Demonstrating Landsat's New Potential to Monitor Coastal and Inland Waters

by

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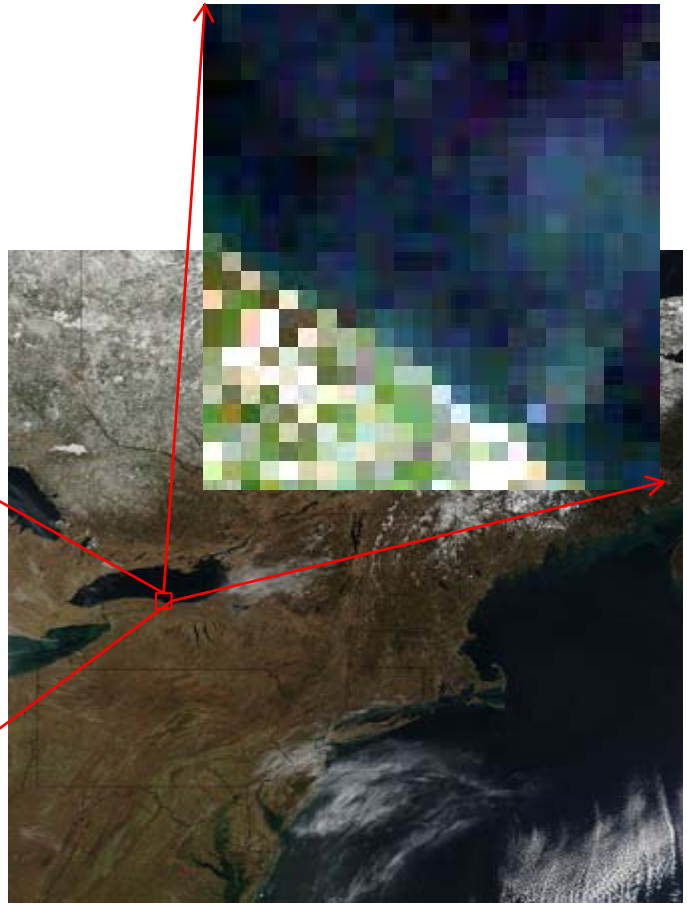
Sponsor: United States Geological Survey (USGS)

Research Motivation

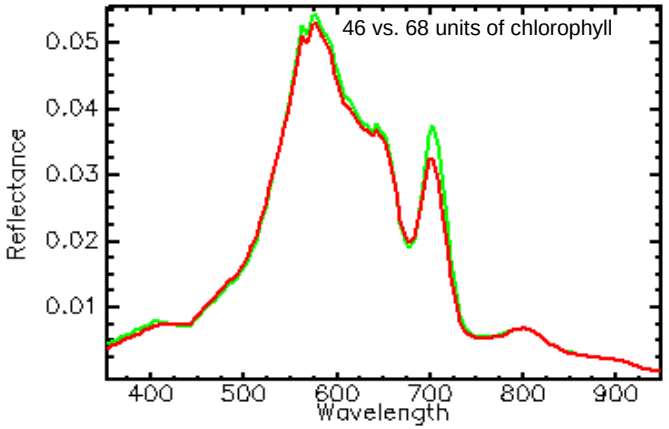
- Desire to monitor the Earth's coastal and fresh water supply.
- No environmental satellite to date has the necessary characteristics…
  - High spatial resolution.
  - High radiometric fidelity.
  - Repeat Coverage.
  - Data are readily accessible.



Rochester Embayment Landsat

Monitoring Fresh and Coastal Waters

- **Spatial Resolution**:
- **Repeat Coverage**:
- **Accessible Data**



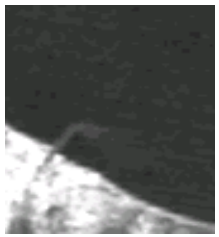
- **Radiometric Fidelity**: Significant changes in constituent concentrations often lead to small changes in water-leaving reflectance.

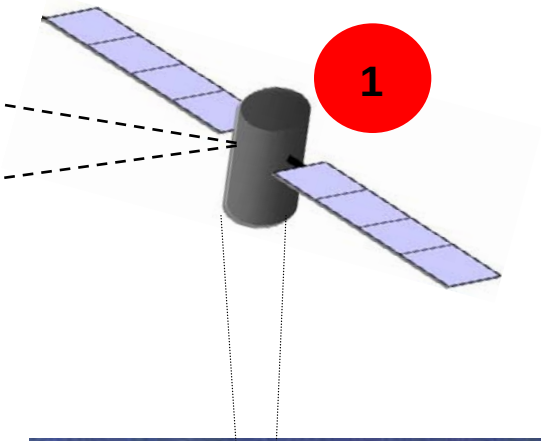
Monitoring Fresh Waters

- **Case 2 Waters:**
  - Inland and coastal waters.
  - Optically complex case 2 waters contain significant levels of...
    - **Chlorophyll-a**
      - phytoplankton
    - **Suspended Materials**
      - runoff
    - **Colored dissolved organic matter (CDOM)**
      - Decaying organic matter

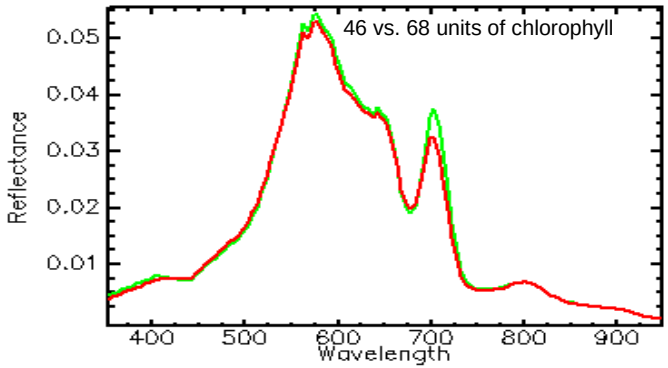
- **Issues:**
  - Determine condition of water through **constituent retrieval process**.
  - Trophic status and trends
  - Characterize sedimentation in river plumes.
    - Predict beach closings.
    - Impact of sediment on the surrounding environment.

Overview of Research



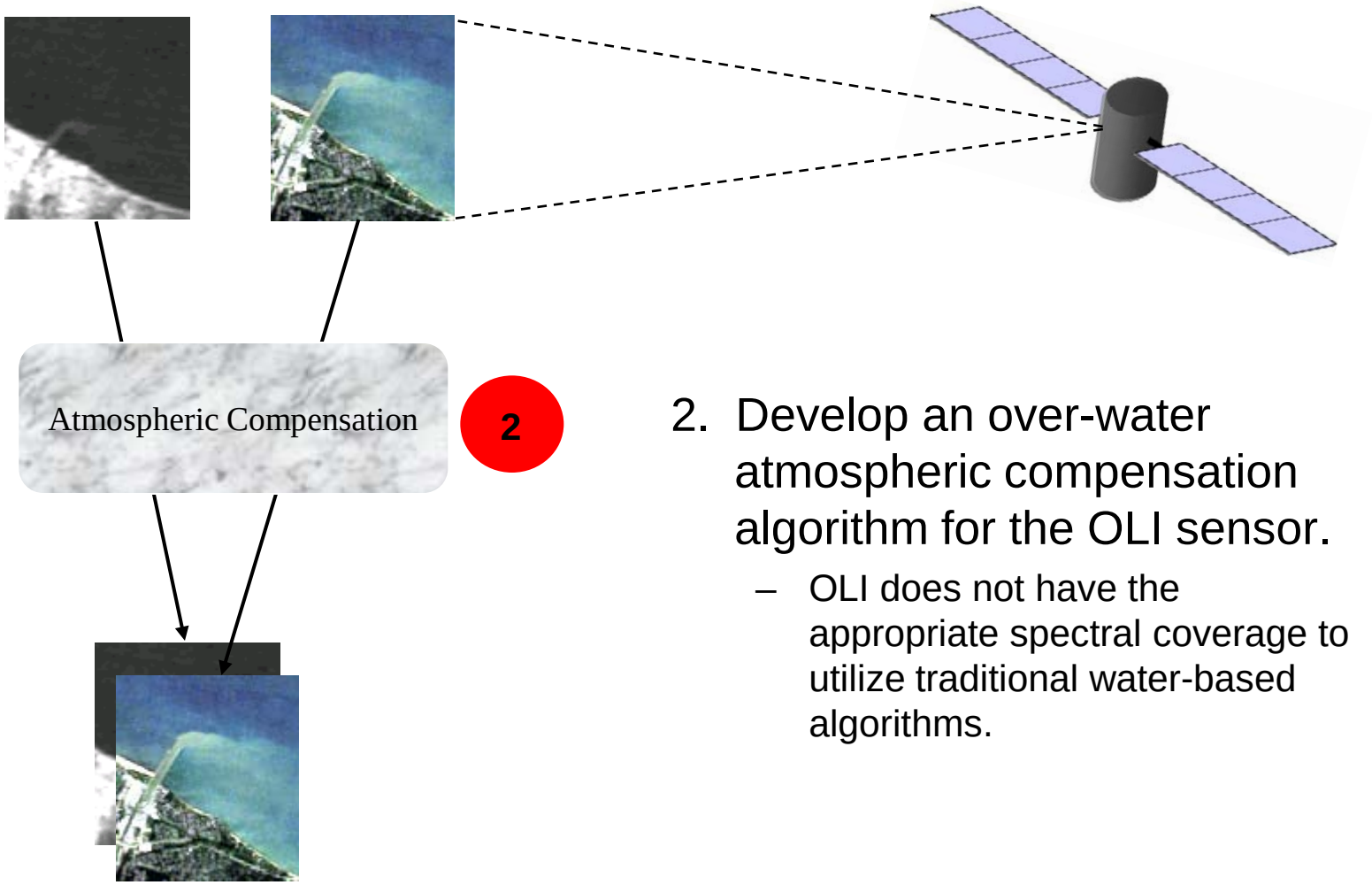


1. Demonstrate that Landsat's new OLI sensor is suitable for studying optically complex case 2 waters.
   - Radiometric fidelity.

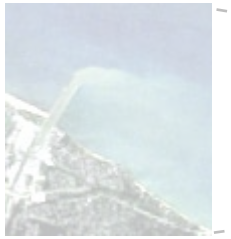


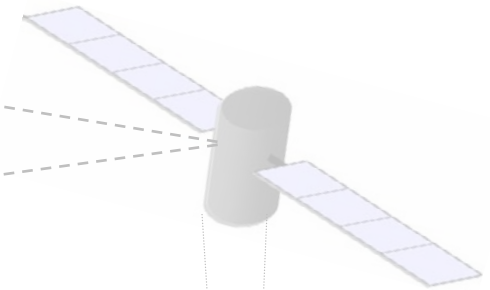
Landsat 5: July 13th, 2009

Overview of Research



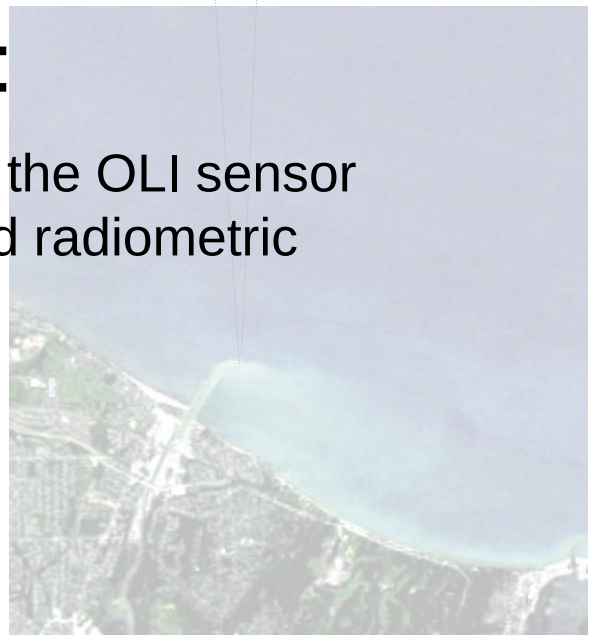
2. Develop an over-water atmospheric compensation algorithm for the OLI sensor.
   - OLI does not have the appropriate spectral coverage to utilize traditional water-based algorithms.





