Land/Water-Sat: Landsat's New Potential to Monitor Case 2 Waters

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Sponsor:

United States Geological Survey (USGS)

Can LDCM be used for water resource studies in fresh and coastal waters?

•Can modest resolution thermal data be generated from near concurrent ModIS data or TIRS sharpened to 30 m to support calibration of aspects of hydrodynamic models?

•Can OLI data be used to map primary coloring agents (constituents) in water ([C].[CDOM] and [SM]) in the absence of atmosphere?

•Can OLI specific over water atmosheric corrections be developed to support water constituent retrieval?

•Can TIRS thermal image data be used to calibrate the meteorological and flow volume inputs to hydrodynamic models using surface temperature model matching approaches?

•Can OLI reflectance data be used to calibrate the concentration inputs and background concentrations in coupled hydrodynamic and radiative transfer models of 3D water volumes?

Research Motivation

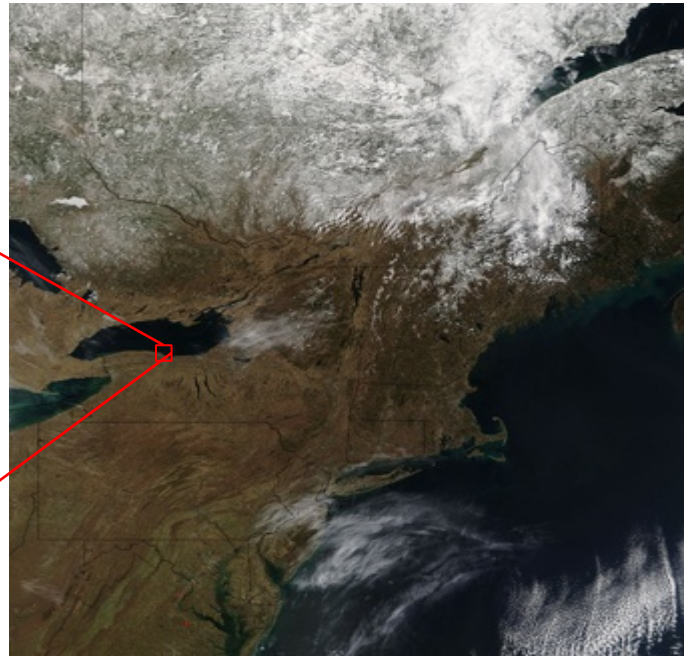
Desire to monitor the Earth's fresh water supply

- Determine levels of water quality parameters (Chlorophyll, Suspended Materials, CDOM).

No environmental satellite has all the necessary characteristics…

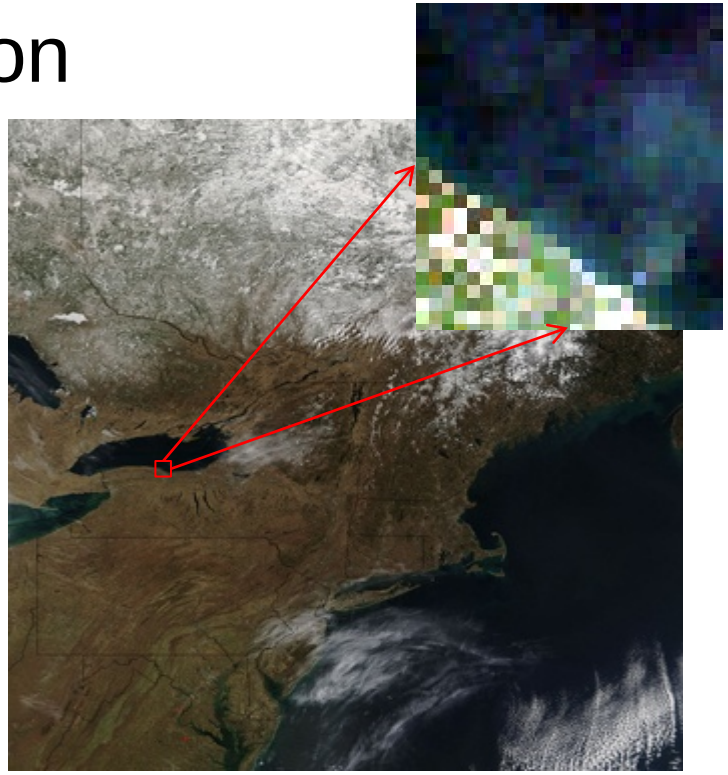
- High spatial resolution to monitor the nearshore.
- High radiometric fidelity.
- Repeat Coverage.
- Data is free and readily accessible.

Rochester Embayment



Research Motivation

	MODIS	SeaWiFS
Spatial Resolution	×	×
Radiometric Fidelity	√	√
Repeat Coverage	√	√
Free Data	√	√

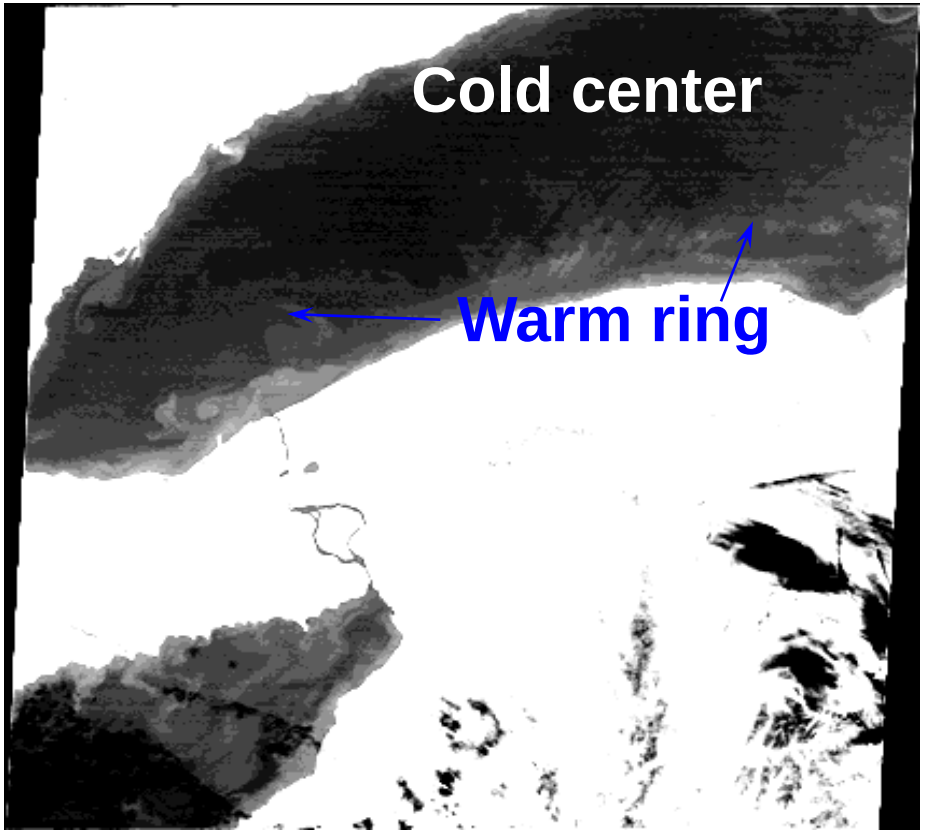


	Landsat	OLI
Spatial Resolution	√	√
Radiometric Fidelity	×	√
Repeat Coverage	√	√
Free Data	√	√

Thermal and Reflective data both very important for water resources studies

True Color Composite

Thermal Channel



Radiometric Sharpening of Thermal Data

As an initial study, we can simulate MODIS data by degrading the Landsat 7 thermal data.

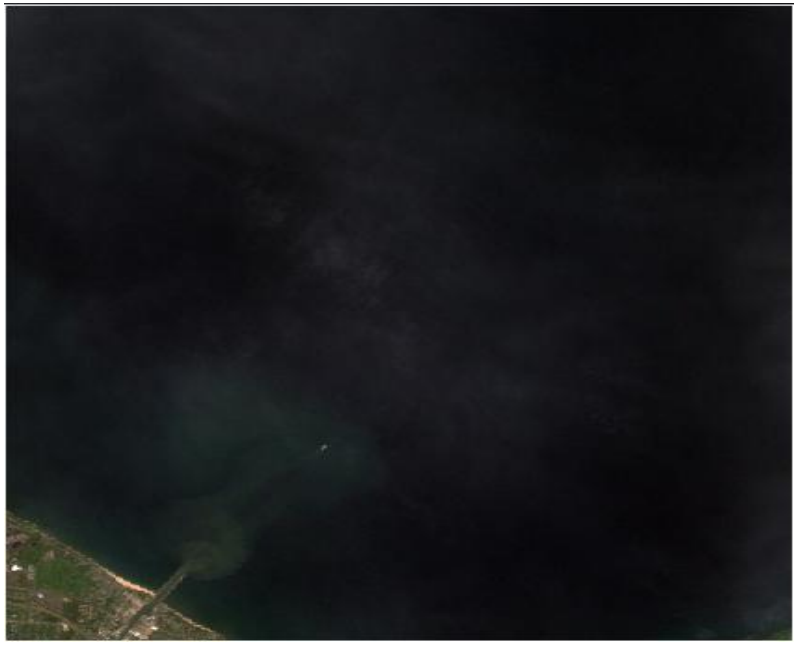
Landsat 7-Thermal Data

Simulated MODIS Data

Radiometric Sharpening of Thermal Data

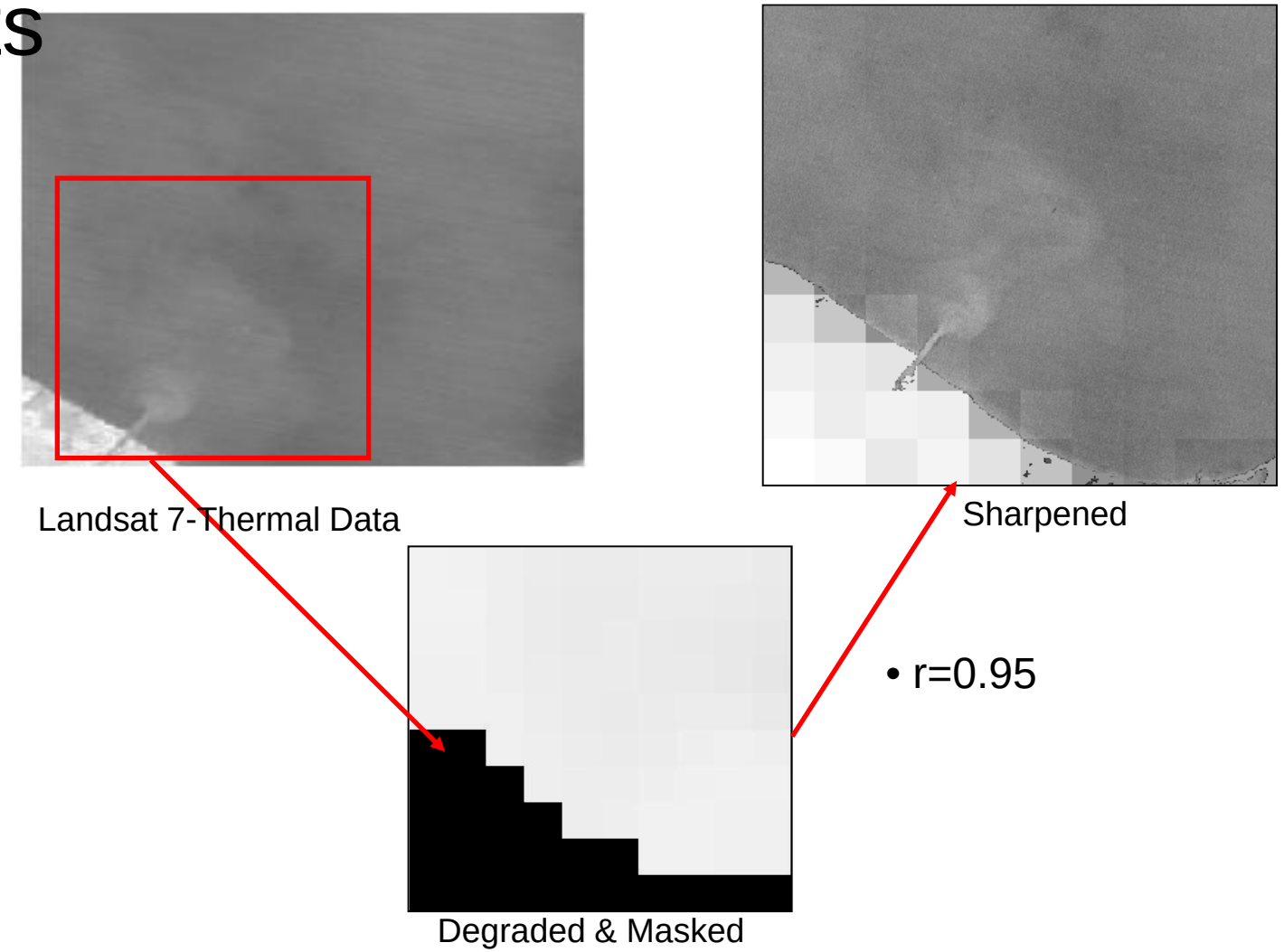
Then use Landsat 7 reflective bands to sharpen.

