Towards Near Daily Monitoring of Inundated Areas over North America through Multi-Source Fusion of Optical and Radar Data

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NASA LCLUC Science Team Meeting, Rockville, MD, April 12 – 14, 2017

Need for Inundation Monitoring

- Surface inundation plays important roles in Earth system processes
  - land-atmosphere energy balance (Krinner 2003),
  - carbon and nutrient cycles (Shindell et al. 2005; Fox et al. 2014; McDonough et al. 2014),
  - surface – groundwater dynamics (Winter 1999; Becker 2006).
- Wetlands and other intermittently inundated areas provide a range of ecosystem services
  - water purification,
  - climate and flood regulation,
  - natural hazards, food and fiber, and recreation (Millennium Ecosystem Assessment 2005),
  - Biodiversity (Millennium Ecosystem Assessment 2005).
- Aquatic ecosystems are being lost at alarming rates (Millennium Ecosystem Assessment 2005).
  - Pressure from a growing human population
  - Climate change
- Inundation affects human welfare
  - Water availability (e.g. for human consumption)
  - Water-borne diseases
  - Flooding

Need for High Spatial Resolutions

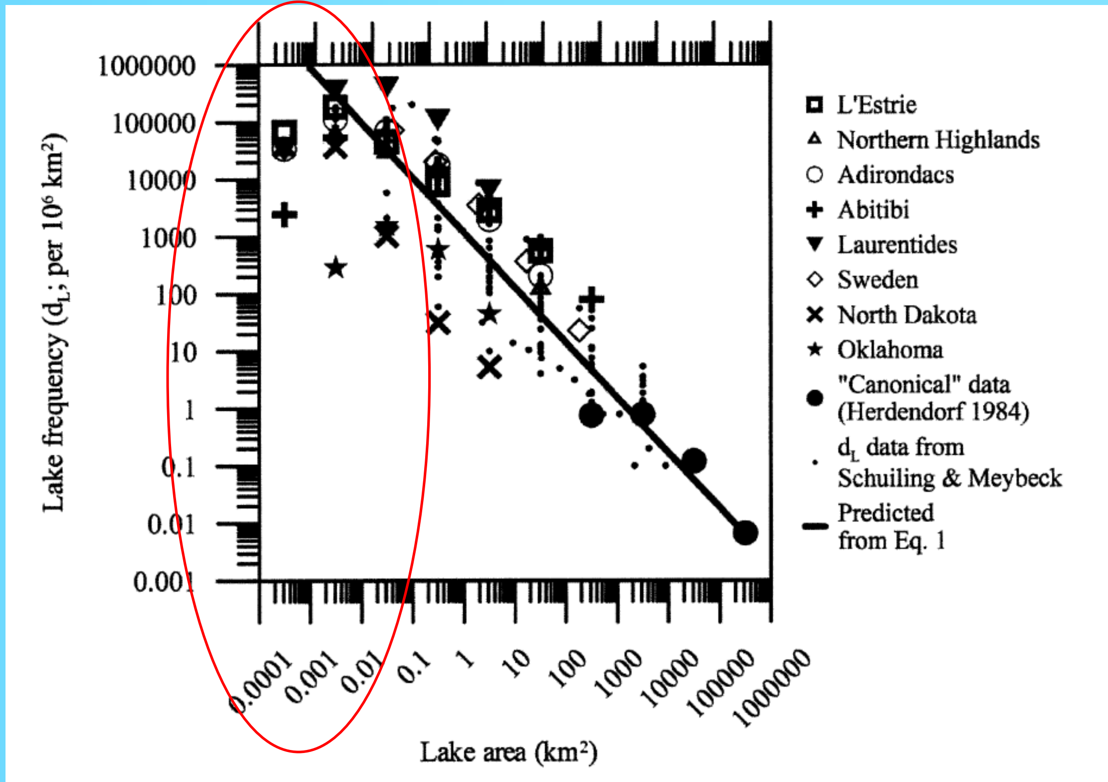
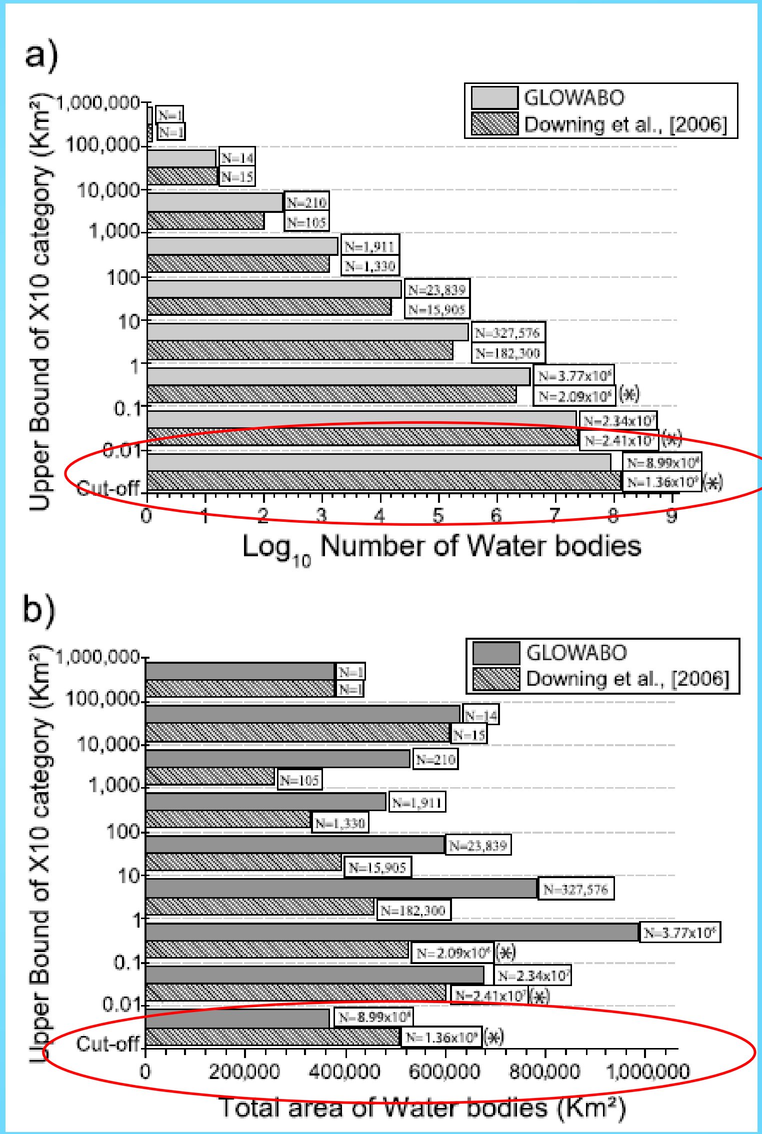


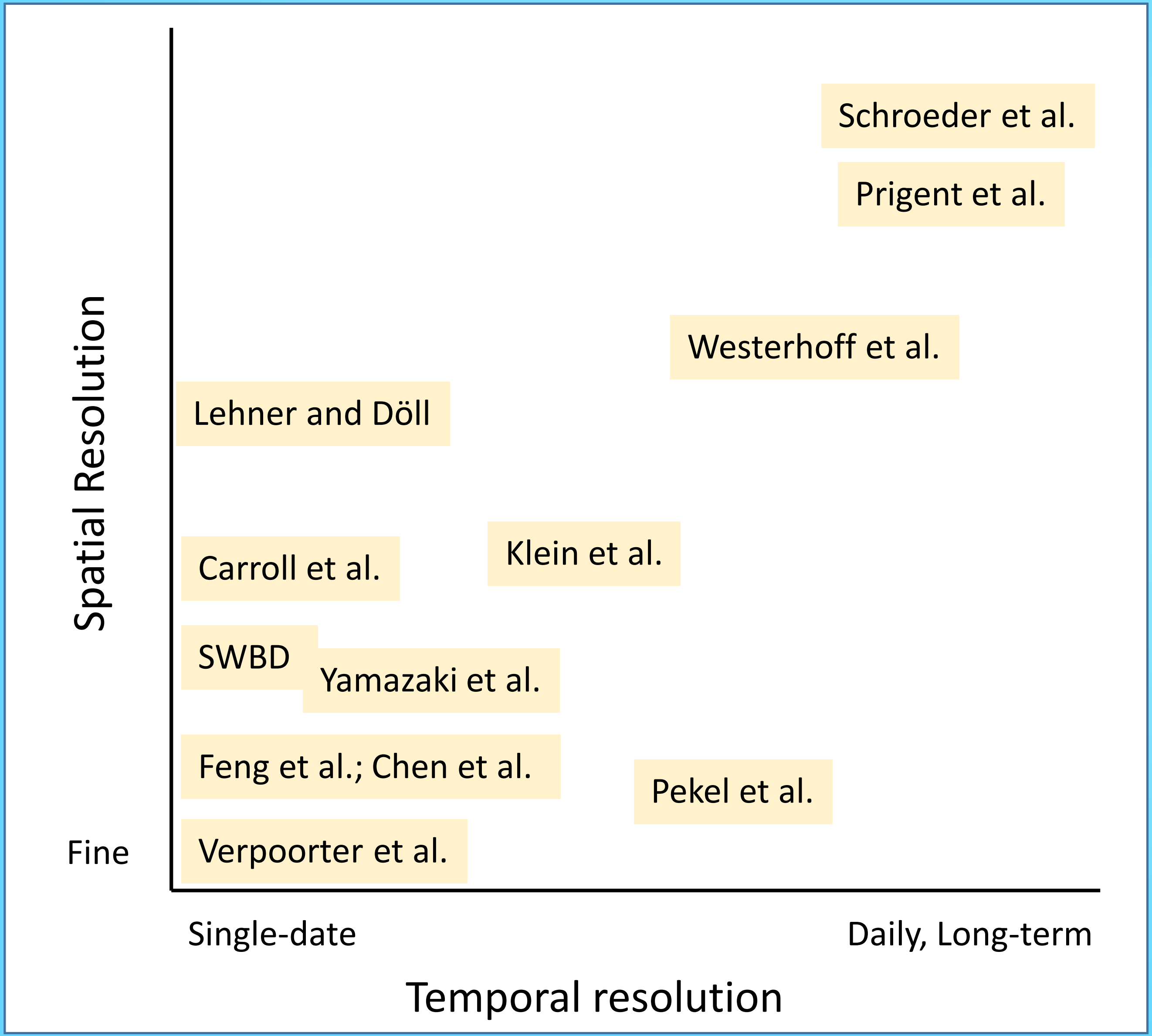
Fig. 2. Relationship between lake surface area and areal frequencies of different sized lakes, determined by detailed GIS analyses (*see sources in Table 1*) and comprehensive counts. The filled dots indicate the frequencies of lake sizes found by Schuiling (1977) and Meybeck (1995). Other regions' lake frequencies are shown by various symbols.

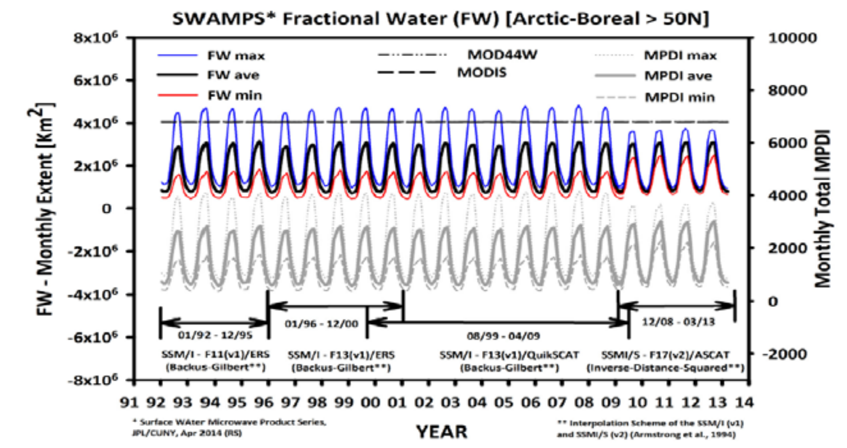
(Downing 2006)



(Verpoorter et al. 2014)

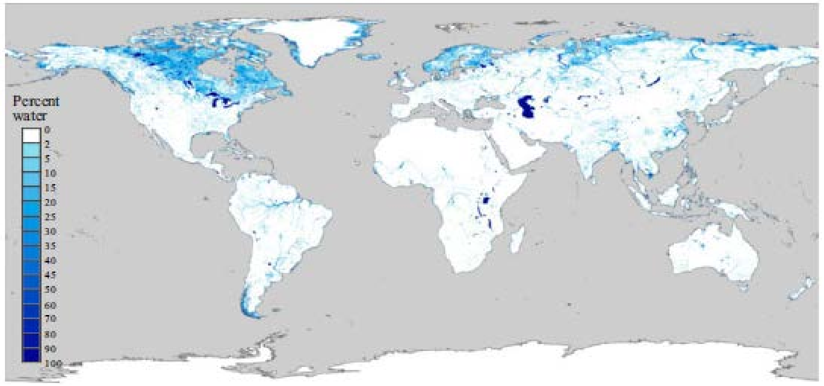
Growing Number of Global Water Datasets





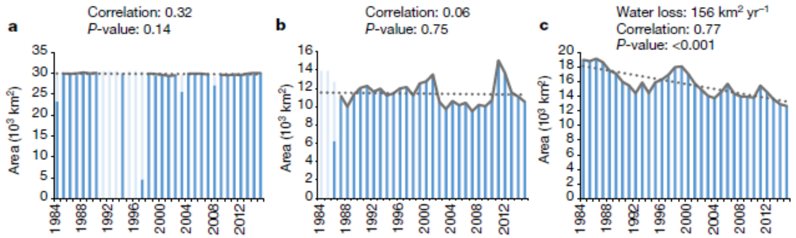
(Schroeder et al. 2015)

- Daily
- 25 km



(Feng et al. 2015)

- 2000
- 30 m



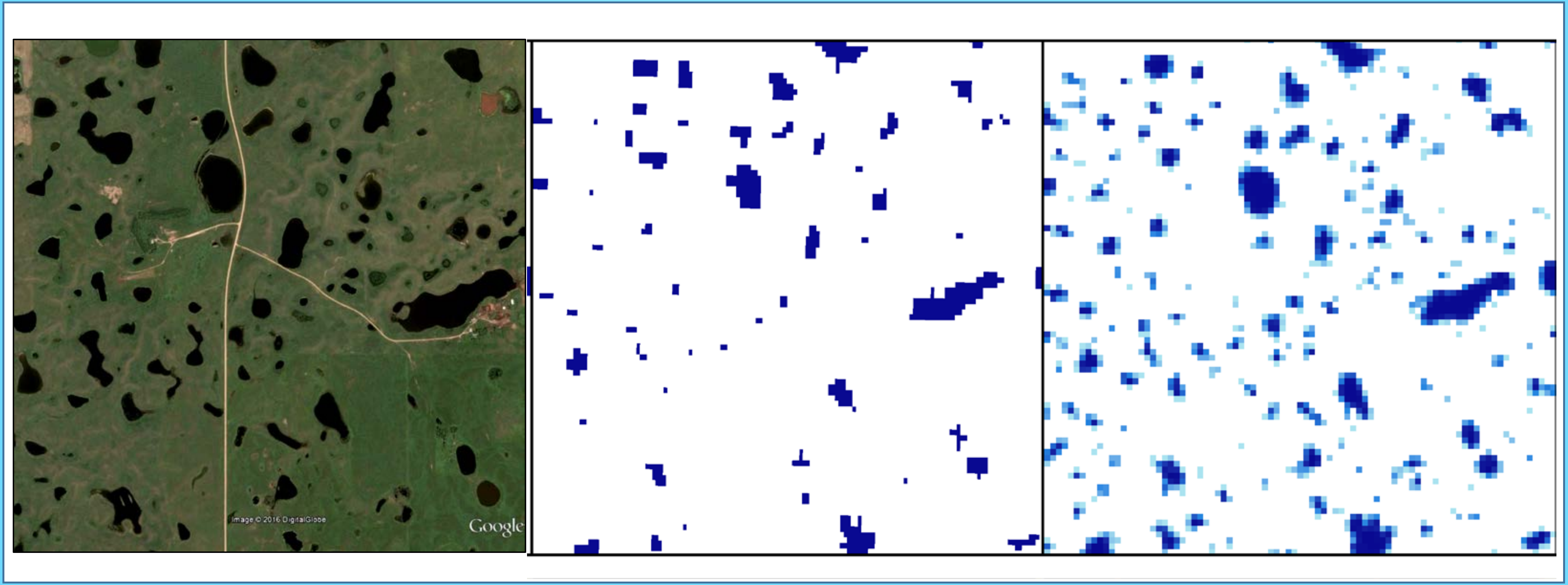
(Pekel et al. 2015)