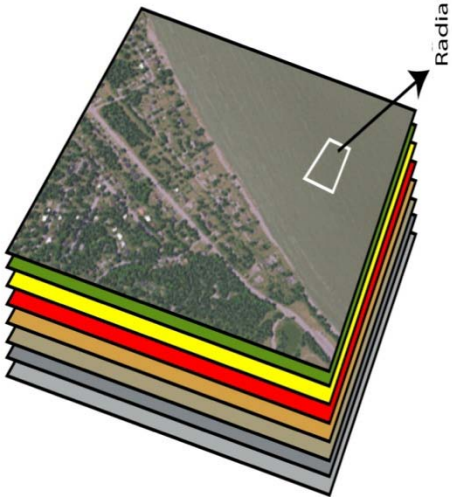
Objective 1:

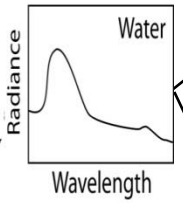
Model the improved features of the OLI sensor and demonstrate its improved radiometric fidelity.



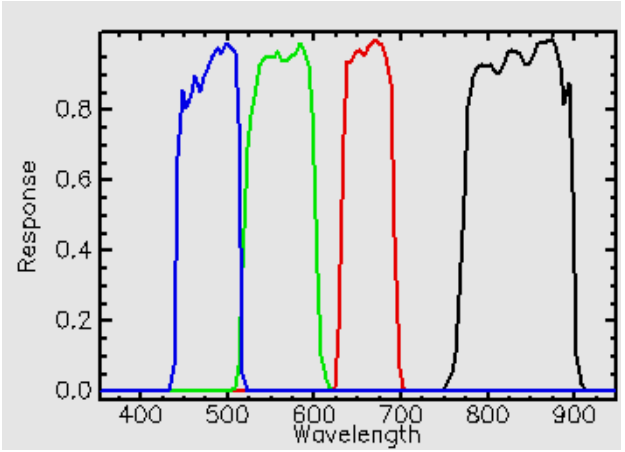
Landsat 5: July 13th, 2009

OLI Features: Enhanced Spectral Coverage

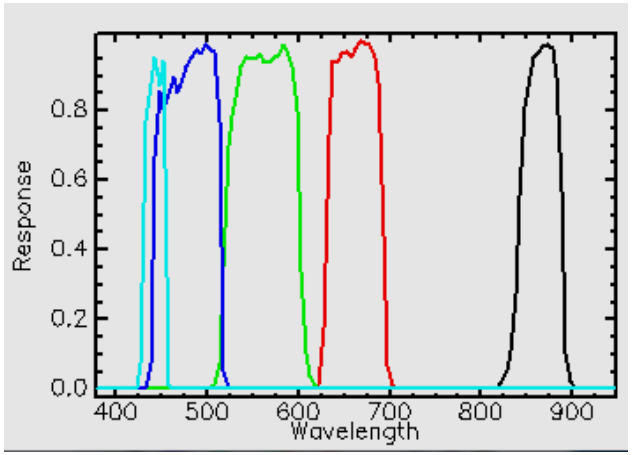




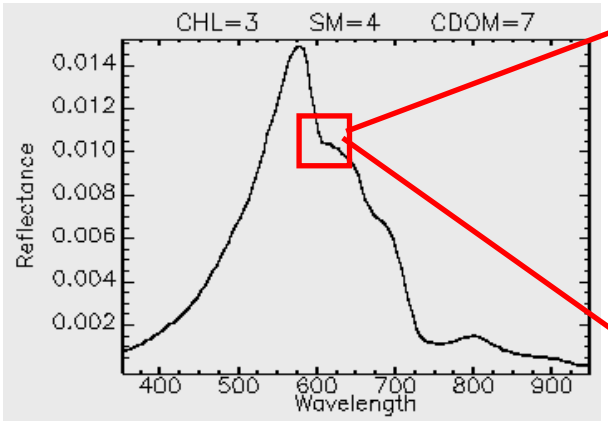
ETM+ Response



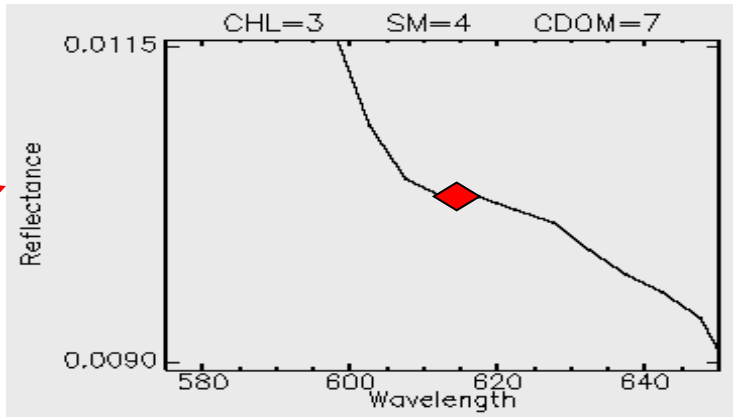
OLI Response



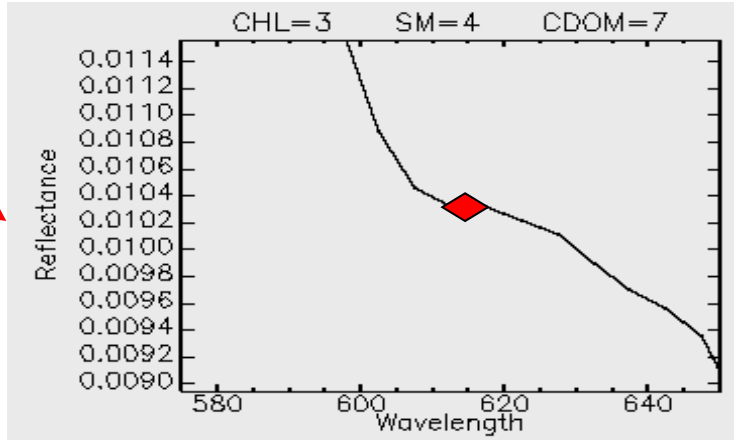
OLI Features: Quantization



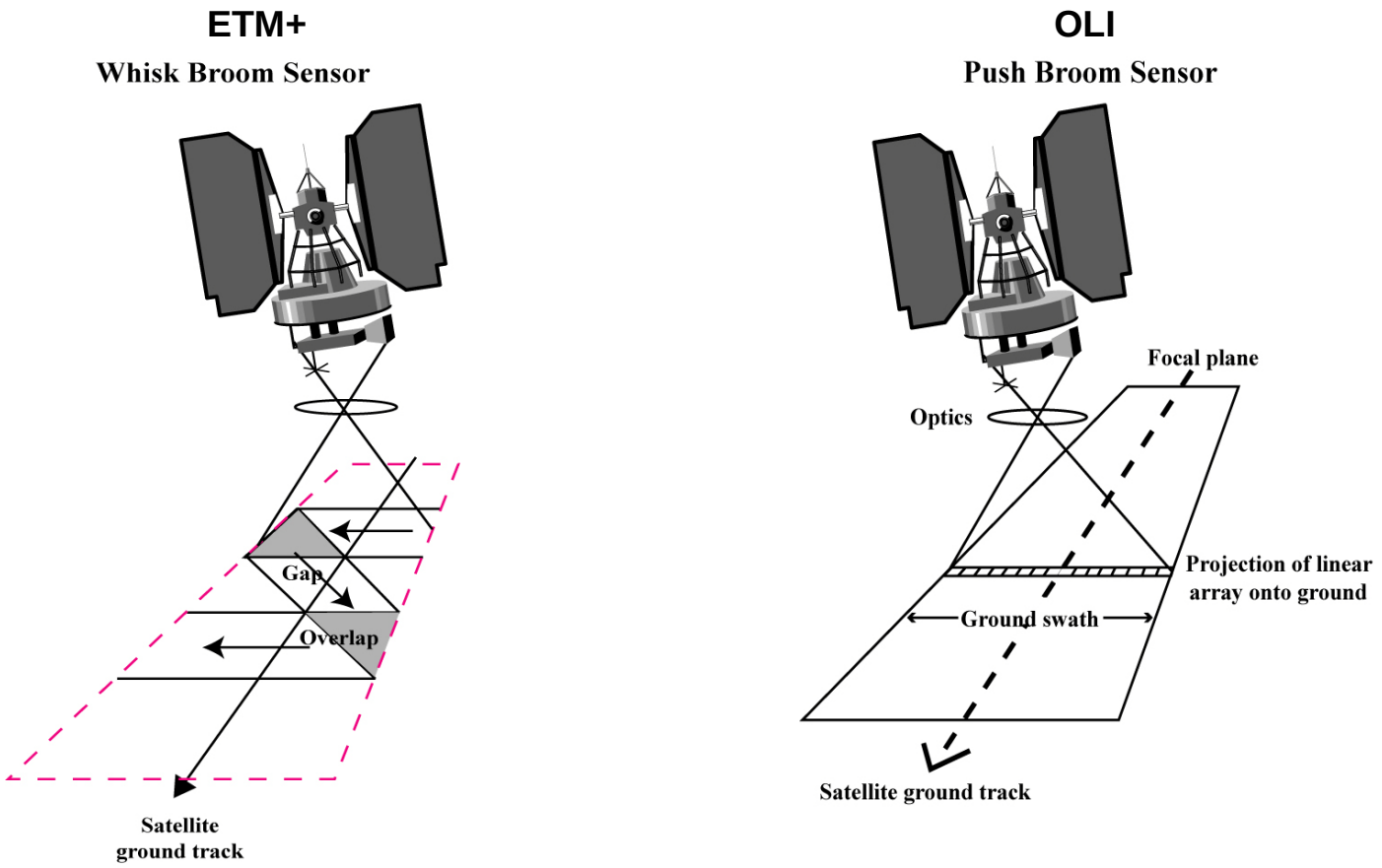
ETM+ (8-bit)



OLI (12-bit)

