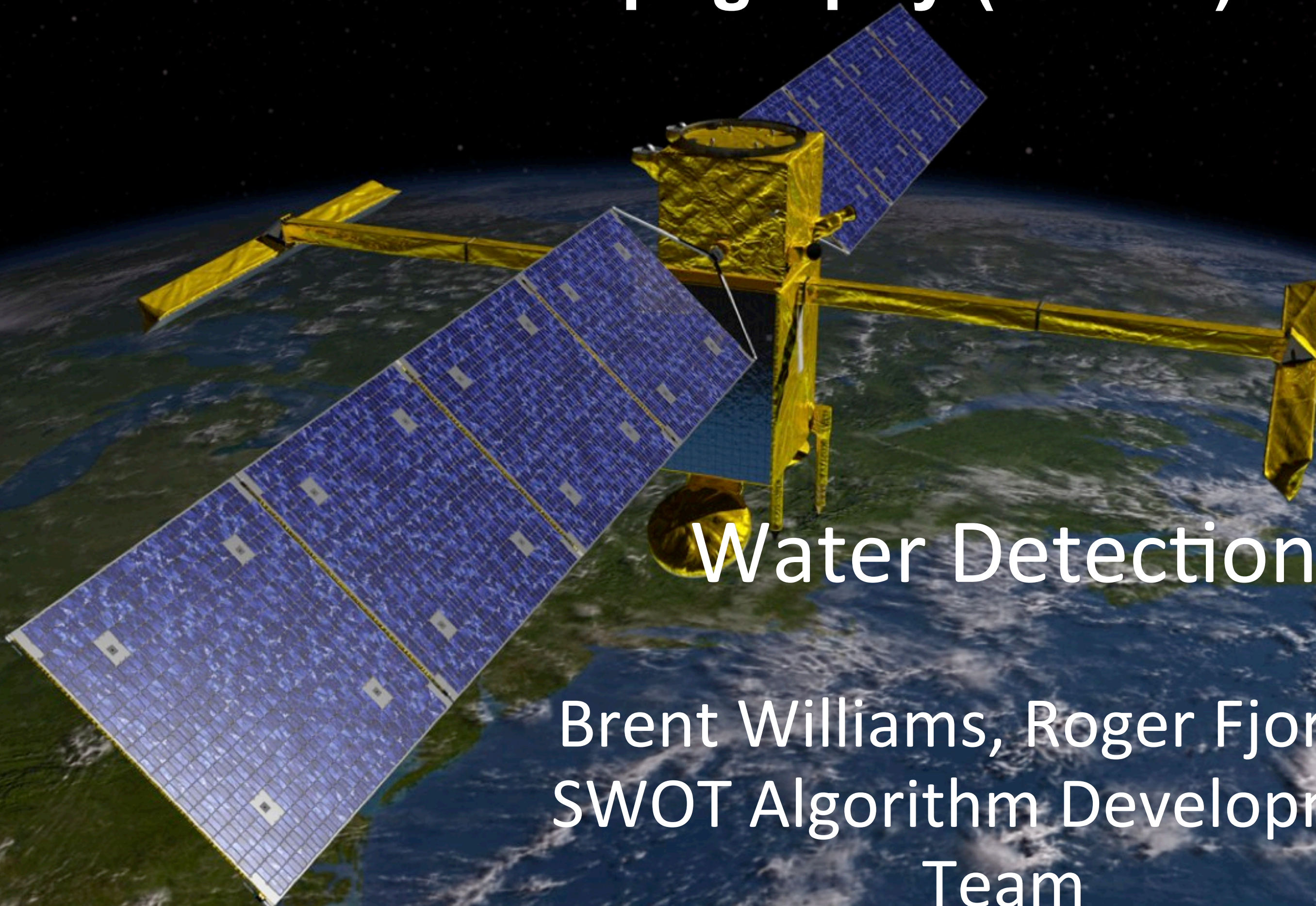
National Aeronautics and Space Administration

Jet Propulsion Laboratory
California Institute of Technology
Pasadena, California