- Monthly to annual
- 30 m

Limitations of Water Classifications

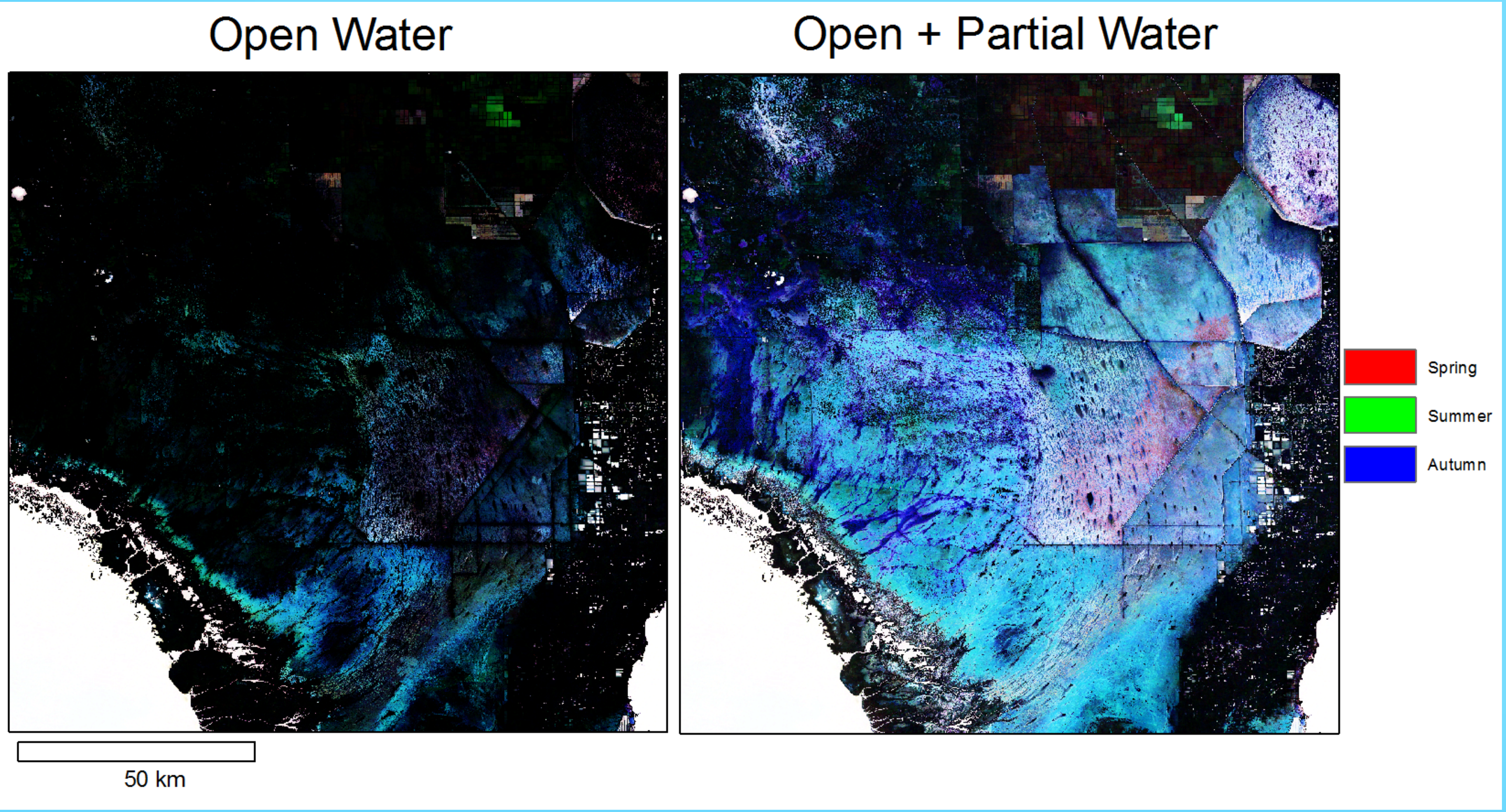
Max extent classification, 1985-2010 (Pekel et al. 2015)

Subpixe water fraction (This study)



Prairie Pothole Region
(Saskatchewan, Canada)

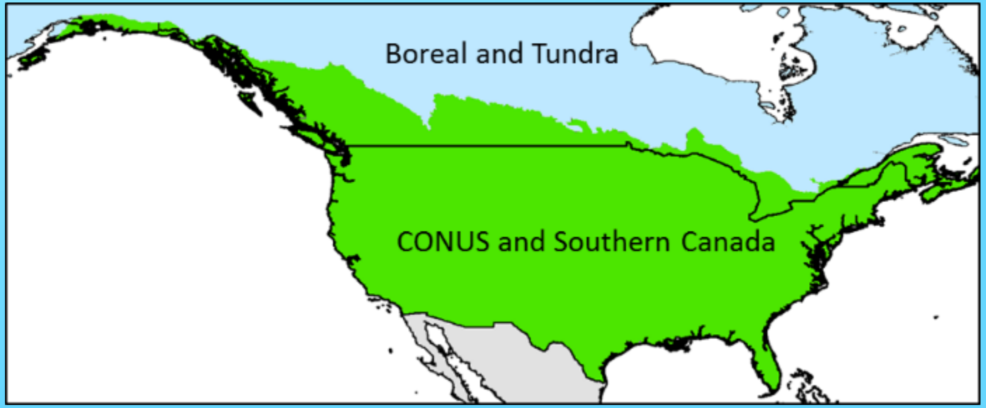
Inundation Highly Variable Over Time



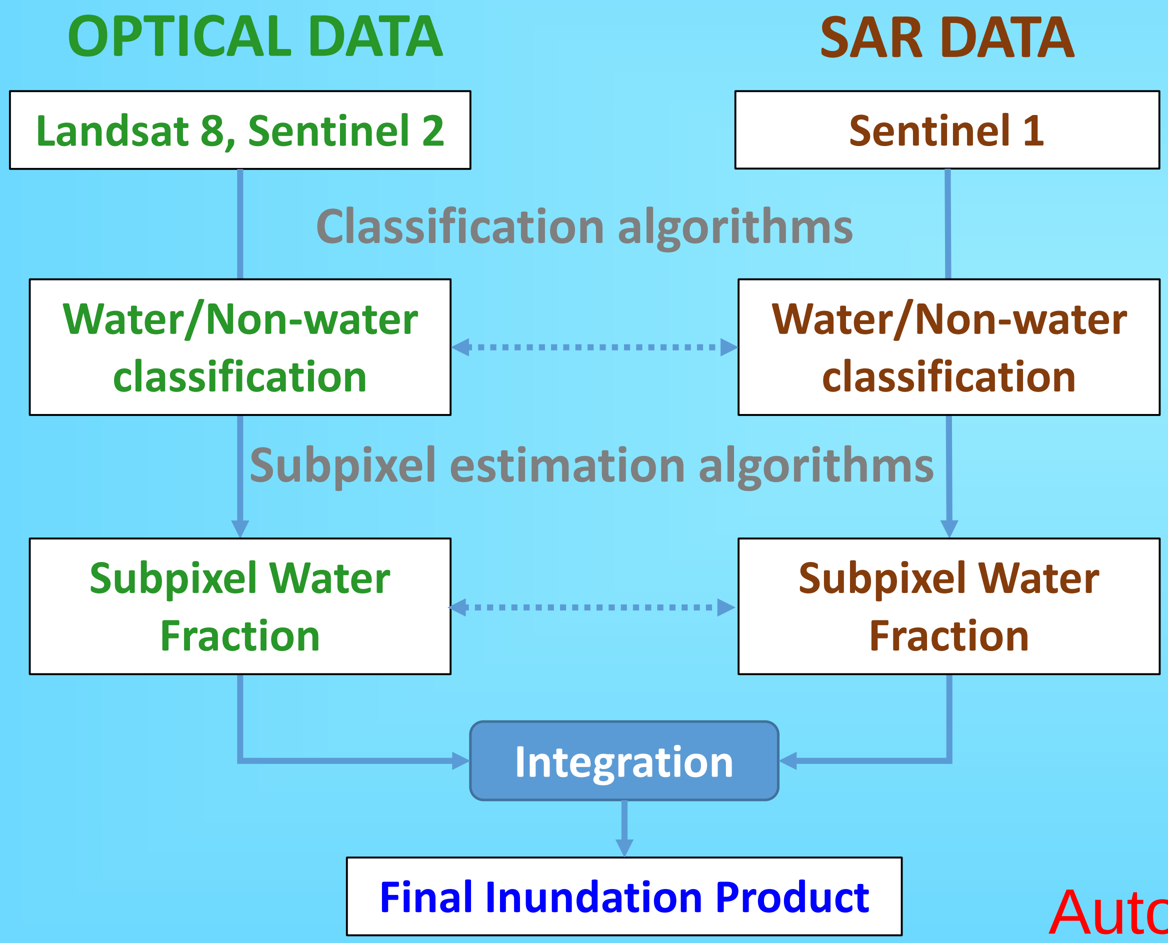
Inundation Probability in Different Seasons over the Last Three Decades over the Everglades

Research Objectives

- Develop and demonstrate improved capability to monitor terrestrial inundation
  - Develop automated algorithms suitable for inundation monitoring at the global scale using Landsat-8/Sentinel-2 (L8S2) optical data and Sentinel-1 (S1) SAR data.
    - Water/non-water classification
    - Subpixel Water Fraction (SWF)
  - Calibrate and test extensively
    - Test sites in US, Canada, Europe, Australia
  - Generate near daily inundation products for United States and southern Canada