Landsat 7-RGB Image Data



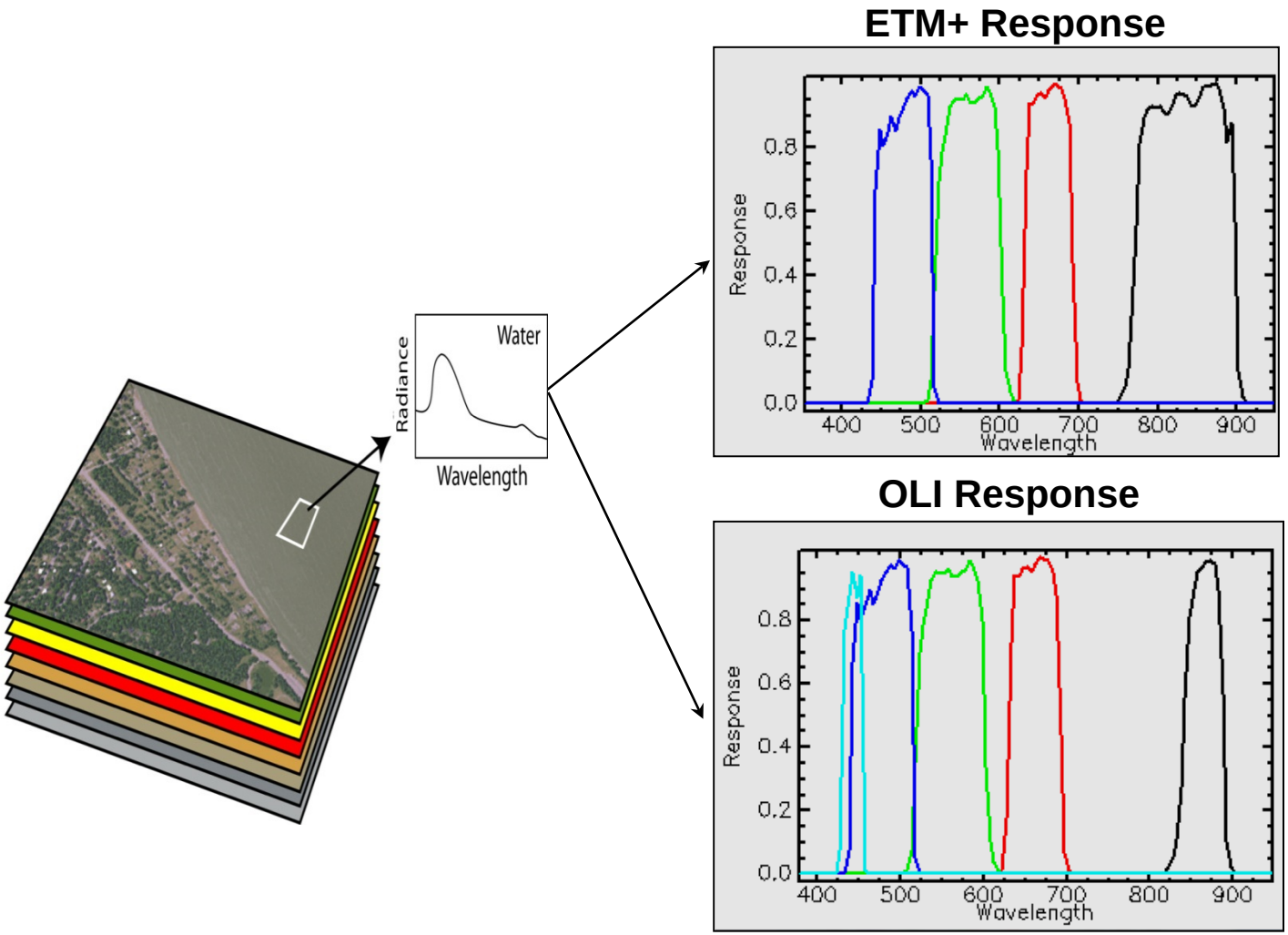
Simulated MODIS Data

Radiometric Sharpening of Thermal Data: Results

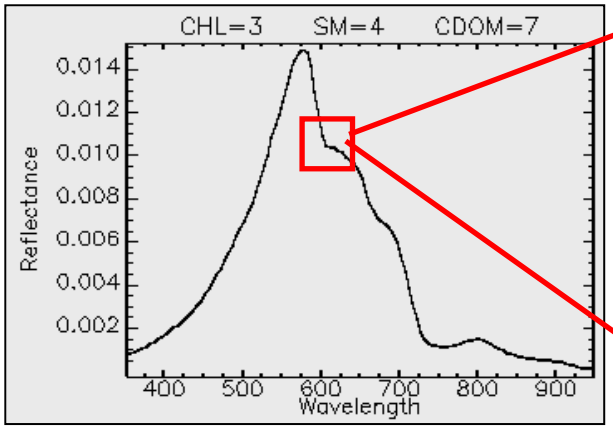


- r=0.95

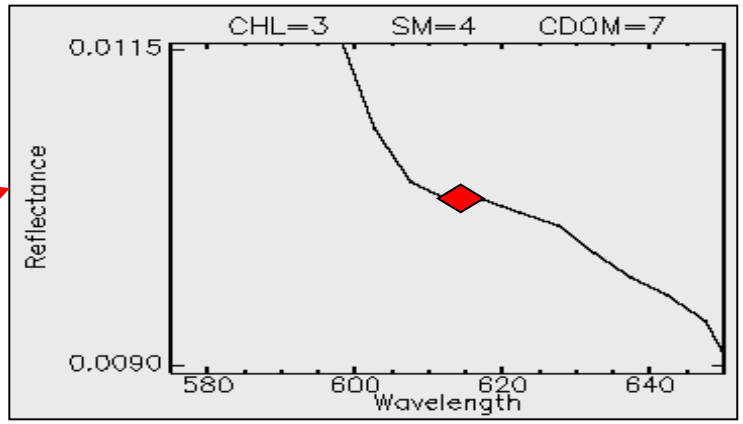
Water_sat
OLI Features: Enhanced Spectral Coverage



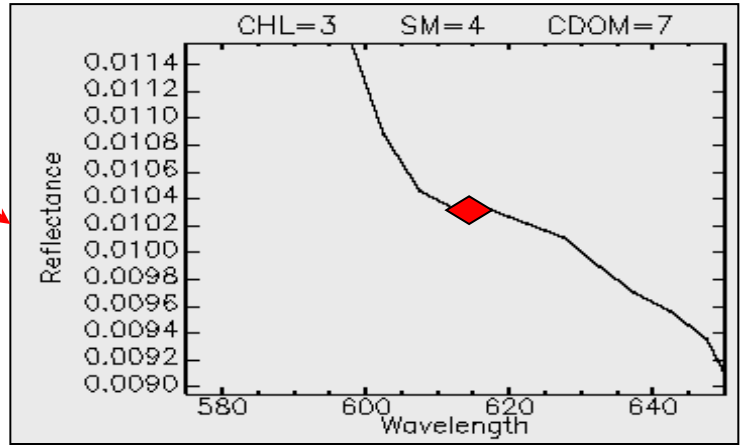
Water_sat
OLI Features: Quantization



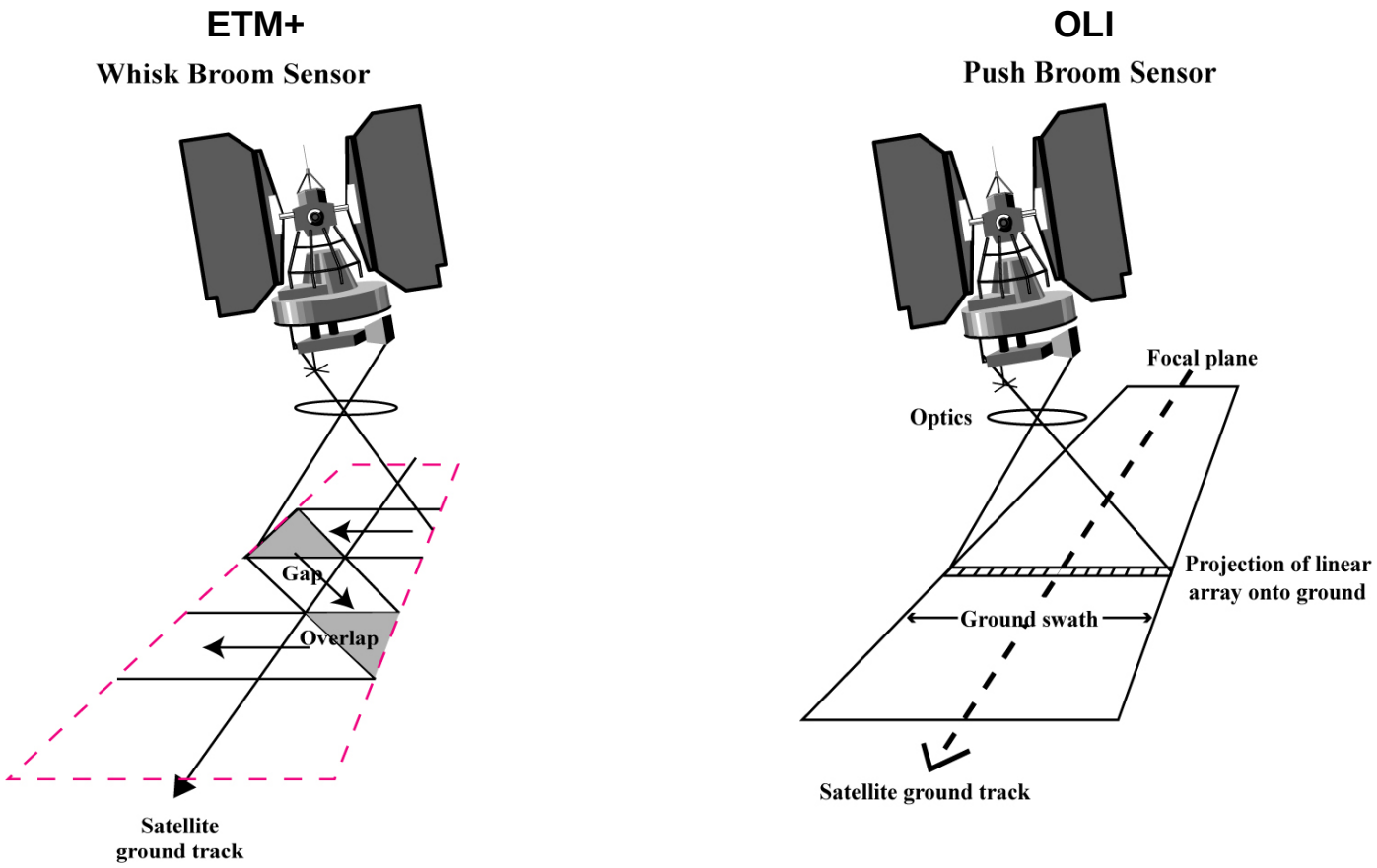
ETM+ (8-bit)



OLI (12-bit)

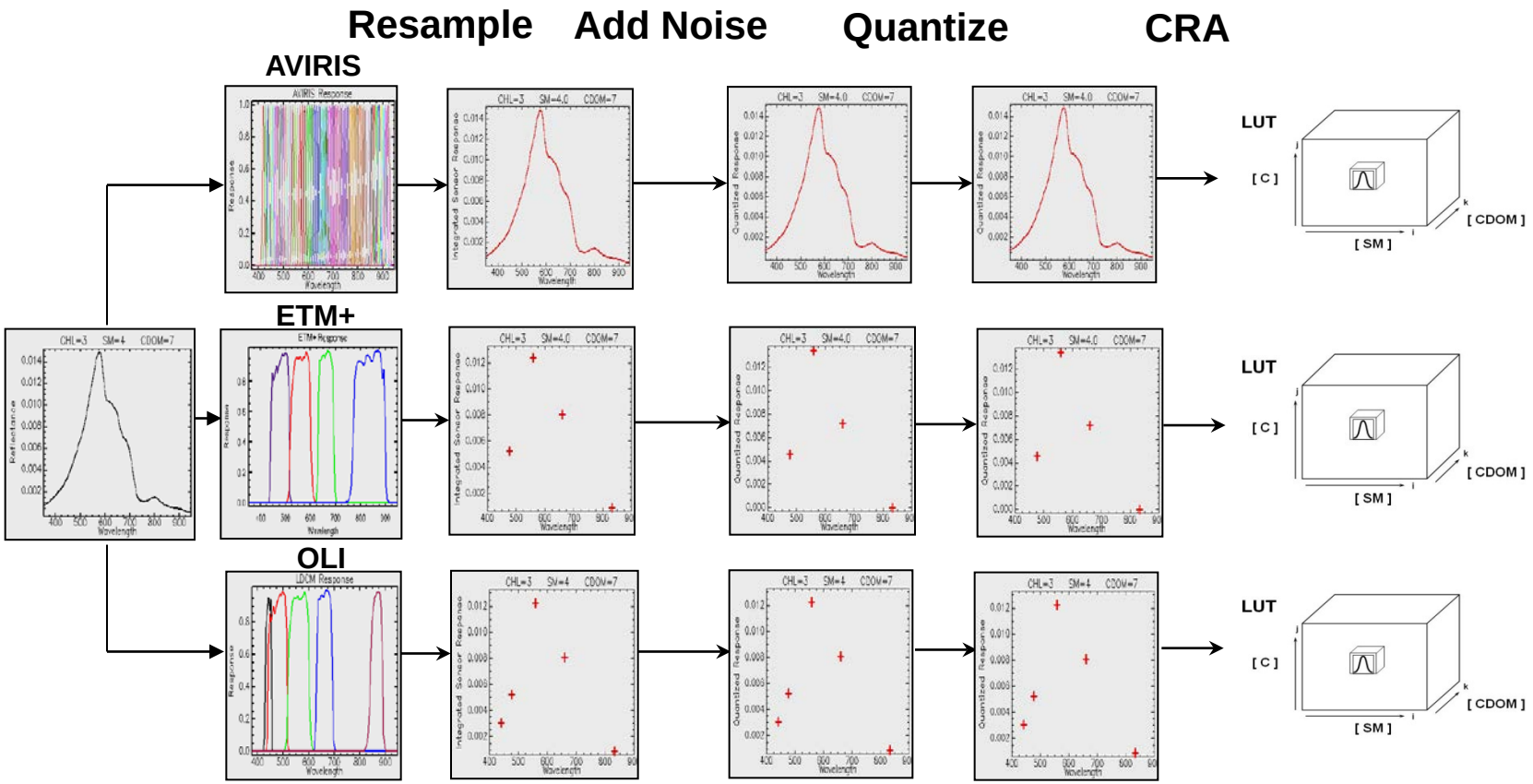


Water_sat
OLI Features: Signal to Noise



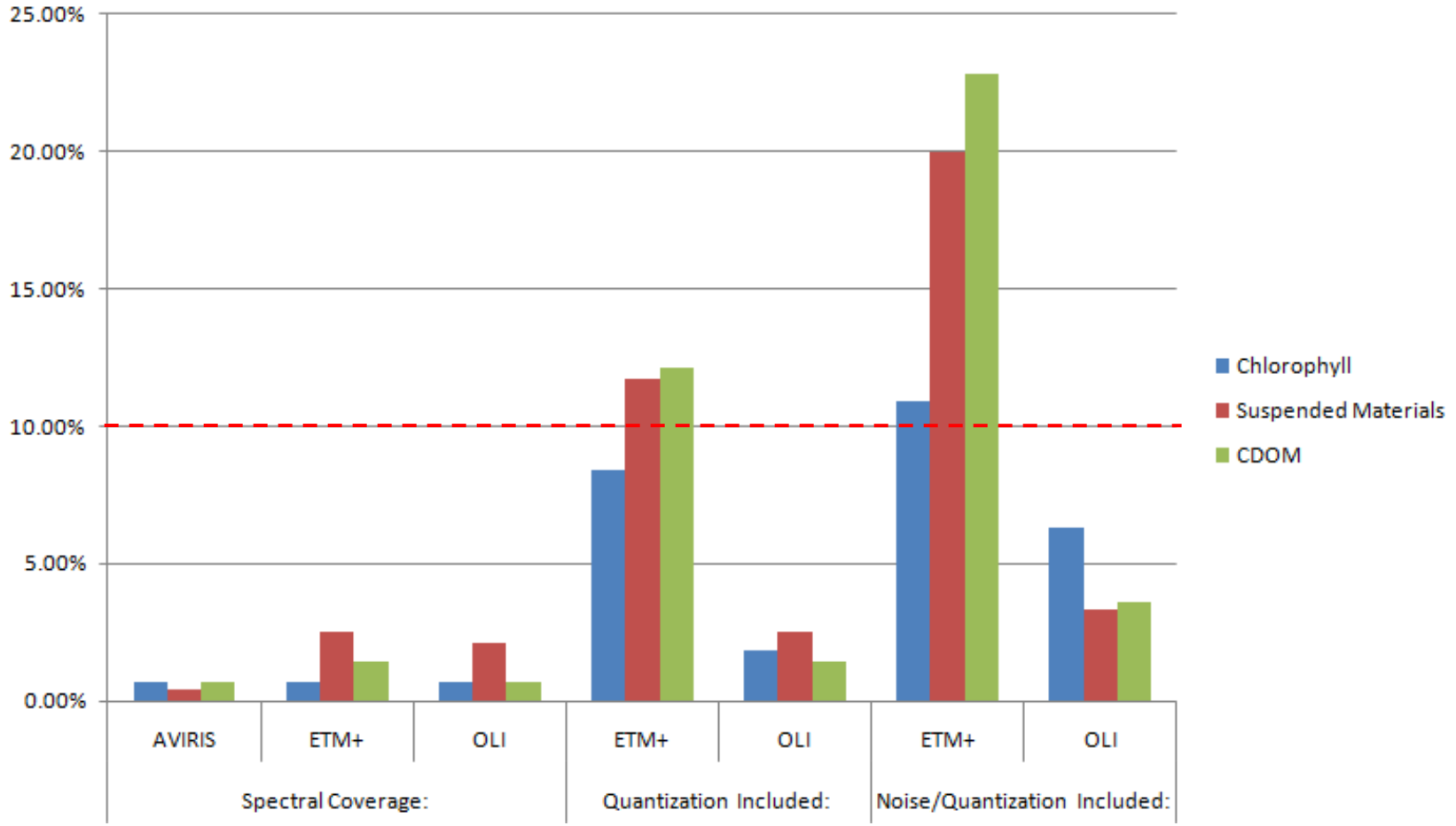
About a factor of 5 improvement in SNR.