Surface Water and Ocean Topography (SWOT) Mission



Water Detection

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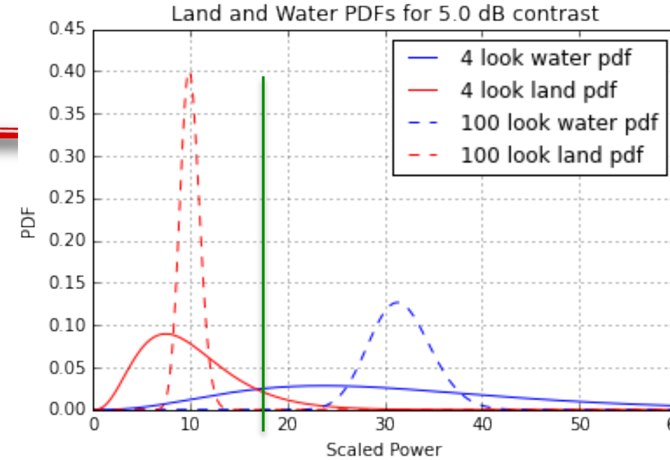
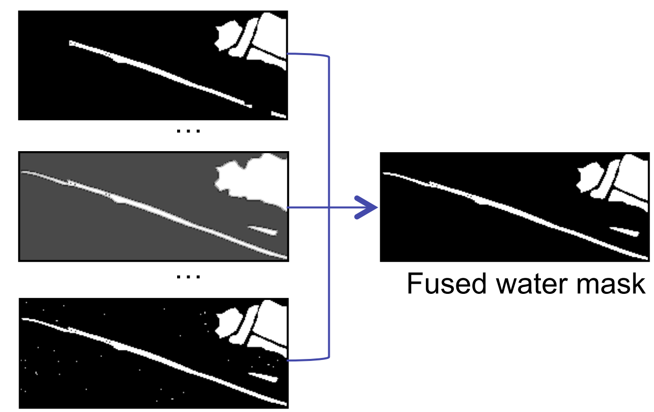
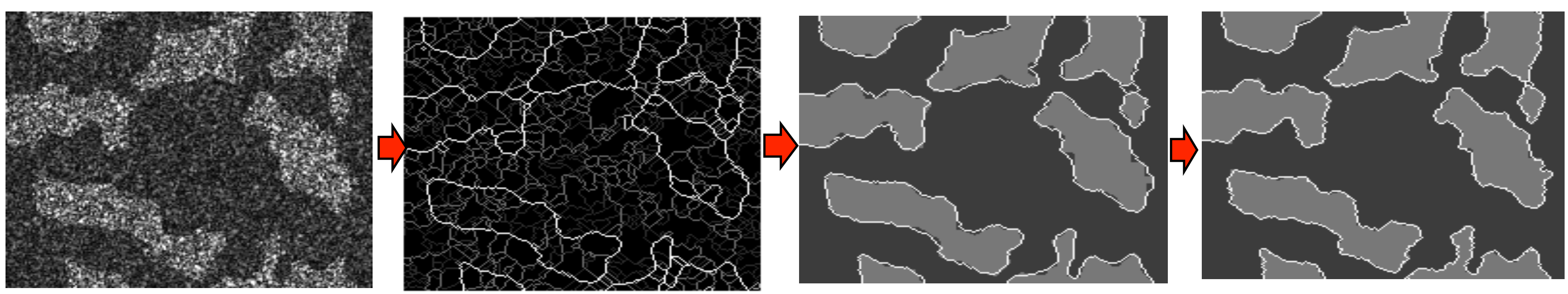
Classification Methods

- Interferogram observables:
  - Power (σ_0), phase (height), coherence
- Power most sensitive to surface type
  - Water is bright, land is dark
- Multiple approaches have been considered
  - Pixel-wise Bayes classification with continuous fractional water estimation
  - Contextual classification (Markov Random Fields)
  - Region-based classification
  - Narrow river detection
  - Fusion of classifiers
  - Various noise versus resolution trades
- Next steps
  - Incorporate prior water masks and/or multi-temporal SWOT data
  - Further explore using coherence and height flatness (looping back after geolocation)