Overall Approach



Classification algorithms

1. DSWE
2. Index/thresholding
3. Machine learning: SVM, RF

Subpixel estimation algorithms

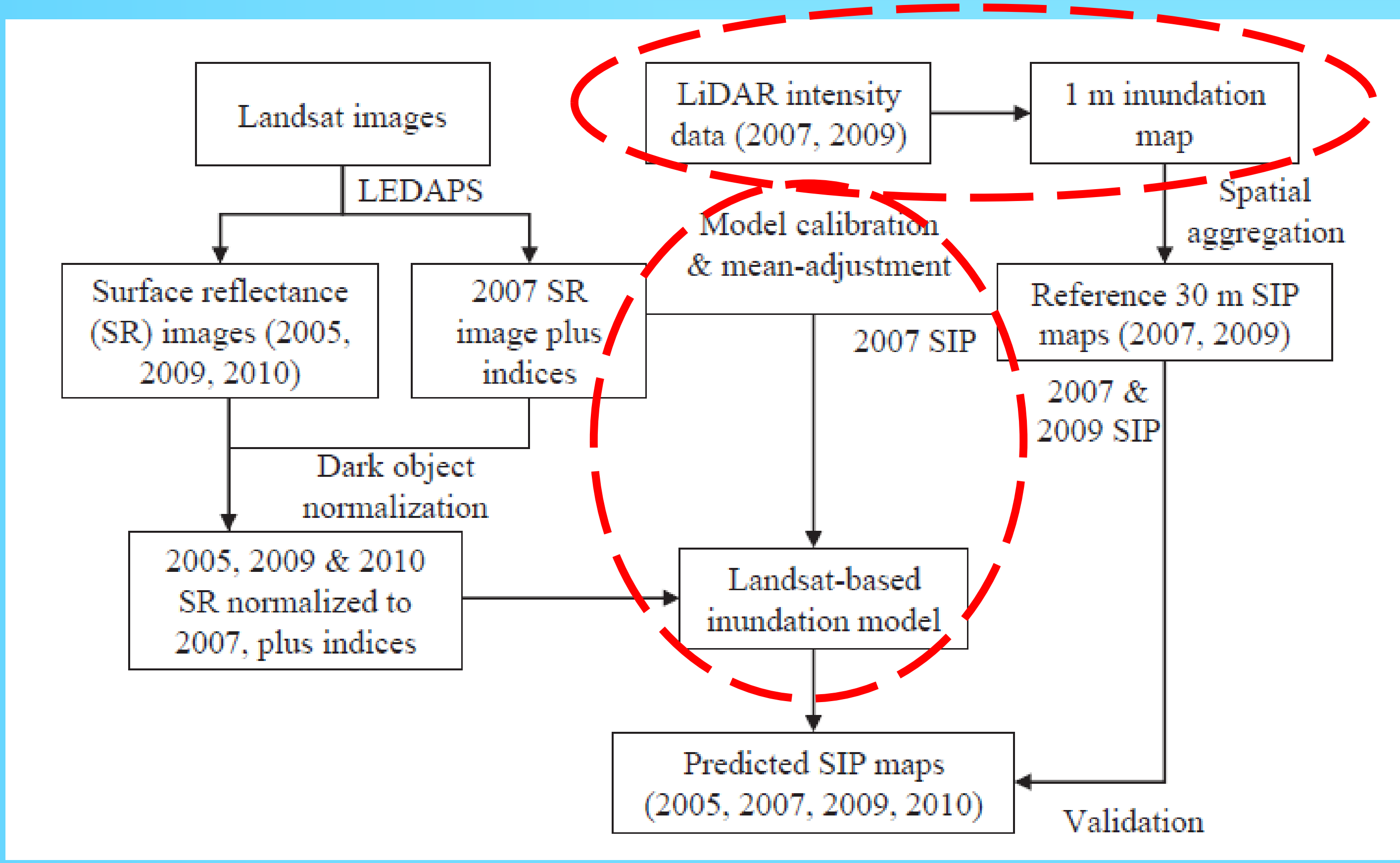
1.Regression Trees
2.Self-training

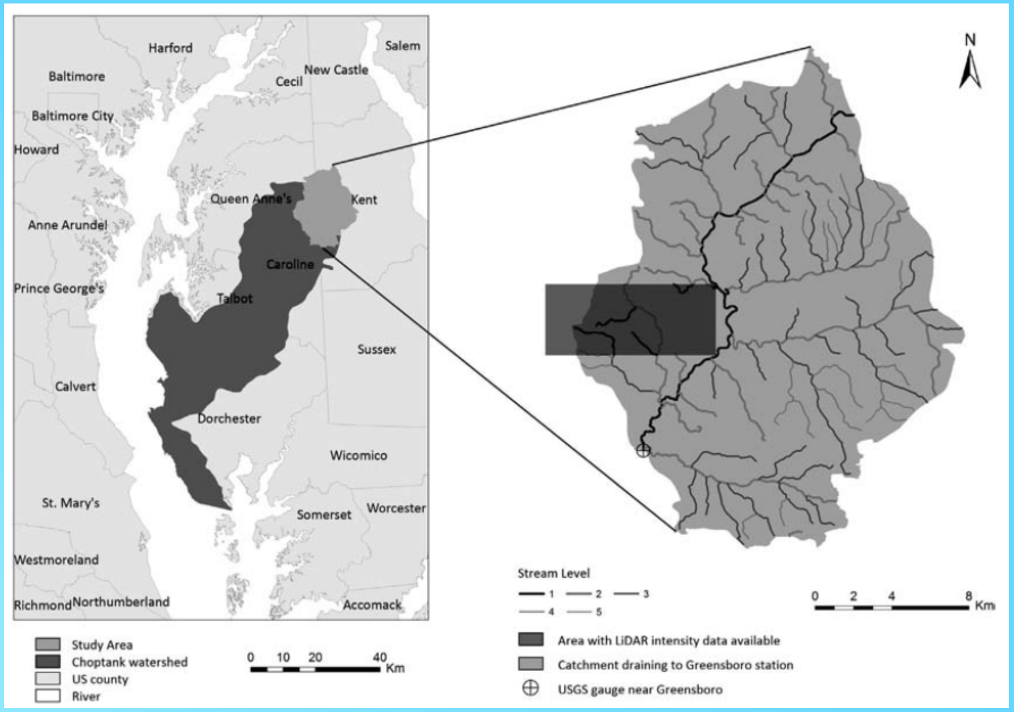
Optical-SAR Integration

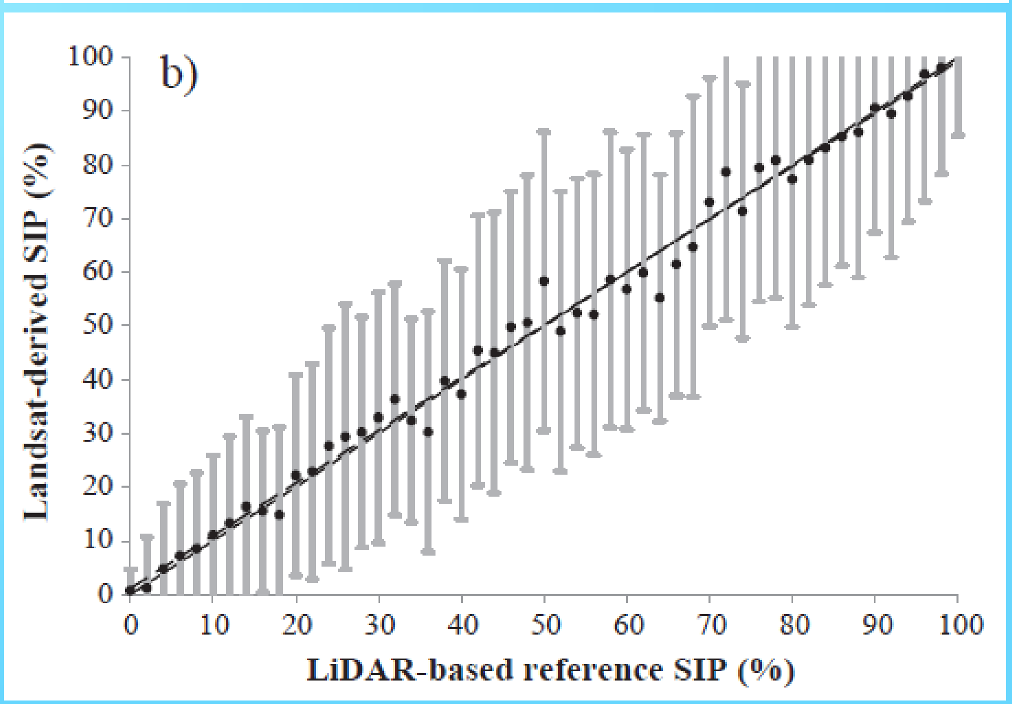
- Cross-sensor calibration
- Time series statistics (e.g. inundation probability)

Automation key to near daily monitoring at continental to global scales.

Inundation Mapping Driven by Lidar Based Training Data







(Huang et al. 2014)

Dynamic Surface Water Extent (DSWE) Classification Algorithm for L8/S2

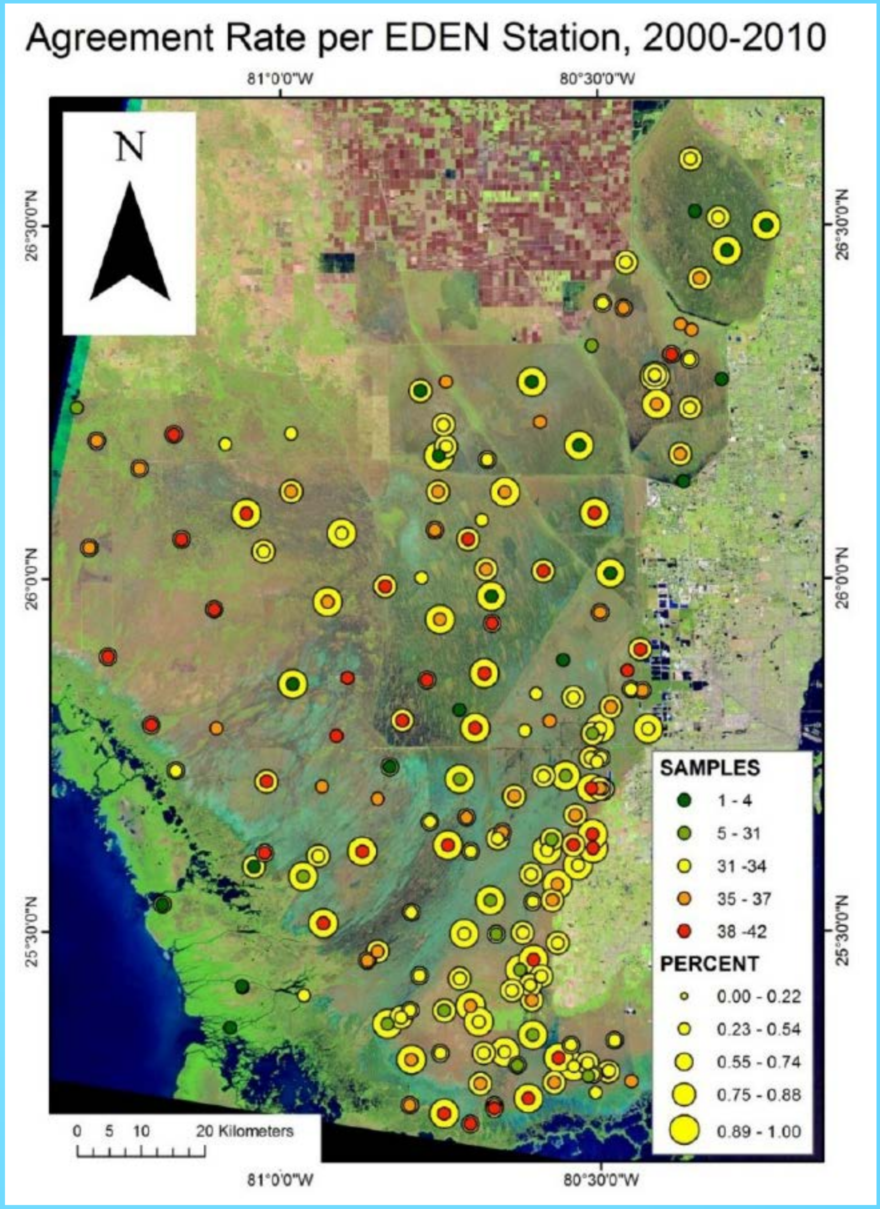
- DSWE tests:
  1. MNDWI > 123 [scaled by 10000]
  2. MBSRV > MBSRN
  3. $AWE_{sh} > 0$
  4. MNDWI > -5000* & SWIR1 < 1000 & NIR < 1500
  5. MNDWI > -5000 & SWIR2 < 1000 & NIR < 2000

$$MNDWI = \frac{G - SWIR1}{G + SWIR1}$$

$$MBSRV = G + R$$

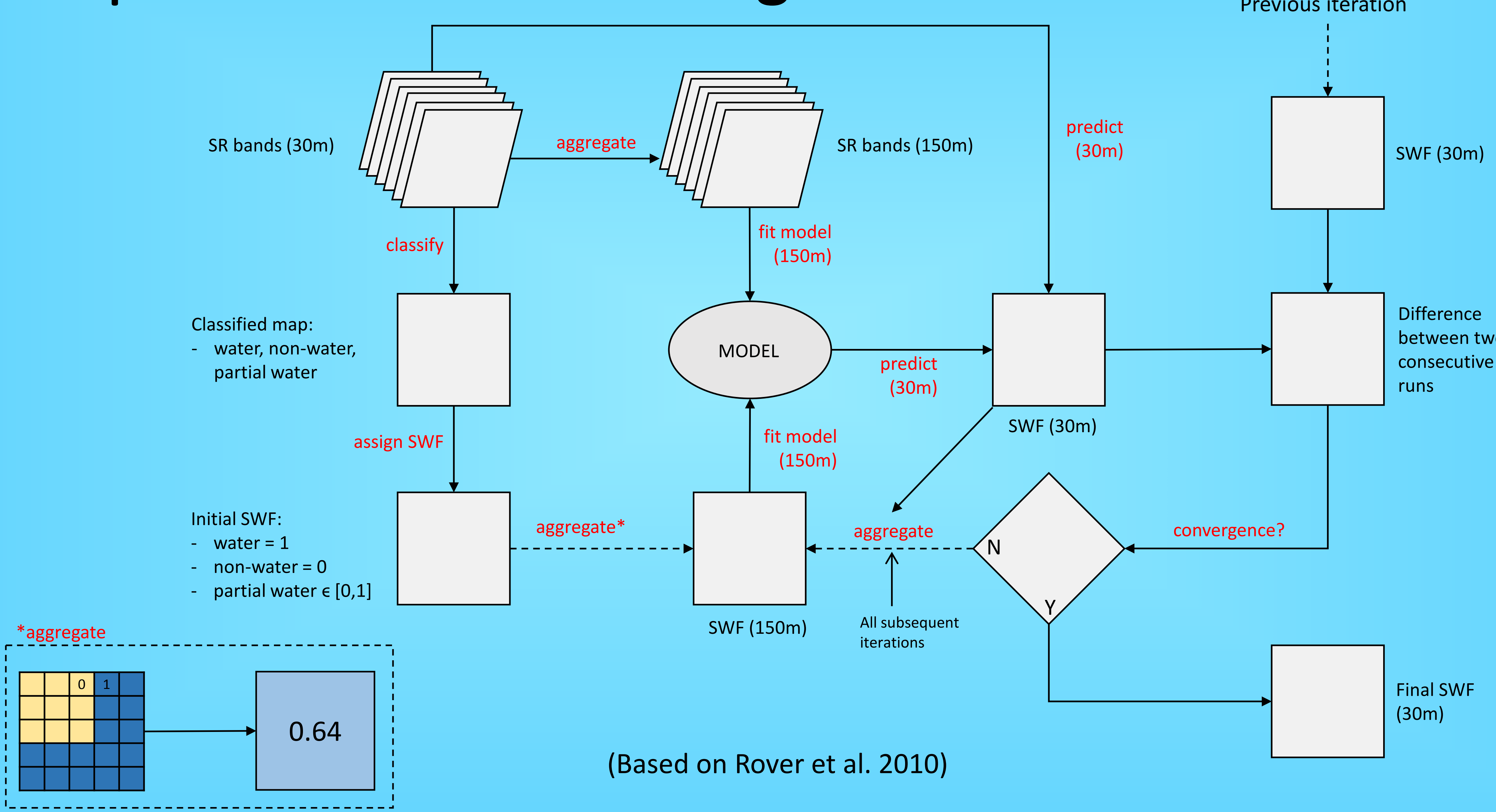
$$MBSRN = NIR + SWIR1$$

$$AWESH = B + 2.5G - 1.5MBSRN - 0.25SWIR2$$



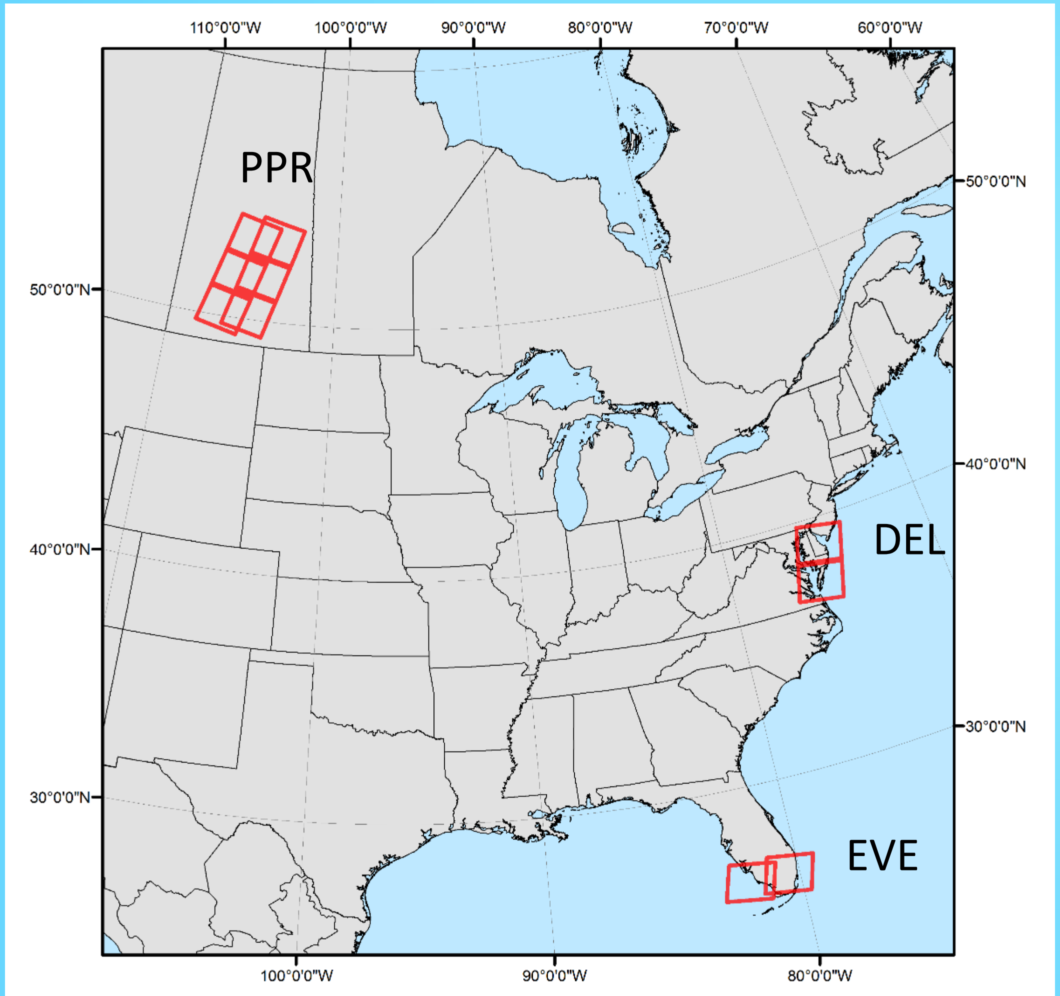
(Jones 2015)