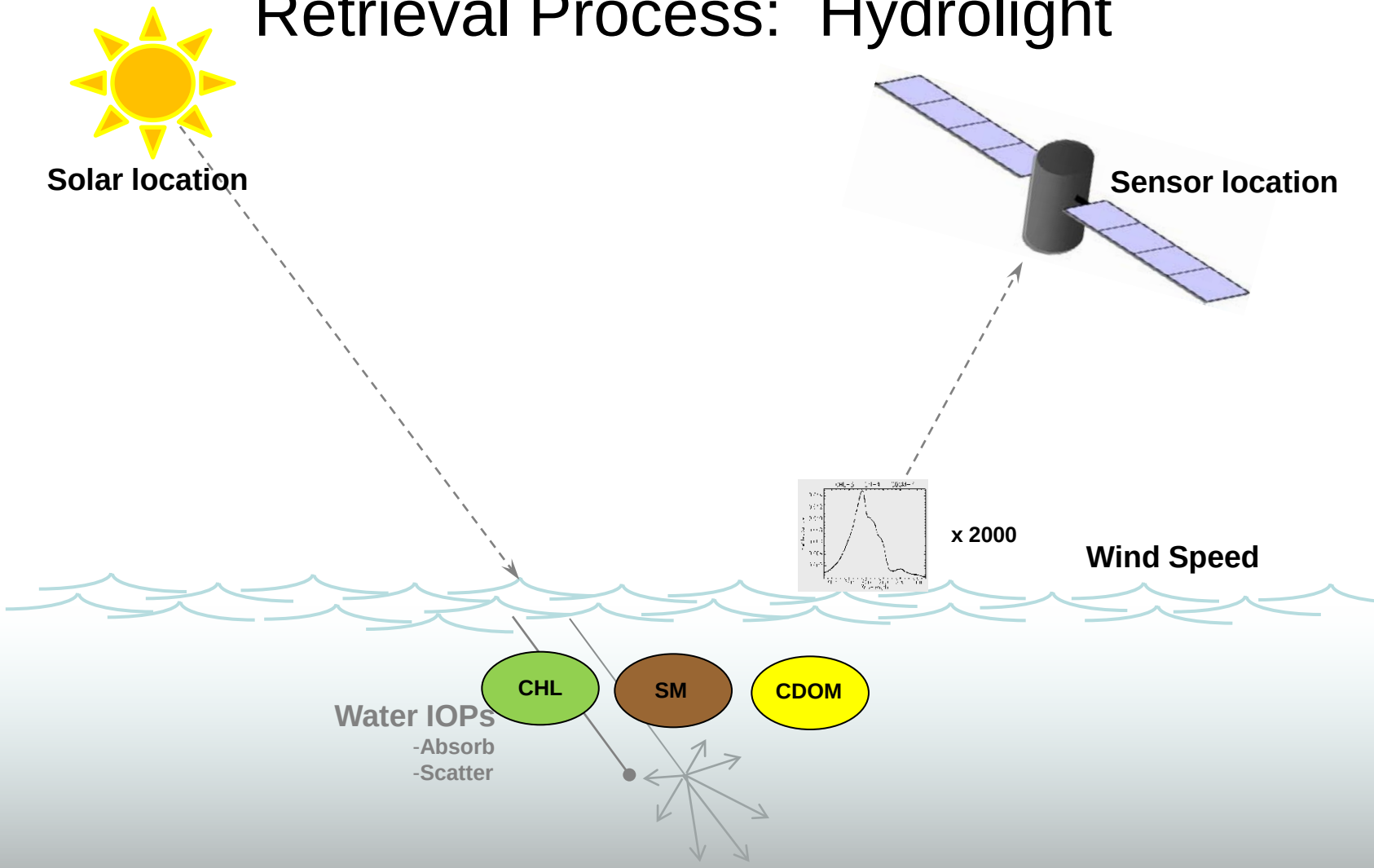


OLI Features: Signal to Noise

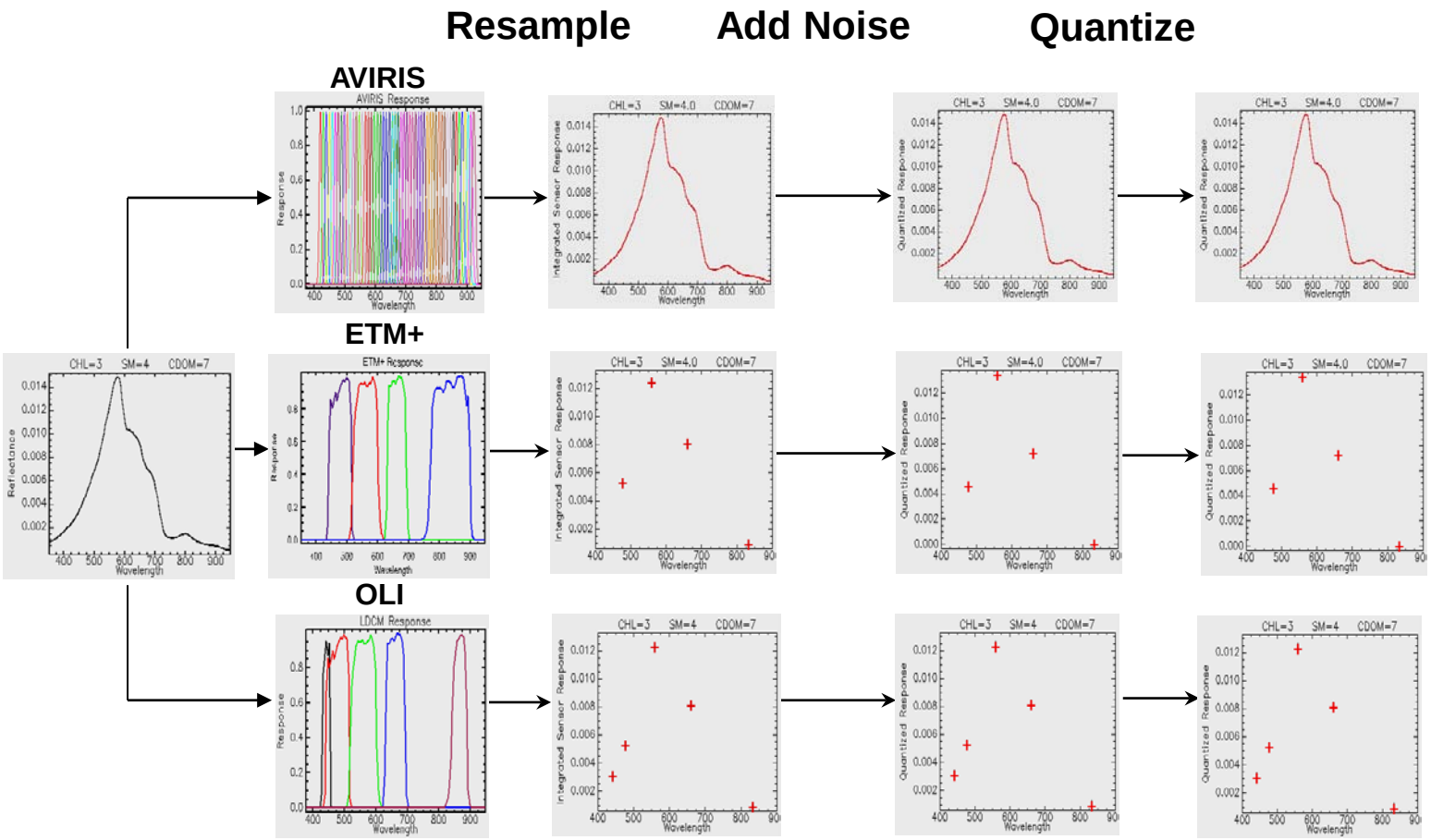


- About a factor of 5 improvement in SNR.

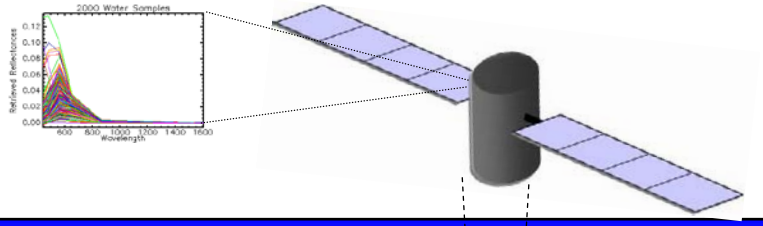
Modeling the Constituent Retrieval Process: Hydrolight



Modeling the Constituent Retrieval Process: At the Sensor



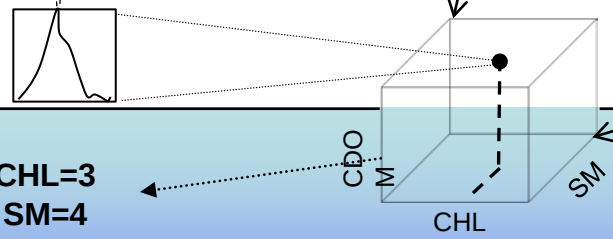
Modeling the Constituent Retrieval Process: CRA



CHL (μg/ L)	SM(mg/ L)	CD OM
0	0	0
.5	.5	.5
1	1	.75
3	2	1
5	4	2
7	8	4
12	10	7
24	14	10
46	20	12
68	24	14