Classification results

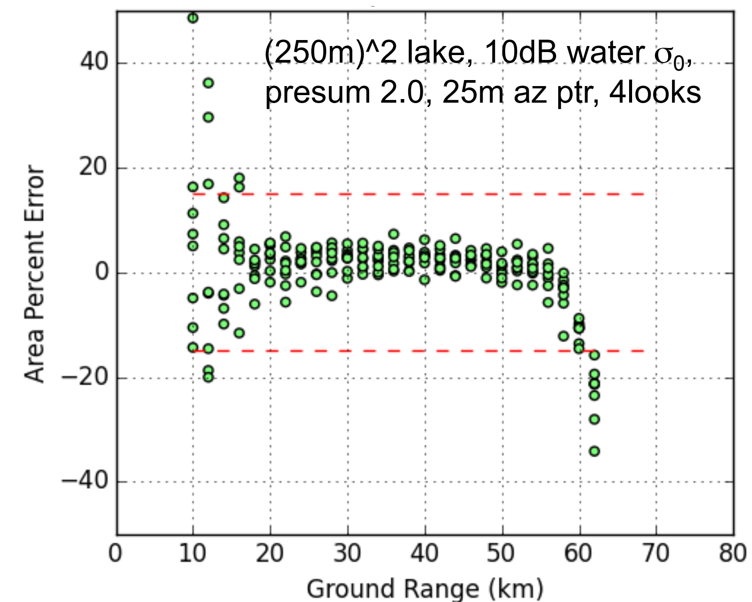


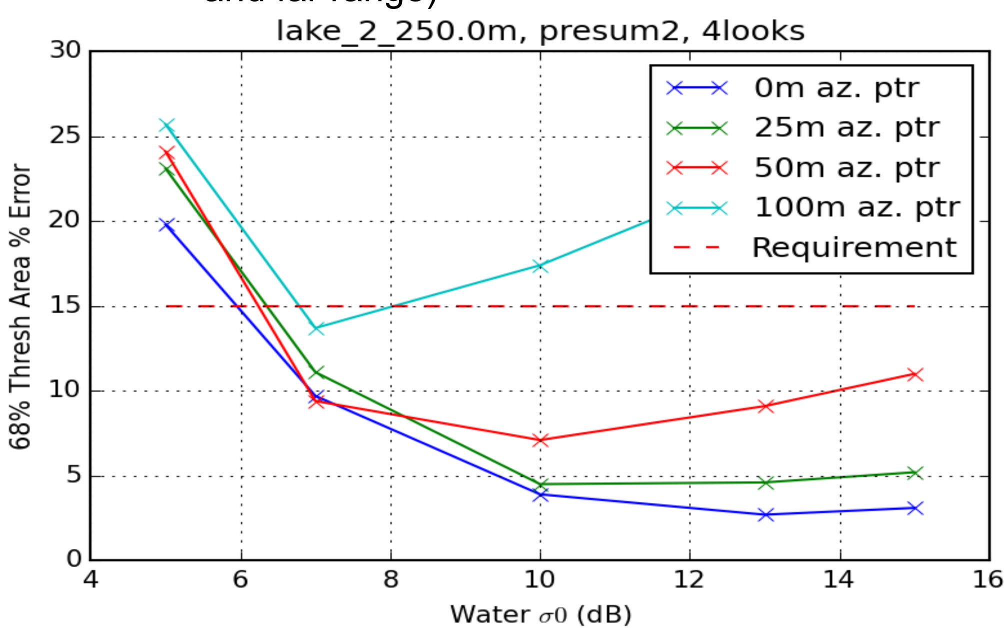
Simulated SAR image | Hierarchical segmentation | Extracted region boundaries before and after position refinement