Subpixel Water Fraction Algorithm



(Based on Rover et al. 2010)

Initial Test Sites



Saskatchewan Prairie Pothole (PPR)

- small seasonal and ephemeral ponds fed by snowmelt in early spring and late summer storms
- airborne LiDAR, field surveys

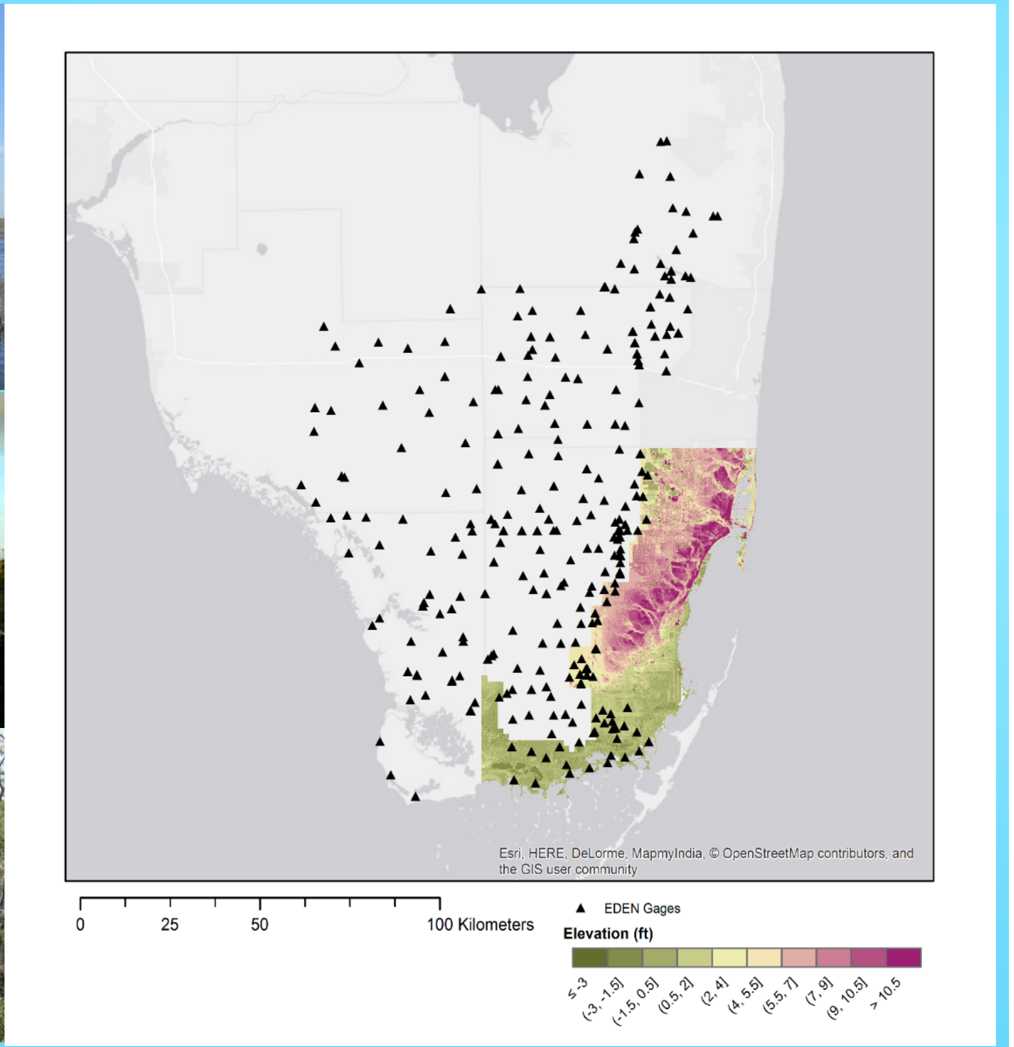
Delmarva Peninsula (DEL)

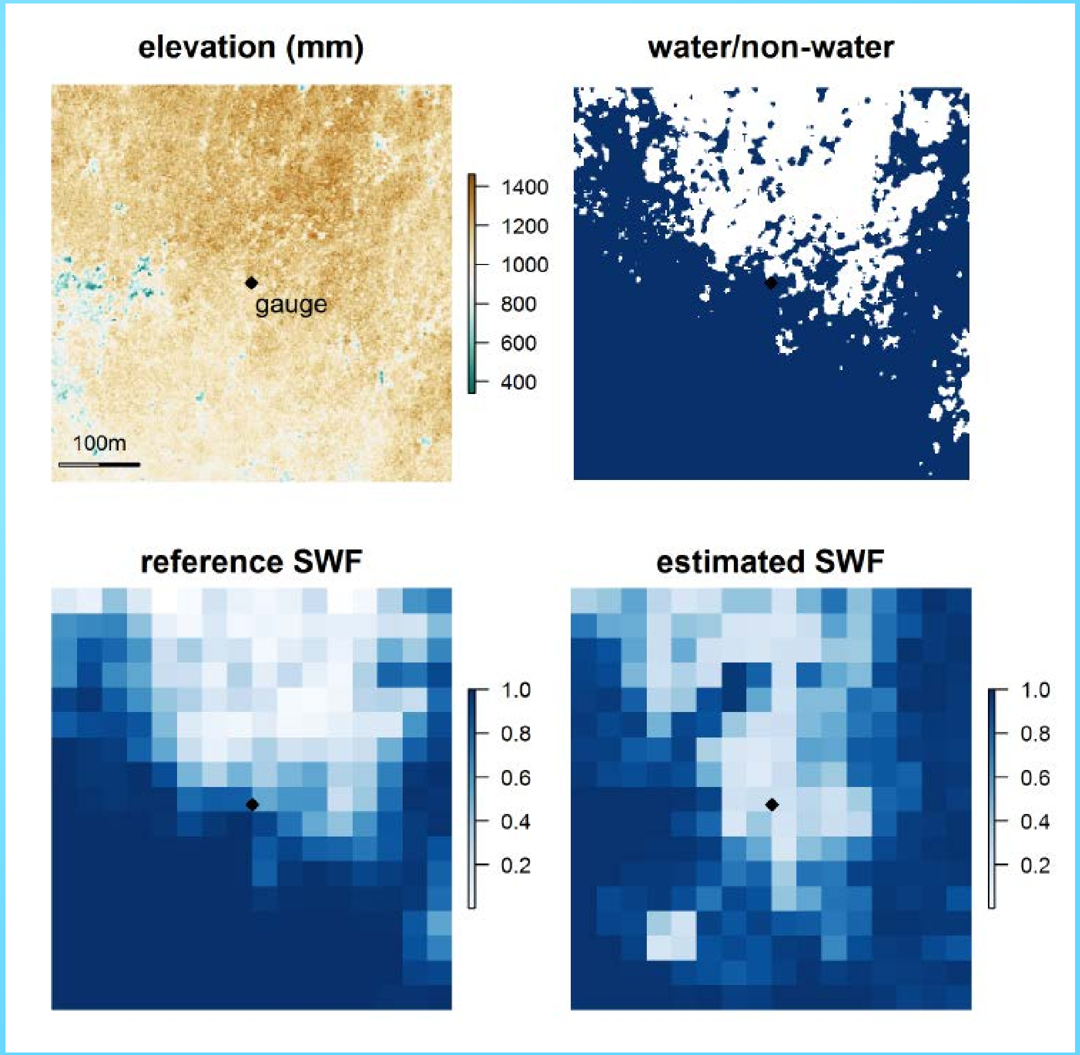
- depressional wetlands (bays), flats and forested wetlands in riparian zones
- airborne LiDAR

Florida Everglades (EVE)

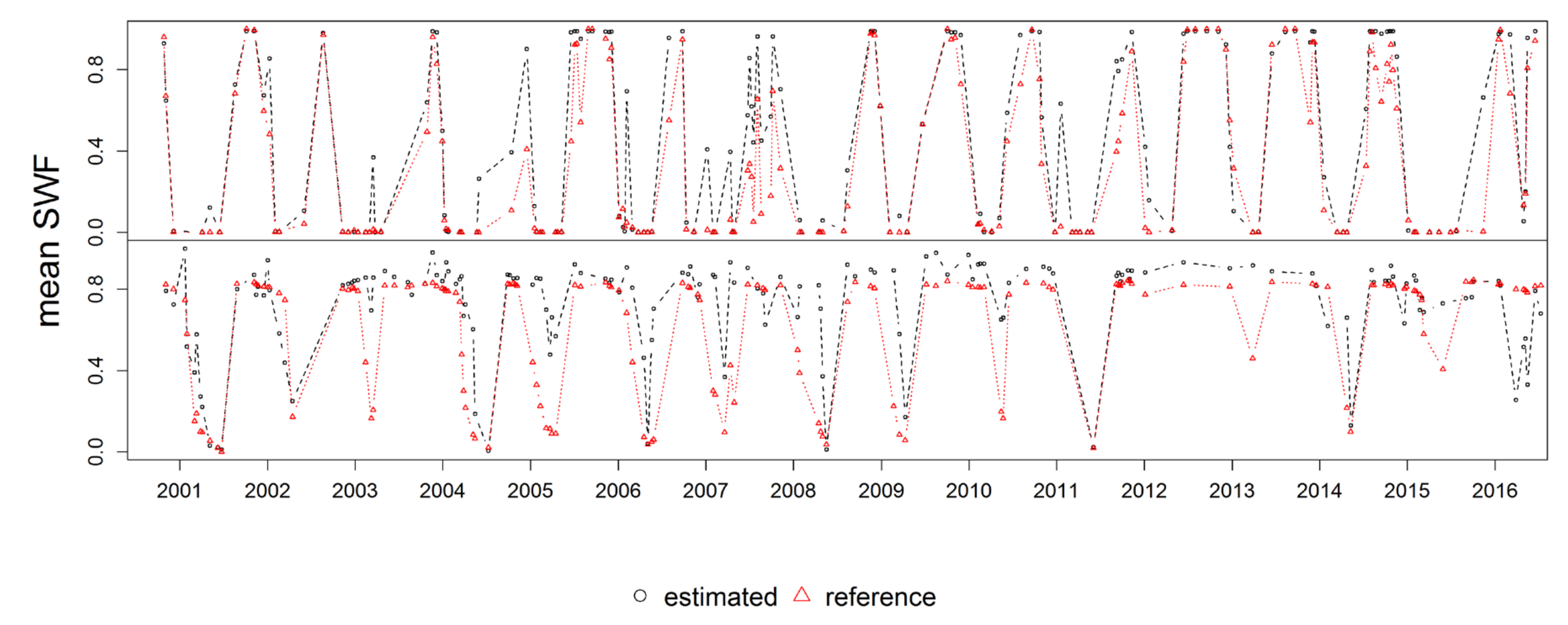
- wet prairie and sawgrass marsh, evergreen forest, mangrove, rush
- water level gauges, local DEM