Does OLI Have the Necessary Radiometric Fidelity?



- Modeled 3 new features of OLI in the absence of atmospheric effects.
- Water quality parameters were randomly varied to generate 2000 water types. CHL [0 – 68], SM [0 – 24], CDOM [0 – 14]
- 10% error is our target for this experiment.

Results


25.00%
20.00%
15.00%
10.00%
5.00%
0.00%
AVIRIS
ETM+
OLI
ETM+
OLI
ETM+
OLI
Spectral Coverage:
Quantization Included:
Noise/Quantization Included:
Chlorophyll
Suspended Materials
CDOM

OLI Over-Water Atmospheric Correction
Case 2 Waters

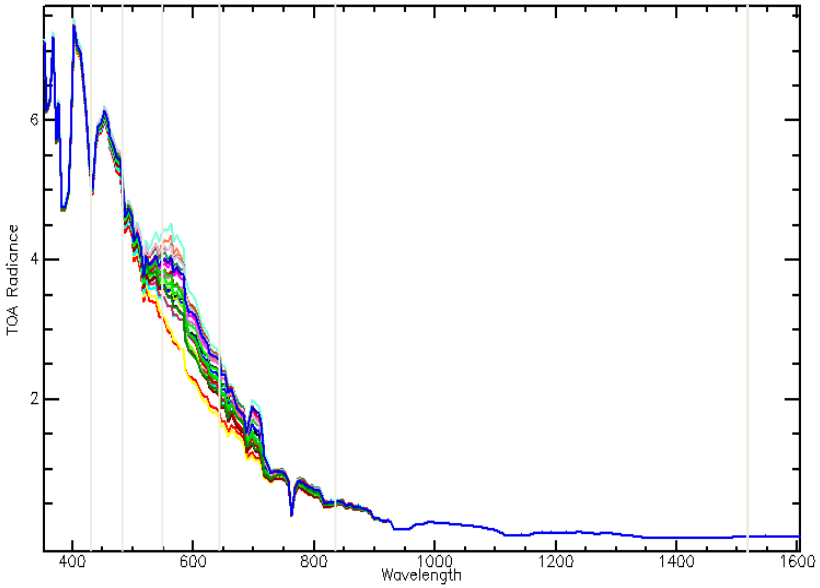
Issue: OLI doesn't have 2 NIR bands which are required by traditional water-based algorithms.

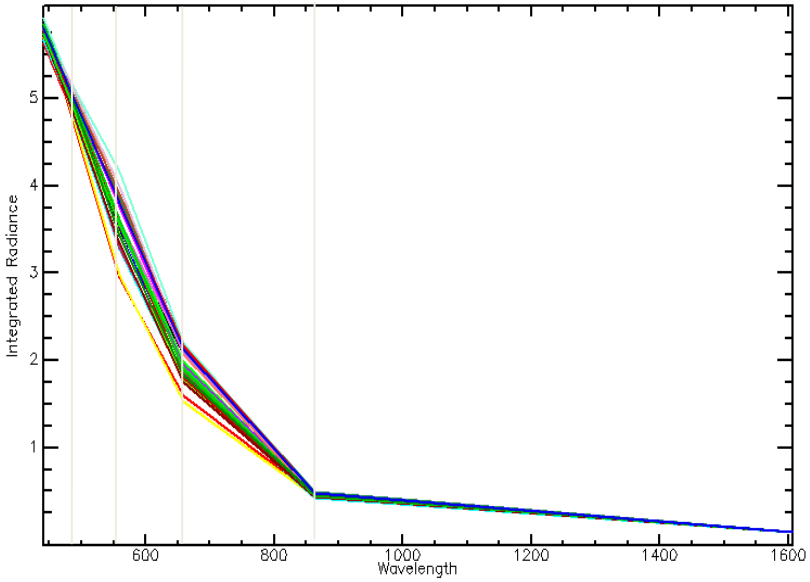
– Gordon's method (SeaWiFS).

2 methods developed:

– Blue Band method.

– NIR/SWIR band ratio method.





OLI Atmospheric Compensation

Experiment 1: Simulated Scene

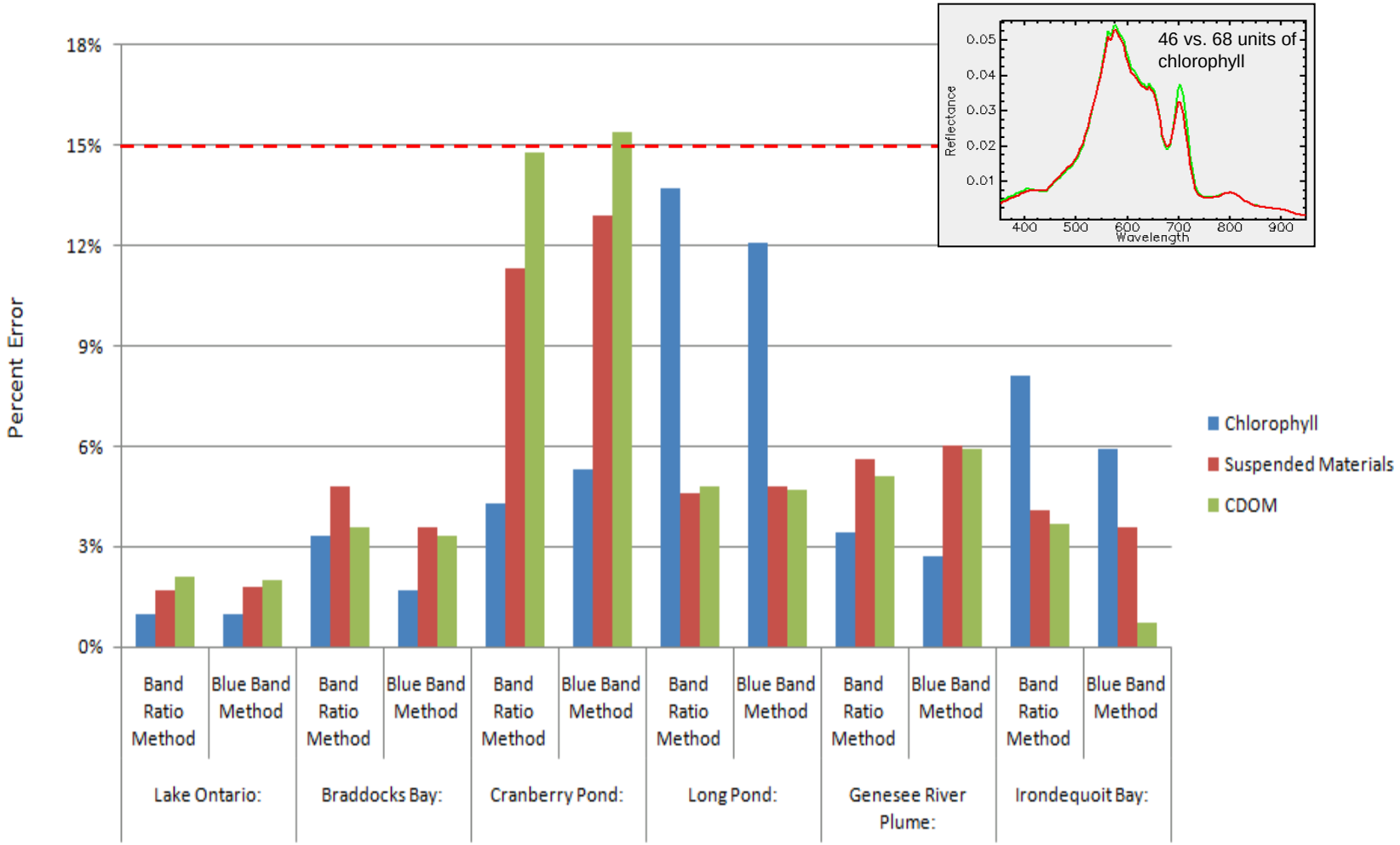
Simulated Image from Landsat 5 data

- Lake Ontario (Dark Water) ROI used to determine atmosphere.
- Chosen atmosphere removed globally from image.
- Constituent retrieval algorithm implemented for 6 ROIs.

Simulated Image

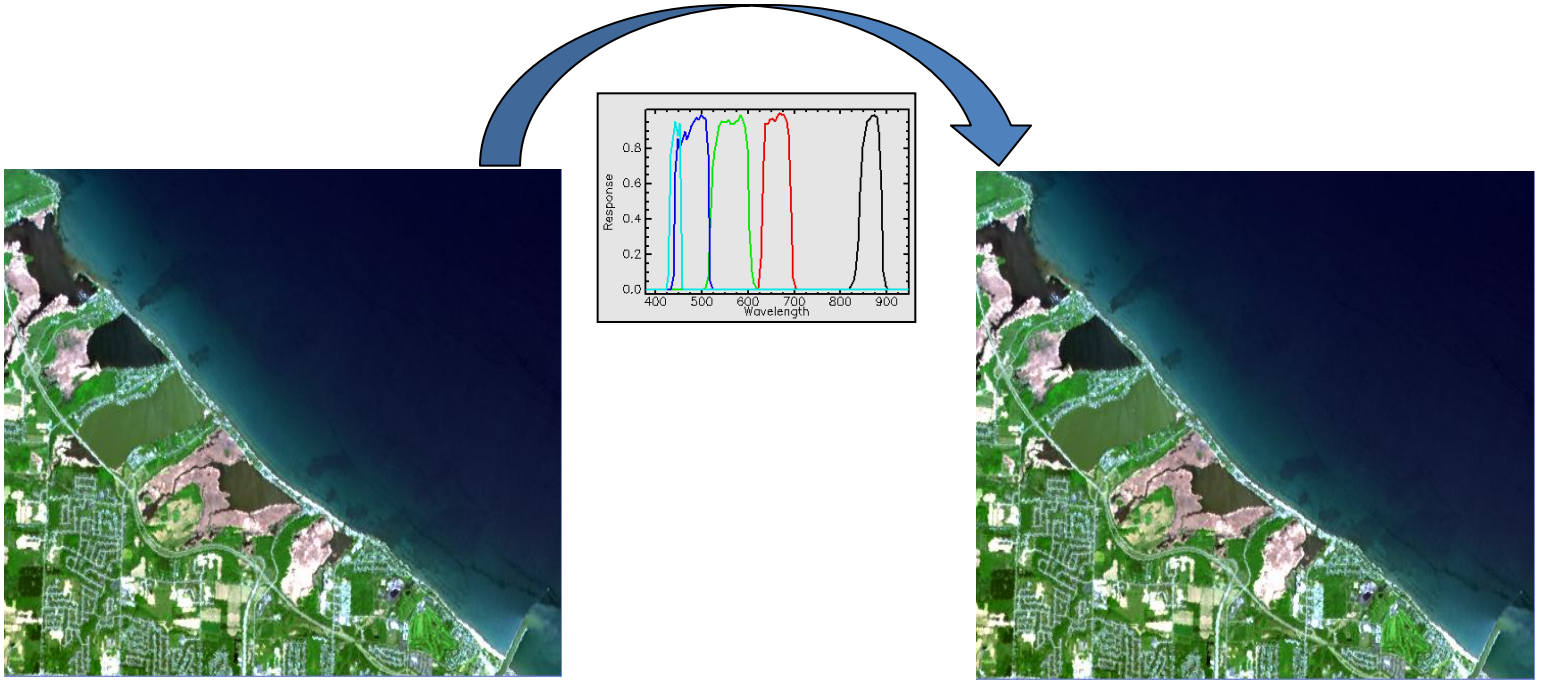
OLI Atmospheric Compensation

Experiment 1: Simulated Scene



OLI Atmospheric Compensation
Experiment 2: Real Data

- AVIRIS data (May 20th,1999) spectrally sampled to OLI's sensor response function.



AVIRIS: May 20th, 1999

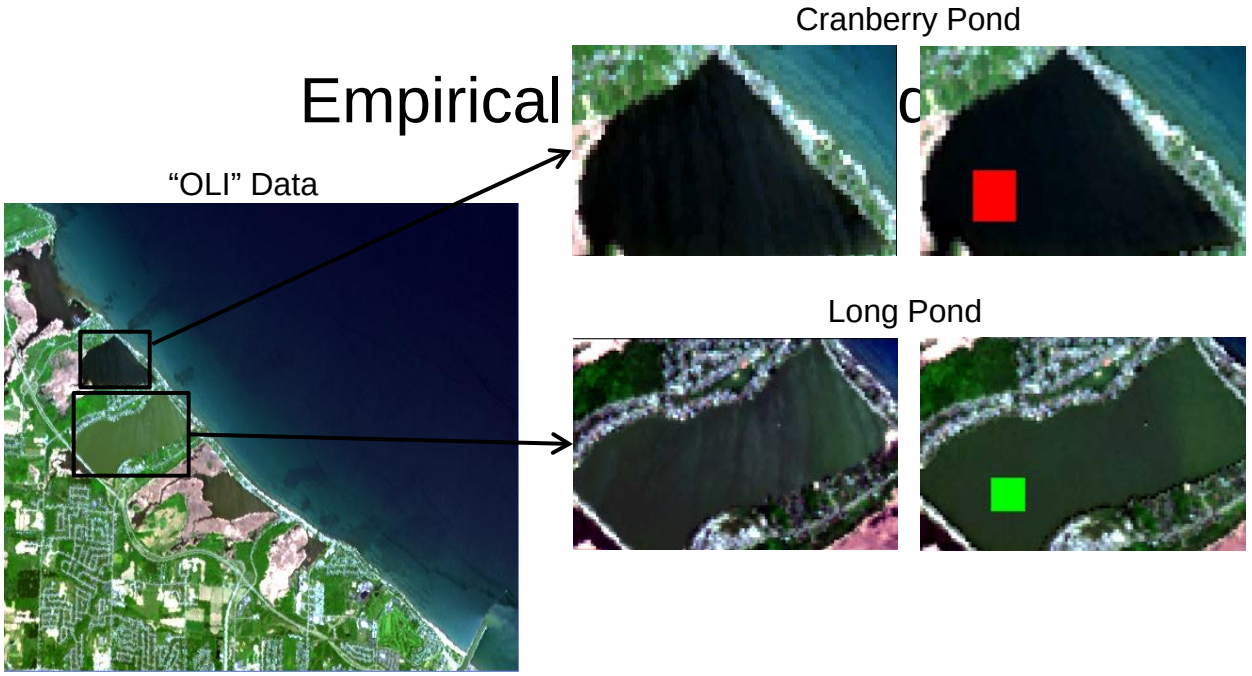
Simulated OLI Data: May 20th, 1999

OLI Atmospheric Compensation

Experiment 2: Real Data

OLI atmospheric compensation method tested over Cranberry Pond and Long Pond.