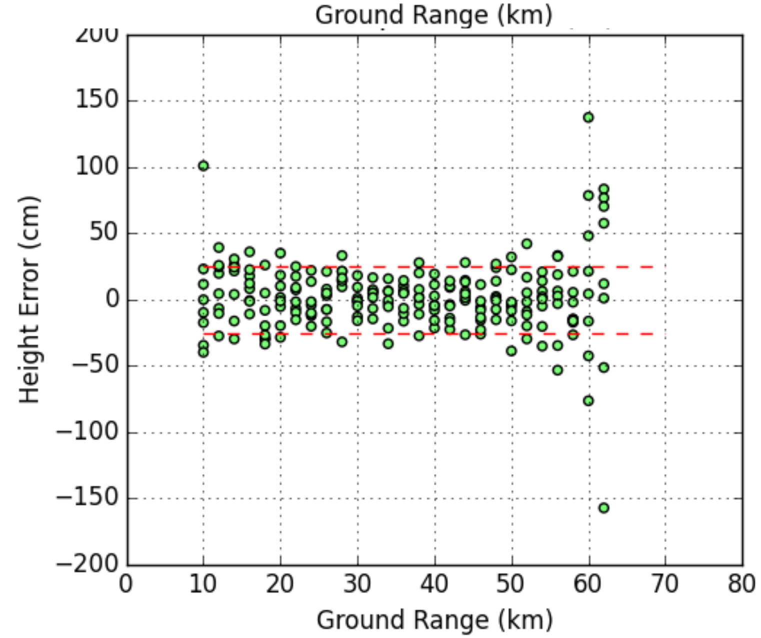
Classification Performance

- Pixel-wise Bayes detection
  - Spatial structure imposed after detection with a ‘clean-up’ filter
  - Analyzed using SWOT Hydrology Simulator for
    - ♦ (250m)^2 lakes and 100m rivers (requirement)
    - ♦ (100m)^2 lakes and 50m rivers (goal)
    - ♦ Flat earth, no layover
    - ♦ Simple lake shape and snake river (with no slope)
    - ♦ Multiple coherence-time smearing (az. ptr)
    - ♦ Multiple water σ_0 (SNR)
  - Meets requirements under nominal assumptions
    - ♦ Higher errors in low water sigma0, higher coherence time smearing, and lower SNR parts of swath (near and far range)