Continuous Water Level Measurements Over the Everglades

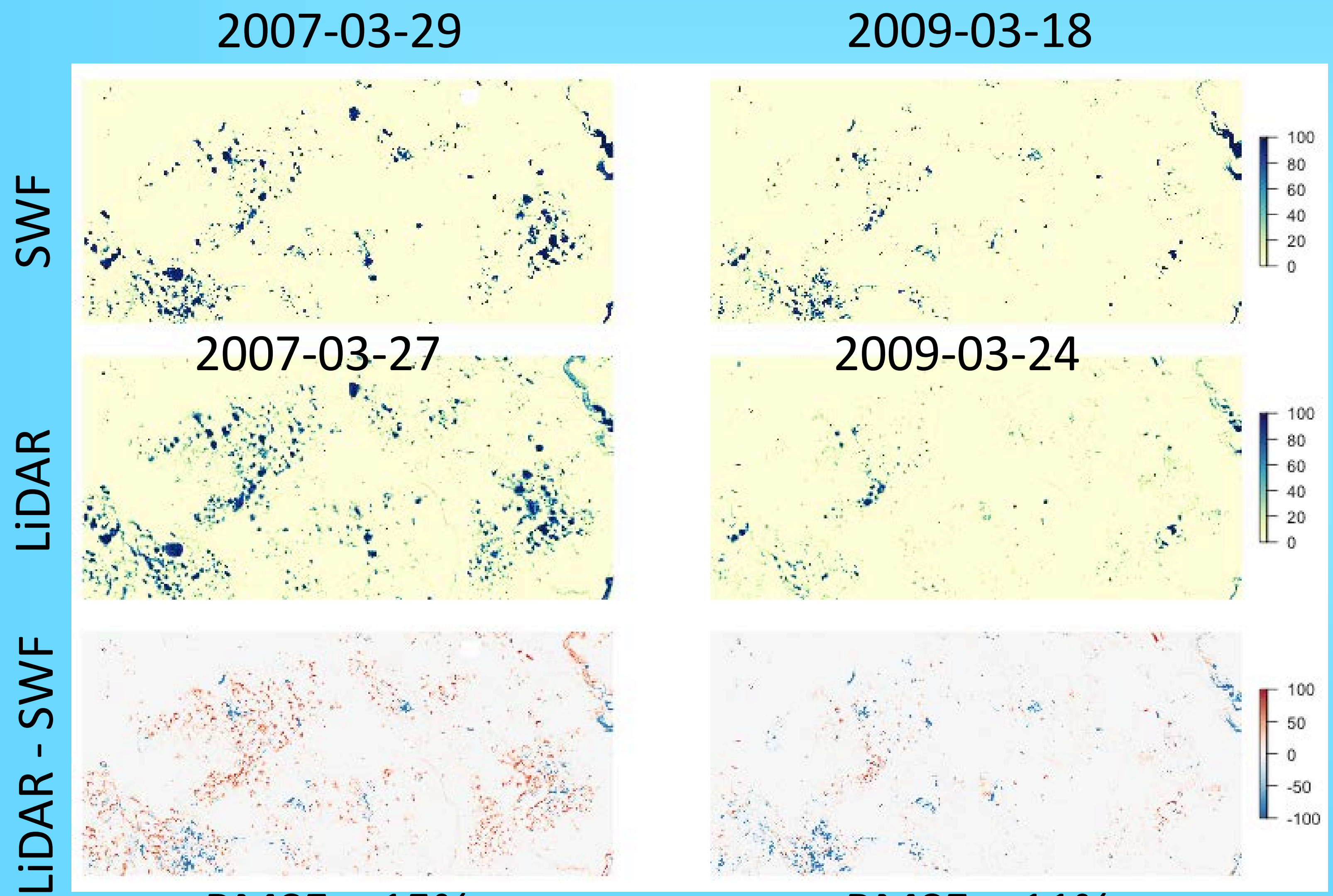




Time Series SWF Tracks Ground Observations

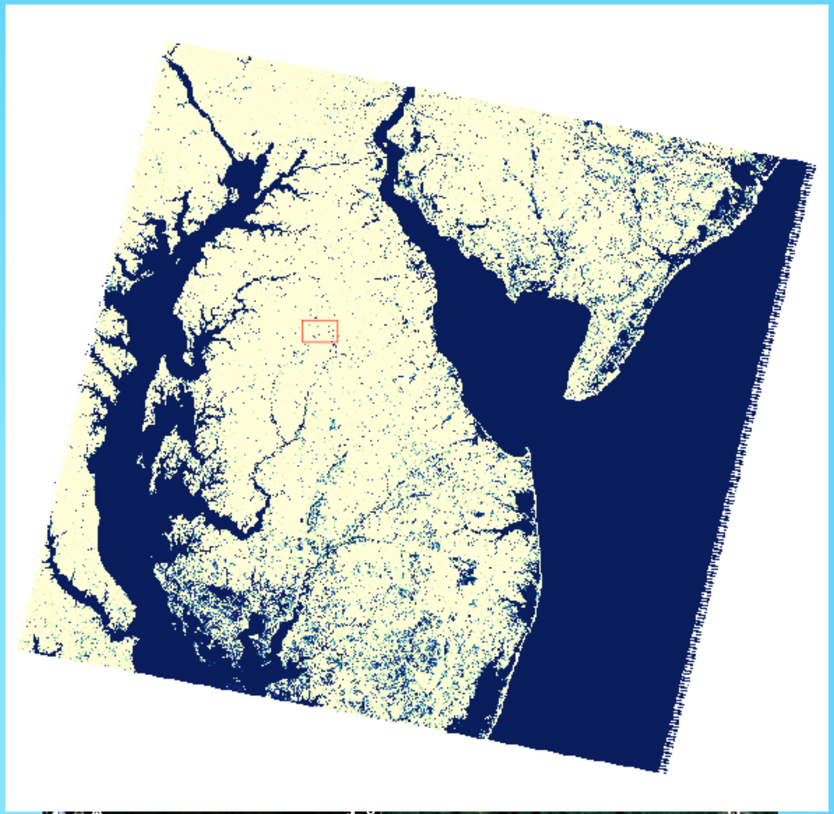


Comparison with Lidar Based Reference Data



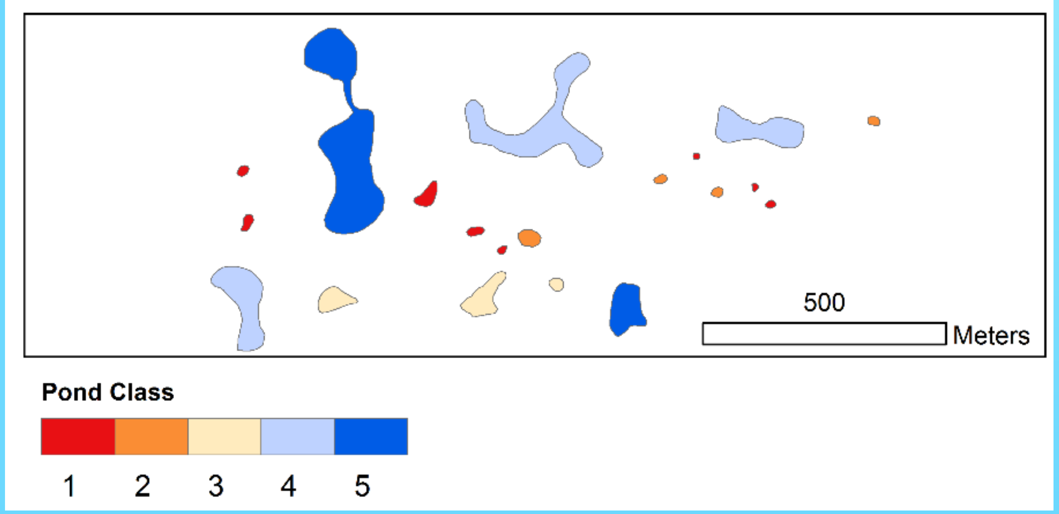
RMSE = 15%

RMSE = 11%

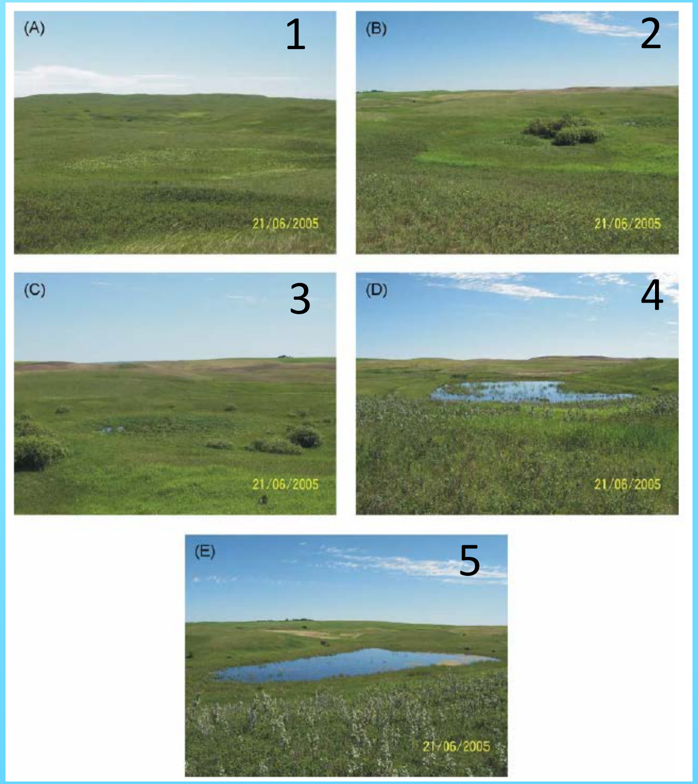


Pond Area Estimation Over Saskatchewan PPR

- Pond perimeters delineated in late spring / early summer of 2005
- Purpose: establishing transects for multi-temporal soil moisture measurements
- Smaller ponds (classes 1-3) likely do not represent inundated area (probably 'potential' inundated surface)



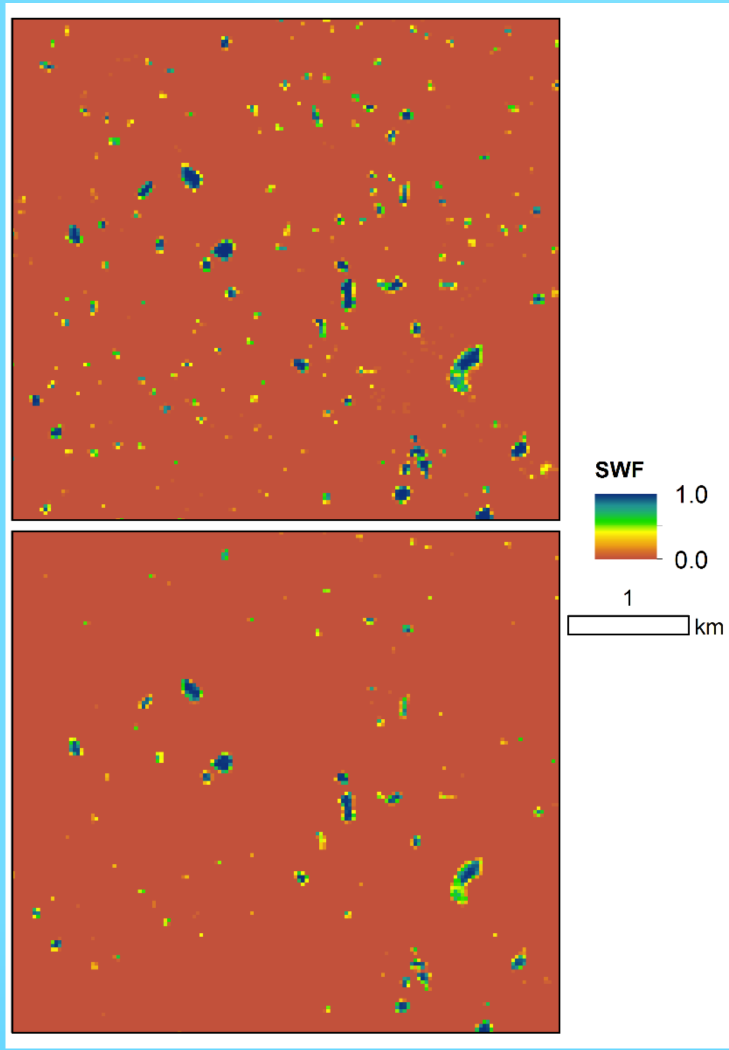
Pond Classes (Carlyle 2006)

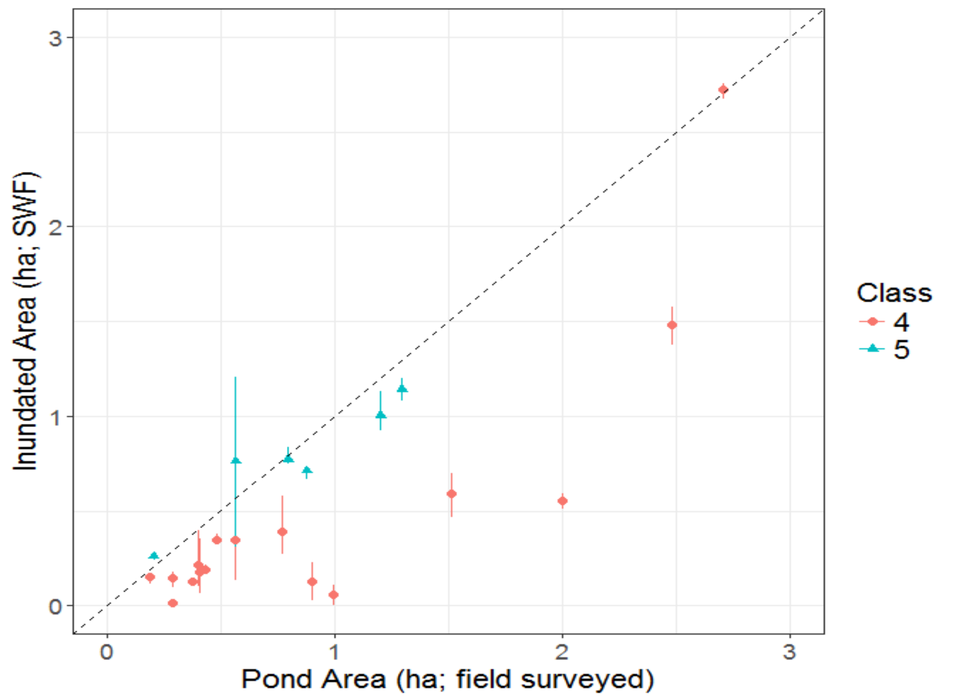


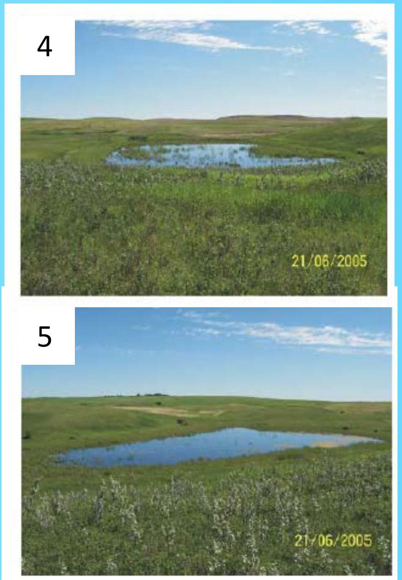
Pond Area Estimation Over Saskatchewan PPR

2005-04-25

2005-05-11







Photos:
Stephen Carlyle (2006)

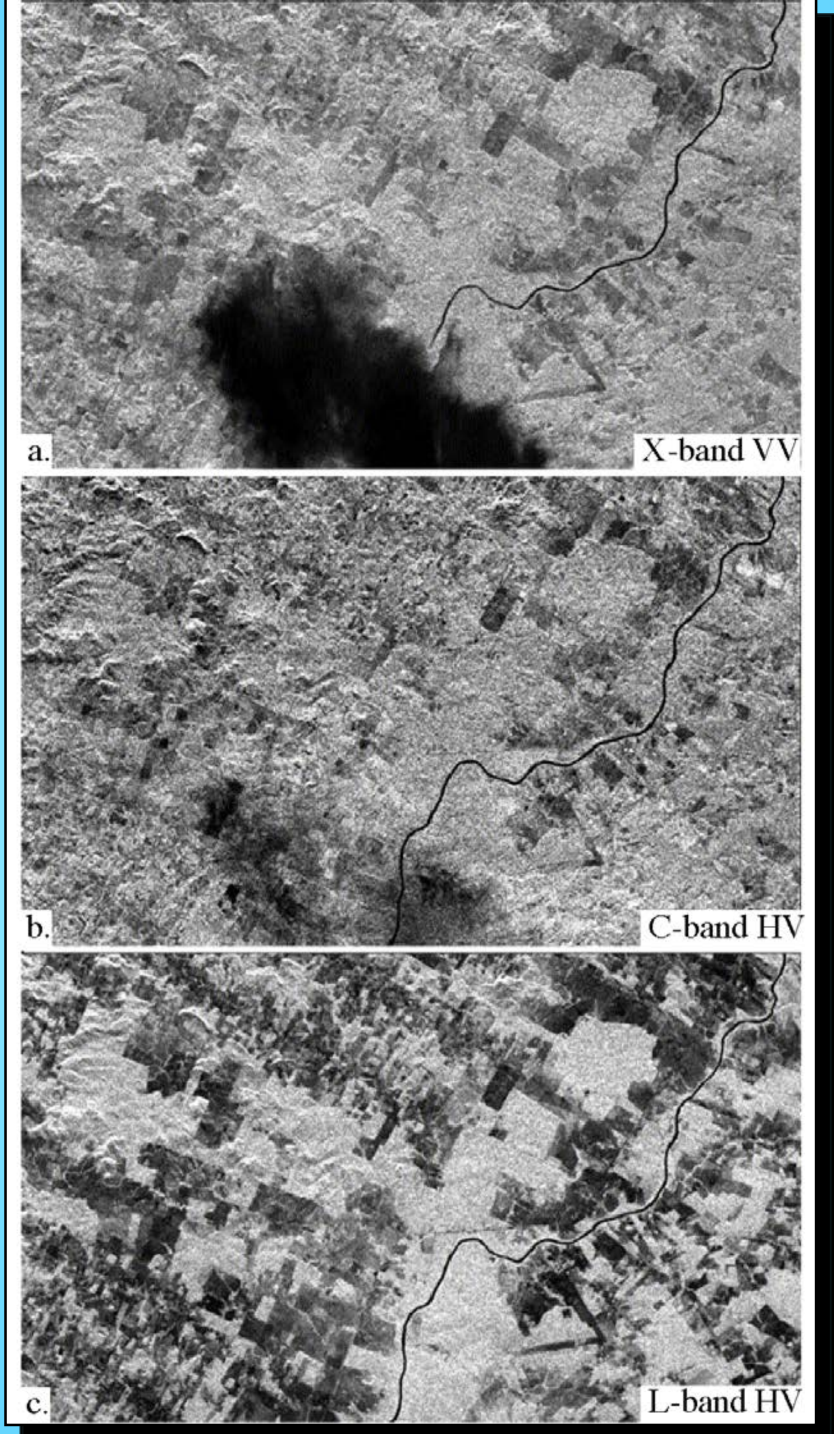
Automated quantification of wetland surface water fraction using optical satellite imagery

Ben DeVries [a,*], Chengquan Huang [a], Megan W. Lang [b], John W. Jones [c], Wenli Huang [a], Irena F. Creed [d], Mark Carroll [e]

