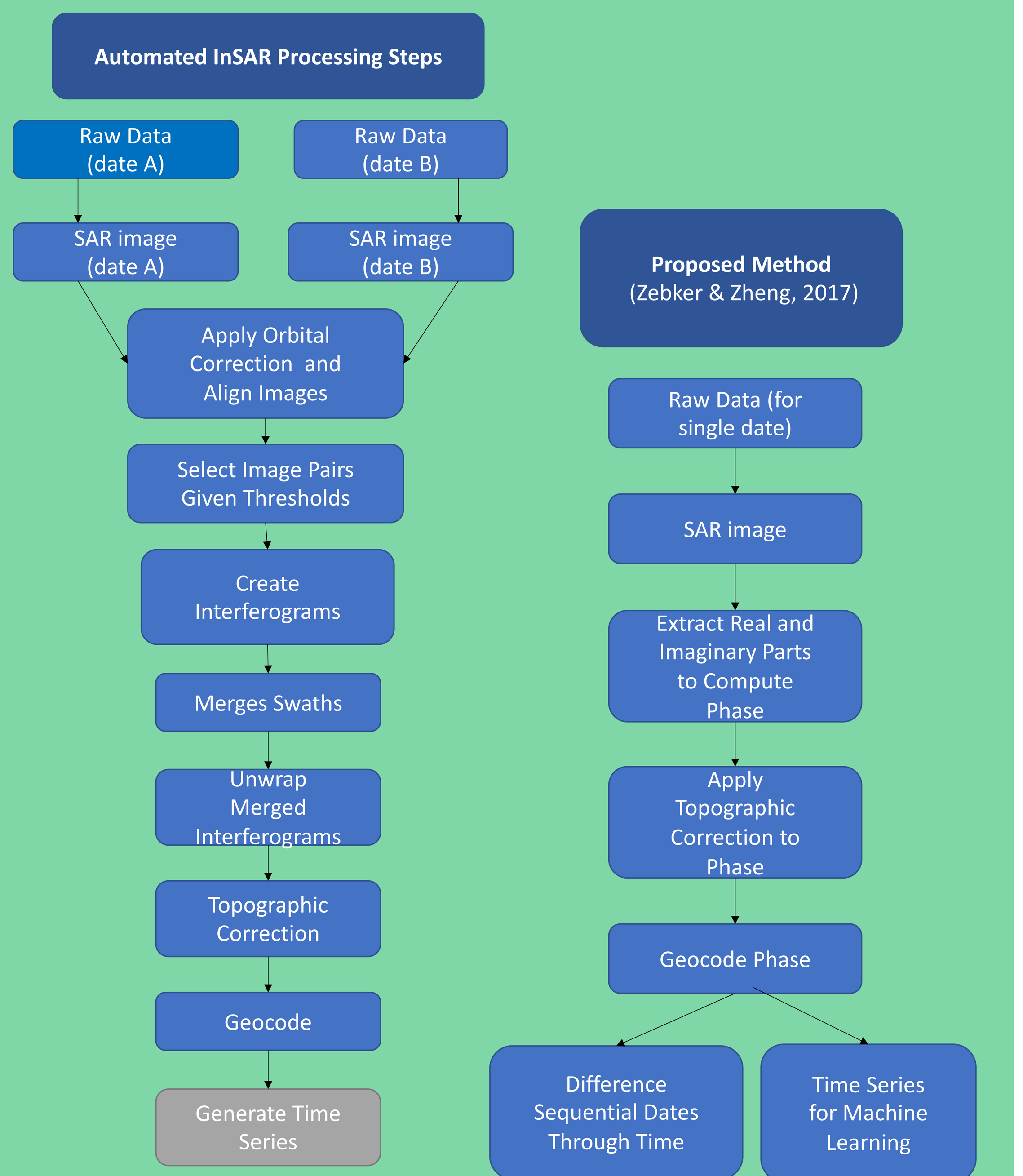