- Deglint image.
- 200 darkest values in bands 5 and 6 were used to determine atmosphere.
- Atmospheric effects removed and constituent retrieval process performed.

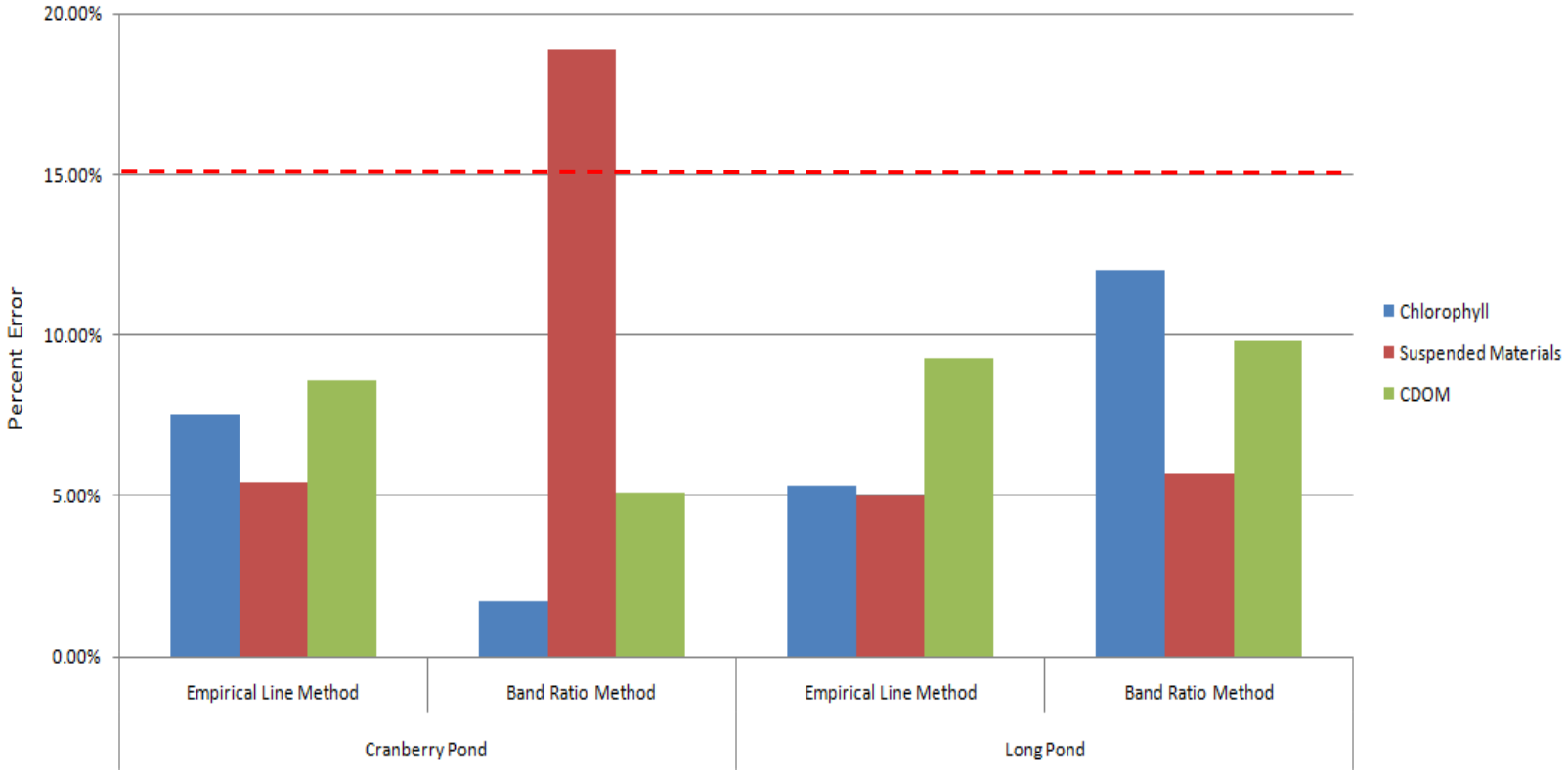


OLI Atmospheric Compensation

Experiment 2: Real Data

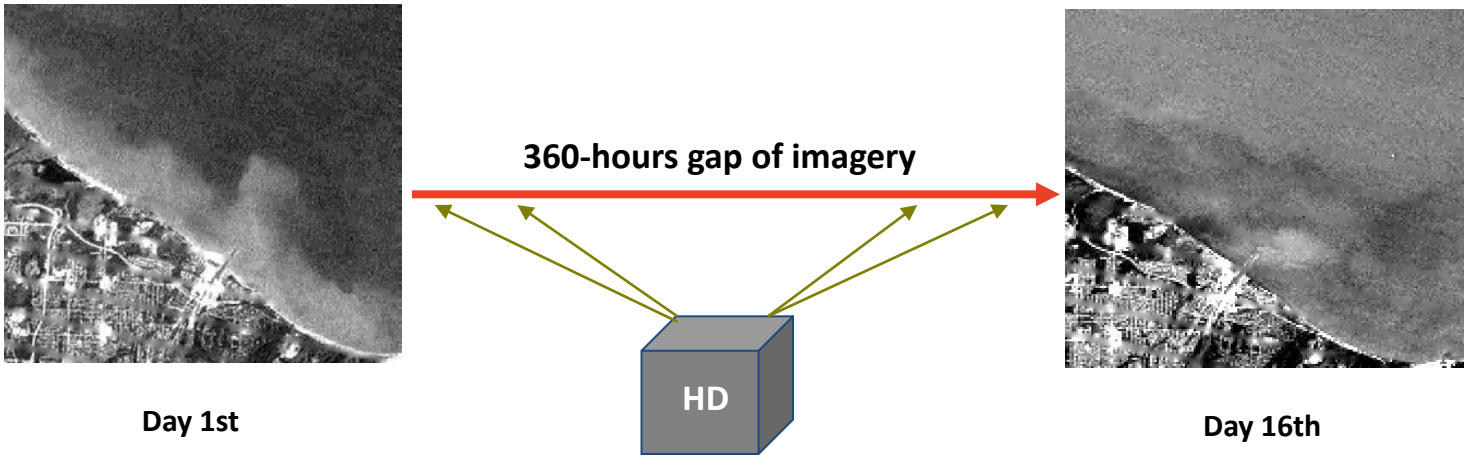
Reasonable retrieval errors are obtained.

- For Cranberry pond, only suspended materials is over 15% retrieval error.
- For Long Pond, retrieval errors for all constituents are less than 15%.

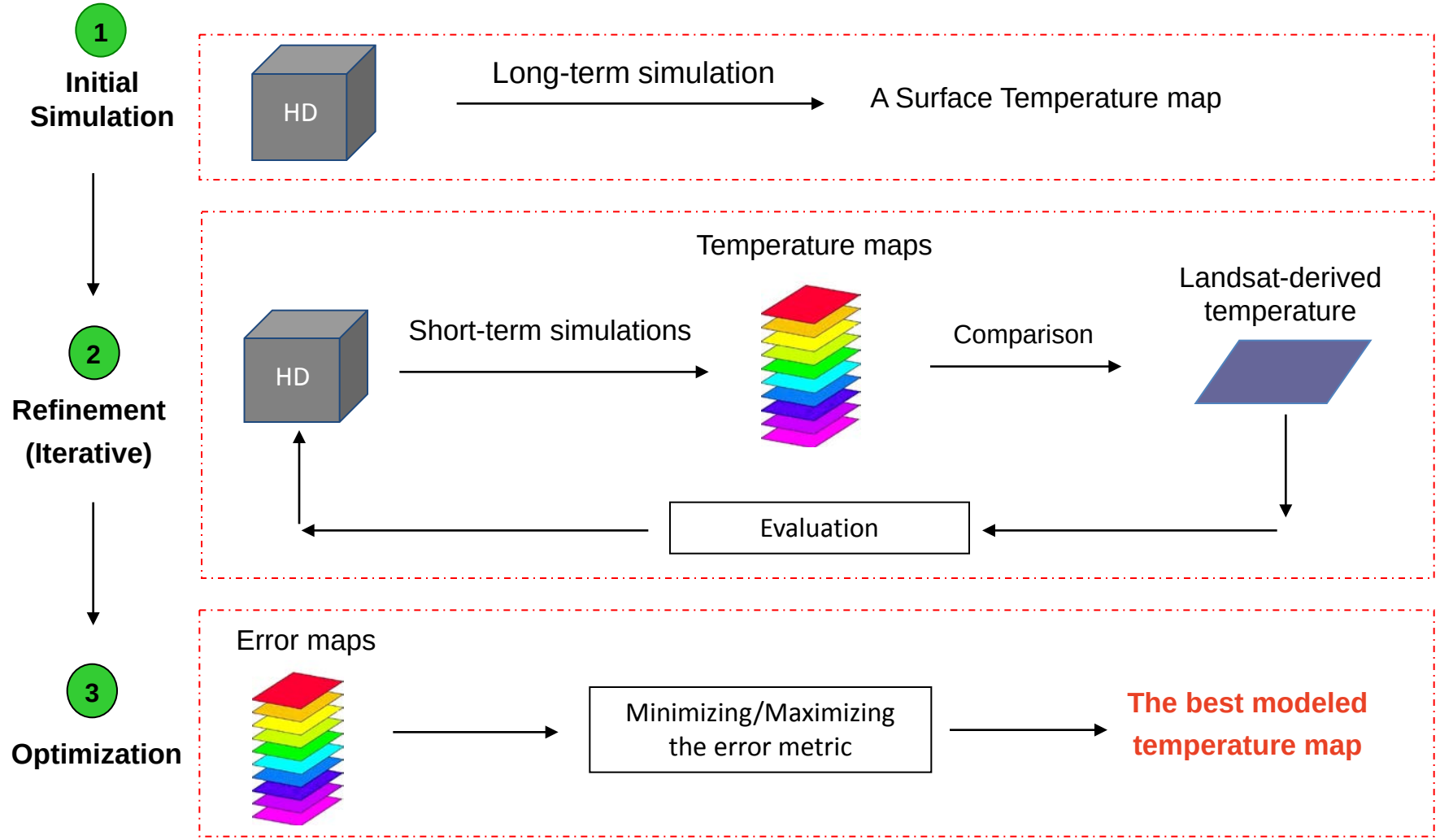


Hydrodynamic models calibrated with LDCM data

- ✓ **Hydrodynamic modeling, when calibrated, can compensate low temporal resolution of Landsat**
- ✓ **A well-calibrated model enables pre-casting and forecasting of the state of the environment**
- ✓ **Hydrodynamic models can provide volumetric data below LDCM penetration**



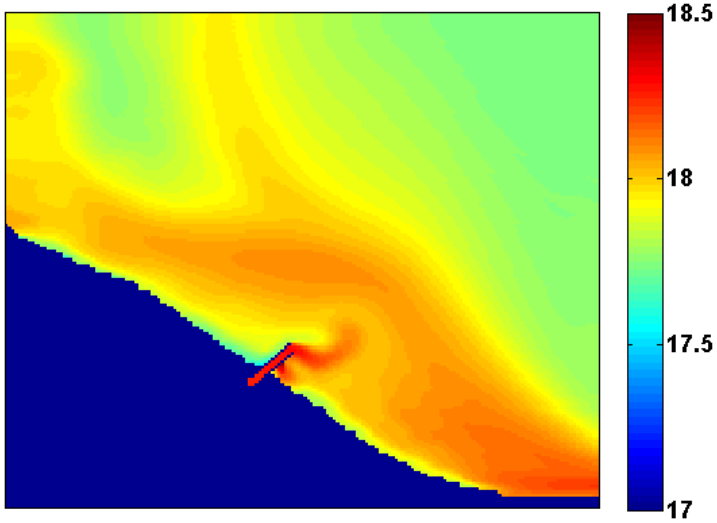
Approach (Phase I): Model Calibration



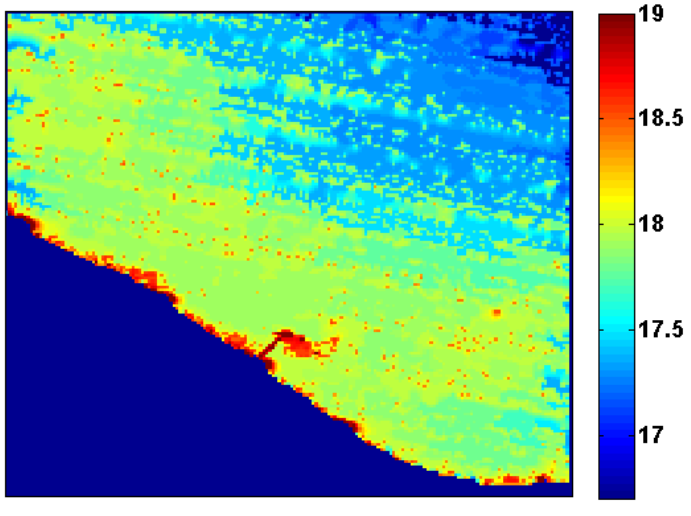
Calibration Results: Genesee Plume

- **Best model out**
  - **Inputs: WS= 122%, WD= +18D, RD= 131%, RT= 106.2%**

Modeled Surface Temperature



Landsat-derived (smoothed)

