

Sarvalanche -S1 Avalanche Detection Pipeline

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What is sarvalanche

- Python package that handles data finding, reprojection, differencing, and detection for avalanche debris. Pytest implemented.
- How does it work? Combines static probabilities of avalanches debris (slope, fcf, runout probability, water mask) with SAR features (local resolution weighted backscatter change currently)
- IO – we get S1 (opera rtcs, local resolution), forest cover, slope angles, UCLA snowmodel SWE, and run the FlowPy debris flow model over a dem to generate runout cell counts.

What is sarvalanche

- Runtime – over most of Sawtooth Mountains full run (including flowpy modeling (95% of time) takes 33 minutes. Non-flowpy run time = 2 minutes, data-loaded already = <1 minute.

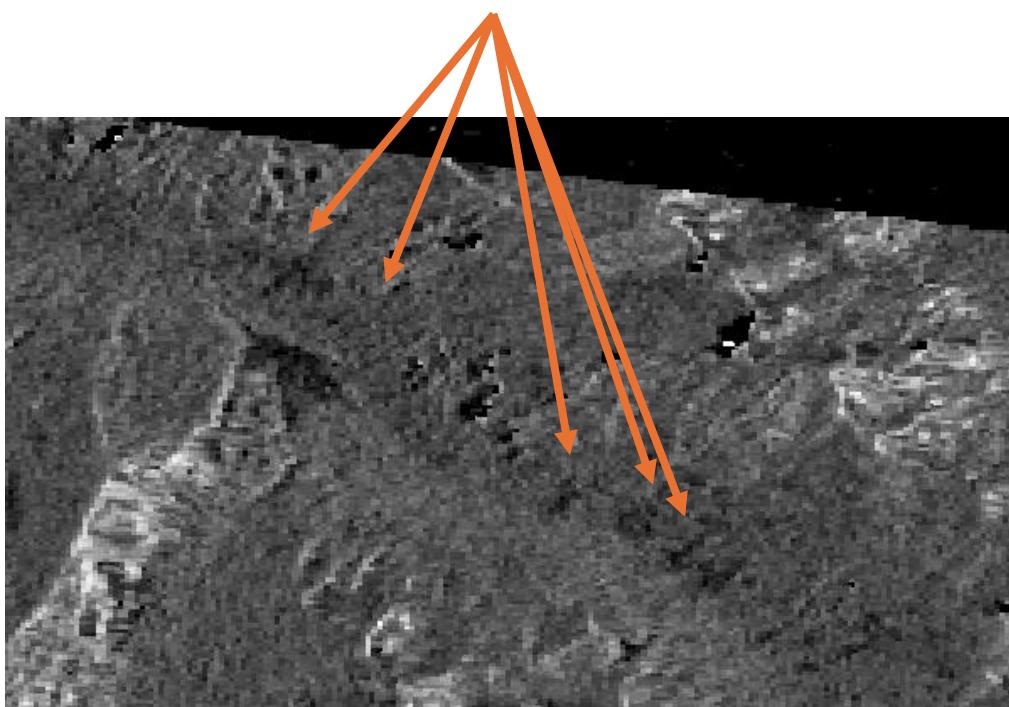
```
2026-02-11 17:11:52 - sarvalanche.utils.timing - INFO - 🕒 PIPELINE TIMING SUMMARY
2026-02-11 17:11:52 - sarvalanche.utils.timing - INFO - =====
2026-02-11 17:11:52 - sarvalanche.utils.timing - INFO -   3_load_assemble_dataset           32m 45s ( 98.4%)
2026-02-11 17:11:52 - sarvalanche.utils.timing - INFO -   8_export_results                 25.1 sec (  1.3%)
2026-02-11 17:11:52 - sarvalanche.utils.timing - INFO -   7_group_detections              3.6 sec (  0.2%)
2026-02-11 17:11:52 - sarvalanche.utils.timing - INFO -   6_pixelwise_probabilities      2.3 sec (  0.1%)
2026-02-11 17:11:52 - sarvalanche.utils.timing - INFO -   5_static_probabilities          98 ms (  0.0%)
2026-02-11 17:11:52 - sarvalanche.utils.timing - INFO -   4_calculate_weights            41 ms (  0.0%)
2026-02-11 17:11:52 - sarvalanche.utils.timing - INFO -   6.5_apply_masks                18 ms (  0.0%)
2026-02-11 17:11:52 - sarvalanche.utils.timing - INFO -   1_validation                   1 ms (  0.0%)
2026-02-11 17:11:52 - sarvalanche.utils.timing - INFO -   2_setup_cache                  0 ms (  0.0%)
2026-02-11 17:11:52 - sarvalanche.utils.timing - INFO - -----
2026-02-11 17:11:52 - sarvalanche.utils.timing - INFO -   TOTAL TIME                      33m 16s
2026-02-11 17:11:52 - sarvalanche.utils.timing - INFO - =====
```

```
2026-02-11 17:55:52 - sarvalanche.vendor.caflowpy.math - INFO - Starting FlowPy calculation (120 tasks, 12 workers)
FlowPy calculation: 100% | 120/120 [31:27<00:00, 15.73s/task]
2026-02-11 17:55:52 - sarvalanche.vendor.caflowpy.math - INFO - FlowPy calculation completed successfully.
```