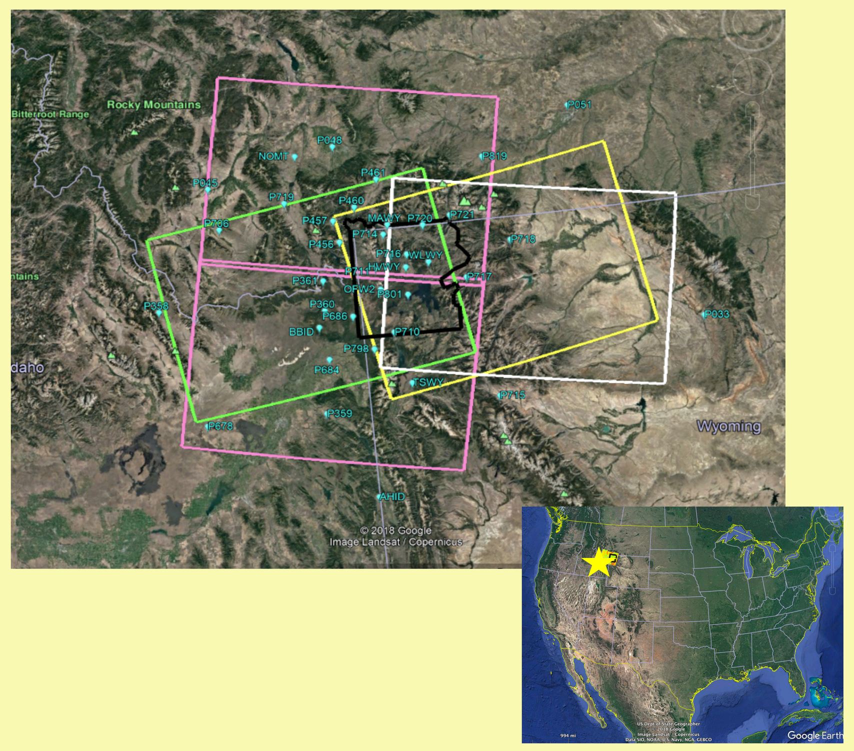