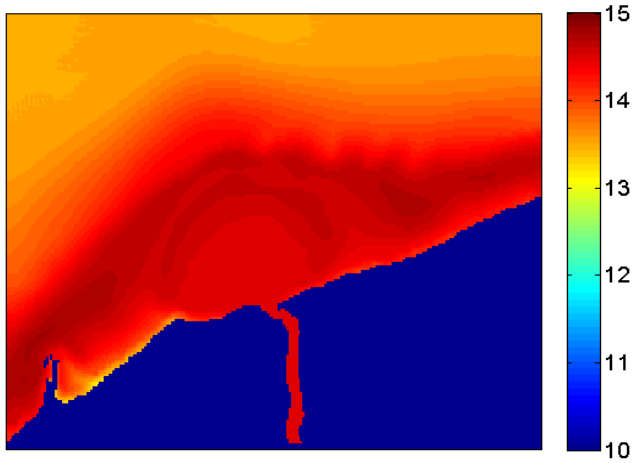


RMSE= 0.27 degree-C

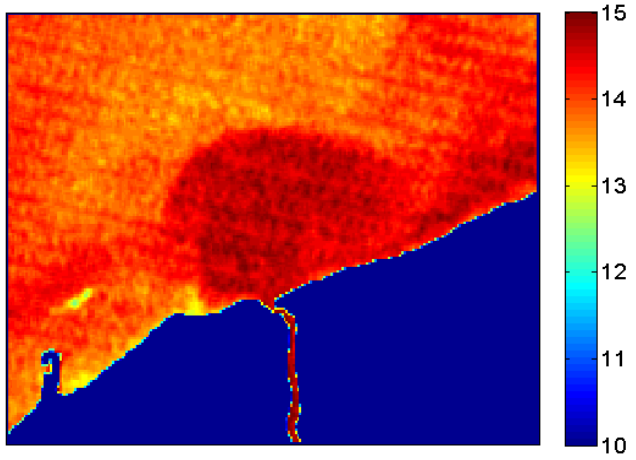
Calibration Results: Niagara Plume

- **Best model out**
  - **Inputs: WS= 119%, WD= +9D, RD= 134%, RT= 105.1%**

Modeled Surface Temperature



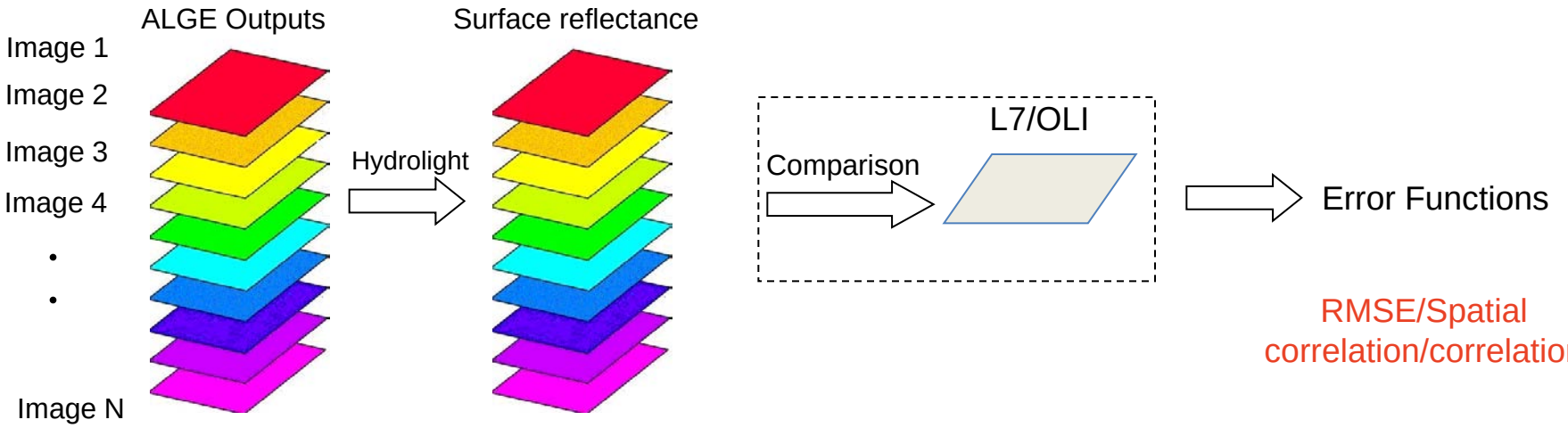
Landsat-derived (smoothed)



RMSE: 0.295 degree-C

Approach (Phase II): Water Constituent Retrieval

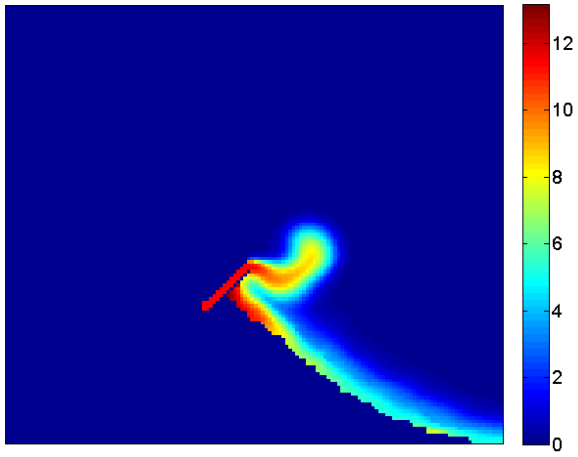
- **Modeling**
  - **Model input variables**
    - **Concentration of Particles (COP)**
    - **Concentration of Dissolved Matter (COD)**



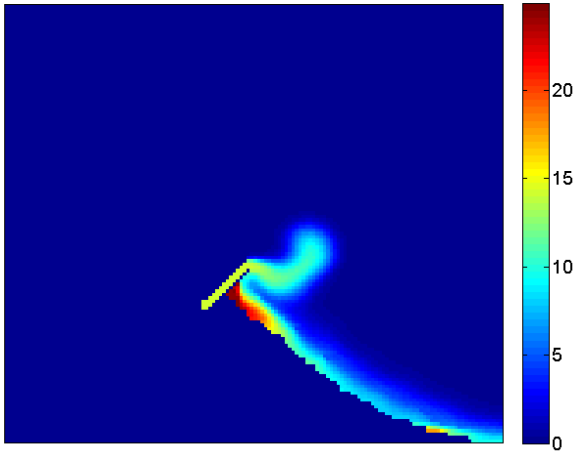
Results: Genesee Plume (no background)

– **Best model output (RMSE <0.55 % reflectance) calculated over the plume area**

TSS (g/m^3)



CHL (mg/m^3)

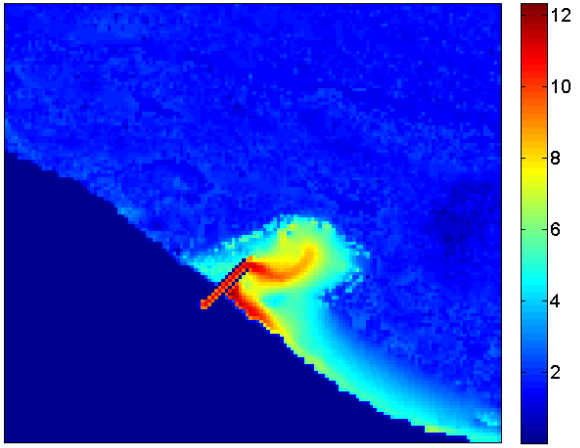


– **ALGE lacks predicting constituent distribution in non-plume areas**

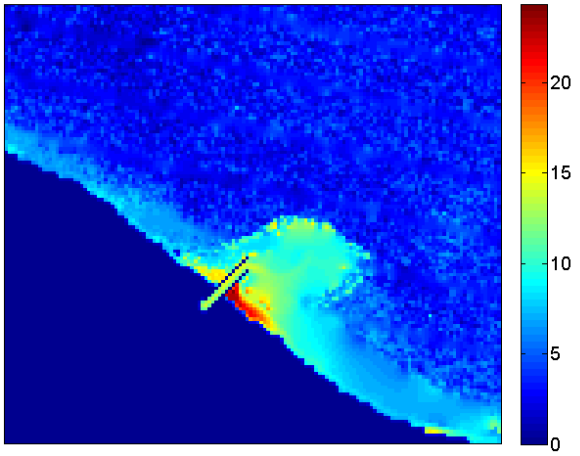
Results: Genesee Plume with Background

– **The background concentrations (surface) was determined through Hydrolight simulations on a pixel-by-pixel basis. In other words, 25 combinations of TSS and CHL (for each pixel) were simulated and optimized against the Landsat-derived reflectance map**

TSS (g/m^3)



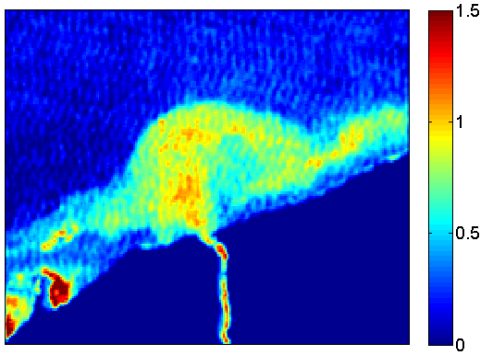
CHL (mg/m^3)



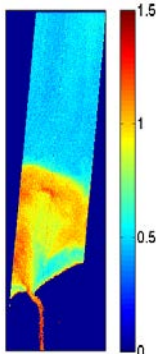
Preliminary Results: Niagara Plume

– **Niagara River plume (Oct10)**

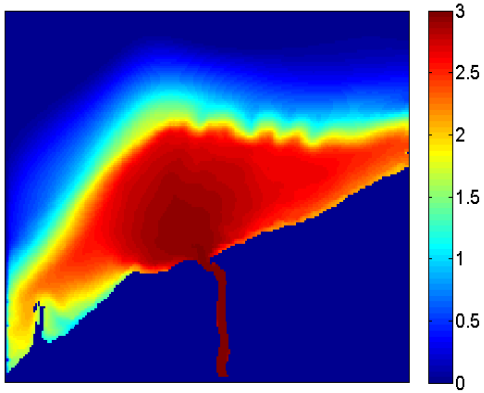
L7 - red channel

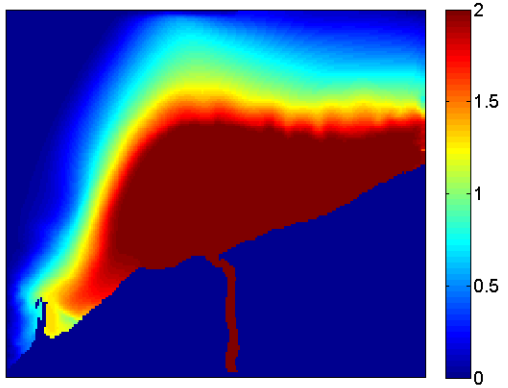


OLI - red channel



TSS Distribution





Dissolve matter Distribution

Can Landsat 8 be used as a tool by water resource managers?

- Can more robust operational procedures be developed for over water atmospheric compensation?
  - Calibration issues
  - Stray light issues
  - Hybridization of existing research grade algorithms?

- Can constituet retrieval algorihms be operationalized?
  - Robustness to calibration and atmospheric compensation errors
  - Compensation for IOP variations

- Can OLI be used for bottom cover mapping?

- Can OLI be used for depth mapping in shallow waters?

- Can TIRS and OLI data be operationally fused to calibrate hydrodynamic models of coastal waters?

Conclusions and Future Work

OLI exhibits the potential to be a useful tool for monitoring water quality.

2 over-water atmospheric correction algorithms were developed for the OLI instrument and have been successfully applied to both synthetic and real data.

We look forward to applying these methods to actual OLI data…December 2012.

Outline

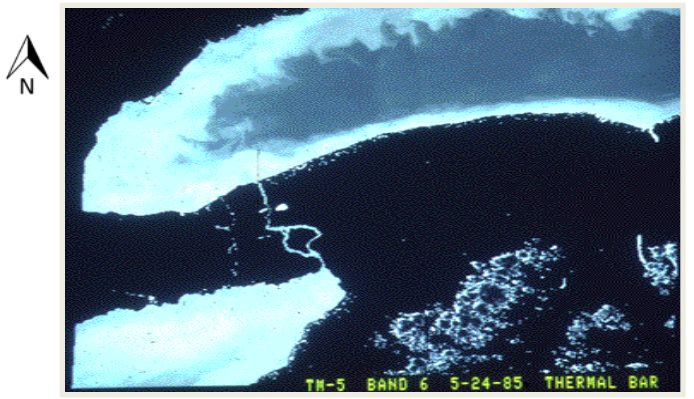
- Statement of the Problem
- Objective
- Study areas and Datasets
- Approach
  - Phase I: Model calibration
    - Remote sensing: thermal processing
    - Hydrodynamic modeling
    - Results
  - Phase II: Constituent retrieval
    - Atmospheric correction
    - Surface reflectance modeling
    - IOP estimation
    - Results
- Future directions

Water-sat?

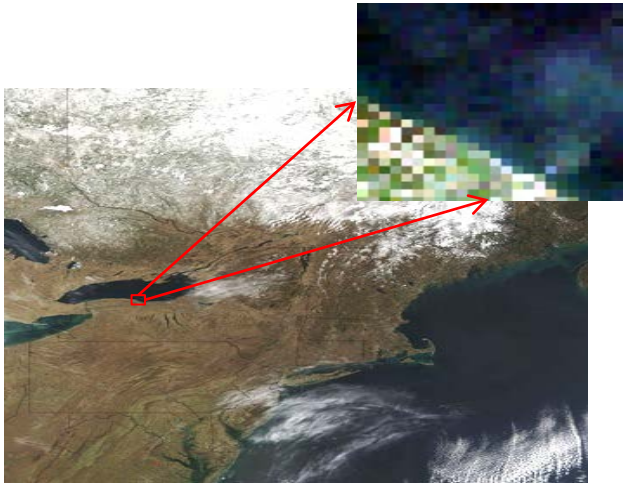
Problem: Monitoring Coastal/Inland Waters

- **Environmental Perspective**
  - **Lake and inland waters**
    - > River plumes
    - > Inland waters are closed systems
    - > Physical processes
- **Remote sensing perspective**
  - **Pros/cons of different flavors of RS data**

	Spatial	Radiometric	Temporal	Free access
MODIS	×	✓	✓	✓
SeaWIFS	×	✓	✓	✓
Landsat 7	✓	×	×	✓
LDCM (Landsat 8)	✓	✓	×	✓
Wv-2	✓	✓	✓	×



Lake Ontario; Landsat thermal image, May 2005



Eastern US: MODIS data

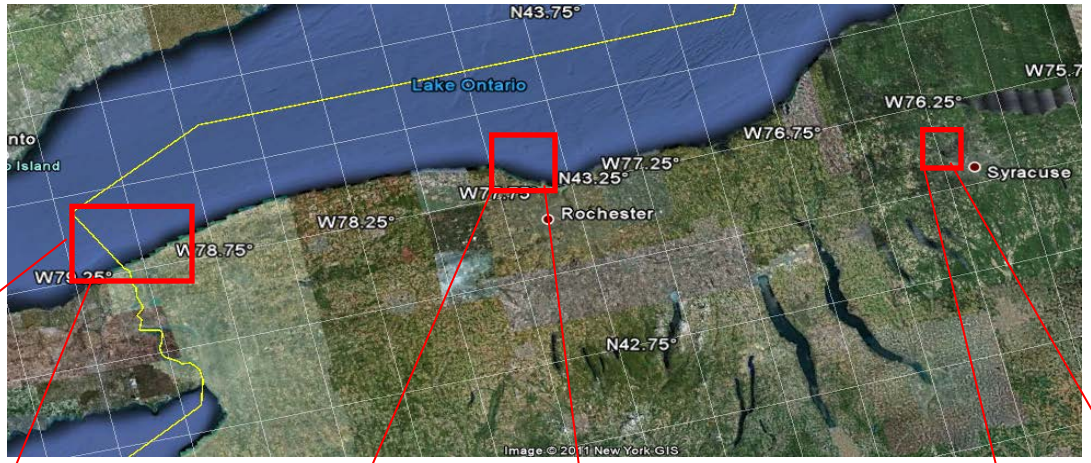
Objectives

- **Integrate physics-based modeling with Landsat-derived products to obtain profiles of water constituents**