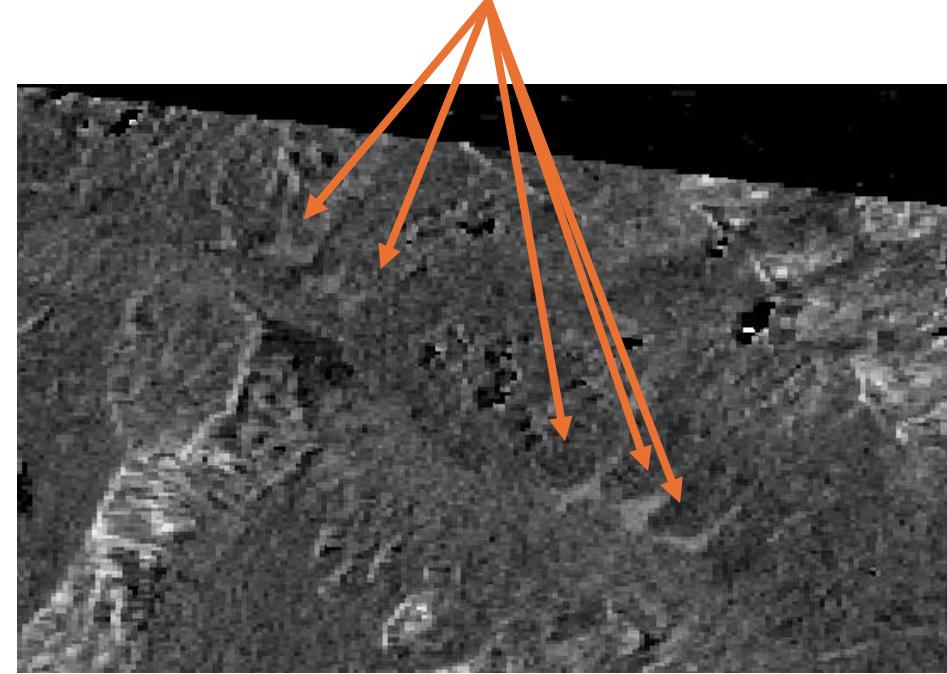
Example

- March 31st – Major earthquake triggered avalanche cycle in the Sawtooths

Before – March 30th – Track 71

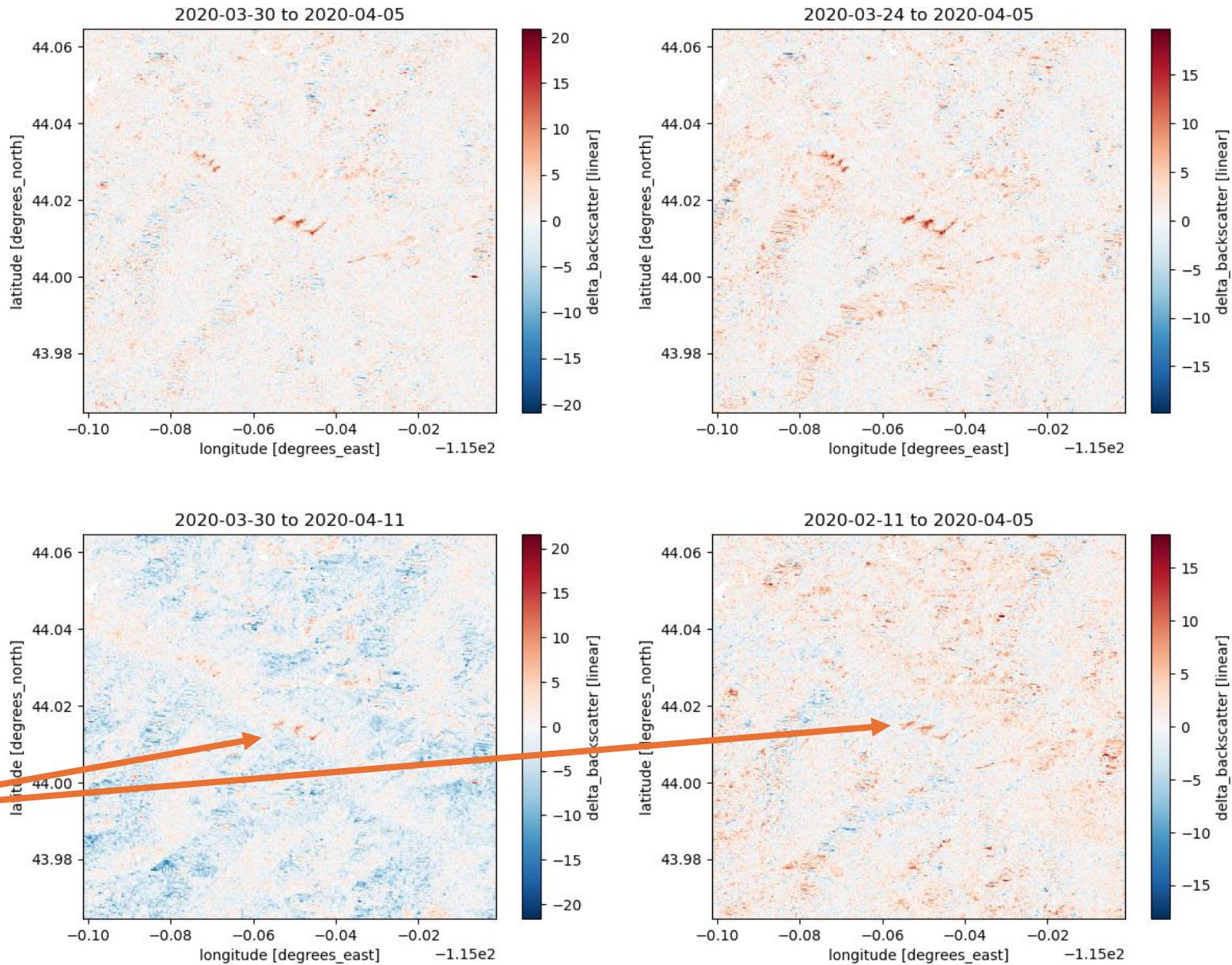


Avalanches – April 5th – Track 71





We start with dB of backscatter change over specific date (2020-03-31) from each track from all possible pairs (within a few months). These are all examples crossing 3/31 from same orbit geometry.

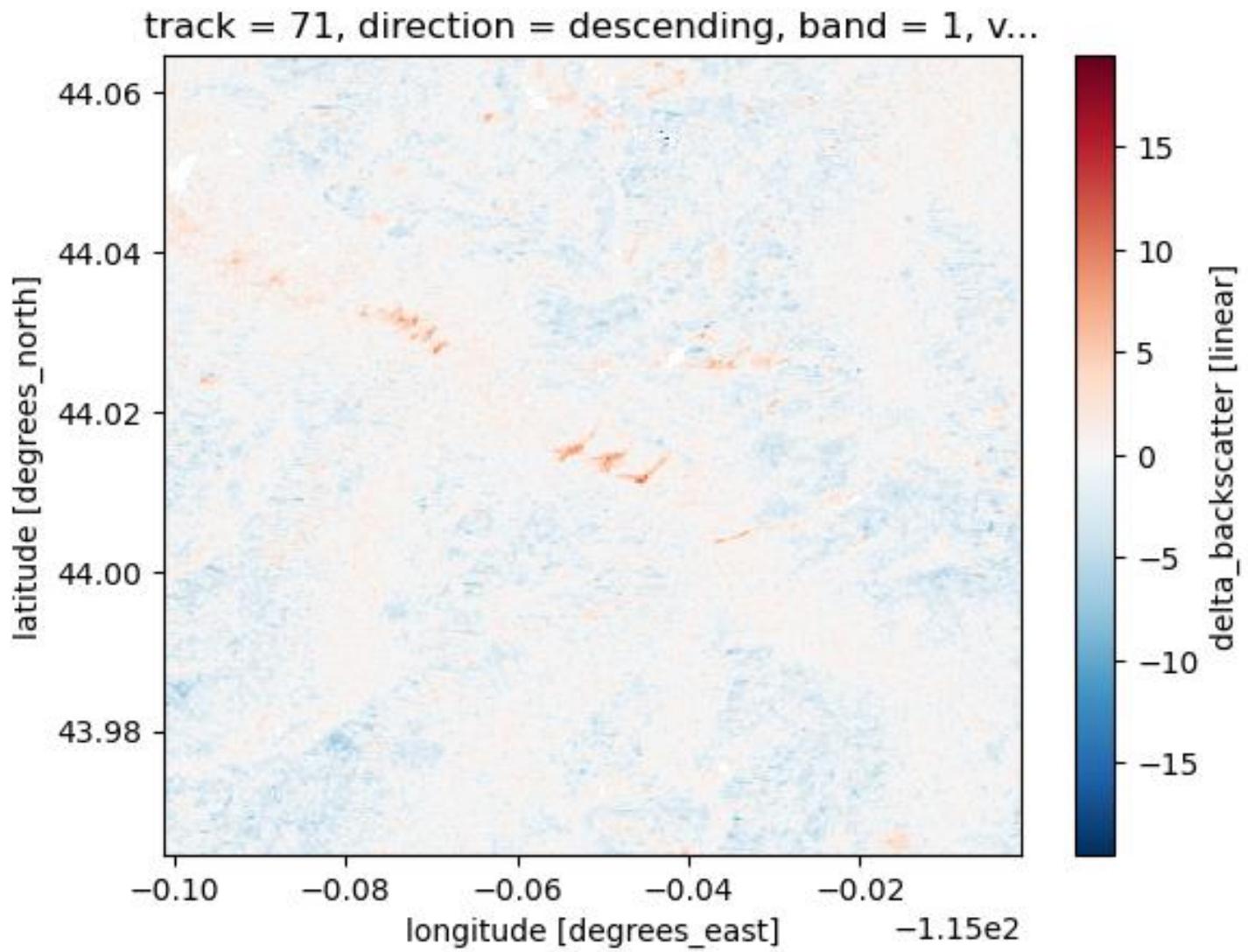


Example avi increases
are visible even for pairs
months apart

These are weighted by temporal distance between each pair to generate a track based mean change that weights closer pairs more