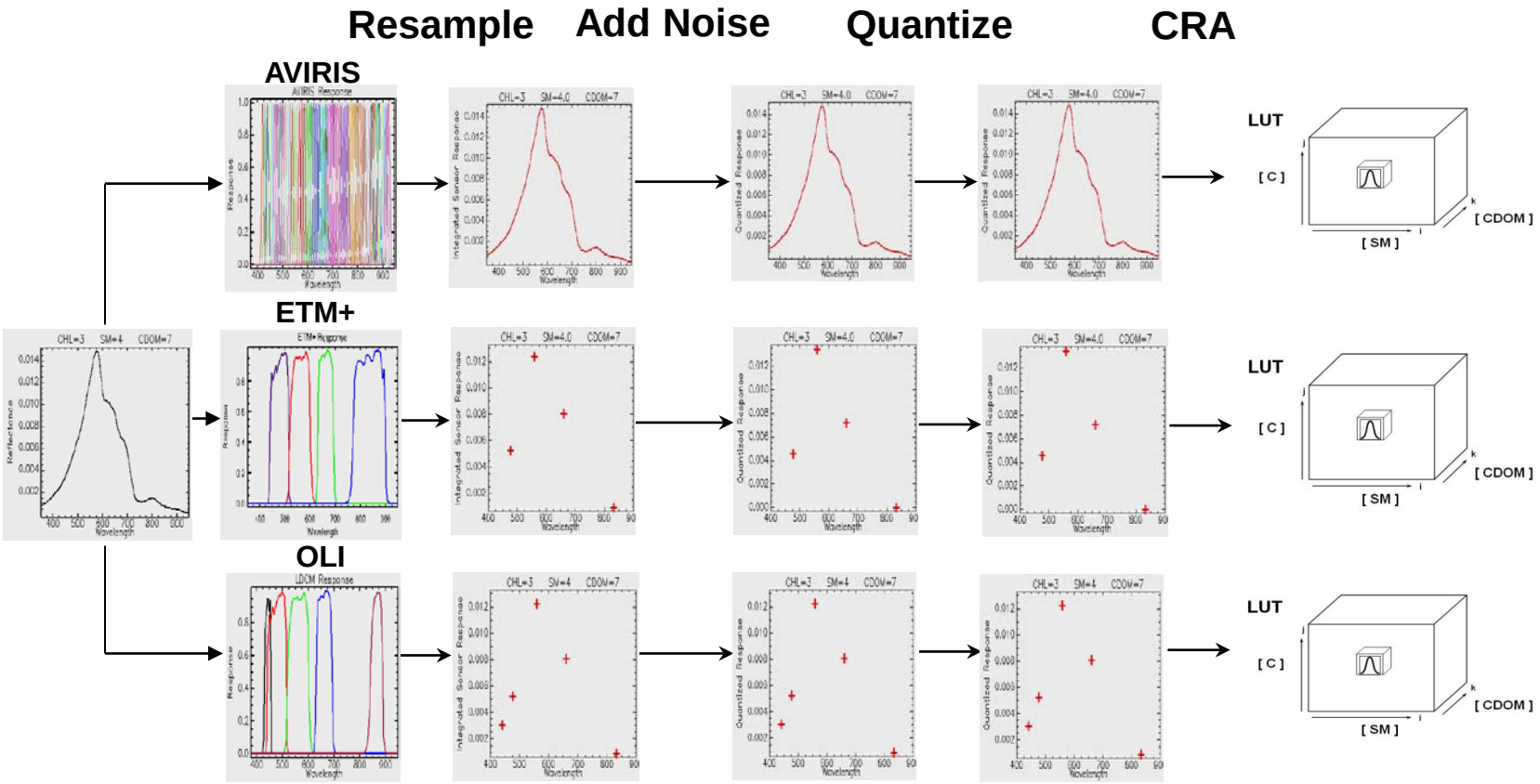
Top of Atmosphere

Air/Water Interface



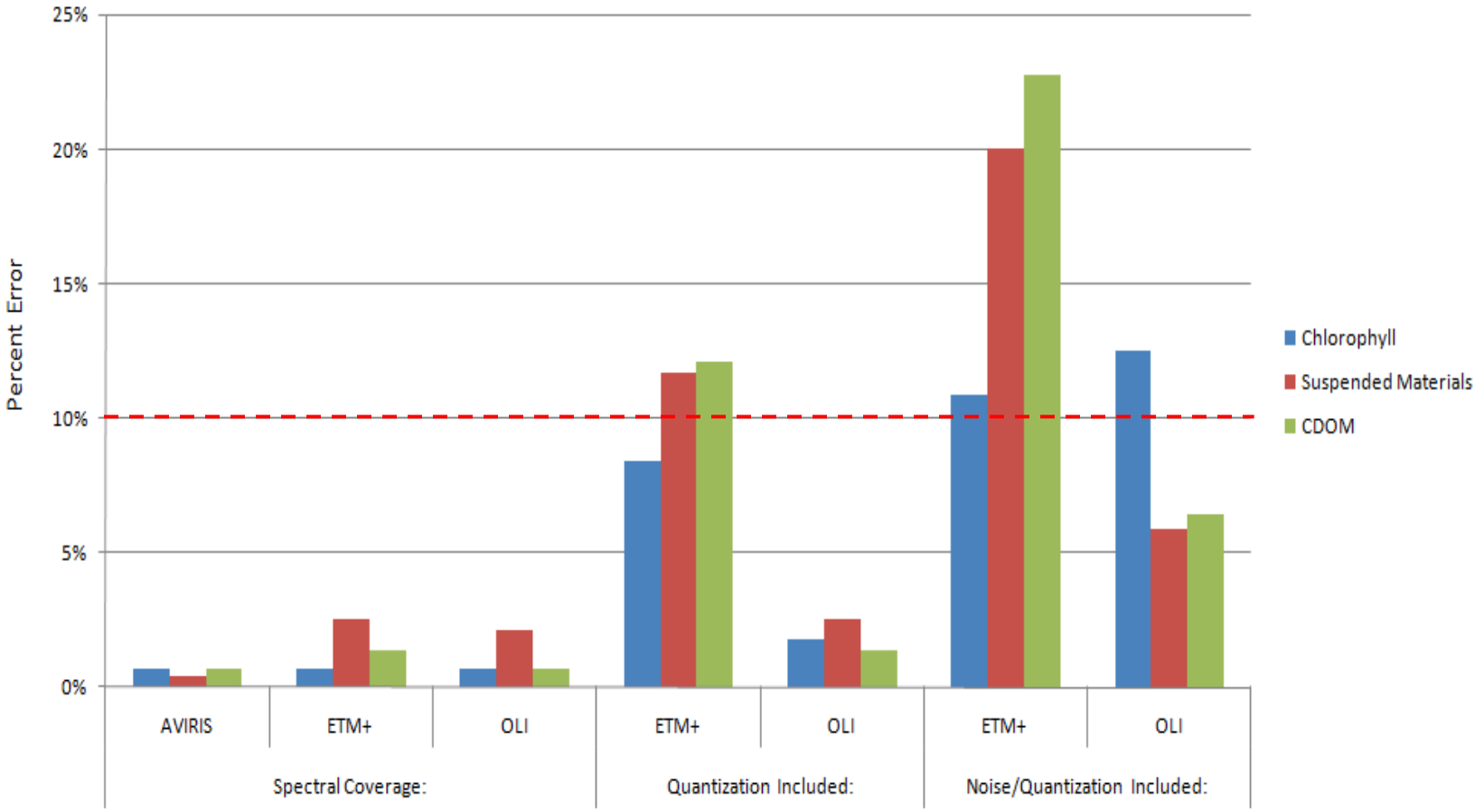
CHL=3
SM=4
CDOM=7

Modeling the Constituent Retrieval Process: Summary

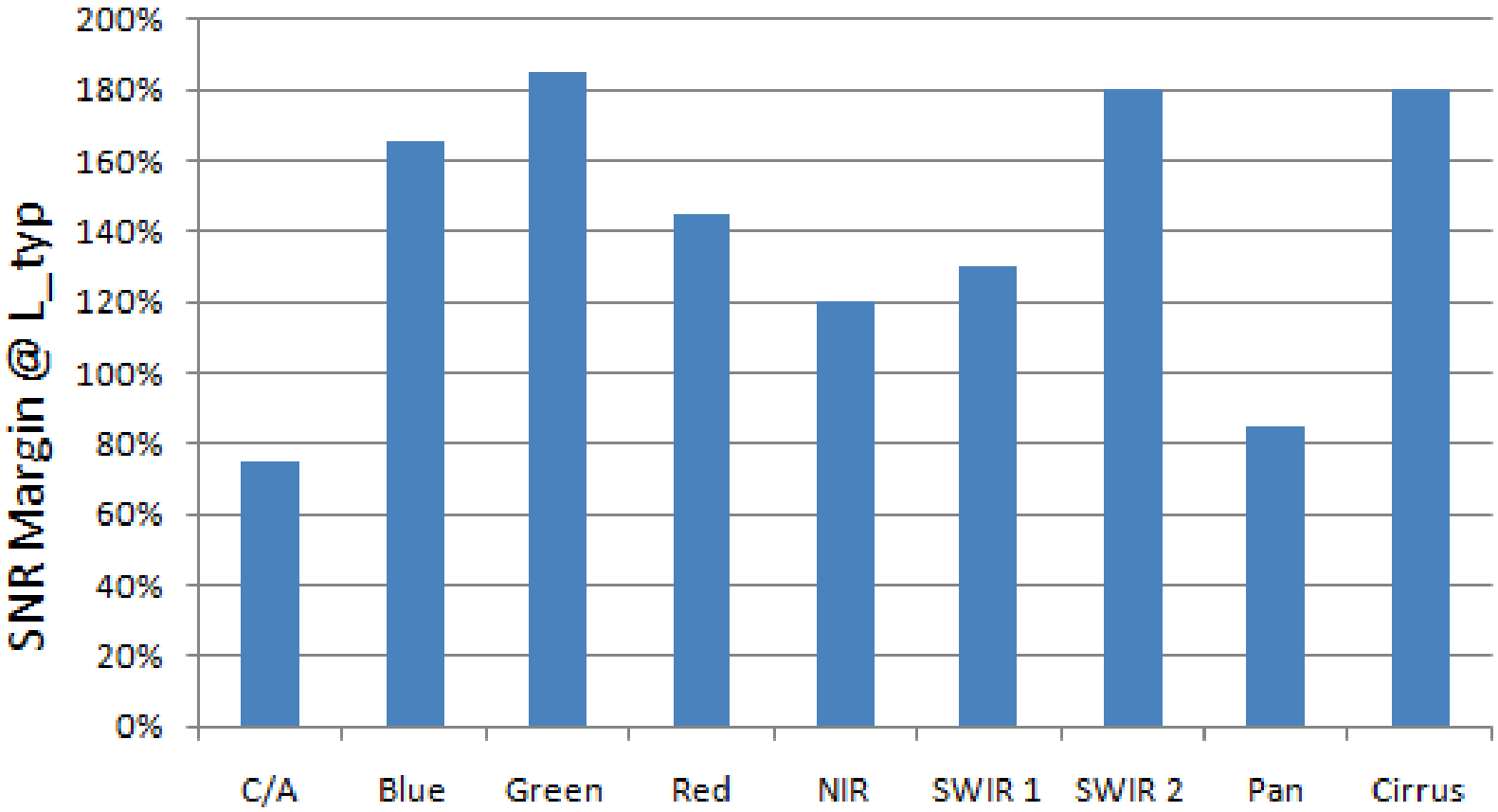


- Average residuals can be expressed as a percent of the total range of constituents.
  CHL [0 – 68], SM [0 – 24], CDOM [0 – 14]
- 10% error is our target for this experiment.