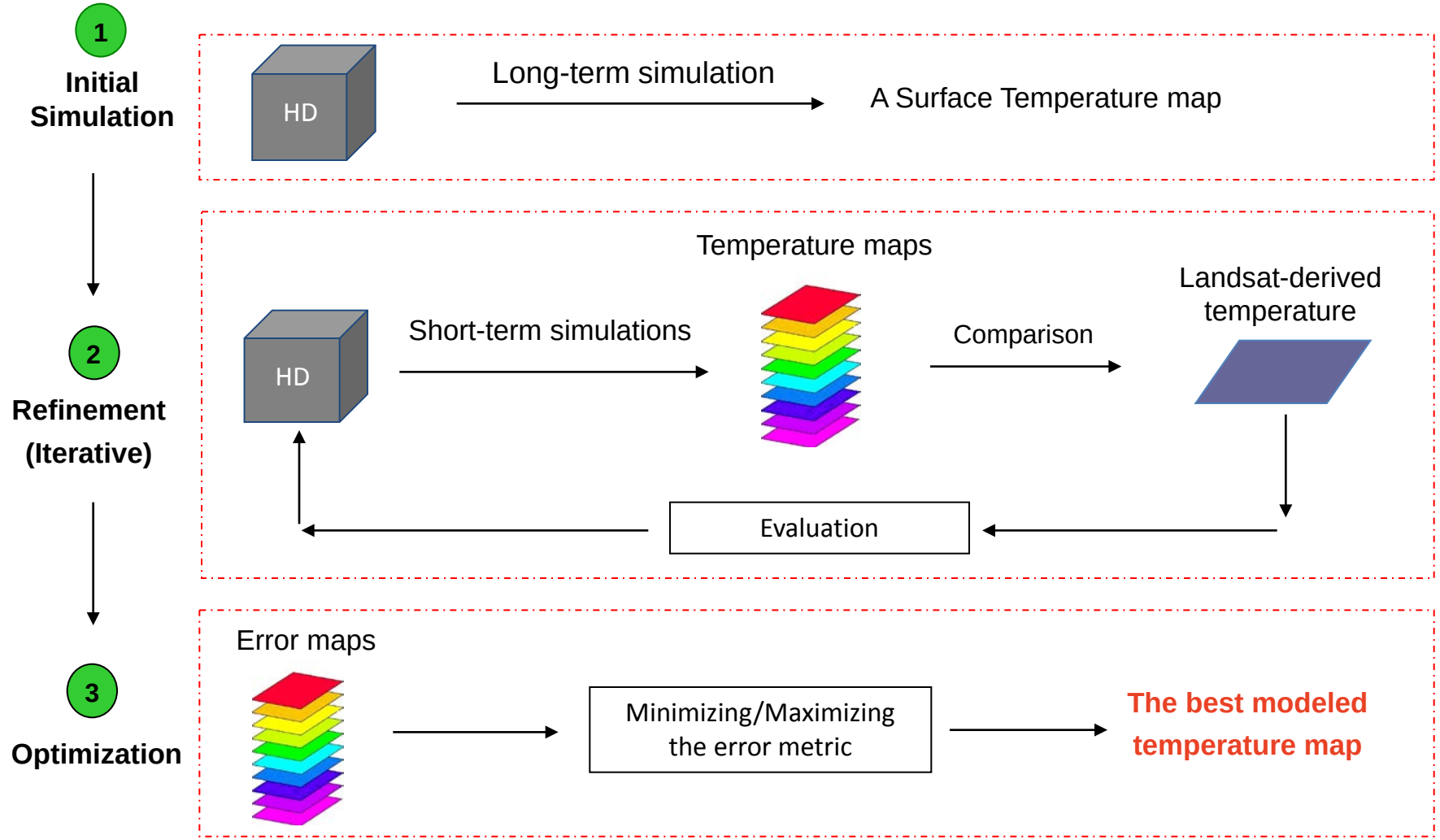
  - **Evaluate the capability of LDCM for monitoring case II waters through coupled modeling**
  - **Retrieve profiles of water constituent on a pixel-by-pixel basis in river plumes and inland waters**

Study Areas and Datasets

- **Niagara River (Oct10/L7 & Hyperion)**
- **Genesee River (July09 10/L7)**
- **Onondaga Lake (May 10/L7)**



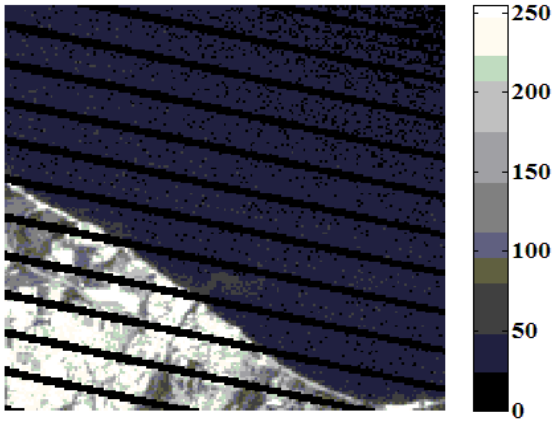
Approach (Phase I): Model Calibration

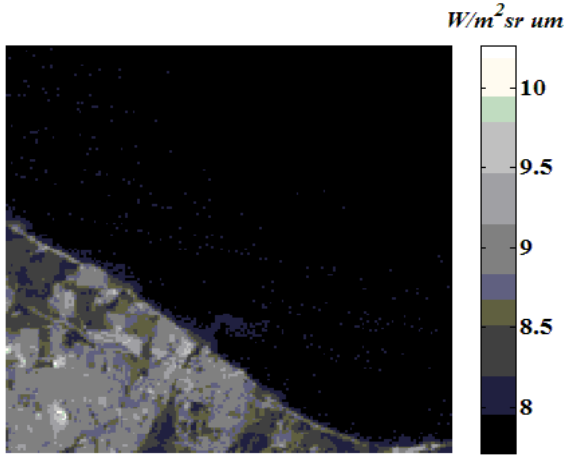


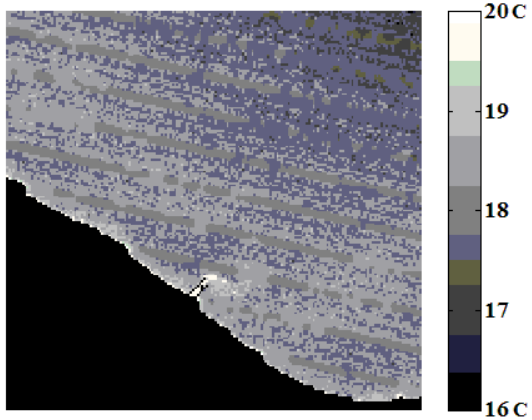
Remote Sensing: Thermal Processing

- **Fundamental RS equation is used to retrieve surface temperature**
- **MODTRAN is used to remove atmospheric effects**

Raw: DN → TOA radiance → Surface Temperature

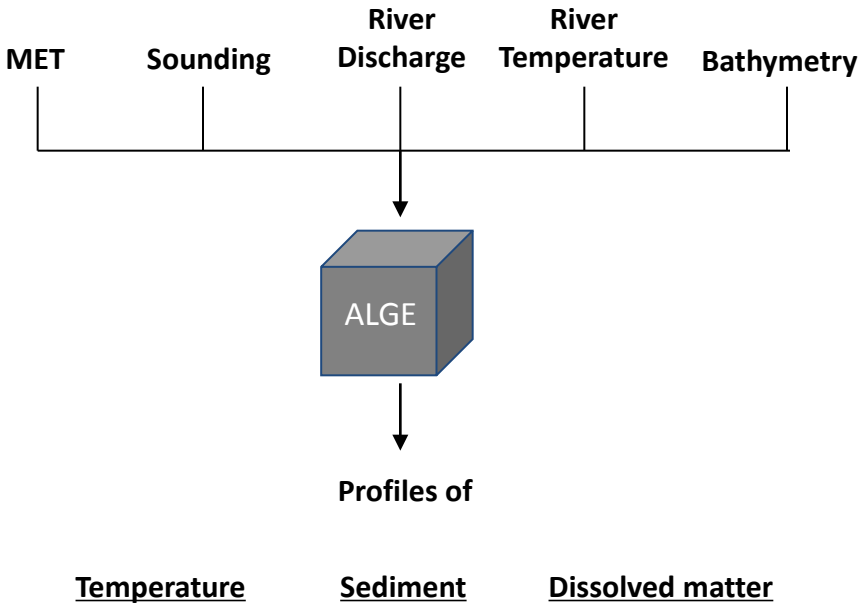


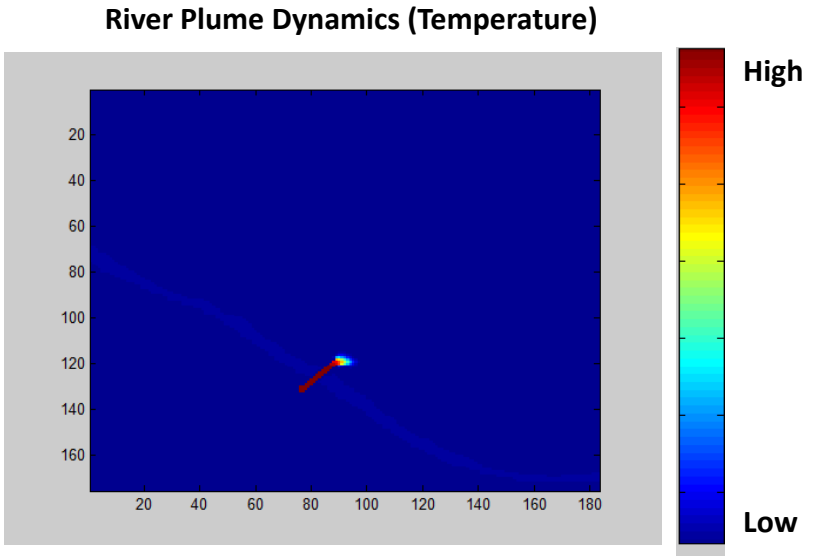




Hydrodynamic Modeling:
Long-term Simulation of the plumes

– **ALGE, provided by the Department of Energy (DOE), is a 3D hydrodynamic model that predicts movements and dissipation of river plumes**





– Run time: 10 days
– Target date/hour: July 14th @ 12PM

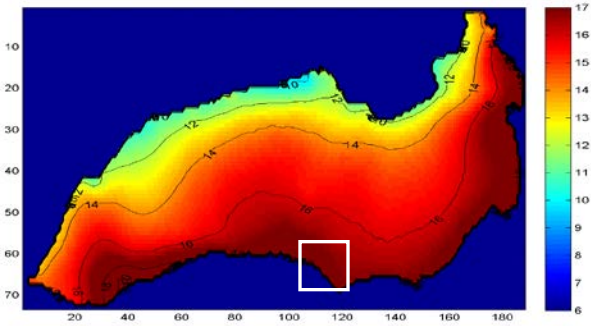
Hydrodynamic Modeling: Lake-wide Simulations

- **Lake (Ontario) circulation patterns affect localized simulations**
- **Surface current velocities are obtained from lake-wide simulations (coarse grid)**

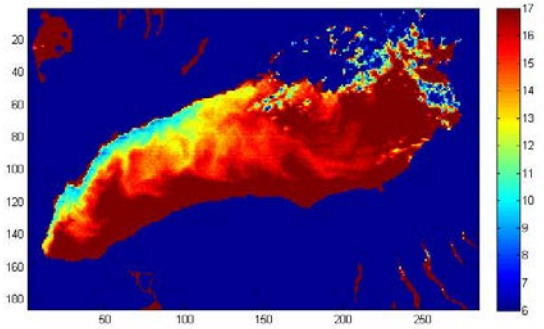
July 09

Surface temperature

Model



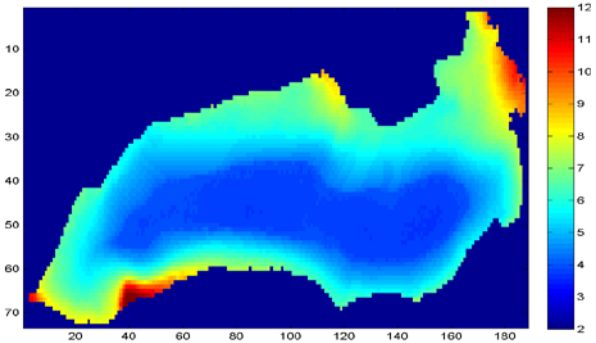
MODIS



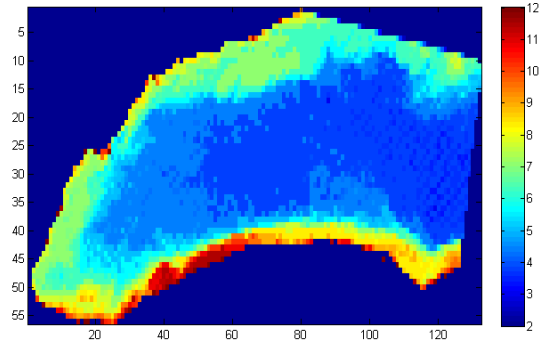
May 09

Surface temperature

Model



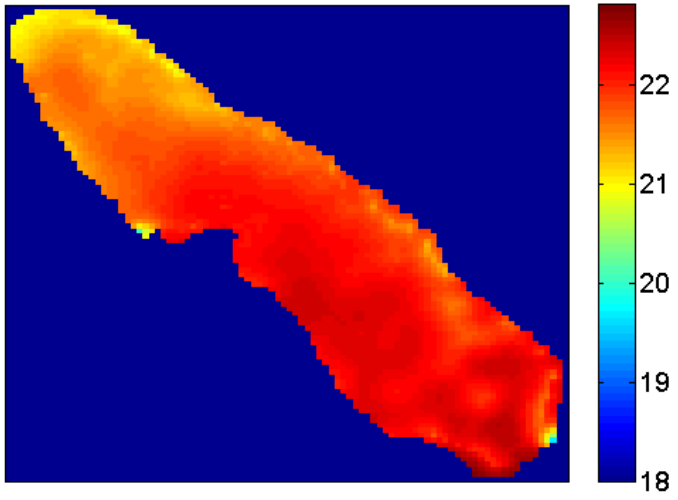
Landsat



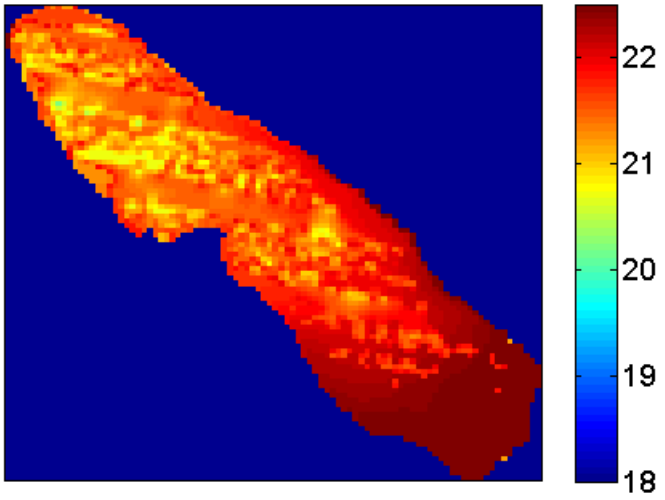
Calibration Results: Onondaga Lake

- **Best model out**
  - **Inputs: WS= 71%, WD= 1D, RD= 104%, RT= 103.1%**

Modeled Surface Temperature



Landsat-derived (smoothed)