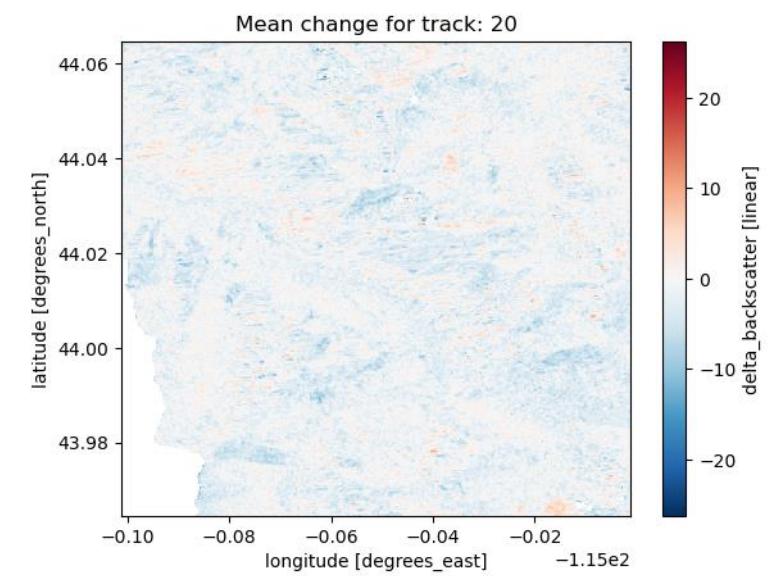
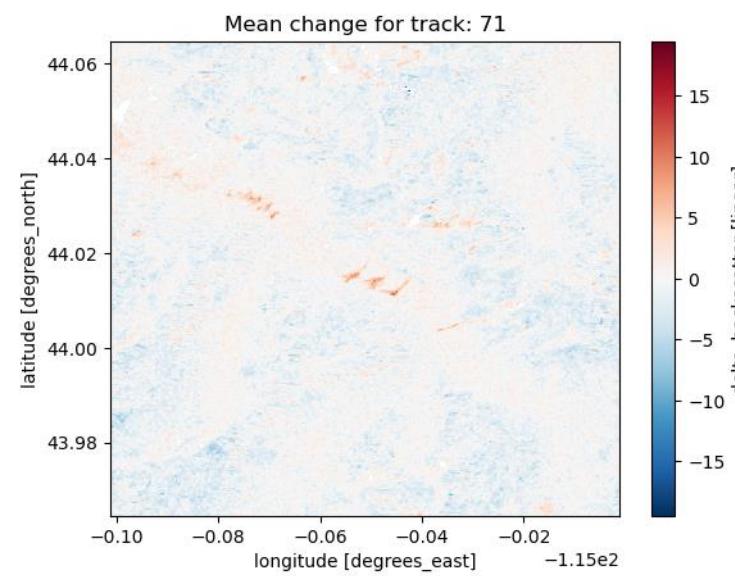
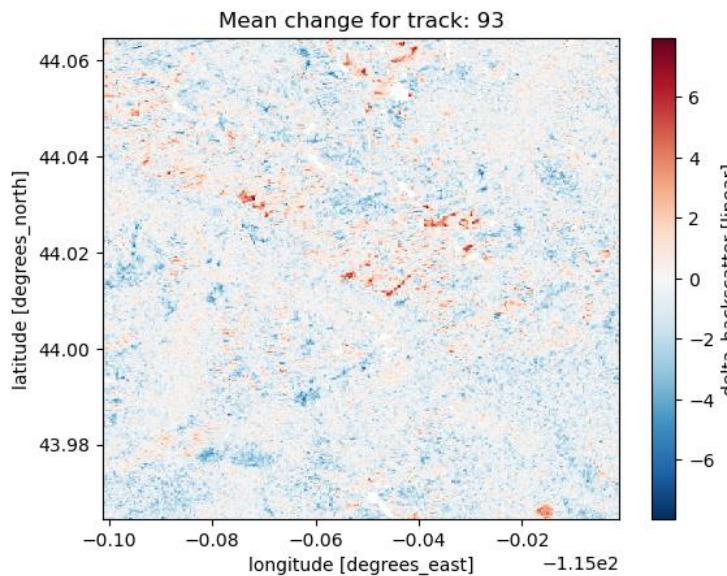
```
w_temporal = np.exp(-  
np.abs(dt_days) /  
tau_days)
```

With $\tau_{\text{days}} = 24$ currently



This is repeated for all available tracks

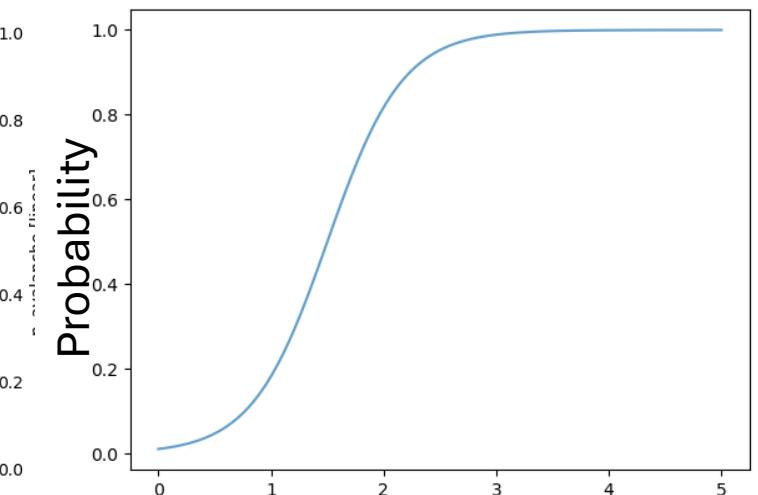
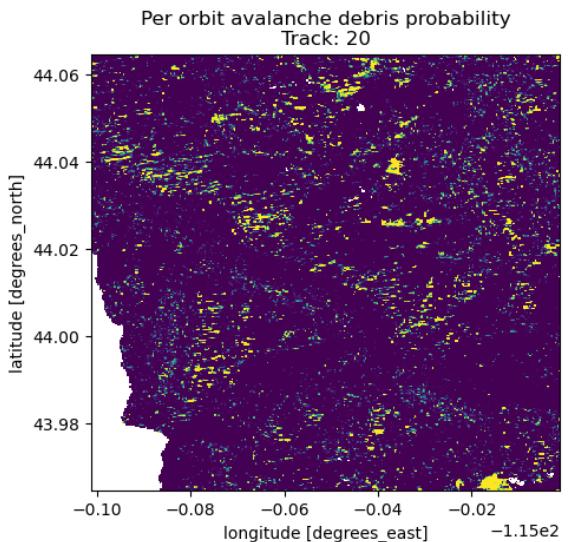
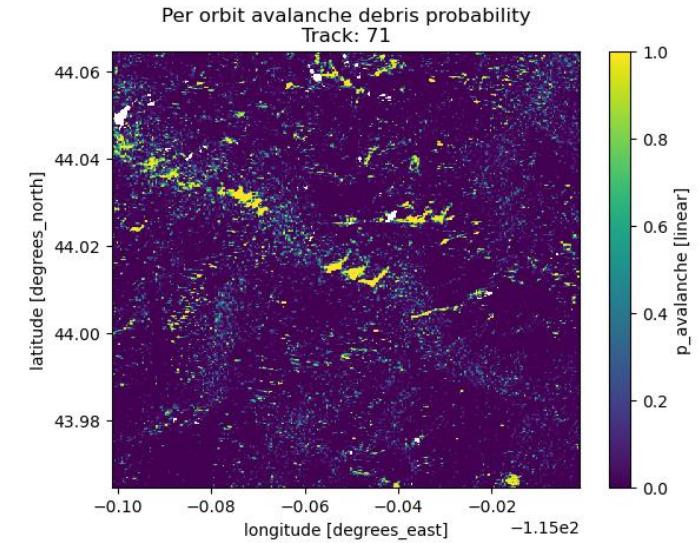
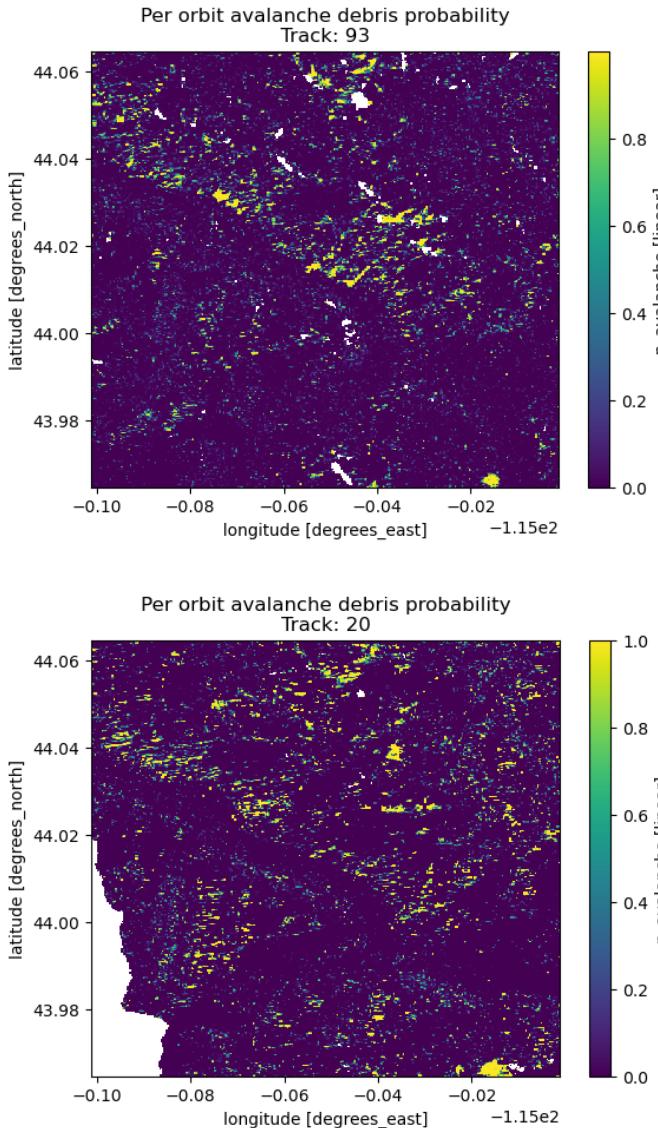
- A track is “orbital geometry” basically the satellite hits the same area going north and south and sometimes on the close and far edges of radar beam.