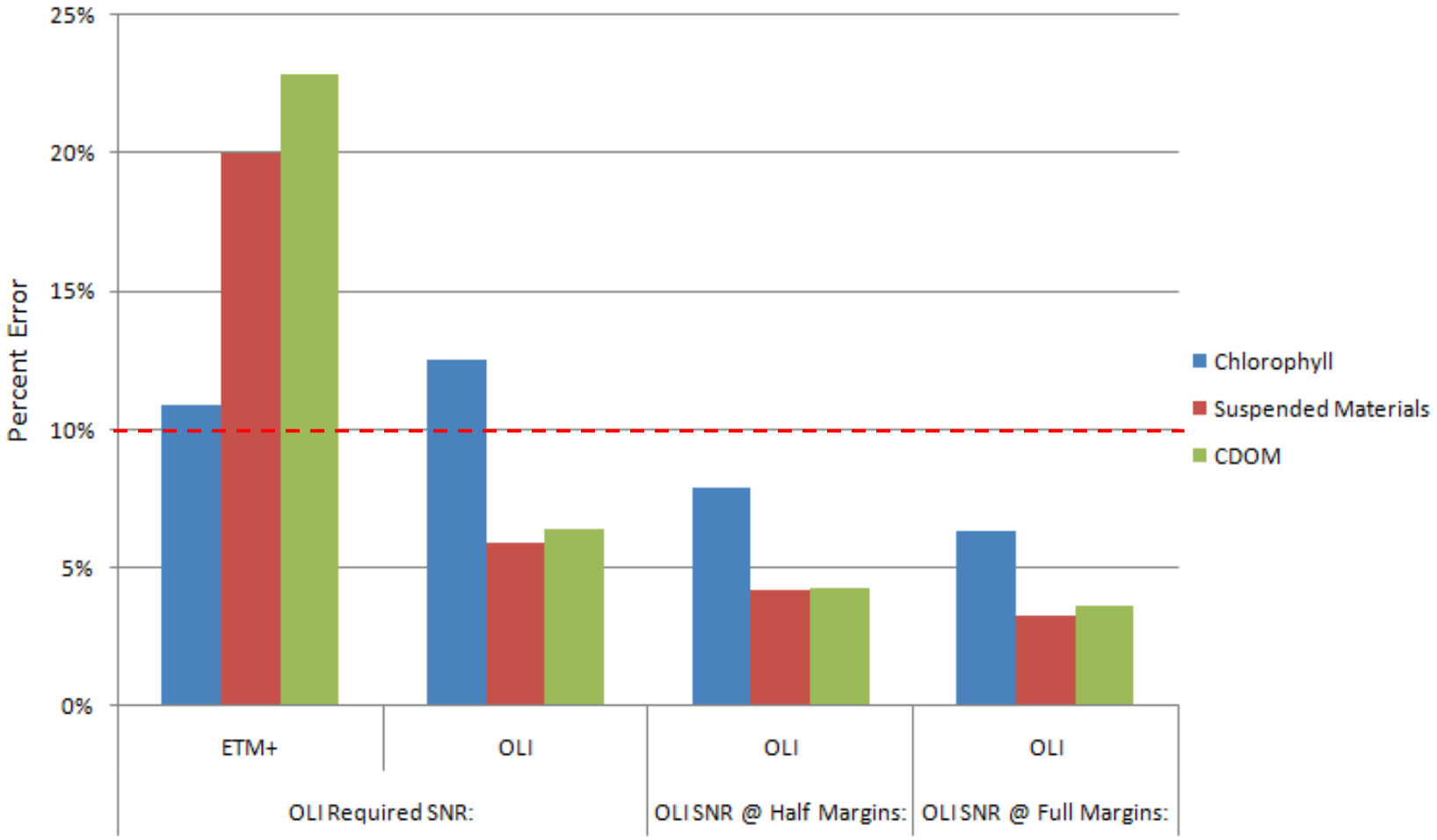
Results


25%
20%
15%
10%
5%
0%
Percent Error
AVIRIS
ETM+
OLI
ETM+
OLI
ETM+
OLI
Spectral Coverage:
Quantization Included:
Noise/Quantization Included:
Chlorophyll
Suspended Materials
CDOM

SNR Margins


SNR Margin @ L_typ
200%
180%
160%
140%
120%
100%
80%
60%
40%
20%
0%
C/A
Blue
Green
Red
NIR
SWIR 1
SWIR 2
Pan
Cirrus

Results

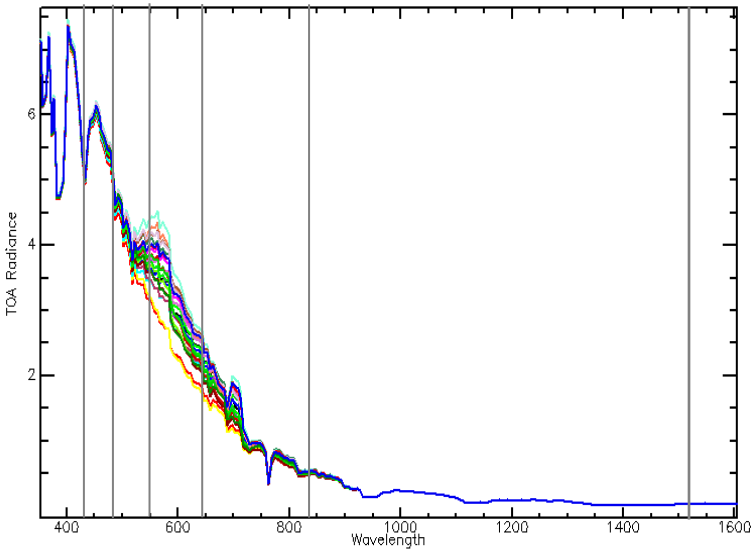

25%
20%
15%
10%
5%
0%
Percent Error
ETM+
OLI
OLI
OLI
OLI Required SNR:
OLI SNR @ Half Margins:
OLI SNR @ Full Margins:
Chlorophyll
Suspended Materials
CDOM

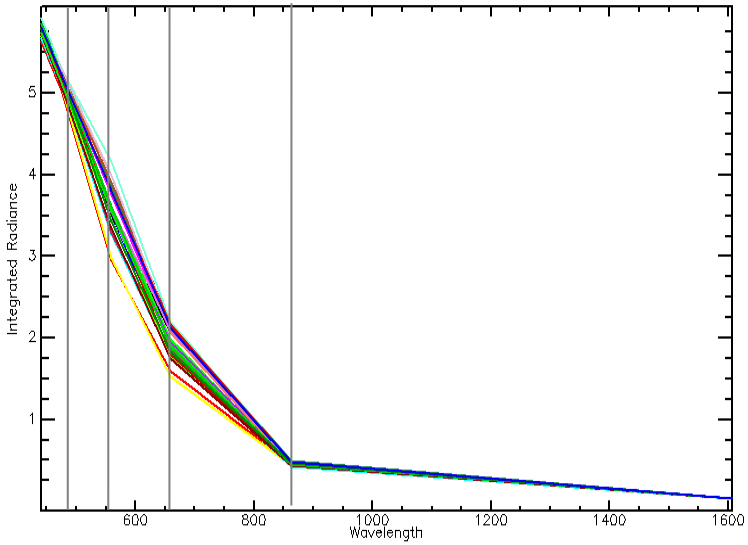
Objective 2:

Develop an over-water atmospheric compensation algorithm specifically for the OLI sensor.

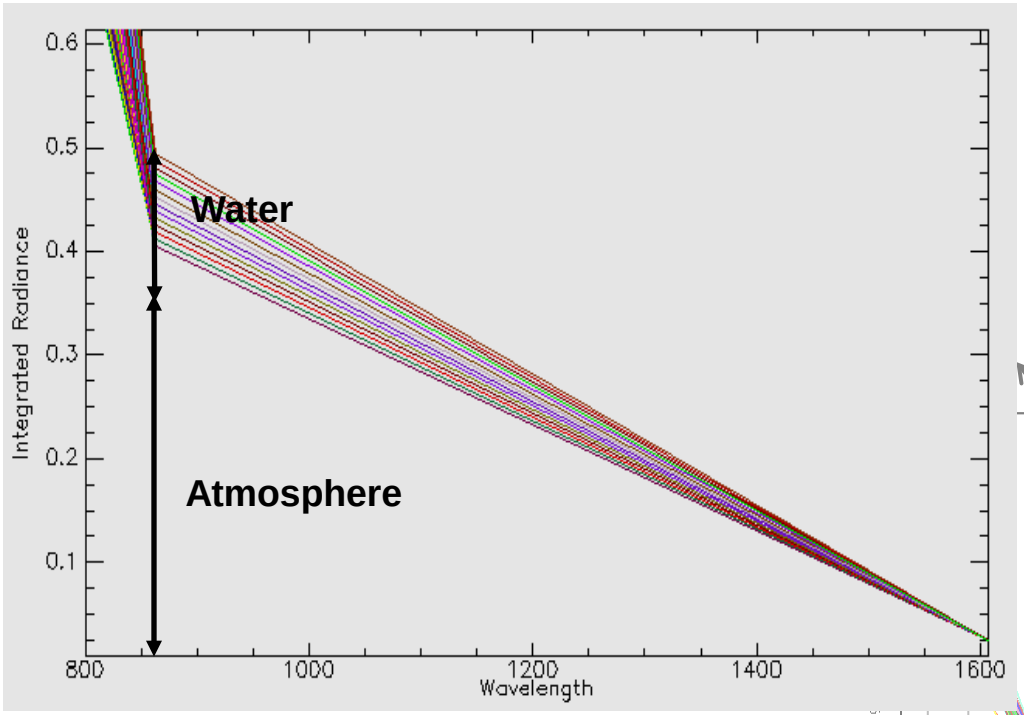
OLI Approach
Case 2 Waters

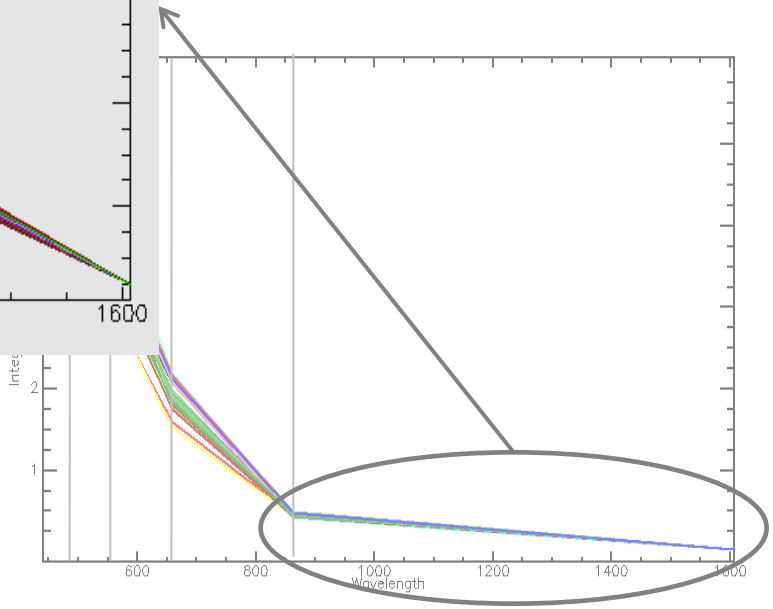
- **Purpose**: Convert TOA radiances to water-leaving reflectances.
- **Issue**: OLI doesn't have 2 NIR bands which are required by traditional water-based algorithms.
  - Gordon's method (SeaWiFS).
- **2 methods developed**:
  - Blue Band method.
  - NIR/SWIR band ratio method.