Errors Vs. Cross-track

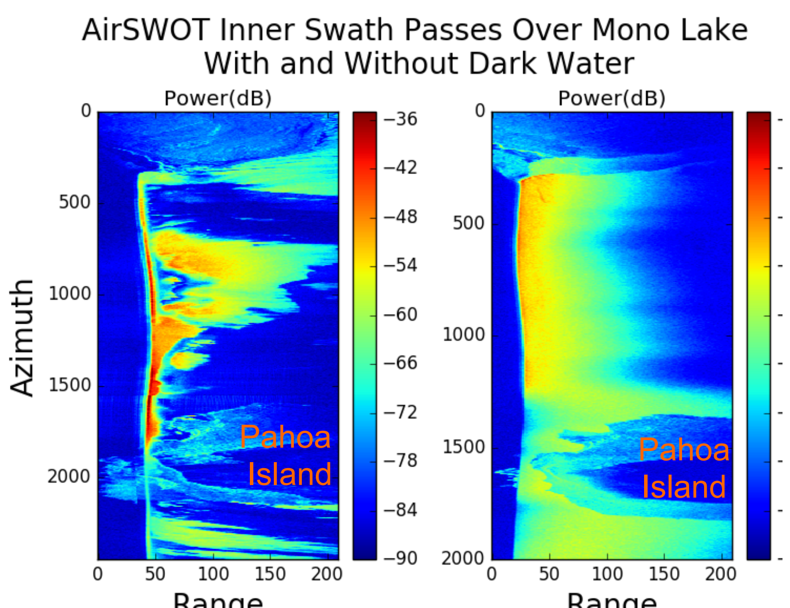




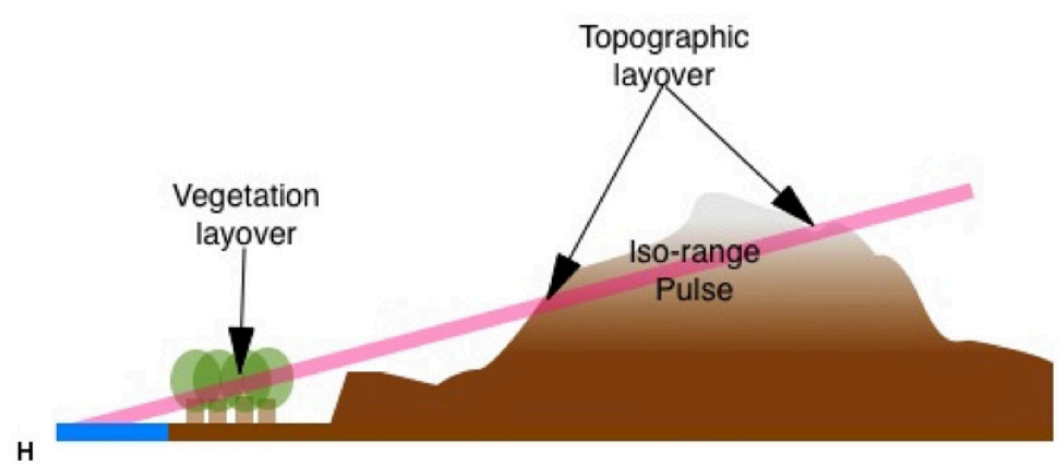


Water Detection Problems and Science Team Interaction

- Developing more complex methods to be more robust to phenomenological uncertainties and measurement artifacts
  - Dark Water: specular reflection over water due to decreased surface stress causes bright return at nadir, but dark at SWOT incidence angles
  - Vegetation: attenuates ground signal, may dampen surface stress (more specular water under vegetation)
  - Layover: modulates power, phase and coherence—limiting science utility of the data
- Many of these approaches involve prior information or the use of multi-temporal data
  - Science Team can provide important feedback on legitimacy/limitations of proposed priors and multi-temporal time scales



surface wind: ~3-4 m/s (left), ~5-7 m/s (right)



Layover figure from SWOT Mission Science Document

Water Detection Uses for Priors

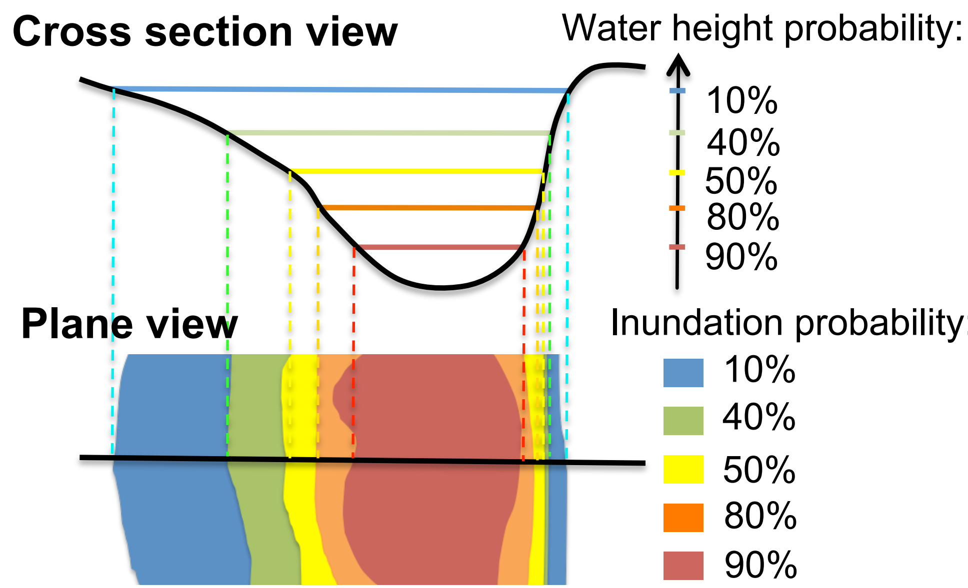
- Two places where water detection can benefit from priors/multi-temporal data

- For data pruning
  - Make sure we keep in the pixel cloud all data that are likely to be water (whether detected as water nor not)
    - ♦ Maximal floodplain extent maps
  - Lake and river databases may be useful here
  - Need to develop a conservative mask for wetlands!