We convert this mean change to a probability

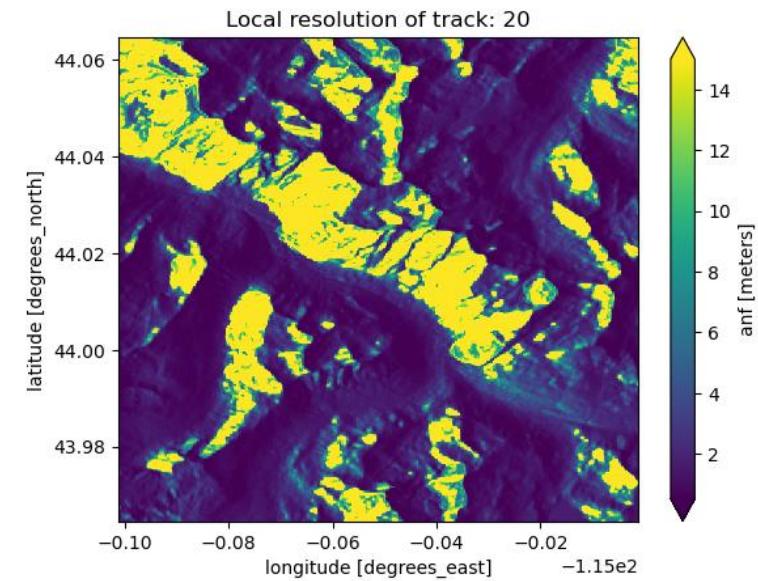
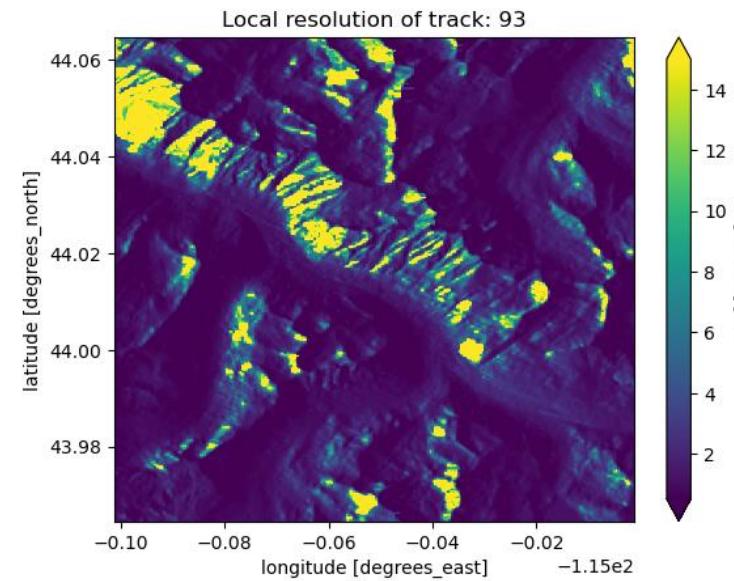
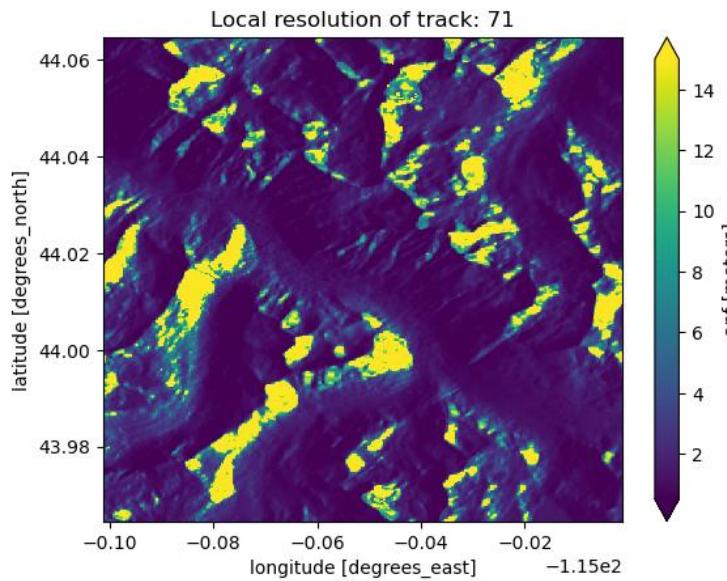
```
prob = scipy.expit(diff -  
threshold_db)*logistic_slope
```