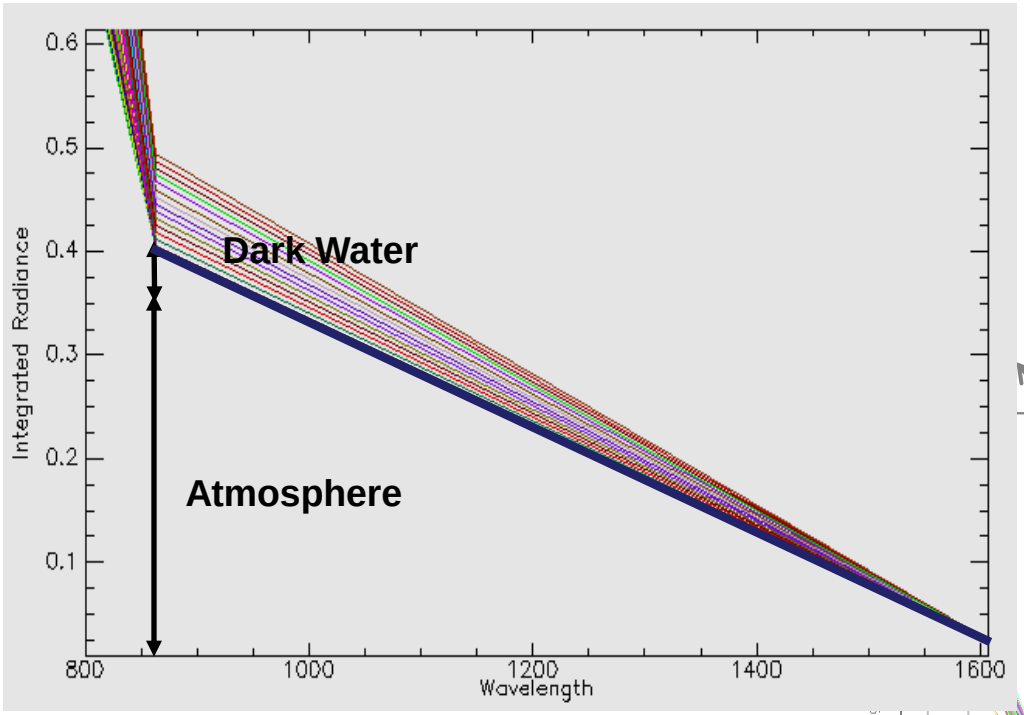
OLI Approach
Case 2 Waters

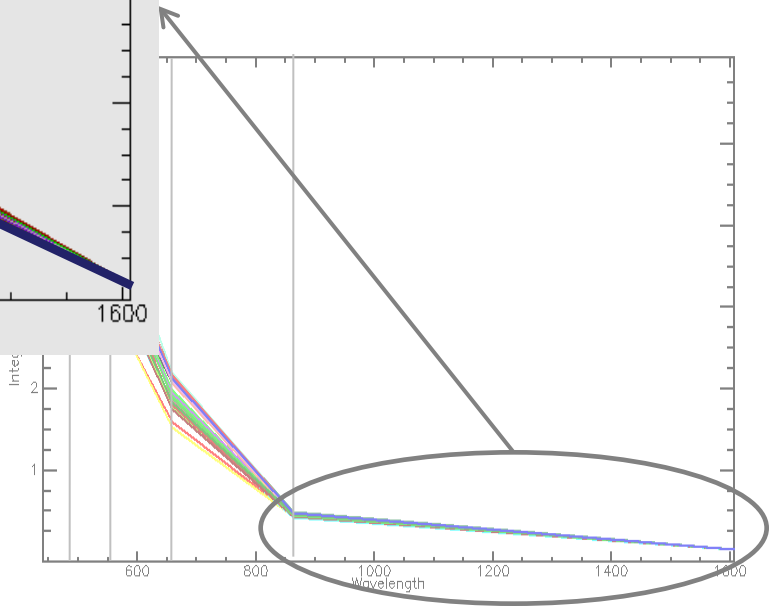




$$\underbrace{\rho_t(\lambda)}_{\text{Image}} = \underbrace{\rho_r(\lambda) + \rho_a(\lambda) + \rho_{ar}(\lambda)}_{\text{Atmosphere}} + \underbrace{T(\lambda)\rho_w(\lambda)}_{\text{Water}}$$

OLI Approach
Case 2 Waters

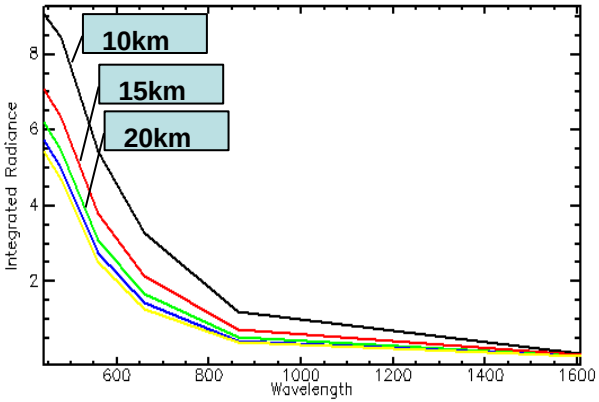




$$\underbrace{\rho_t(\lambda)}_{\text{Image}} = \underbrace{\rho_r(\lambda) + \rho_a(\lambda) + \rho_{ar}(\lambda)}_{\text{Atmosphere}} + \underbrace{T(\lambda)\rho_w(\lambda)}_{\text{Dark Water}}$$

OLI Approach
Case 2 Waters

- Incorporate dark water component into an atmospheric LUT.



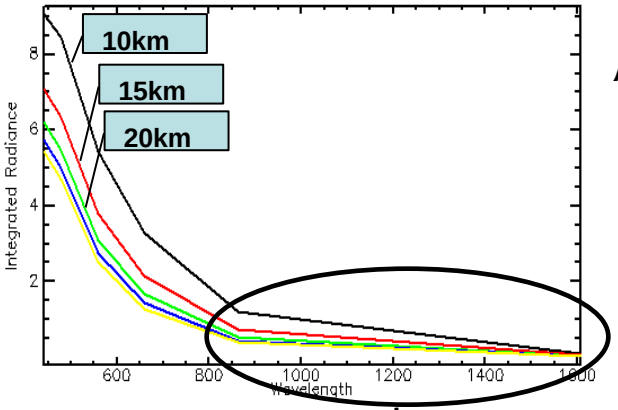
$$\rho_t(\lambda) = \underbrace{\rho_r(\lambda) + \rho_a(\lambda) + \rho_{ar}(\lambda)}_{\text{Atmosphere}} + \underbrace{T(\lambda)\rho_w(\lambda)}_{\text{Dark Water}}$$

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

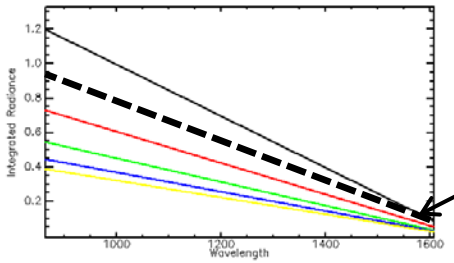
AVIRIS: May 20th, 1999

OLI Approach
Case 2 Waters

- Incorporate dark water constant into an atmospheric LUT.



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

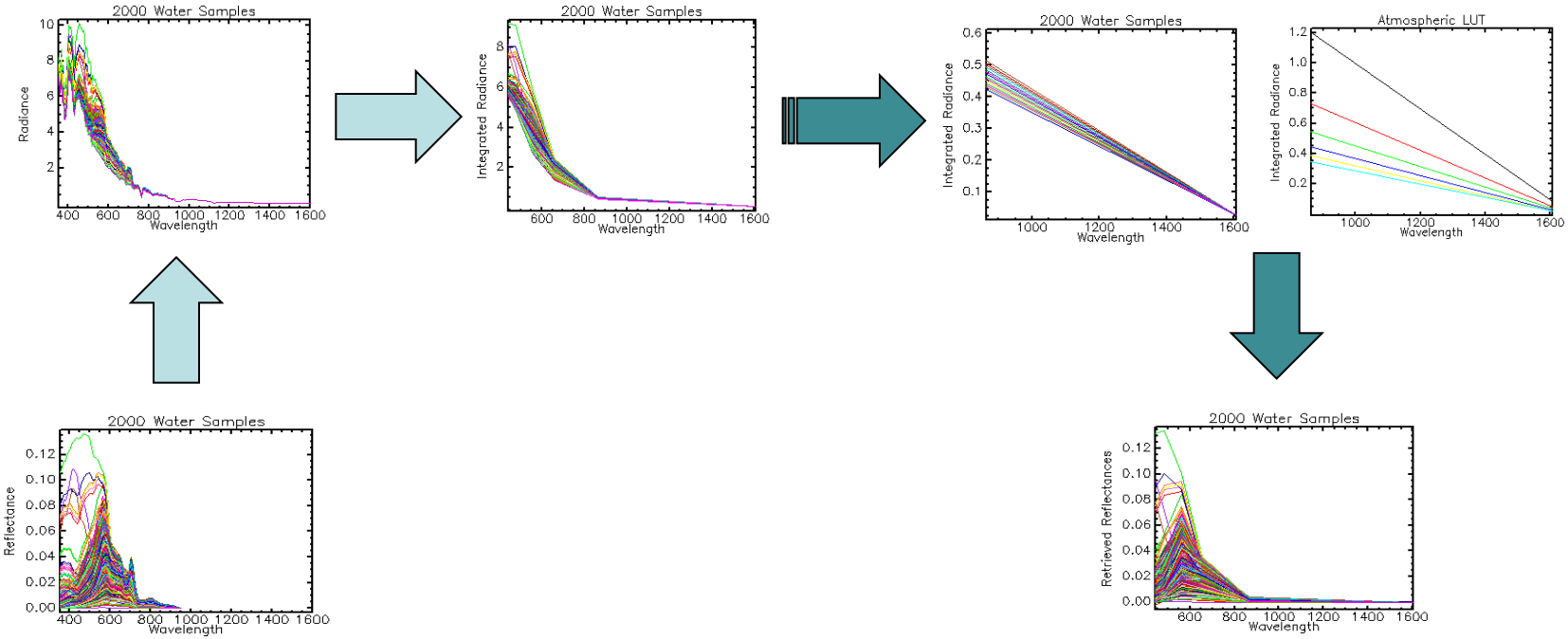


AVIRIS: May 20th, 1999

OLI Atmospheric Compensation

Experiment 1: Simulated Data

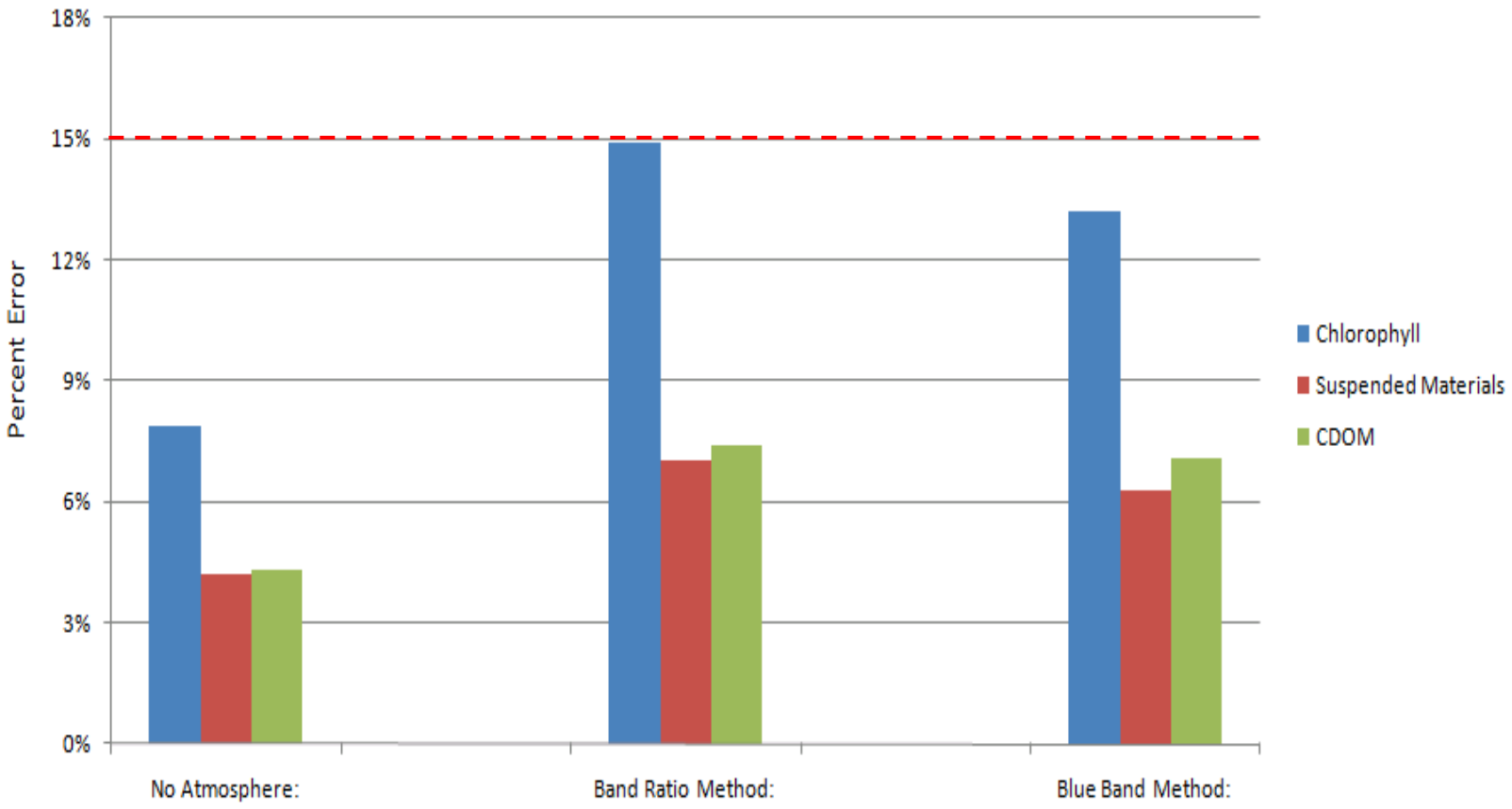
- Use same 2000 water pixels described in first experiment.
  - Propagate to the top of 23 kilometer visibility modeled atmosphere.
  - Signals are then spectrally sampled to OLI, half margin noise is added, and quantization effects included.
  - Average darkest 5% of signals in band 5 to determine atmosphere (22.97km).
  - Chosen atmosphere removed spectrally from all modeled pixels.