- To improve the robustness of water detection
  - Improve performance in presence of dark water, bright land (layover, man-made structures, etc), vegetation, rain, ice, etc…
  - Beginning to explore the use of **water probability maps** or **flood-pain DEMs** that may be more useful here than lake/river databases
  - Other types of priors that may be useful to consider
    - ♦ Vegetation type maps
    - ♦ Vegetation gap fraction maps
    - ♦ Ice/snow maps (frozen probability maps)
    - ♦ σ_0 maps (seasonally varying?)
    - ♦ Low wind speed masks (prior probability of dark water)
    - ♦ Maps of industrialized areas, roads, railways
    - ♦ DEMs (e.g., for defining water exclusion zones)

Priors for Water Detection

- Water mask priors for water detection
  - Need to accurately represent complex shapes of water bodies (e.g., braided rivers)
  - Need to change with water height
  - May need to be updated regularly to handle dynamic changes in floodplain
  - These characteristics not captured by static prior river/lake databases nor by static binary water masks



Graphic Courtesy of Claire Michailovsky

- Potential candidates:
  - Use previous SWOT passes
  - Water probability maps
    - ♦ Global water probability map based on 30 years of Landsat data by J.-F. Pekel et. al. *
  - Floodplain DEM
  - Use other sensor data (LandSAT, Sentinel, NISAR, etc)

- Floodplain DEM and probability maps are interrelated
  - For static bathymetry
  - Thresholding the probability maps gives a unique water mask for
    - ♦ A given water height (for flat non-flowing systems)
    - ♦ A given stage for rivers

* 30 Years' Global Scale Mapping of surface Water Dynamics at 30 m resolution, J.-F. Pekel et. al. http://due.esrin.int/mwbs2015/files/1_Pekel_200dpi.pdf