We show the probability to
backscatter change to the right



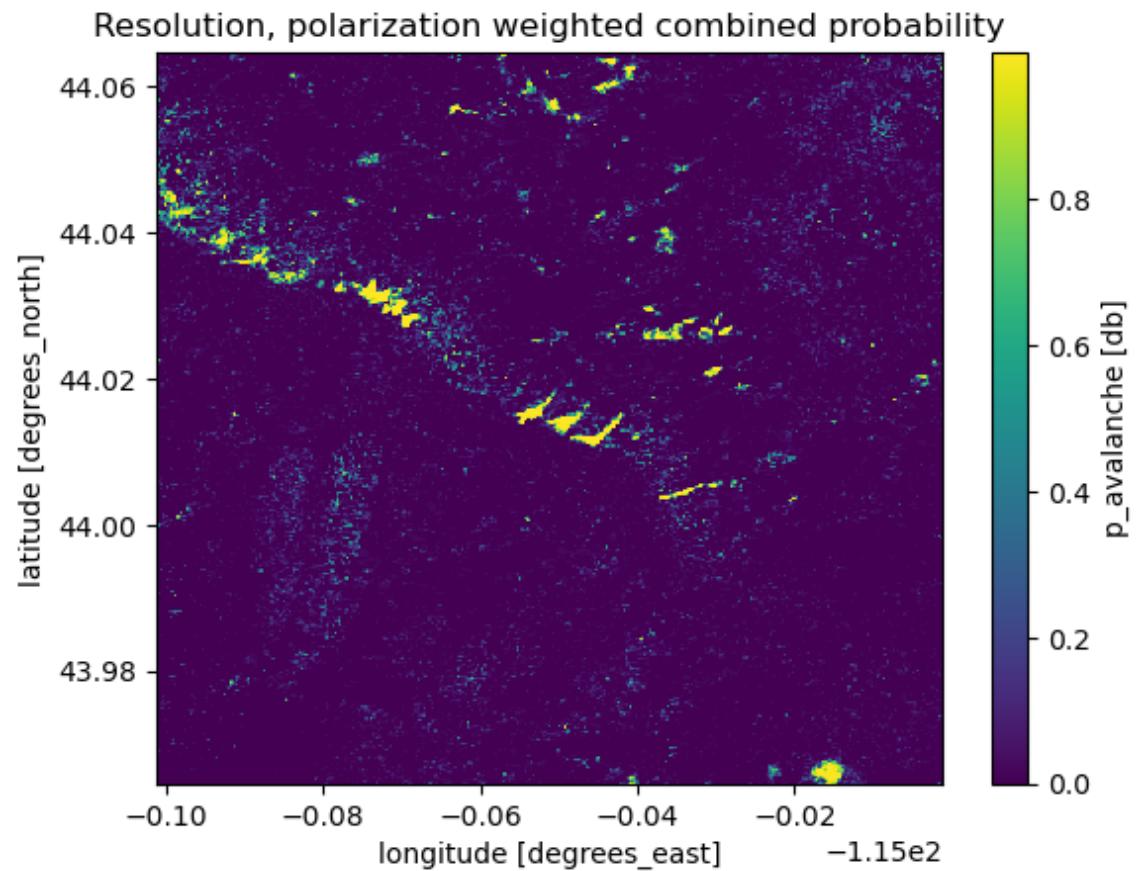
These are then combined using the inverse of local resolution of each pixel to weight the relative tracks.

- So lower local resolution == less weight for final probability
- Radars look to the side and sample based on fixed time slices so steeper incidence angles have less ground covered (local resolution) by a fixed time snippet of the radar response.
- We also use a relative weighting of VV vs VH (1.0 vs 0.8)



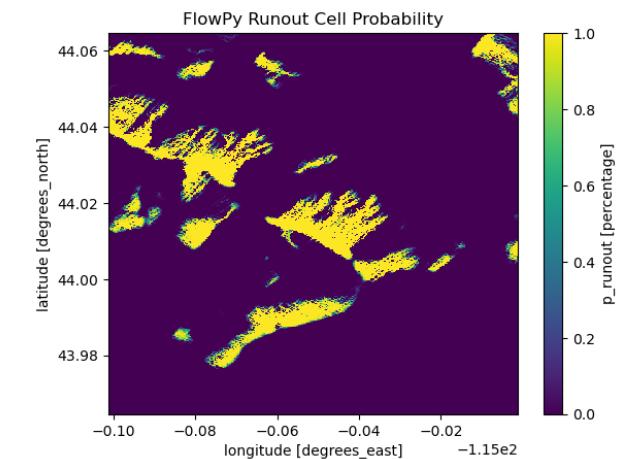
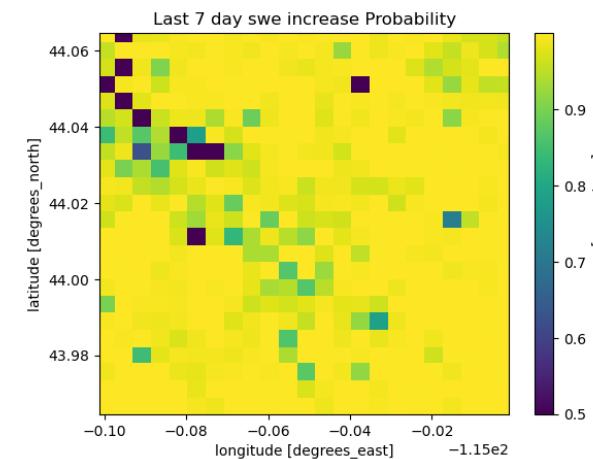
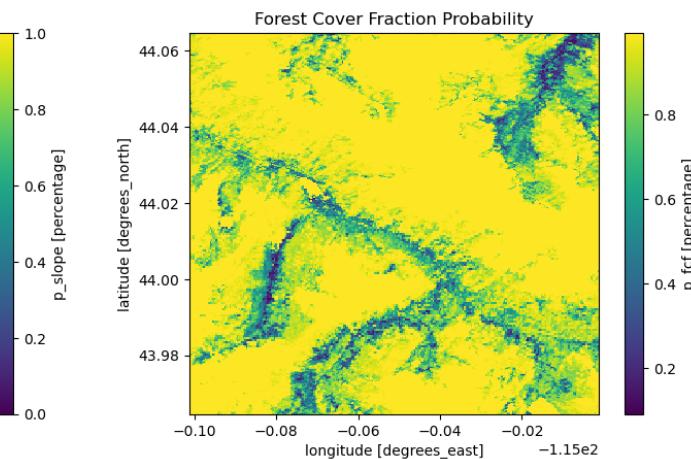
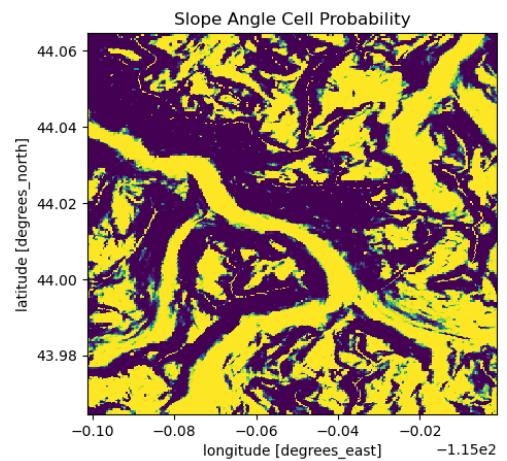
Combining probabilities from multiple tracks

- We combine using log odds to minimize outliers
- We also add an “agreement” boost when multiple orbits show greater than 0.5 probability.
- The result is probabilities that are seen from multiple change pairs, multiple orbits, in high resolution areas all get higher probability.