OLI Atmospheric Compensation

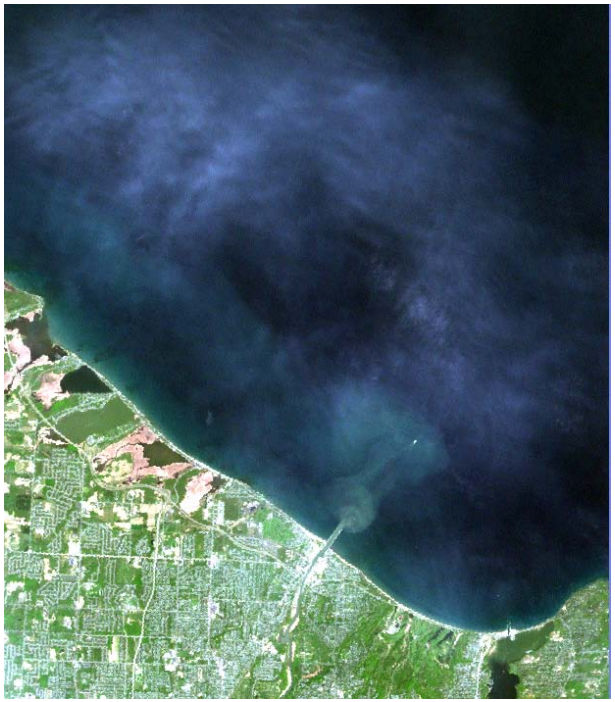
Experiment 1: Simulated Data

- 15% is our target error when atmospheric effects are included.
- A typical scene contains hundreds of thousands of water pixels!



OLI Atmospheric Compensation
Experiment 2: 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.

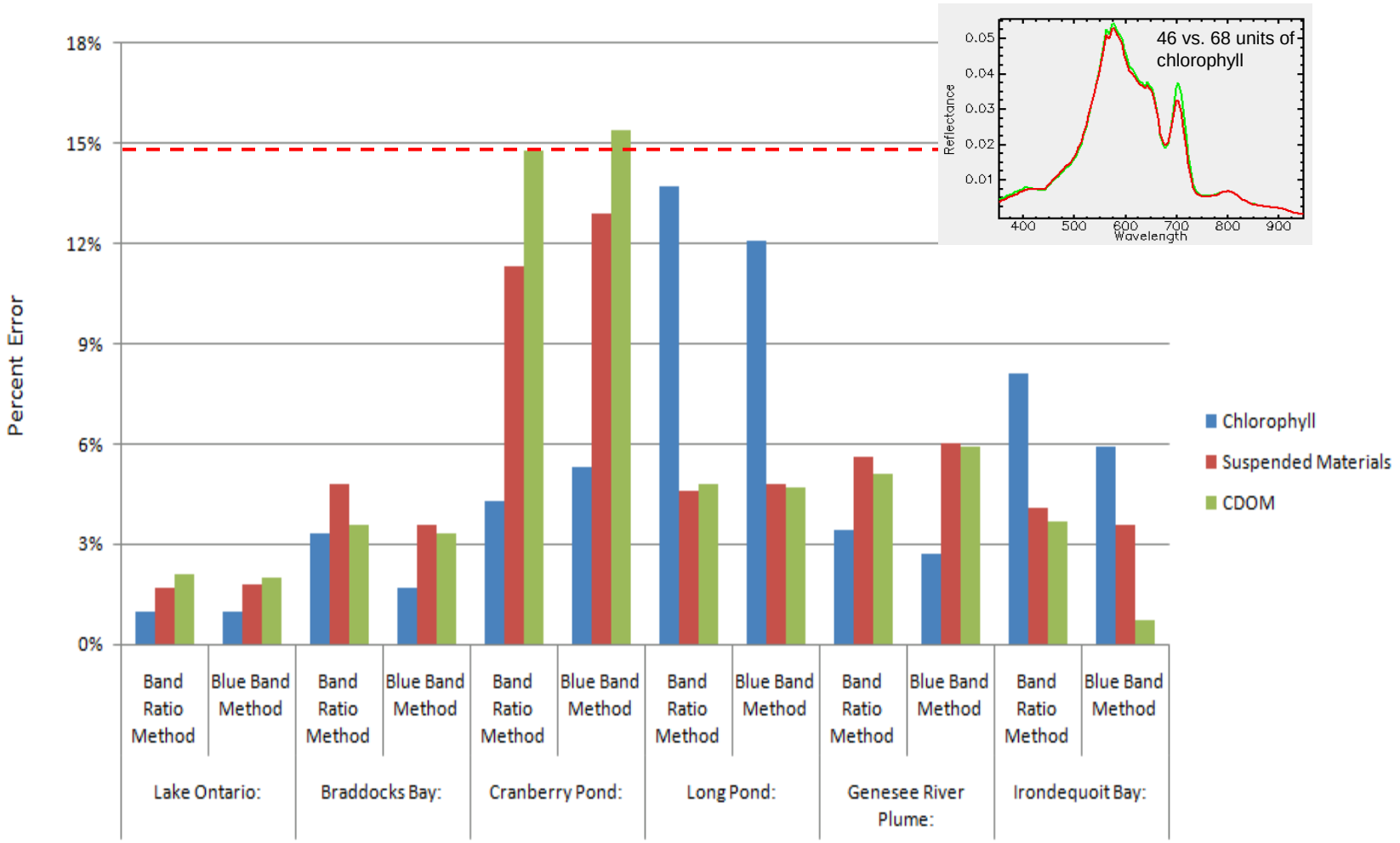


Landsat 5: May 16th, 1999

Simulated Image

OLI Atmospheric Compensation

Experiment 2: Simulated Scene



Ongoing

- Develop tool to spatially sharpen TIRS data With OLI
  - Done
- Use TIRS thermal data to calibrate flow field of hydrodynamic model.
  - Alge outpus surface temperature
  - Proof of concept complete
- Use Landsat reflective data to calibrate color of hydrodynamic model.
  - ALGE outputs sediment profiles.
  - Initial tool under test
- Continue to investigate OLI atmospheric compensation.
  - 3 band method, perhaps.