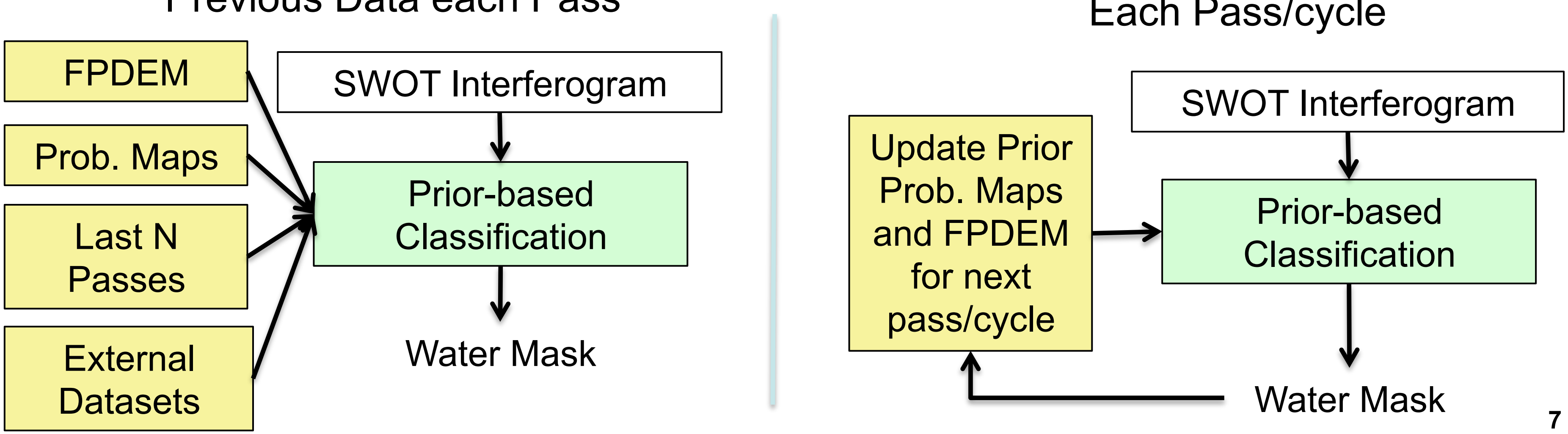
Combining and Updating Priors

- Multiple priors can be combined
  - Convex combinations of prior PDFs
  - Fusion/voting of classification using different priors
- Floodplain DEM and/or probability maps can be updated using SWOT data on a regular basis
  - Inline as part of the algorithm flow for each pass or cycle
  - Offline on other time scales season, year?
- Need to analyze the trade space to find the best solution that is both practically implementable and effective
  - Science Team input on appropriate time scales needed

Load in Static Priors and Previous Data each Pass

vs.

Dynamically Update Priors for Each Pass/cycle



Interaction between Water Detection ADT group and Science Team

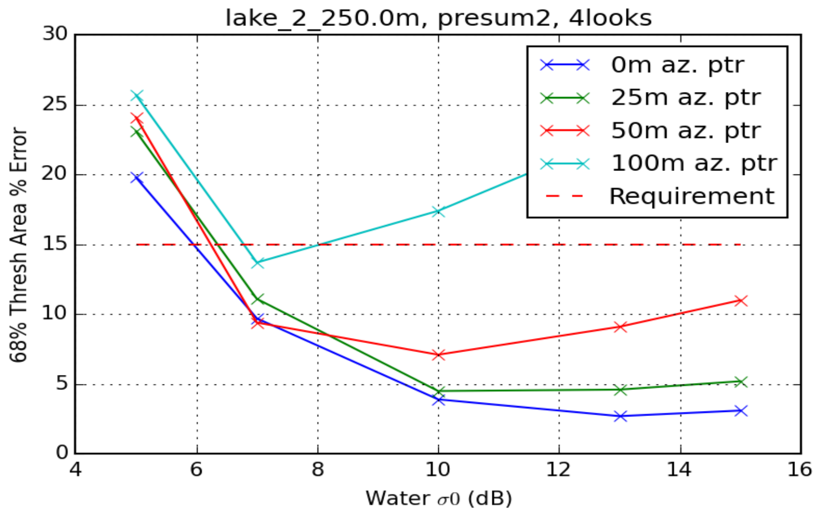
- ADT to provide to ST:
  - Propose and implement water detection and flagging algorithms and provide performance assessments
  - Provide appropriate documents for review (ATBDs, product description documents, etc…)

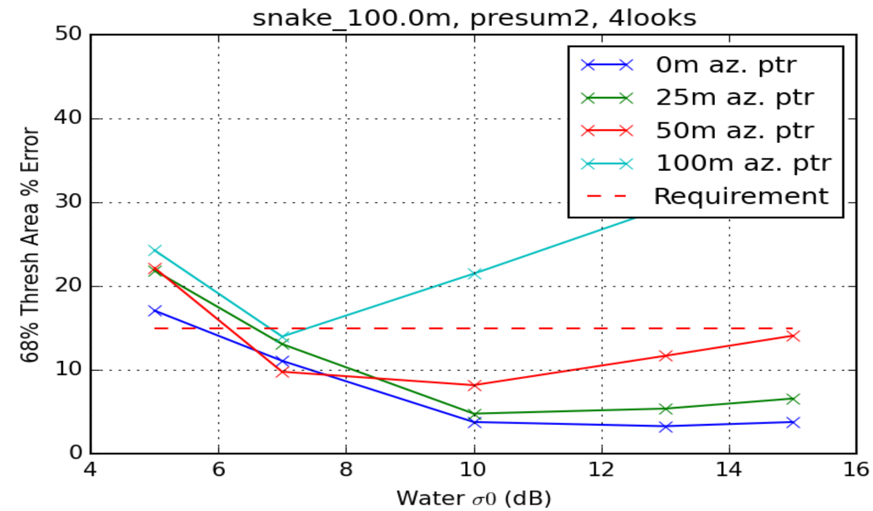
- ST to provide to ADT:
  - Feedback on legitimacy of using proposed priors (and multi-temporal data and time scales)
  - Expert advice on existing datasets/priors, with limitations, global availability etc
  - Aid in the development of a global wetland maximum extent map
  - Assess the science impact (inform non-official science "desirements" that are not captured by the formal requirements in the SRD)