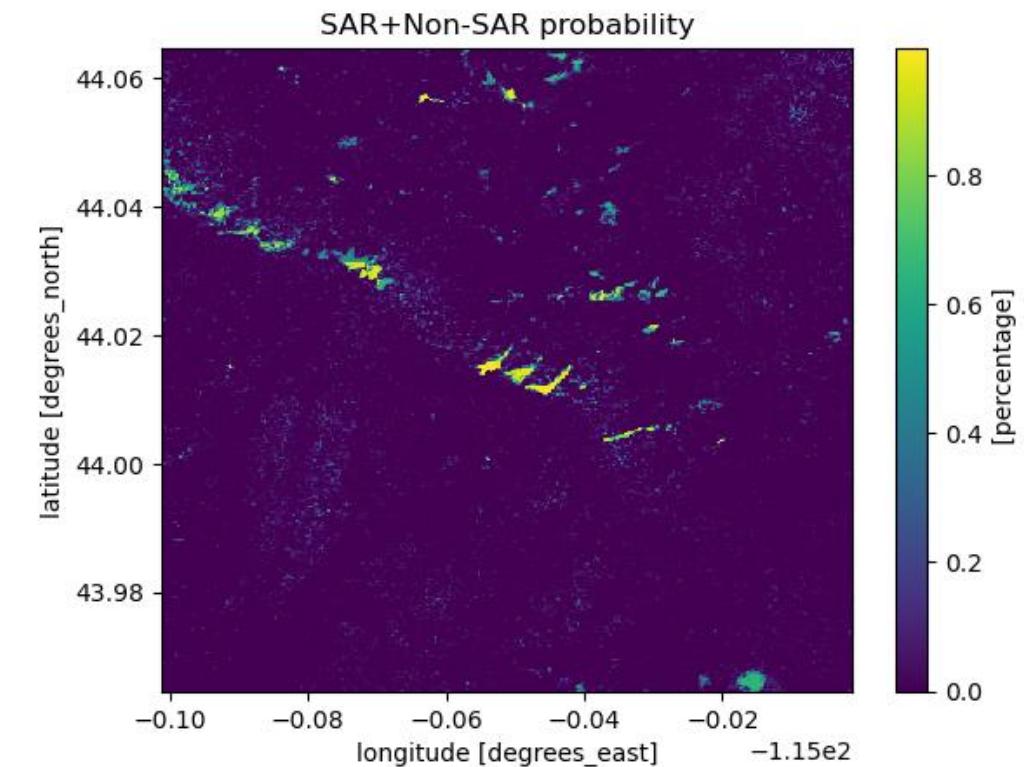
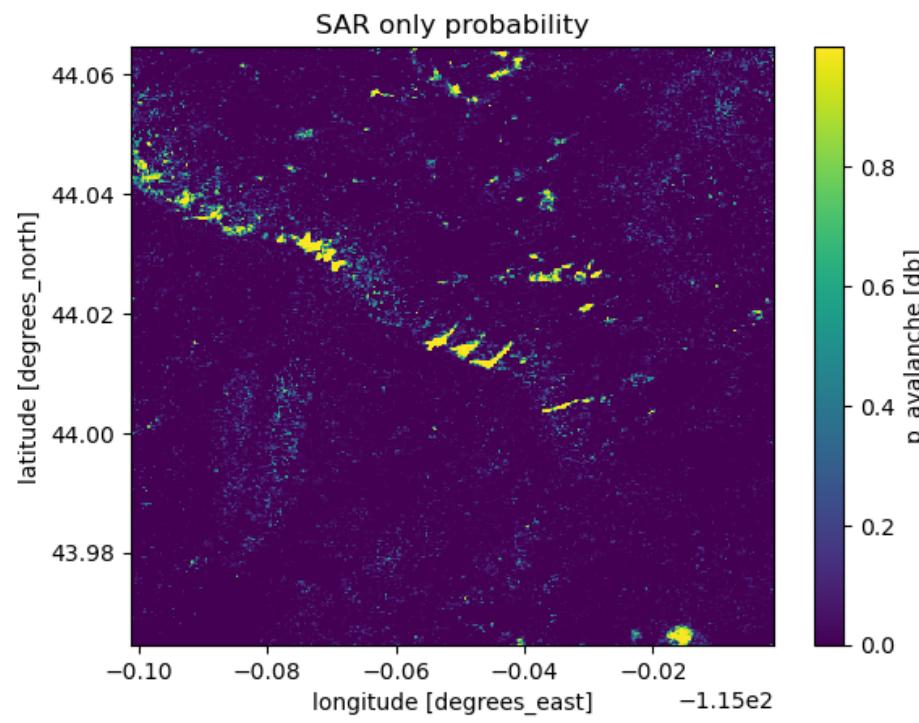
This is then combined (geometric mean this time) with non-SAR probabilities

- Probably all intuitive except for:
 - Runout Cell – does this pixel get “hit” by any start zones in the flowpy model
 - SWE increase – does that pixel see SWE increases over the alst 7 days?

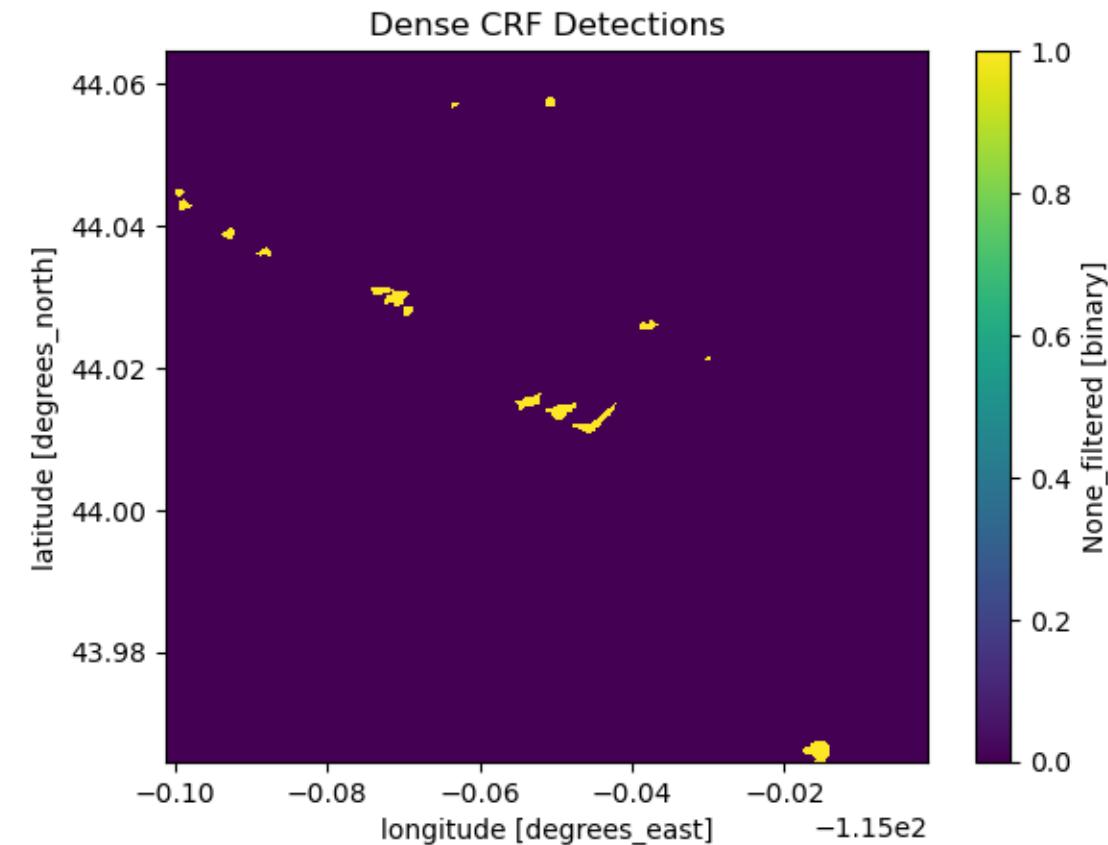
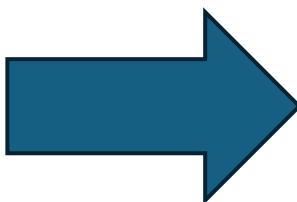
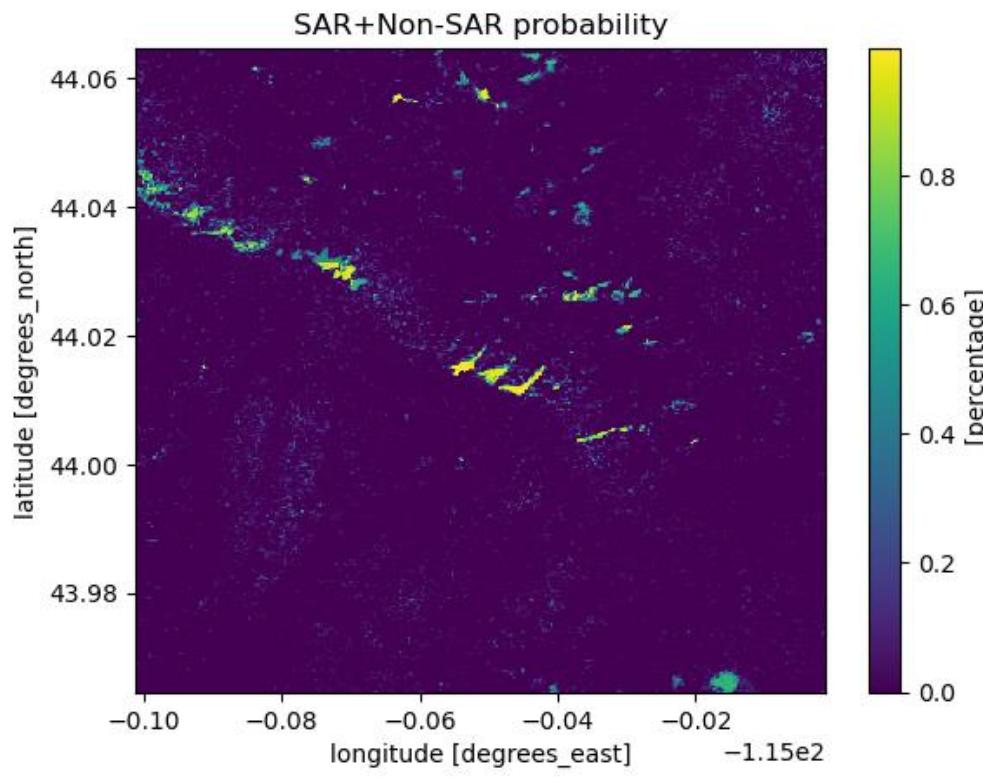