RMSE: 0.345 degree-C

Remote Sensing: Atmospheric Compensation Methods

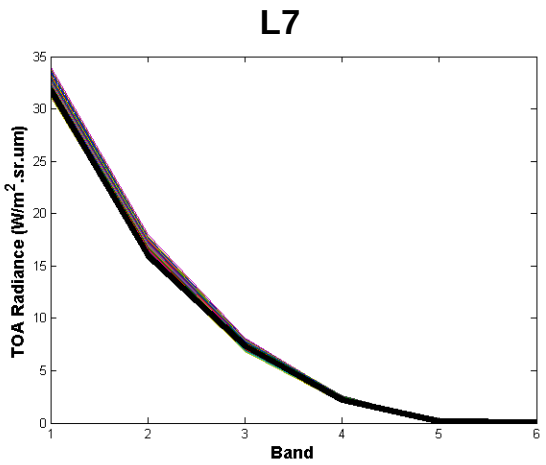
- **Reduce atmospheric effects to obtain surface reflectance (*r*)**
  - **Empirical Line Method (regression)**

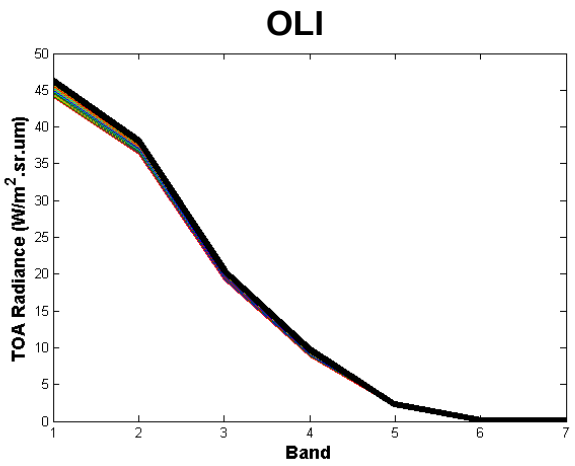
    Only requires bright and dark targets with known surface reflectance
    - **Beach sand and deep water spectra were used to correct July09 (Genesee plume) and May10 imagery**
    - × **Impractical for October 10 imagery due to lack of homogenous beach sand nearby Niagara River plume**

  - **Pseudo Spectral Matching (PSM)**
    - **Generating LUTs of various aerosol visibility and measure similarities with sensor-derived TOA radiance**

Type: Rural

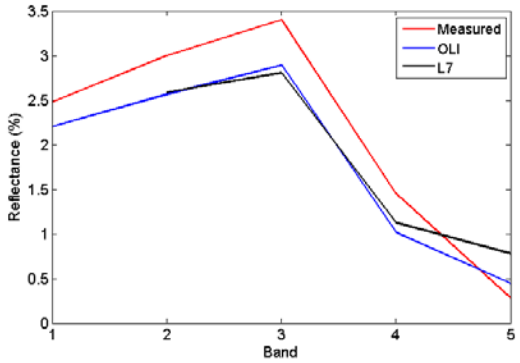
Vis= 94km



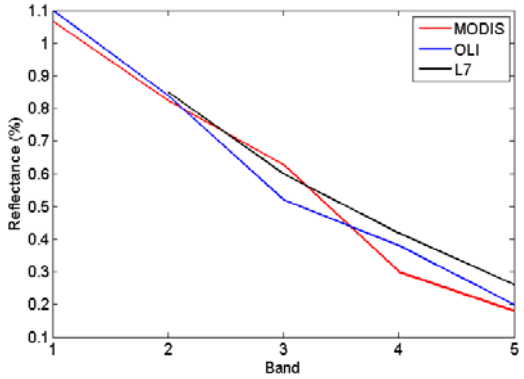


Atmospheric Compensation: Cross-validation of Surface Reflectance (Oct10)

– **The measured surface reflectance (resampled to OLI) is compared against that of obtained from L7 and OLI in the plume in the vicinity of river mouth**

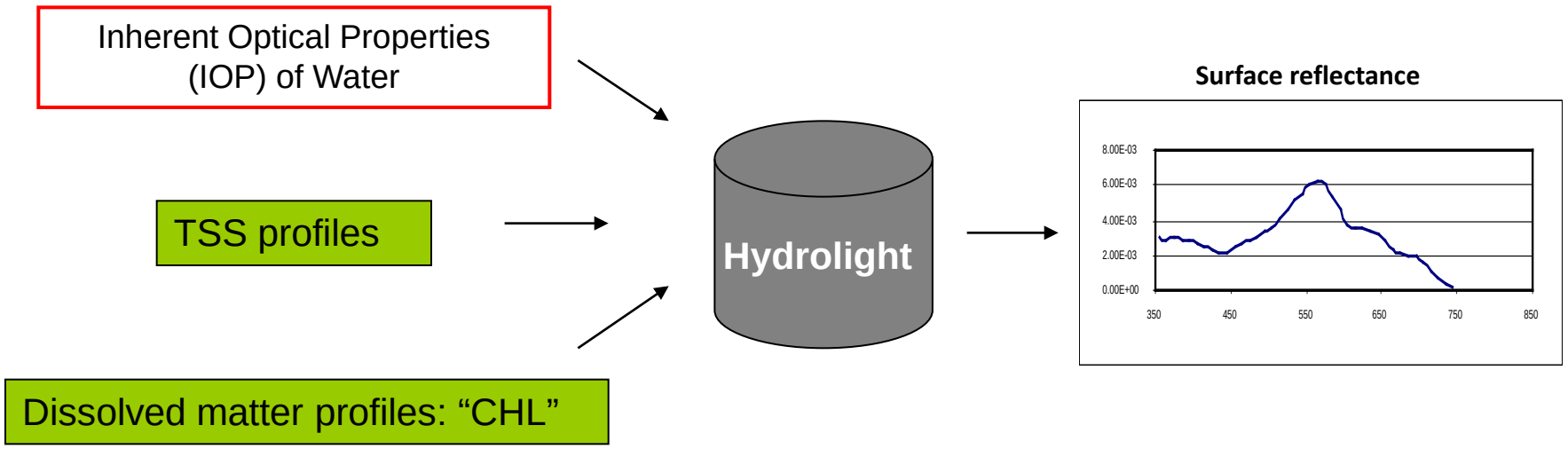


– **Deep water reflectance comparison between MODIS, L7 and OLI**



Surface Reflectance Modeling: Water Constituents

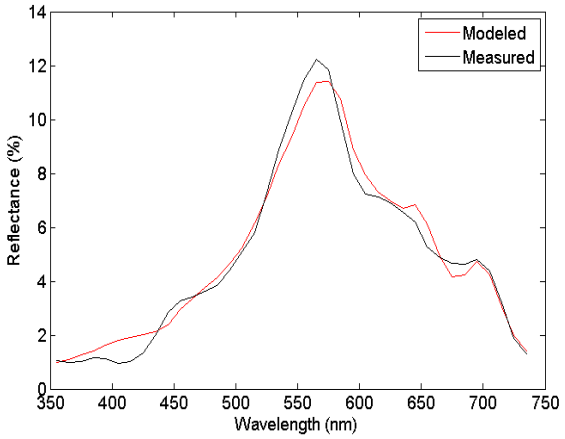
- **Optically active components of water, which influence water "color", are**
  - **Chlorophyll**
  - **Total Suspended Solids (Inorganic/Organic particles)**
  - **Colored Dissolved Organic Matter (CDOM)**



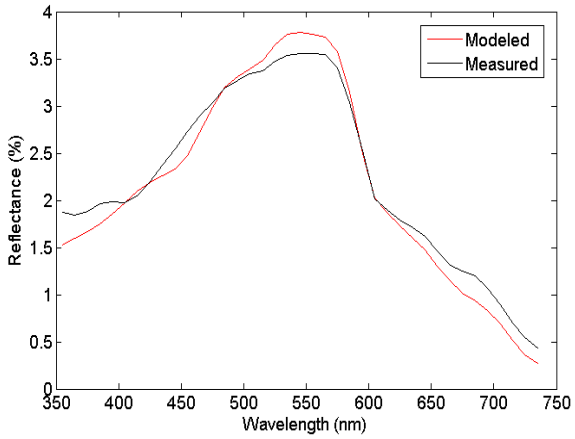
Surface Reflectance Modeling:
Measuring/Estimating IOPs

- **Absorption spectra are measurable through filtering techniques**
- **Scattering coefficients can be estimated by fitting various reflectance spectrum to the measured spectrum. This approach assumed that the constituents are known on the first order.**

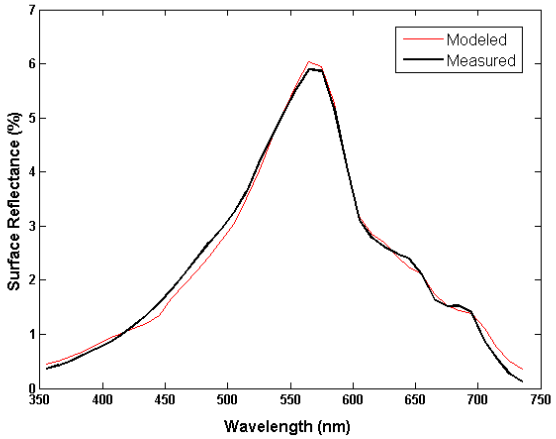
Genesee plume



Niagara plume



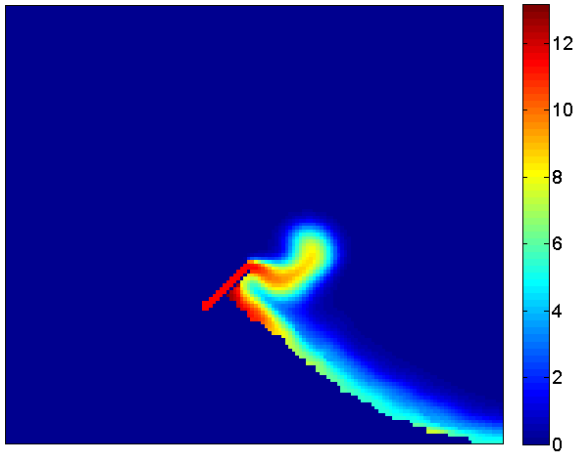
Onondaga Lake



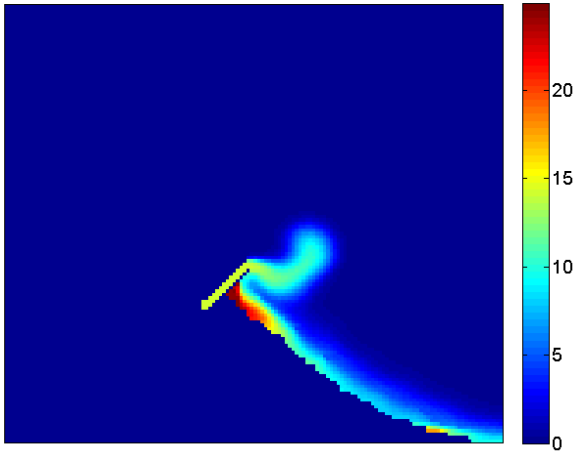
Results: Genesee Plume (no background)

– **Best model output (RMSE <0.55 % reflectance) calculated over the plume area**

TSS (g/m^3)



CHL (mg/m^3)

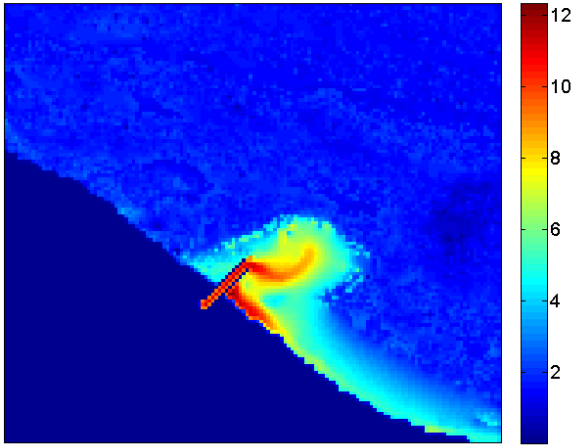


– **ALGE lacks predicting constituent distribution in non-plume areas**

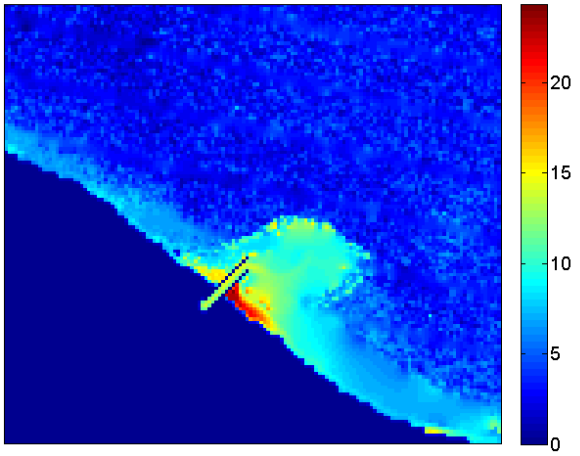
Results: Genesee Plume with Background

- **The background concentrations (surface) was determined through Hydrolight simulations on a pixel-by-pixel basis. In other words, 25 combinations of TSS and CHL (for each pixel) were simulated and optimized against the Landsat-derived reflectance map! Error maps for this optimization are available if you need them!**

TSS (g/m^3)



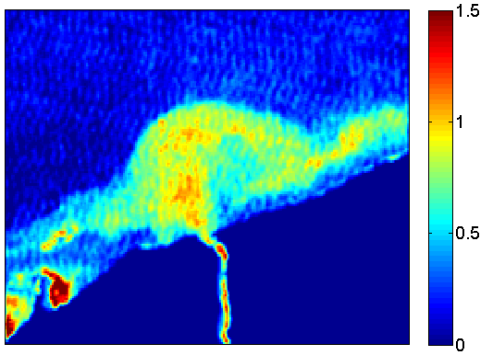
CHL (mg/m^3)