Manuscript Near Ready for Submission

Cloud Is A Major Problem in Optical Observations, But Far Less in SAR Data

Penetration through heavy rainfall in C- and L-band



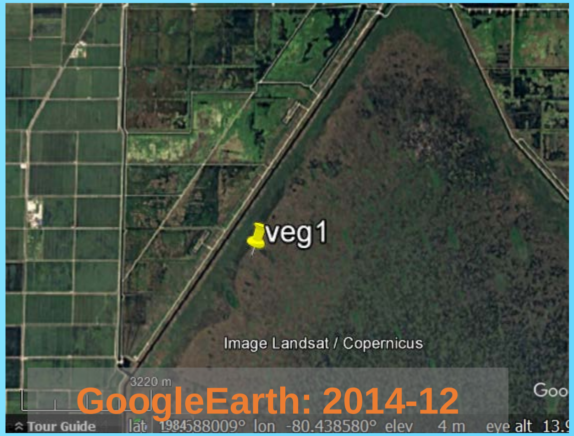
(Zhong Lu)

SIR-C/X-SAR Images of a Portion of Rondonia, Brazil, April 10, 1994

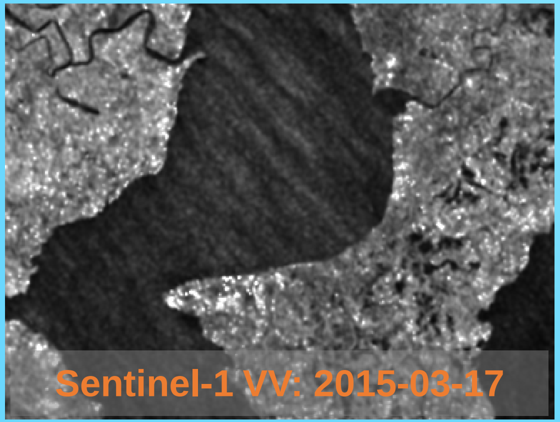
Water Signal Highly Variable in Radar

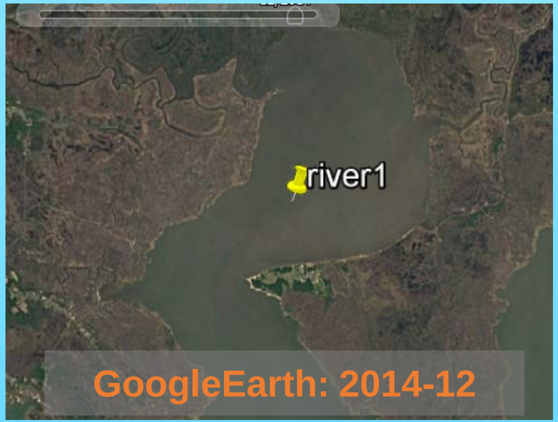
Open water

Water with vegetation

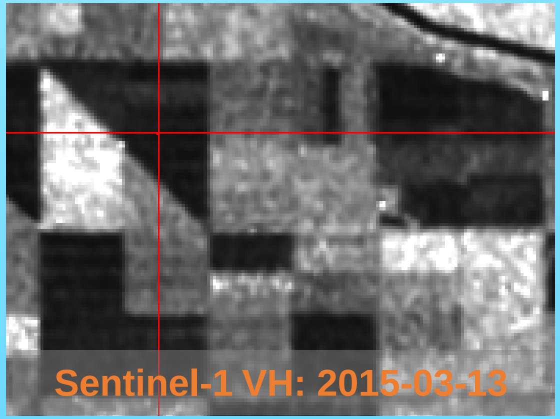


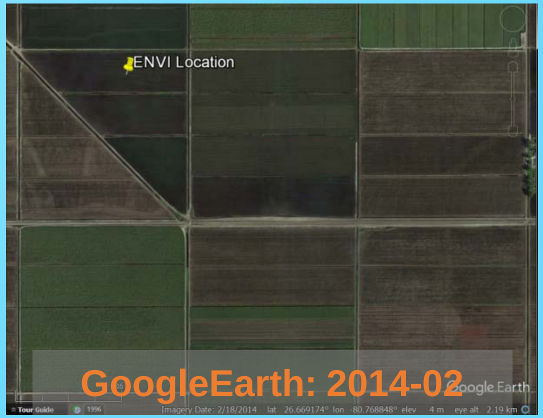
Open water with waves



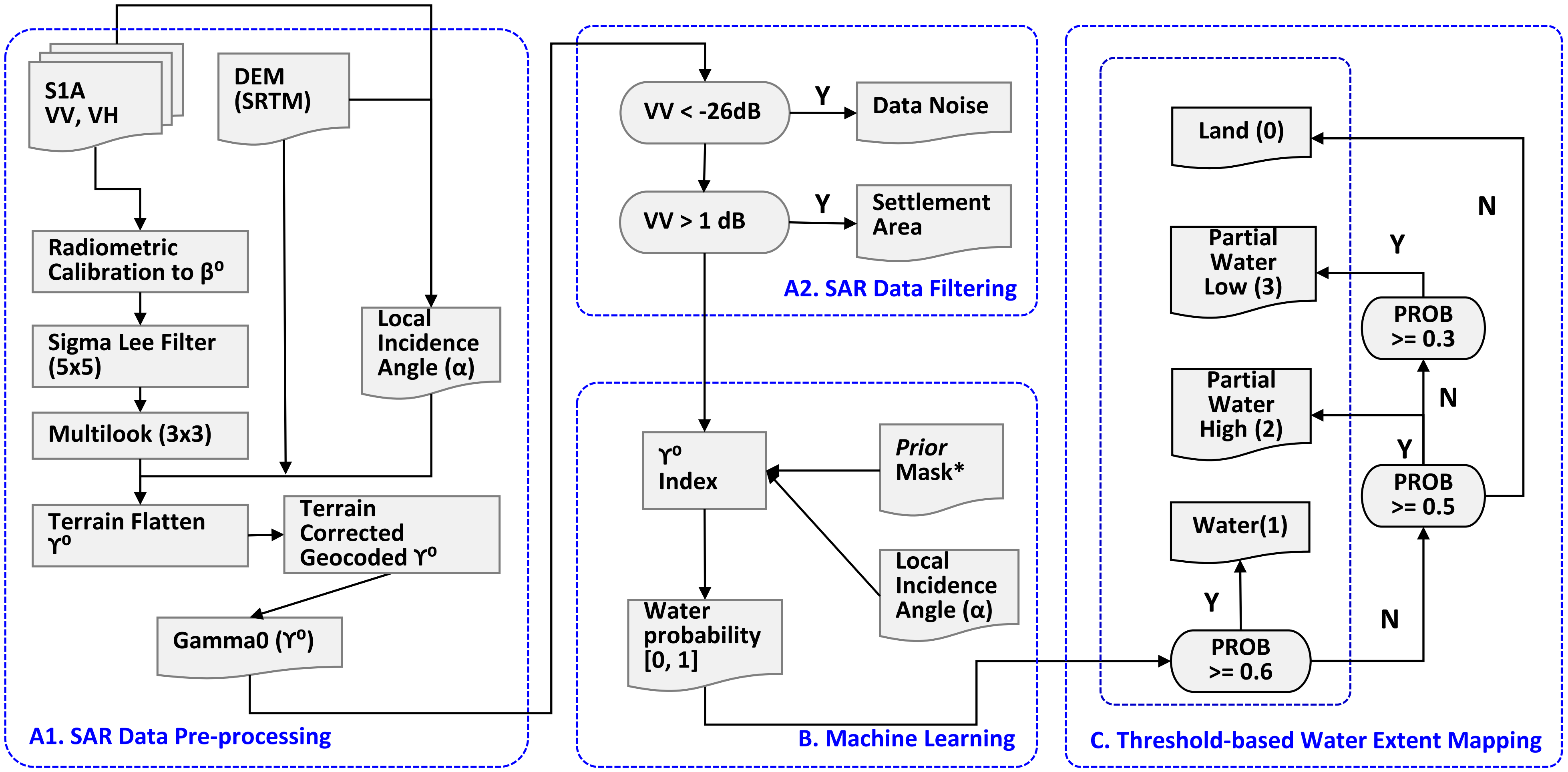


Dark soil / agriculture





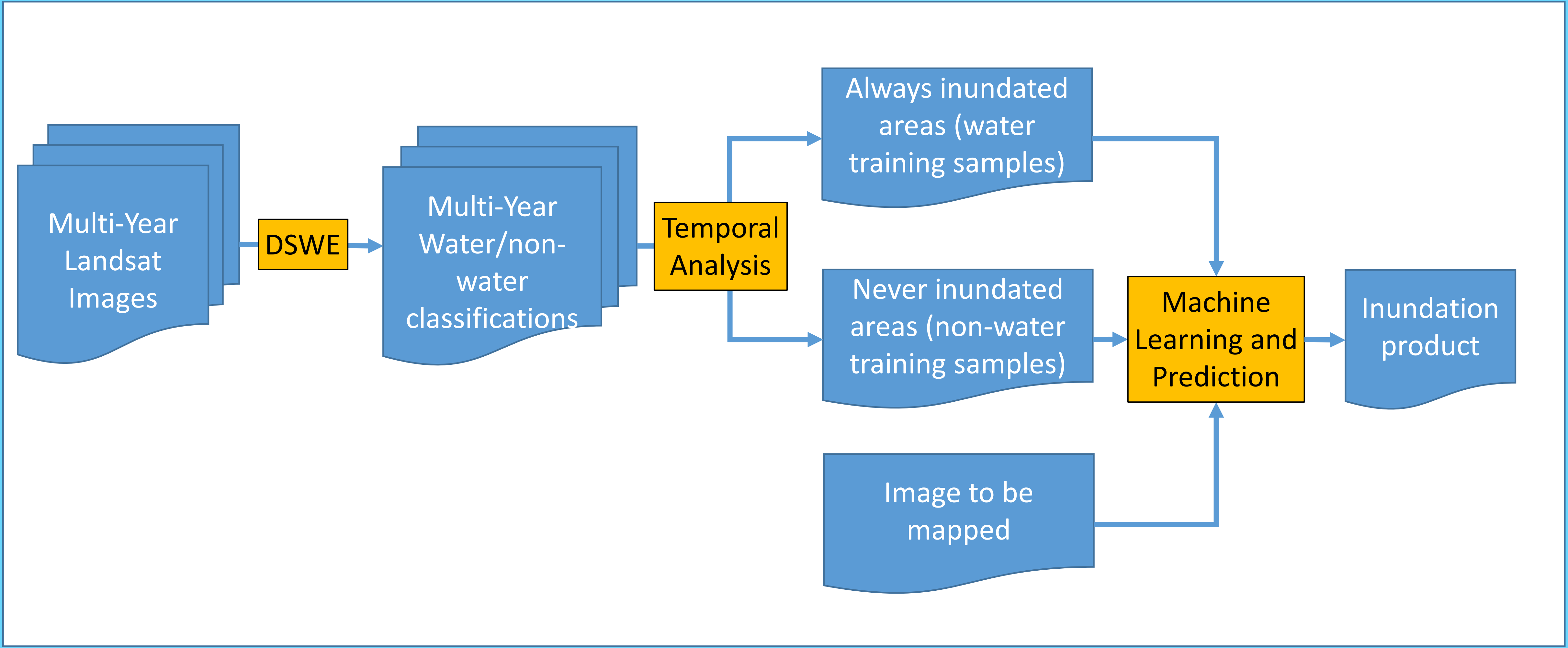
Sentinel-1 SAR Water Extent Mapping



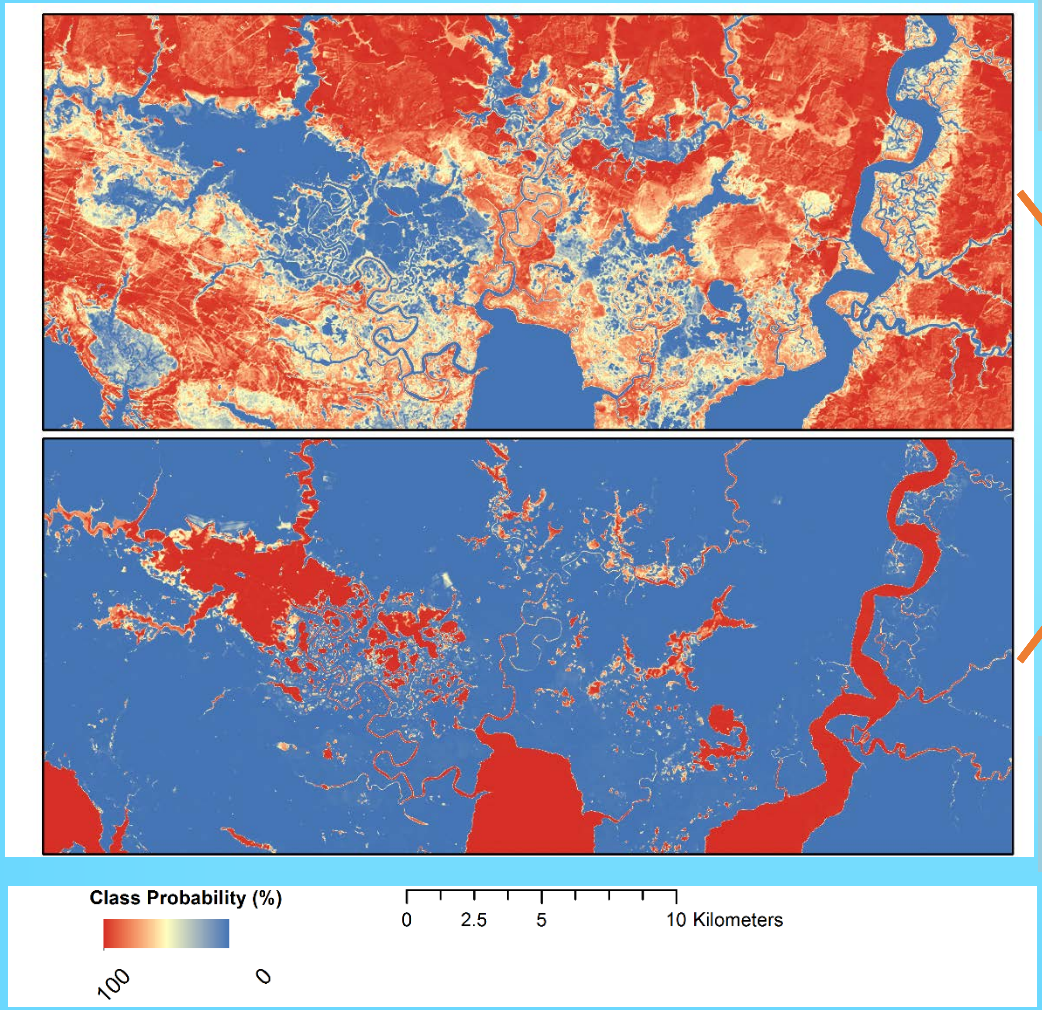
Υ^0 = Gamma naught, α = Incidence angle

**Prior* Mask: DSWE=Dynamic Surface Water Extent, Multi-temporal class probability

Mapping Algorithm 1: Machine Learning Approach



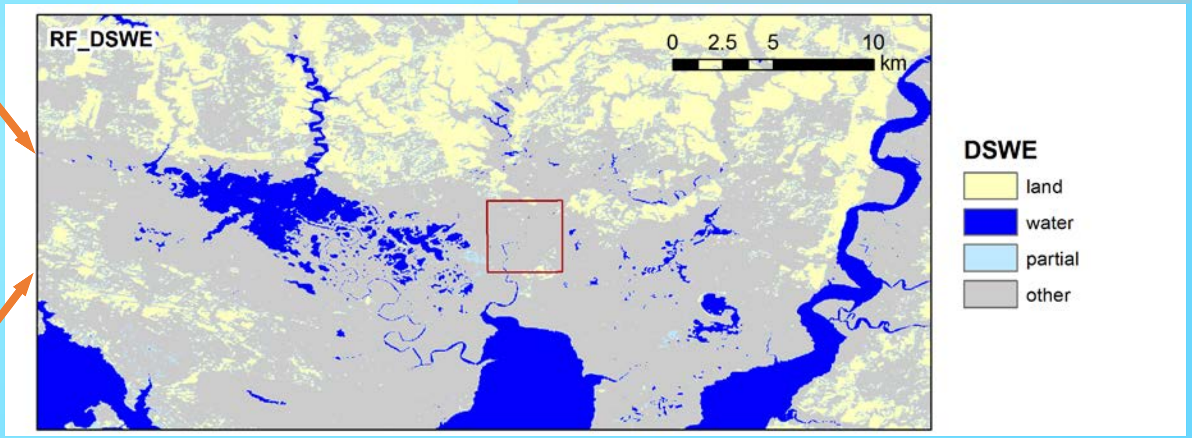
Training Data Derivation Using Multi-Temporal DSWE Products