Combine SAR and Non-SAR probabilities.

- Non-SAR layers can not increase pixel-wise probability from SAR results but can decease it.
- Reduces probability when 1. not in runout zones, 2. steep angle, 3. high fcf, 4. little recent SWE.
- Completely masks: urban and water



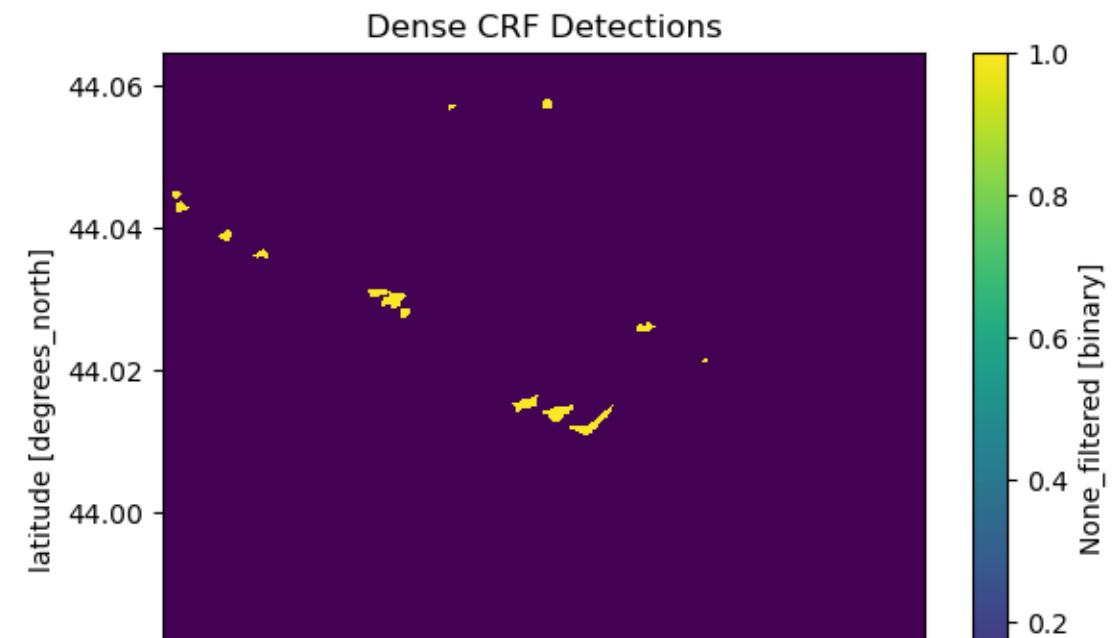
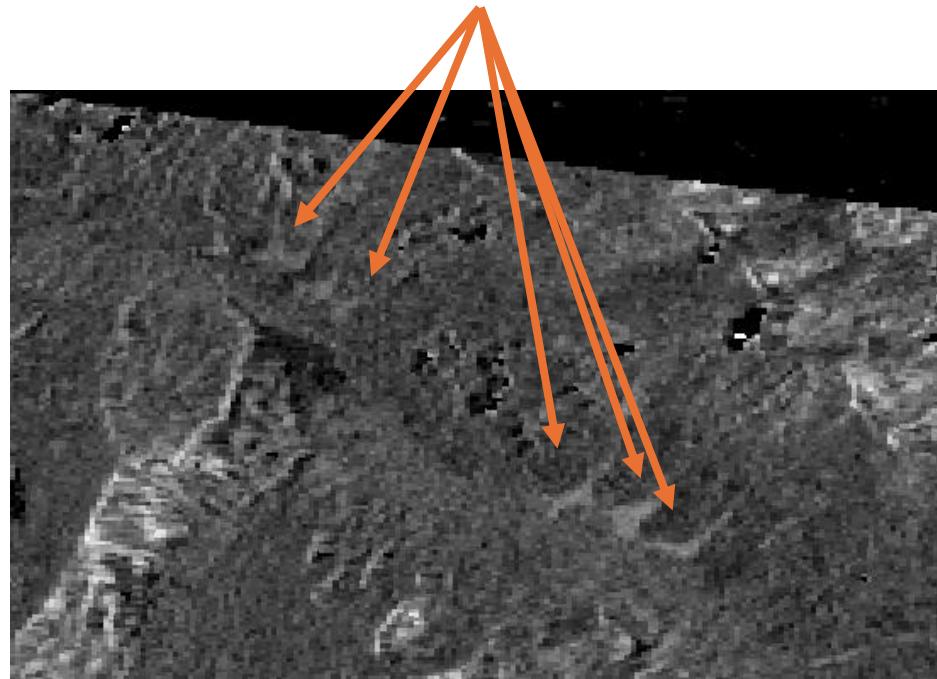
Last step: Use dense conditional random fields (CRF) to give weight to pixels near other debris pixels and remove sharp changes in debris/background