Backup

Area % Error, Swath Average

68% threshold indicates 1 sigma error, means 68 % of the data has absolute area % error less than this threshold

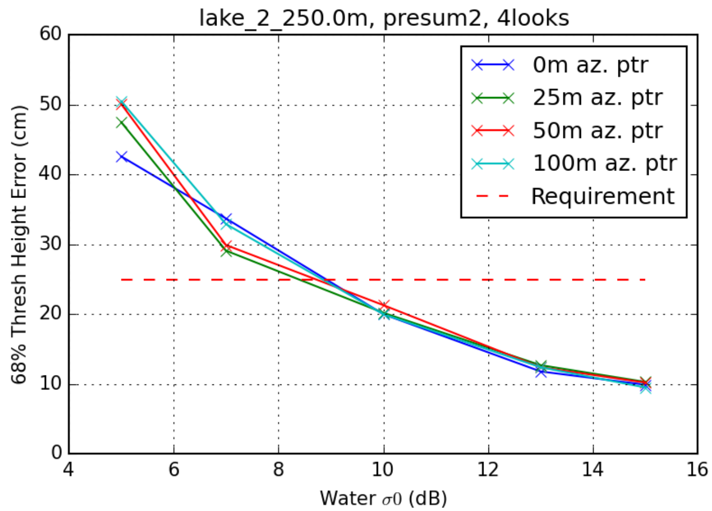


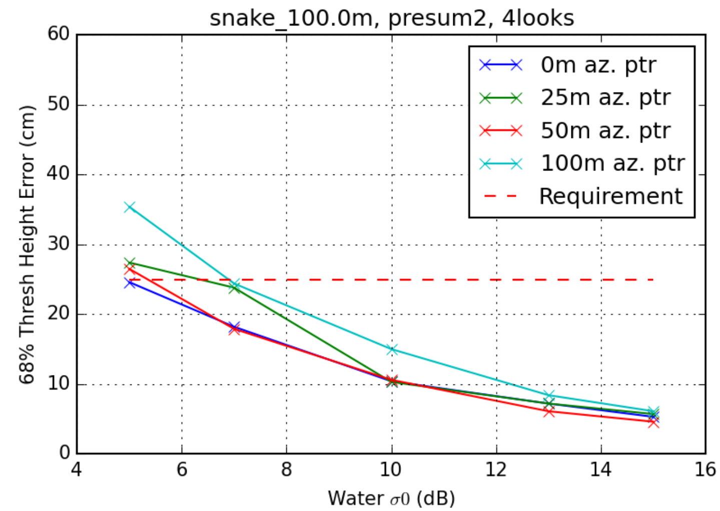


- Bias is a function of SNR/contrast and coherence time
- Methods to improve bias may improve area estimates
- Meet requirements for
  - Coherence times <= 50m (magnitude) smearing
  - Water sigma0 >=7dB (10dB without coherent gain)
- Resolution preserving pre-smoothing or contextual approaches may improve classification in low SNR swath edges

Height Error, Swath Average

68% threshold indicates 1 sigma error, means 68 % of the data has absolute height error less than this threshold





- Height biases due to misclassification are not directly handled (flat scene for both land and water)
  - Edge pixels can be flagged and discarded to address land misclassified pixels corrupting the heights, with the cost of having fewer pixels to average increasing the random error
- Height errors meet requirements for nominal water brightness irrespective of coherence time smearing
  - Small lakes with low SNR (and more missed detections) may not enable enough averaging to beat down height variability, likely to improve with better classification
- Rivers more sensitive to coherence time since they contain more edge pixels
- River reaches are ~2km for this case (485m)^2