Figure 1: The left diagram shows how our automated InSAR code generates time series on GMT5SAR (blue) and GIAnT (gray). The entire process can take multiple days to compute on the Summit Supercomputer in Boulder. The diagram on the right shows our interpretation of Zebker & Zheng's more efficient approach, which can take only hours to compute.



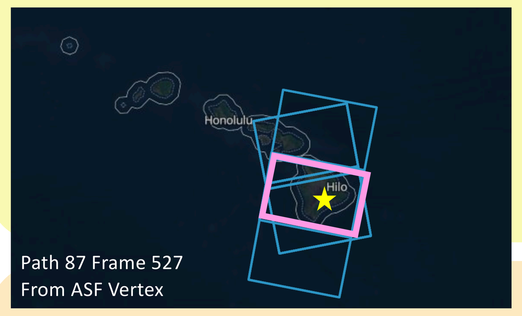


Figure 3: Above are SAR scenes over Yellowstone National Park and below are scenes over Hawaii Island. SAR scenes from multiple satellites using various wavelengths are integrated into a single time series of ground deformation using the Multidimensional Small Baseline Subset (MSBAS) method (Samsonov and D'Oreye, 2012).

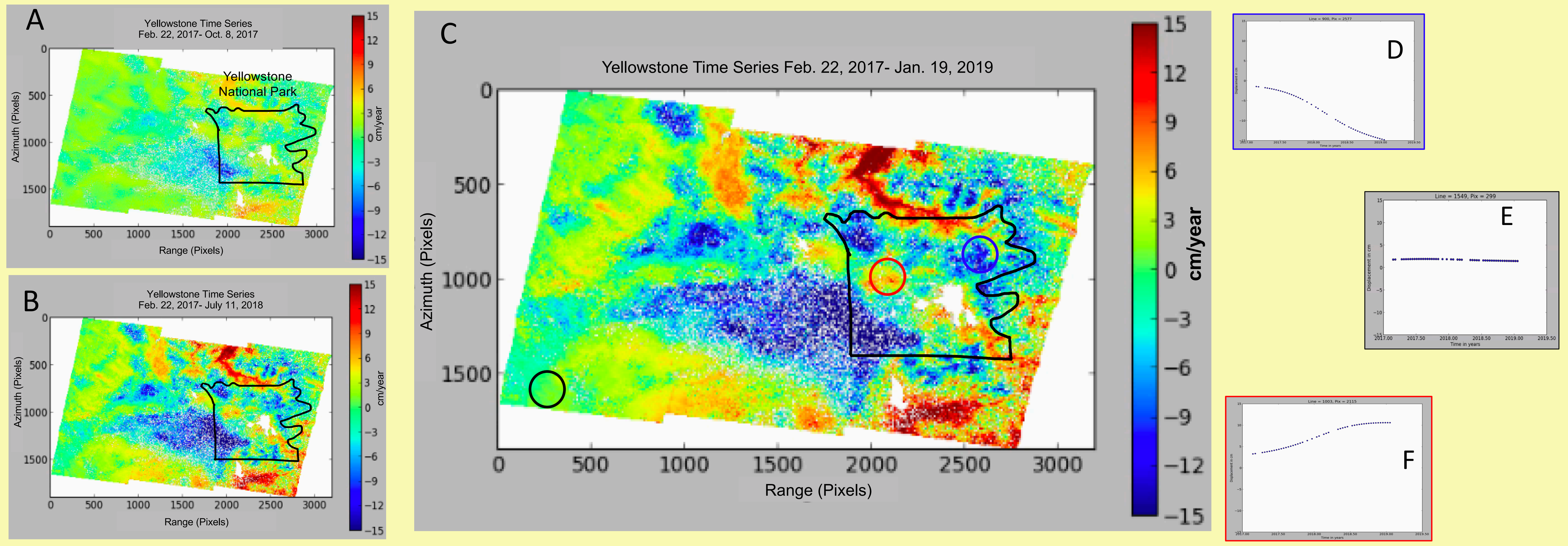


Figure 2 (above): Cumulative LOS displacement time series maps from Sentinel-1 data over Yellowstone National Park from Feb. 22, 2017 to A) Oct. 8, 2017, B) July 11, 2018, and C) Jan. 19, 2019. The complete time series, as shown in C, is generated using 117 interferograms produced on GMT5SAR and GIAnT using descending Path 100 and Frames 441 & 446, (as of 12/3/19 and outlined in pink in Figure 3). Figures D-F show the time series at a specified pixel, corresponding to the appropriate colored circle in C.