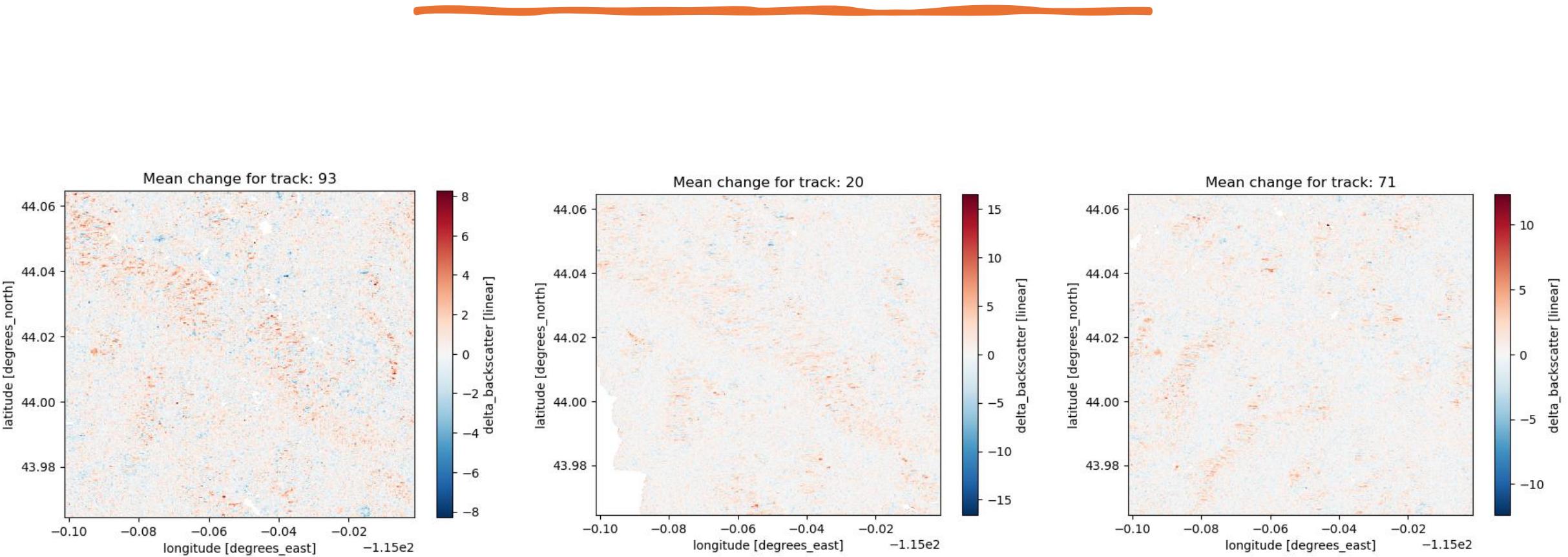
Re state example with detections

- March 31st – Major earthquake triggered avalanche cycle in the Sawtooths

Avalanches – April 5th – Track 71



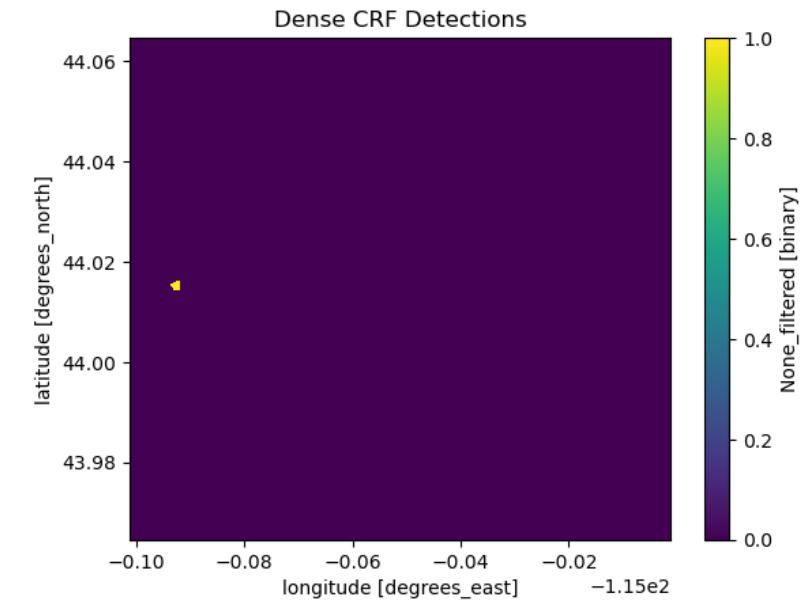
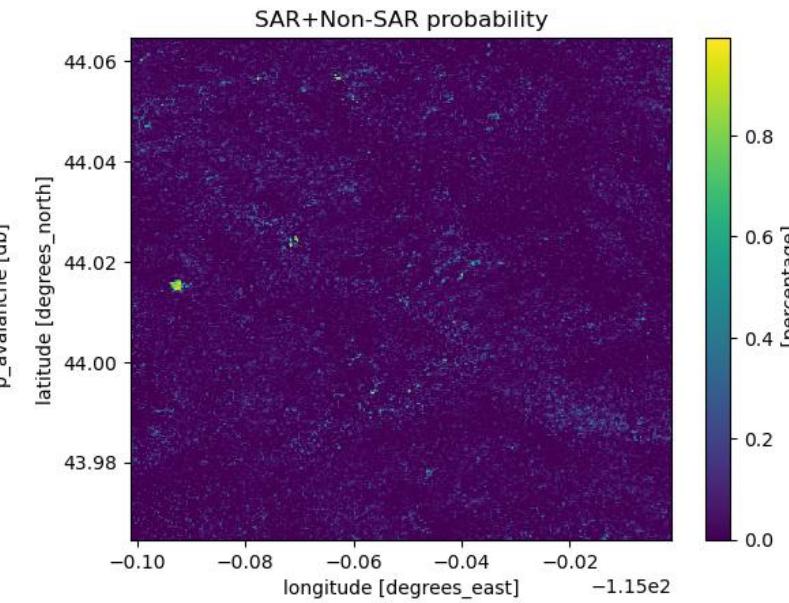
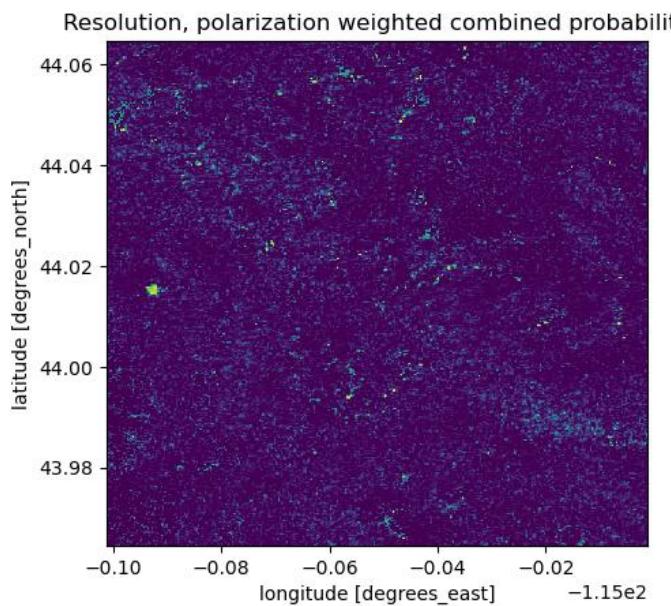
Re-run again on Jan 31st, 2020 for an example of minimal avalanches



Re-run again on Jan 31st, 2020 for an example of minimal avalanches



Single detection for
non-avalanche date



None_filtered [binary]

Next Steps?

- **ISSW presentation** – run over last 5 years over each of the western US avalanche regions to generate database for other researchers. What level of temporal specificity? Yearly? Monthly? Daily?
- **Processing improvements:**
 - Multi-temporal. When does an avalanche first appear in a SAR scene = set as detection date.
 - Use backscatter distributional changes in addition to backscatter change
 - Use empirical detections to train ML model (unet) based on empirical detections and then re-run and capture more detections
 - Incorporate other/more sentinel-1 coherence and NISAR based pixel based probability pipelines.