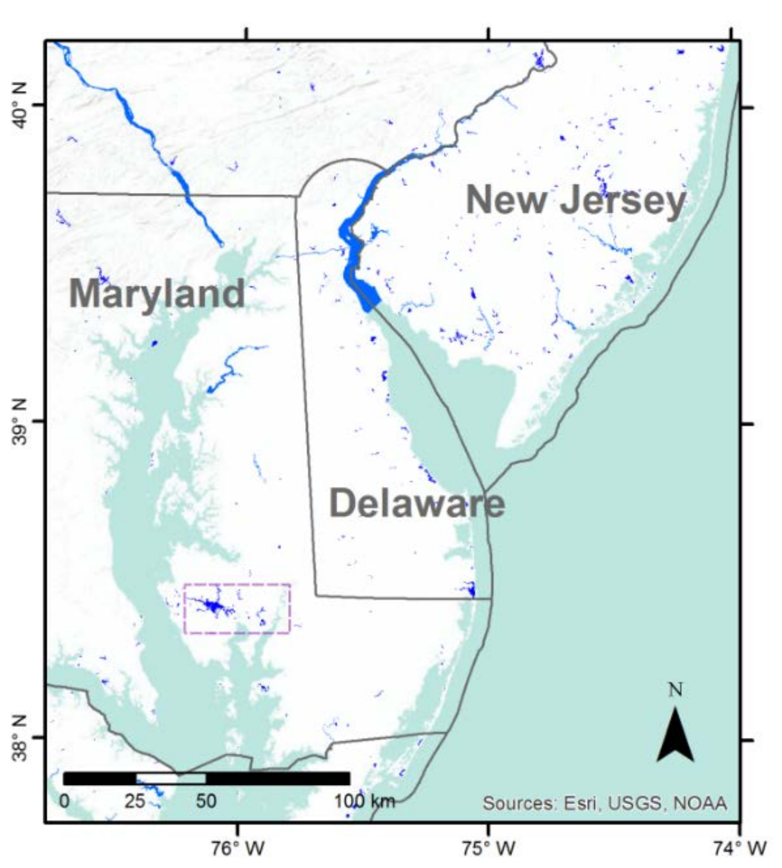
A. Multi-year land probability

B. Multi-year water probability

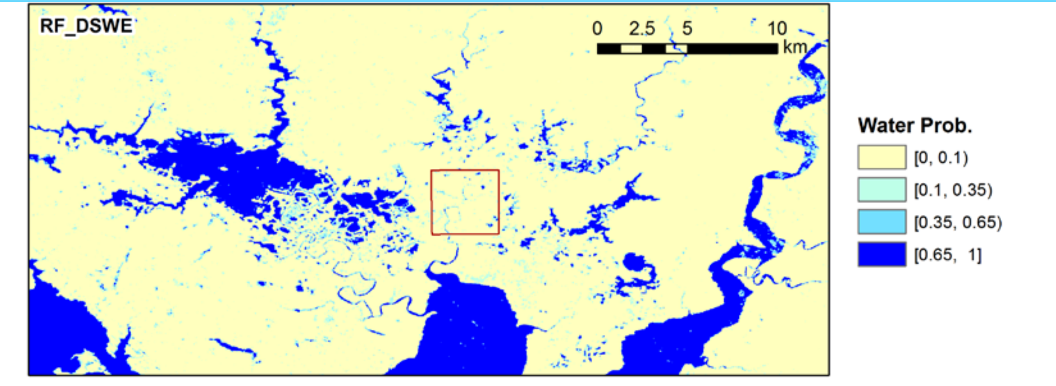
C. Highly confident (>95%) training samples