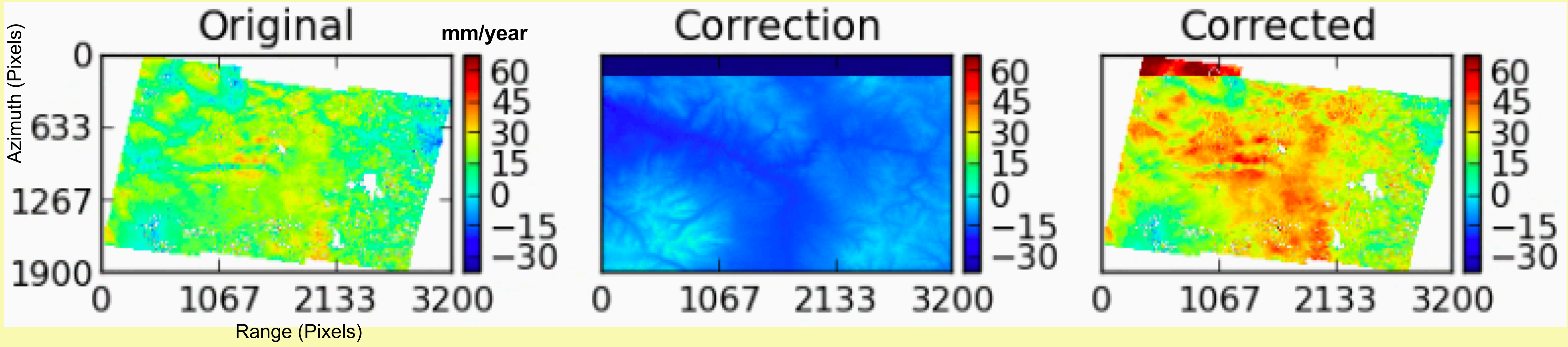


Figure 4 (above): Atmospheric correction in SAR interferograms from the Generic Atmospheric Correction Online Services (GACOS). The interferogram spans dates 09/02/17-10/20/17. This is a more extreme case that demonstrates how DInSAR results can be significantly effected when applying an atmospheric correction.

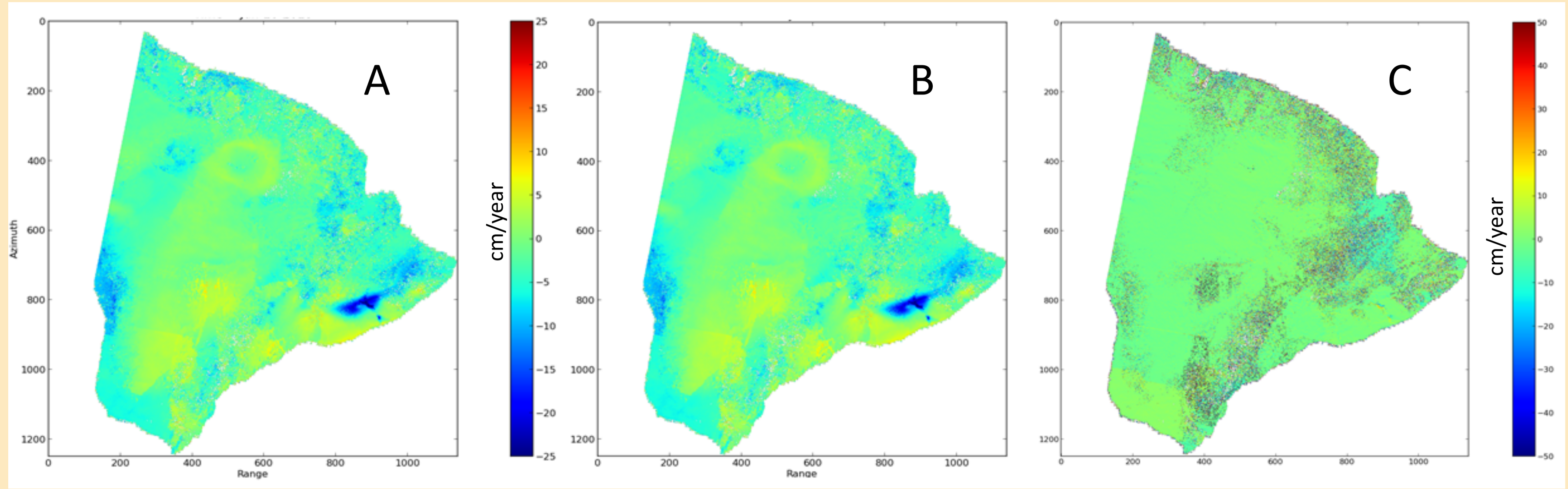


Figure 5 (left): Impact of using precise and real-time orbits in time series over Hawaii from Oct. 2017 to June 2018. A) Uses only precise orbits. B) 39 images using precise orbits and 6 using real-time. C) The difference between A and B. (Note change in scale)

Next Steps:

1) Integrating additional data set/time series into the streaming analysis.
2) Modeling of volcanic processes, specific to both Hawaii and Yellowstone
3) Machine learning analysis of integrated time series.

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