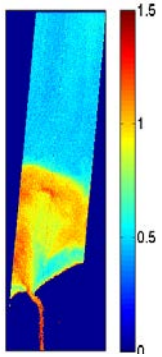
Preliminary Results: Niagara Plume

– **Niagara River plume (Oct10)**

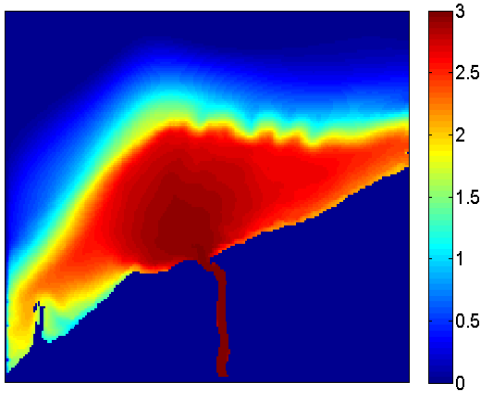
L7 - red channel

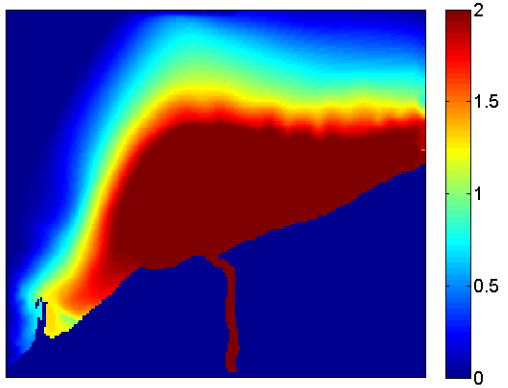


OLI - red channel



TSS Distribution



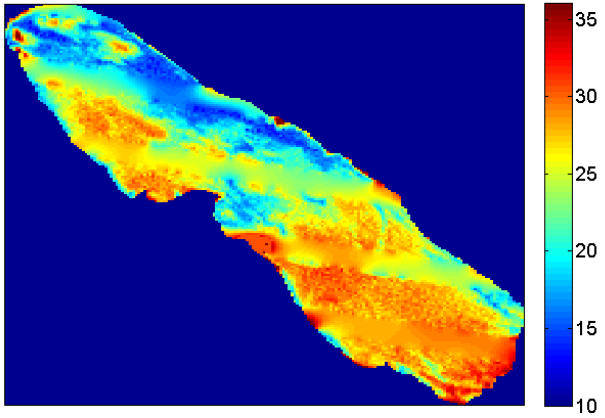


Dissolve matter Distribution

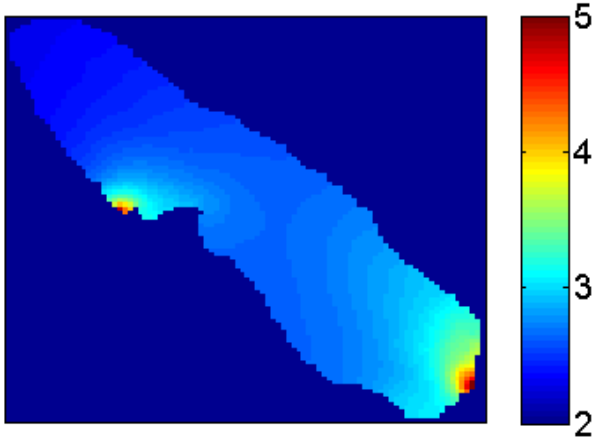
Preliminary Results: Distribution of Water Constituents

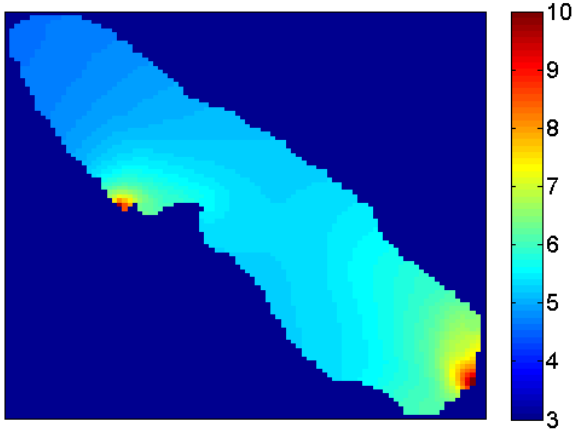
– **Onondaga Lake (May10)**

L7 - red channel
TOA Radiance units



TSS
Distribution





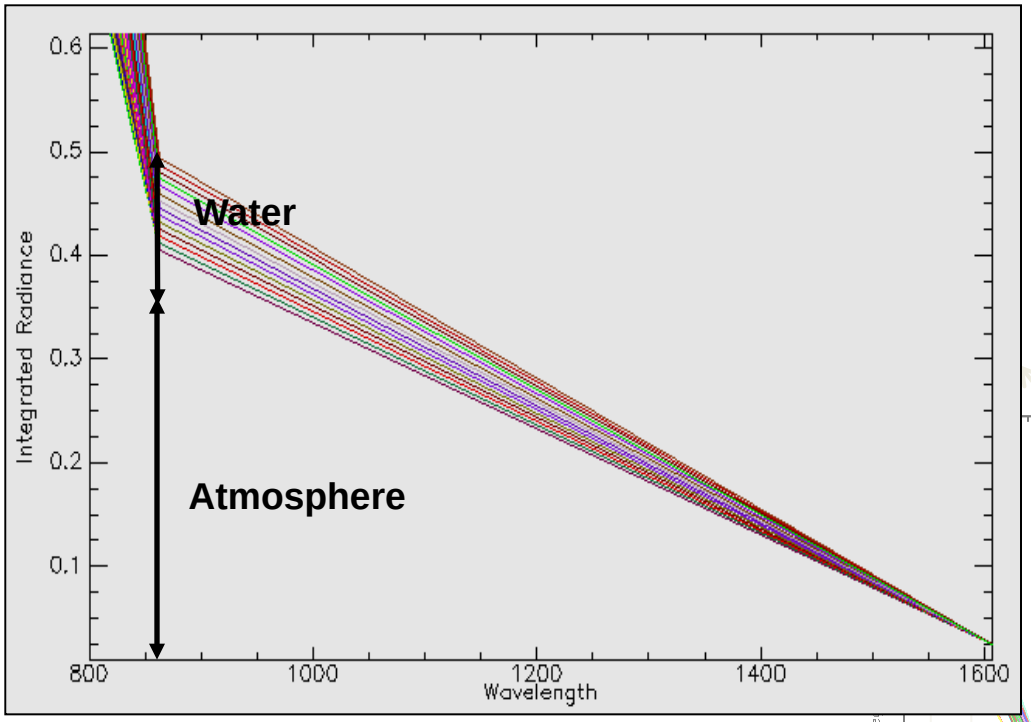
Dissolve matter
Distribution

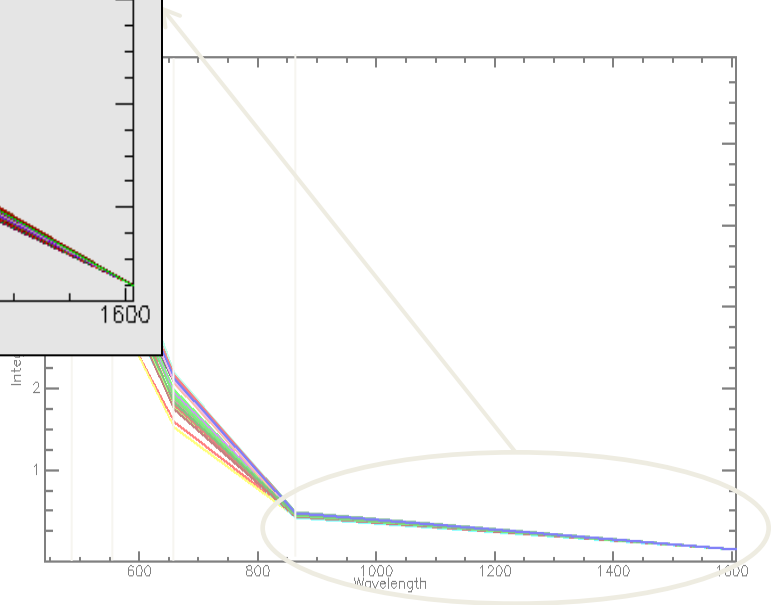
Future Directions

- **Implementing the method in Onondaga Lake for spring of 2011 (Field data are available-only L7)**
- **Praying for ideal condition for a field collect under L7/Hyperion at Genesee site**
- **Determine the improvement level of water constituent retrieval using OLI**

OLI Approach

Case 2 Waters

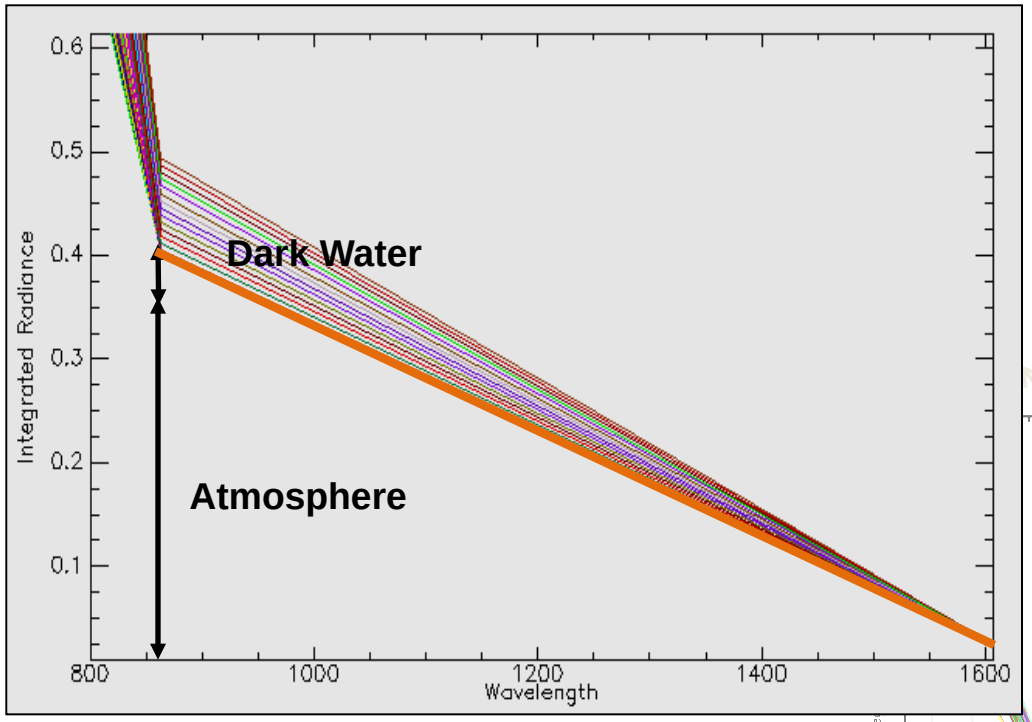


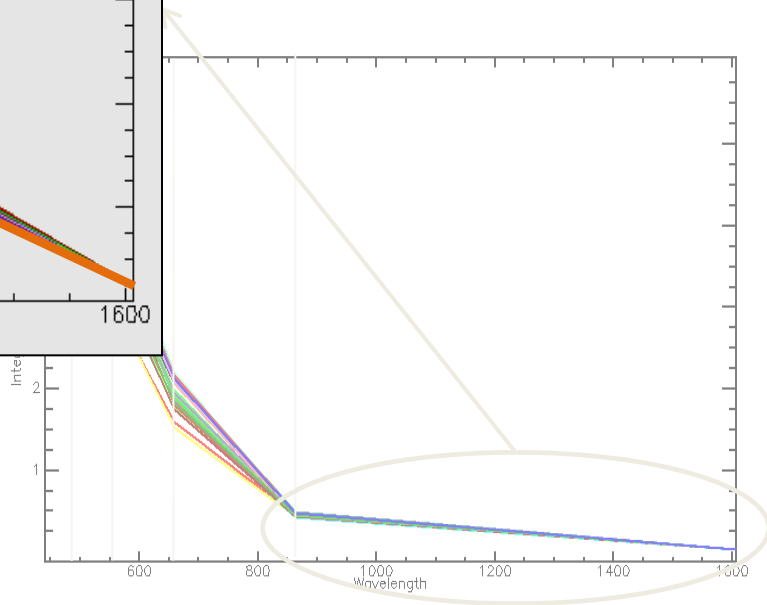


$$\underbrace{\rho_t(\lambda)}_{\text{Image}} = \underbrace{\rho_r(\lambda) + \rho_a(\lambda) + \rho_{ar}(\lambda)}_{\text{Atmosphere}} + \underbrace{T(\lambda)\rho_w(\lambda)}_{\text{Water}}$$

OLI Approach

Case 2 Waters



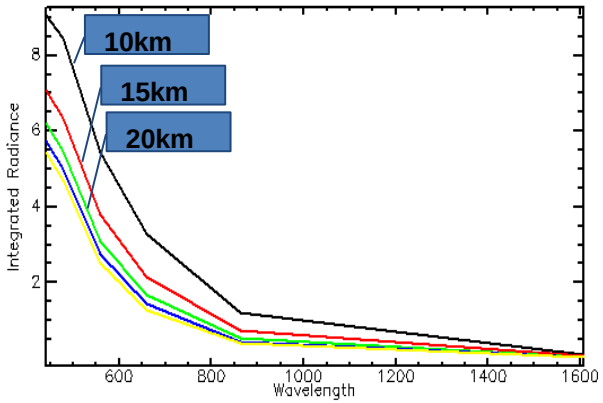


$$\underbrace{\rho_t(\lambda)}_{\text{Image}} = \underbrace{\rho_r(\lambda) + \rho_a(\lambda) + \rho_{ar}(\lambda)}_{\text{Atmosphere}} + \underbrace{T(\lambda)\rho_w(\lambda)}_{\text{Dark Water}}$$

OLI Approach

Case 2 Waters

Incorporate dark water component into an atmospheric LUT.



$$\rho_t(\lambda) = \underbrace{\rho_r(\lambda) + \rho_a(\lambda) + \rho_{ar}(\lambda)}_{\text{Atmosphere}} + \underbrace{T(\lambda)\rho_w(\lambda)}_{\text{Dark Water}}$$

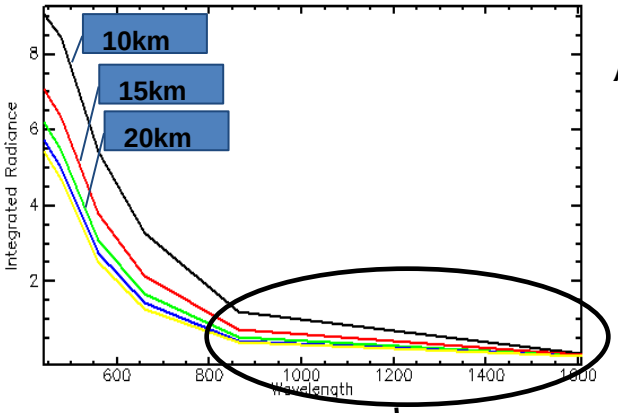
- Mid-latitude Summer profile.
- May 20th, 1999.
- Standard gases
- Rural aerosols
  - Varied visibility between 5 and 60 kilometers.

AVIRIS: May 20th, 1999

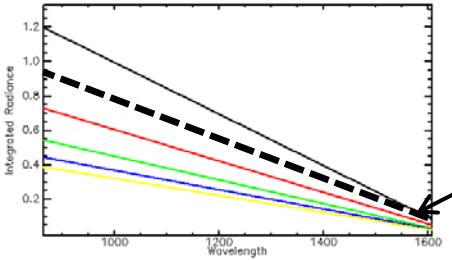
OLI Approach

Case 2 Waters

Incorporate dark water constant into an atmospheric LUT.



$$\rho_t(\lambda) = \underbrace{\rho_r(\lambda) + \rho_a(\lambda) + \rho_{ar}(\lambda)}_{\text{Atmosphere}} + \underbrace{T(\lambda)\rho_w(\lambda)}_{\text{Dark Water}}$$



AVIRIS: May 20th, 1999

Radiometric Sharpening of Thermal Data: Algorithm

- On a Super-pixel-by-pixel basis, solve regression coefficients for…

$$L_{T_{obs}} = a_0 + a_1\overline{L_1} + a_2\overline{L_2} + \ldots + a_n\overline{L_n}$$

- Estimate thermal radiance associated with each subpixel by applying coefficients…

$$\widehat{L}_{T_i} = a_0 + a_1 L_{1_i} + a_2 L_{2_i} + \ldots + a_n L_{n_i}$$

- Once thermal estimates have been made for all subpixels in the superpixel, the radiances are scaled…

$$L_{T_i} = \frac{\hat{L}_{T_i}}{\hat{L}_{T_{ave.}}} L_{T_{obs.}}$$