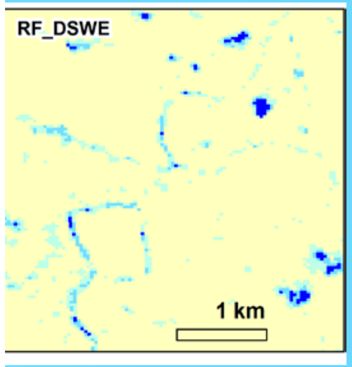


Machine Learning Approach Over Delmarvar

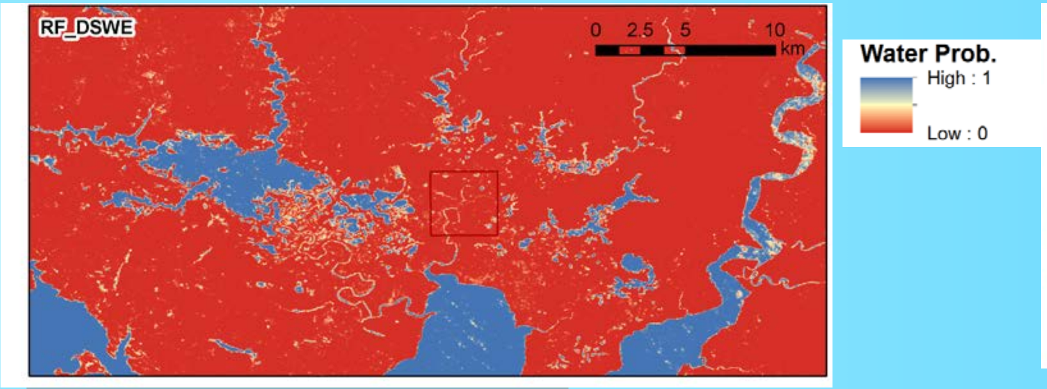


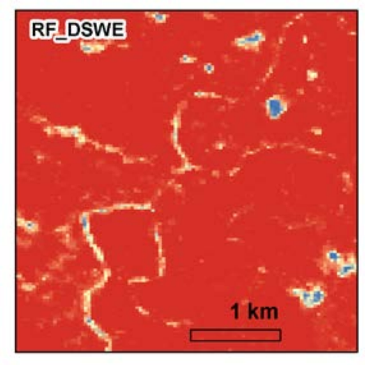
RF_DSWE: Class 2015-03-17





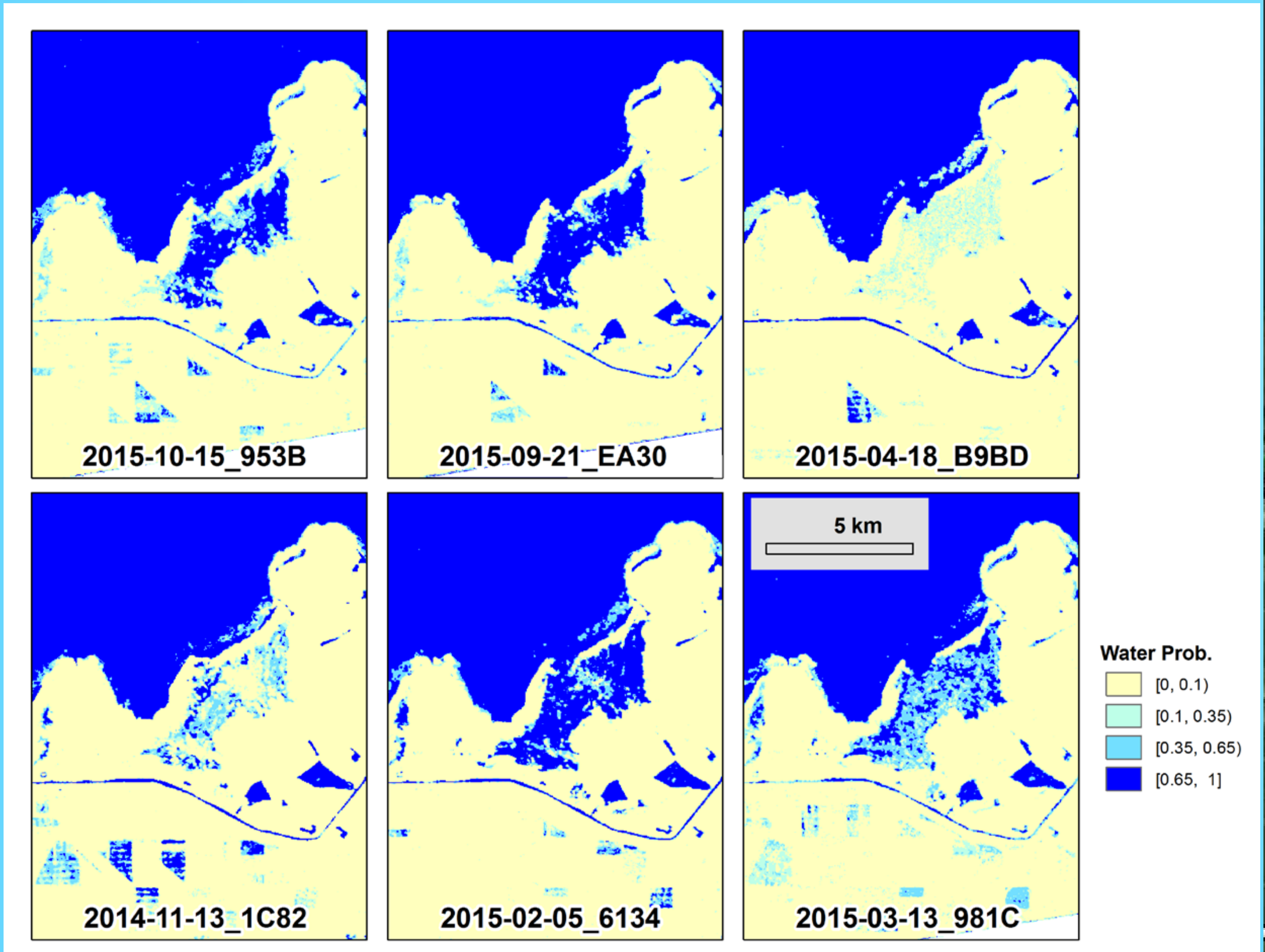
RF_DSWE: Prob. 2015-03-17



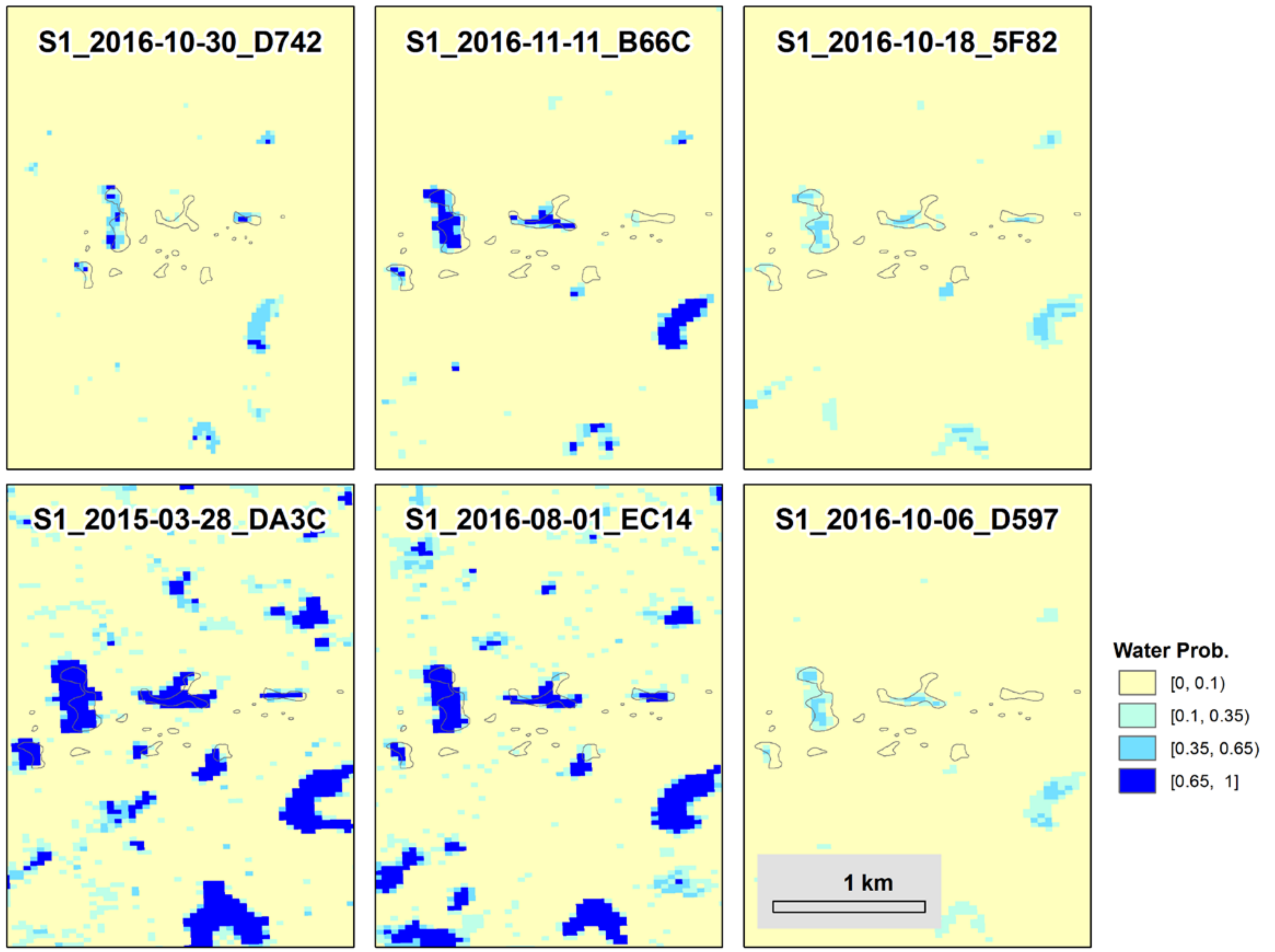


Google Earth 2013-10-20

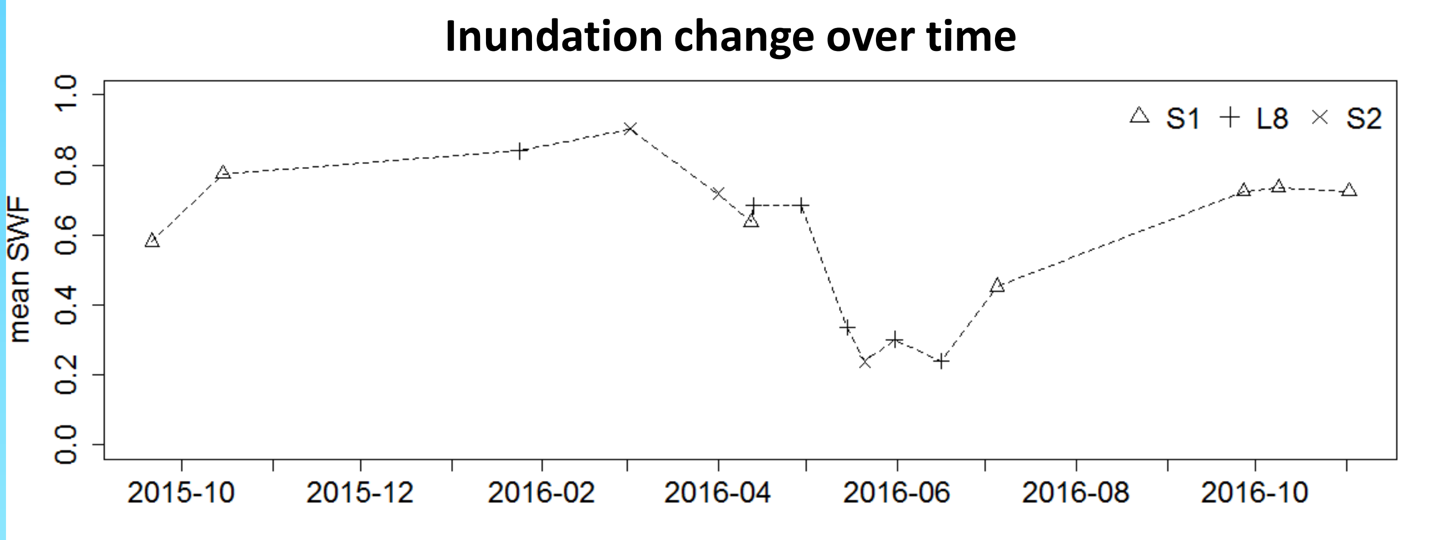
S1 Radar Mapping Over Everglades

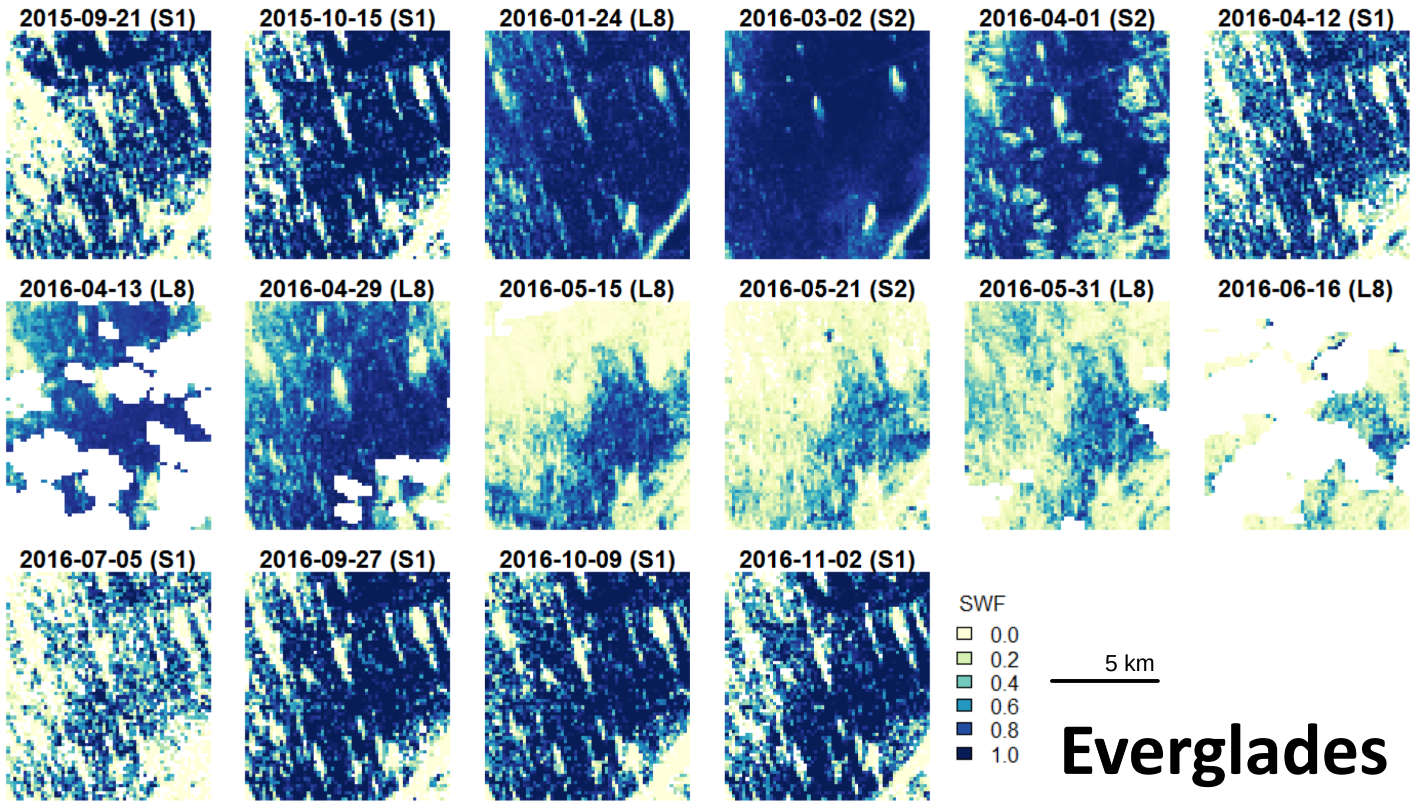


S1 Radar Mapping Over Saskatchewan Prairie Pothole Region

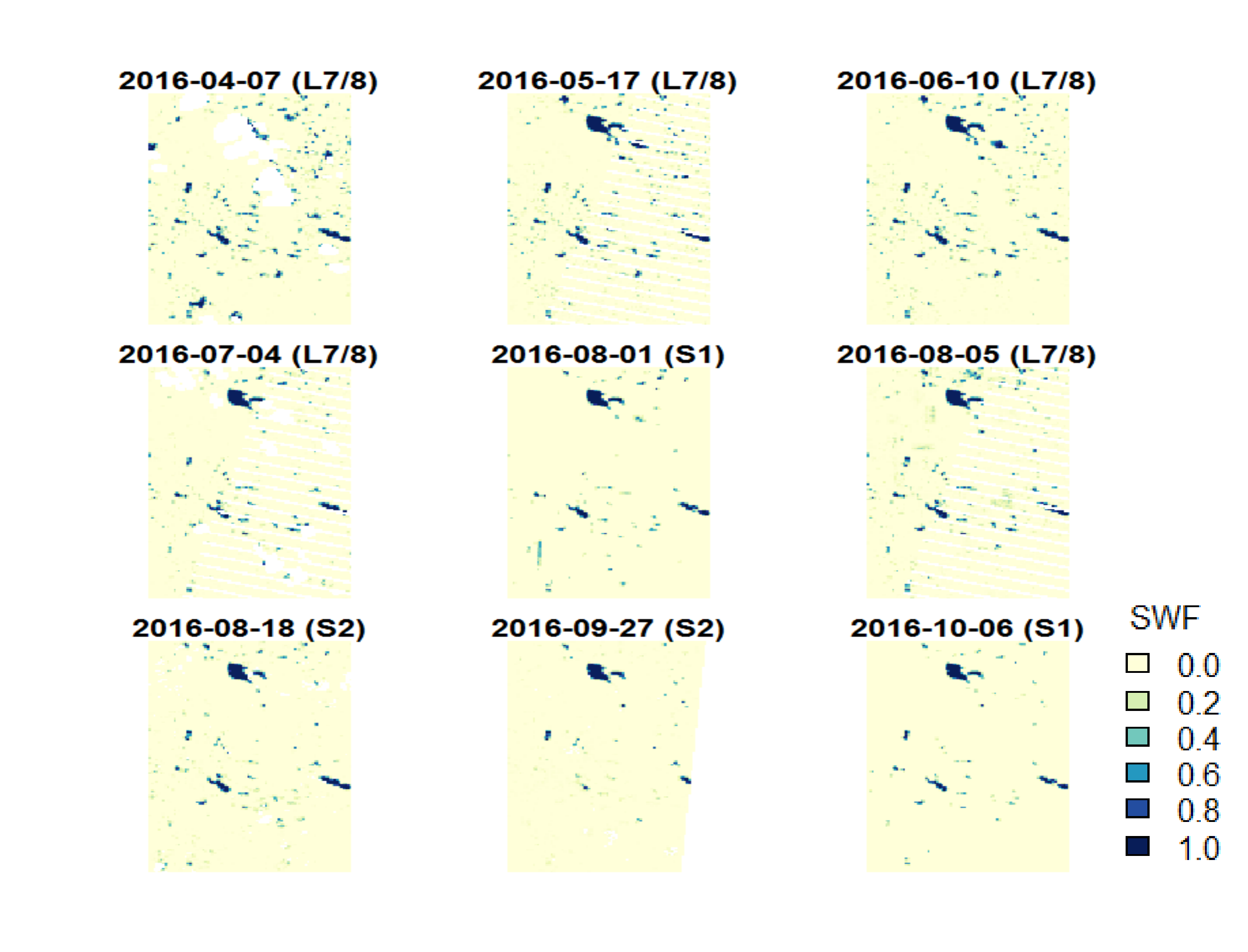


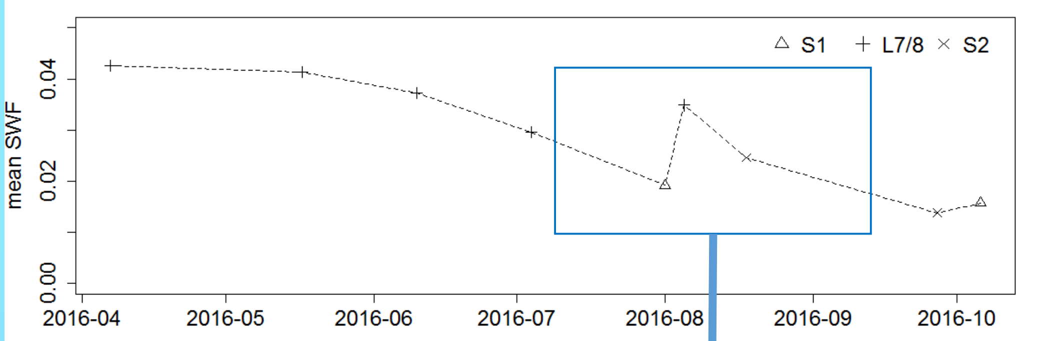
Prototype Inundation Time Series from L8/S2/S1

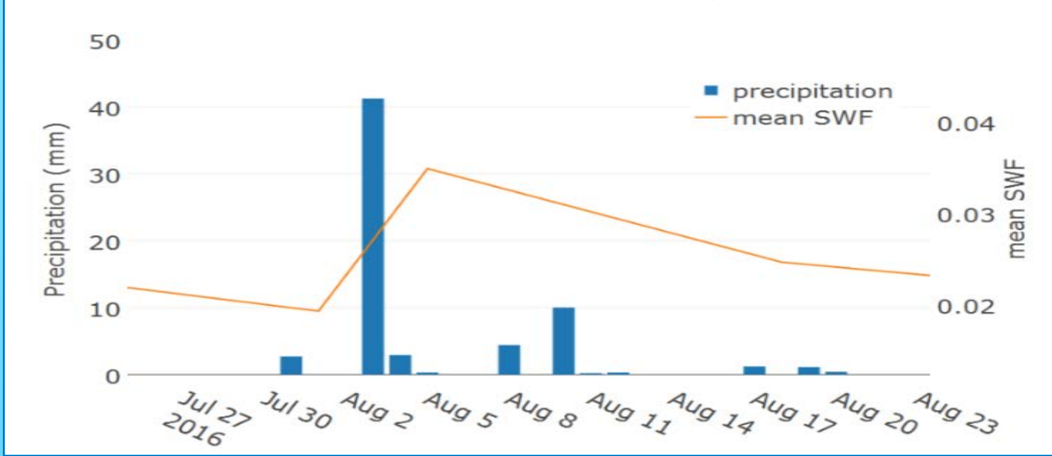




Prototype Inundation Time Series from L8/S2/S1

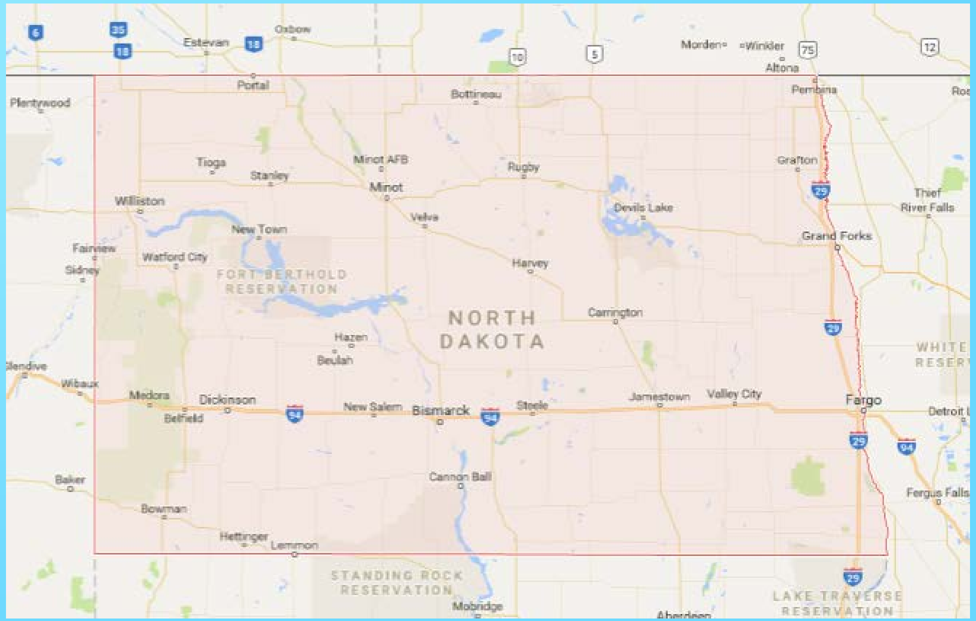






Large Area Prototype Over North Dakota

- Entire state
- All images available from 04/01/2016 to 10/31/2016
- Landsat 8
  - 234 images
  - Order and SR/cloud mask: ~3 days
  - Mapping: ~30 h x 10 CPUs
- Sentinel-2
  - 841 granules
  - SR/cloud mask: ~28 h x 10 CPUs
  - Mapping: ~35 h x 10 CPUs
- Sentinel-1
  - 59 images
  - Preprocessing: ~36 h
  - Mapping: ~6 h



Large Area Prototype Over North Dakota

Repeat intervals: 1 – 16 days

Summary

- Automated surface water mapping algorithms developed
  - Optical methods
    - Mature for Landsat
    - A manuscript ready for submission
    - Some adjustment needed for S2
  - Radar methods
    - Tested over multiple sites
    - Need more quantitative assessment
- Limited validation possible
  - High resolution data for determining subpixel fraction
  - Temporal matching critical
  - Gauge data with good DEM desirable
- Initial large area test over ND
  - Tried all available L8, S2, S1 images for summer 2016
  - Preprocessing time >> mapping time
  - Huge saving if preprocessed data available
    - Optical data: at least 50%
    - Radar: > 80%
- Next steps
  - Try out HLS data
  - Ensure optical-radar consistency
  - Develop more validation data sets
  - Scale up to US and Southern Canada
  - Analyze regional/national results