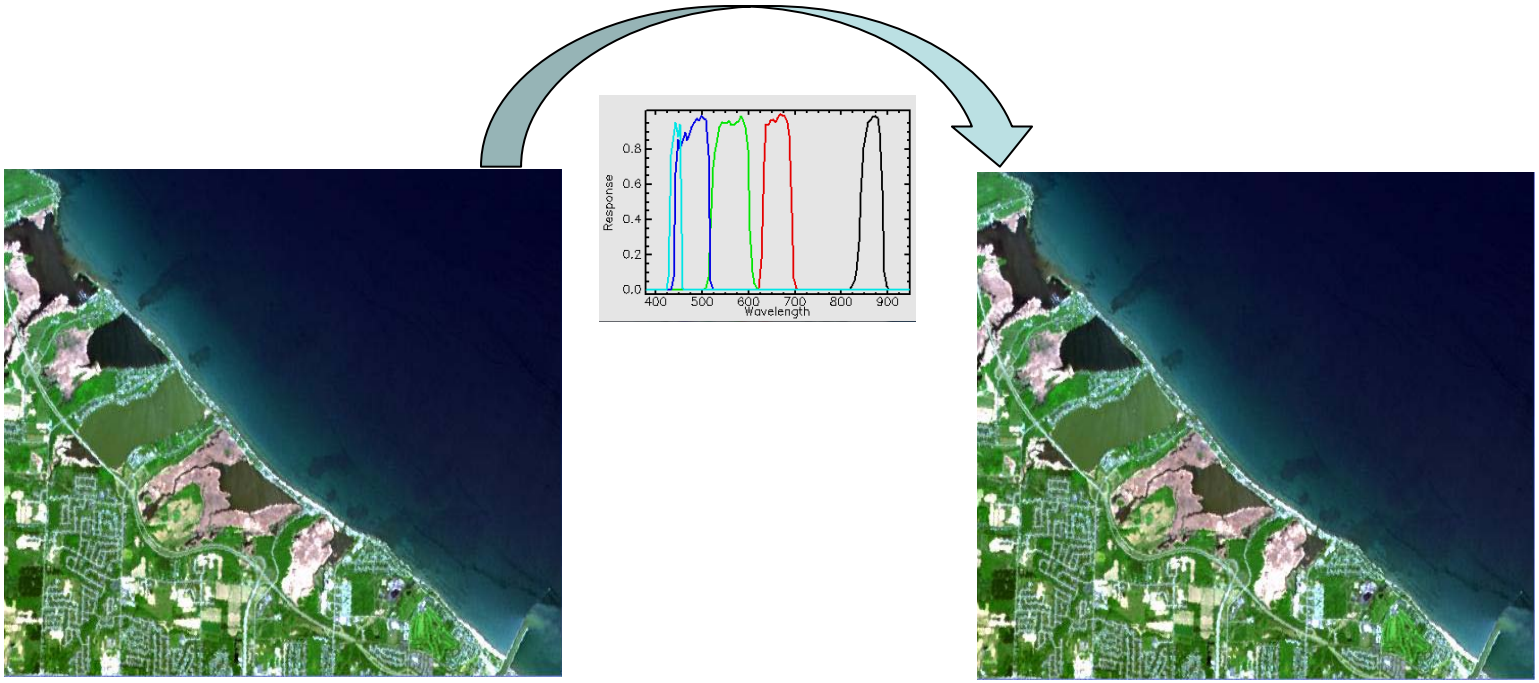
R·I·T

Back up

OLI Atmospheric Compensation

Experiment 3: Real Data

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



AVIRIS: May 20th, 1999

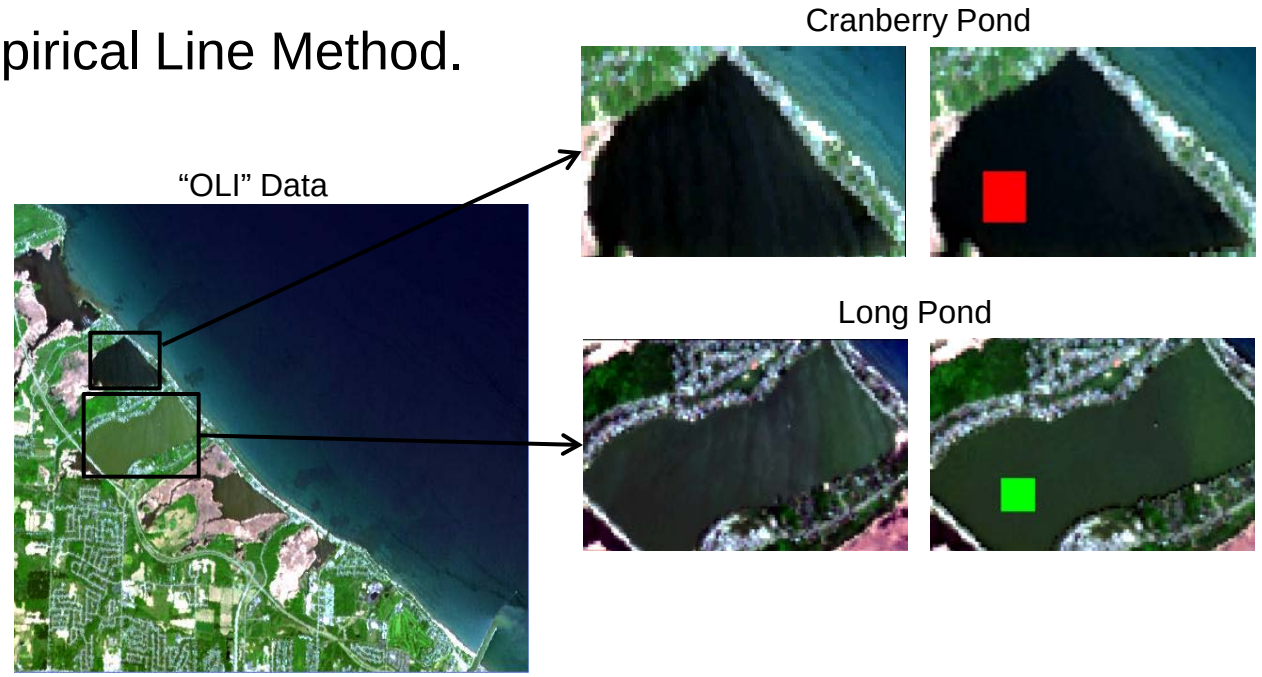
Simulated OLI Data: May 20th, 1999

OLI Atmospheric Compensation

Experiment 3: 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.

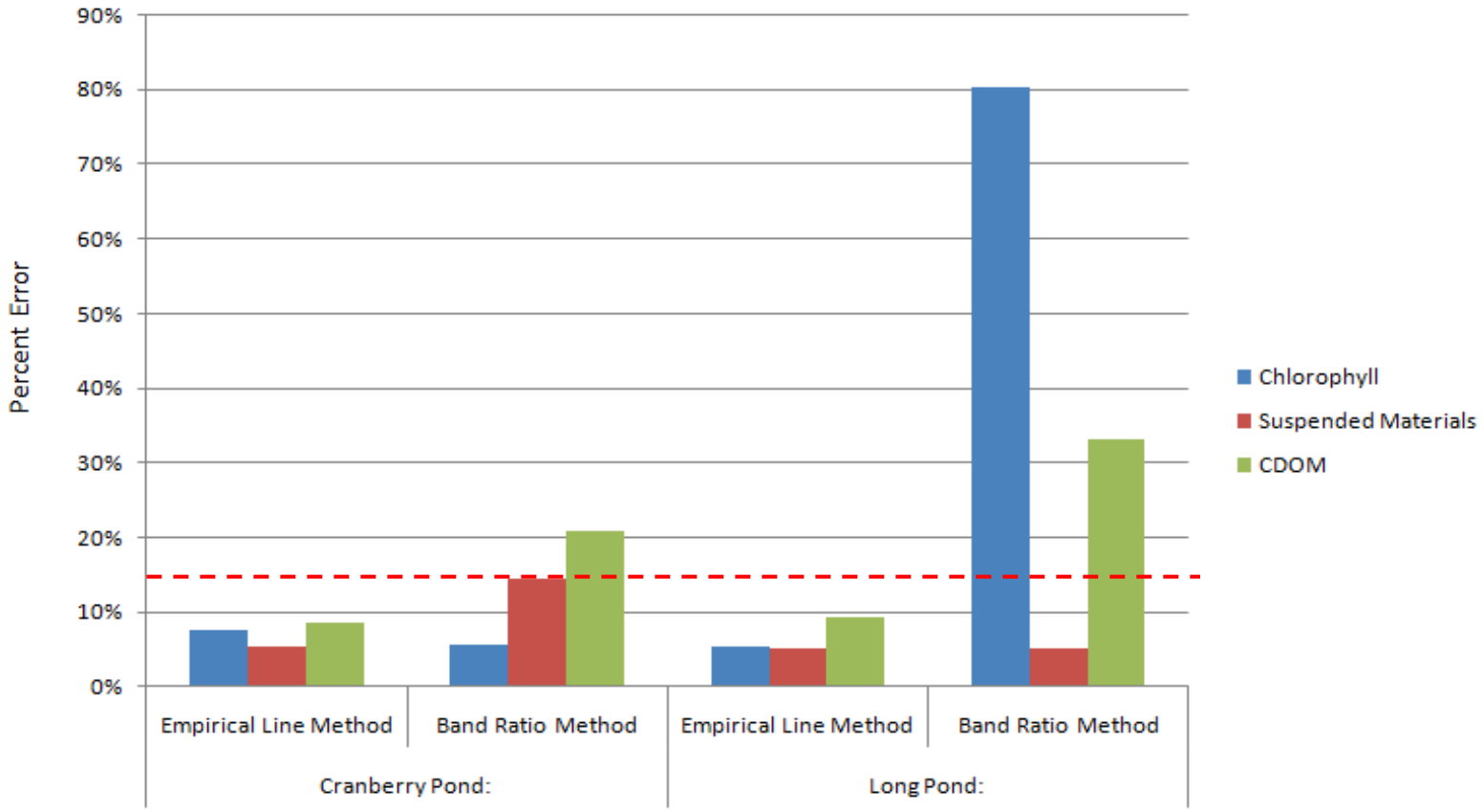
- Empirical Line Method.



OLI Atmospheric Compensation

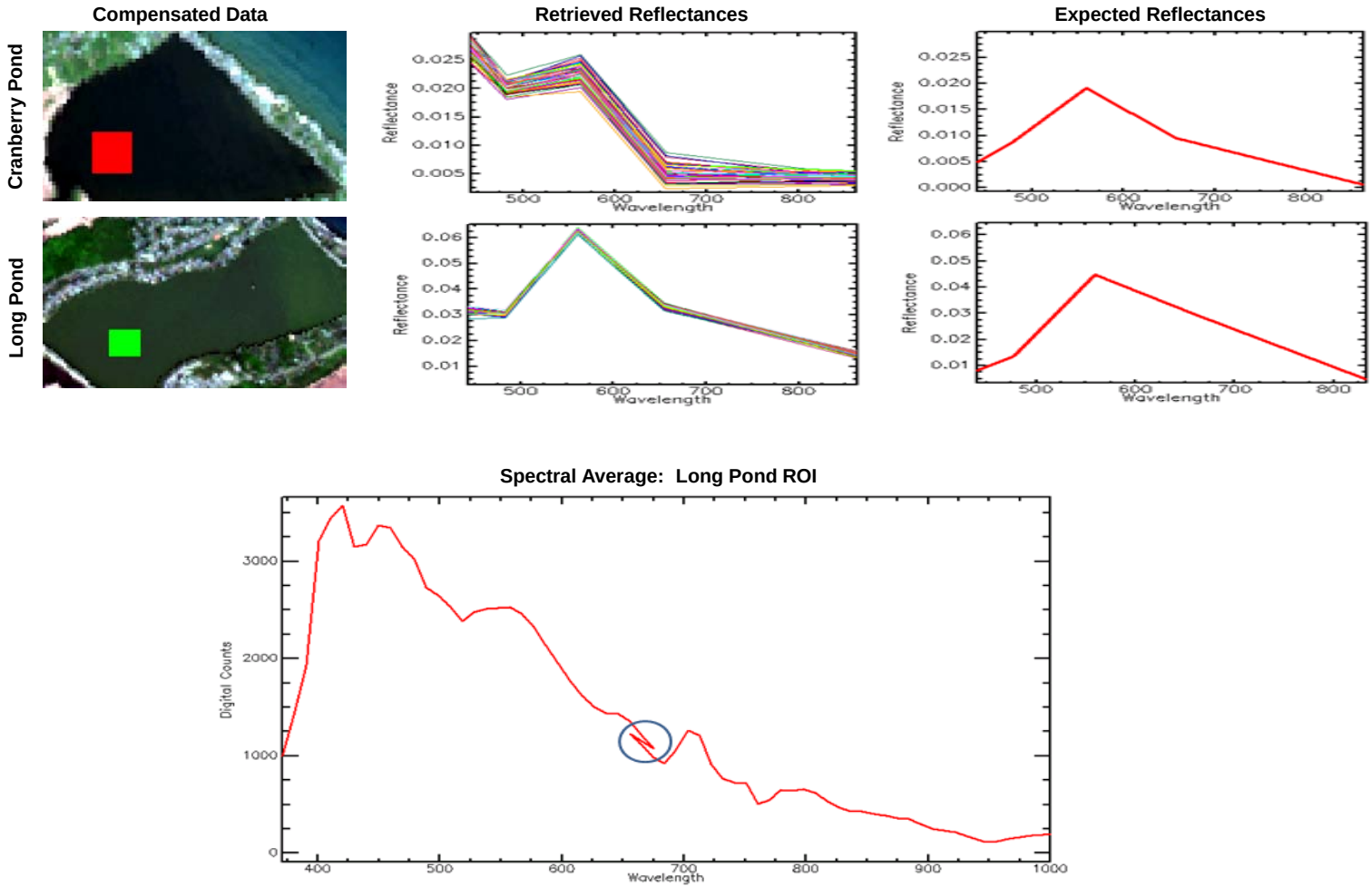
Experiment 3: Real Data

- Initial errors are discouraging.
  - For Cranberry pond, CDOM retrieval is over 20%.
  - For Long Pond, retrieval errors for 2 constituents are greater than 30%.



OLI Atmospheric Compensation

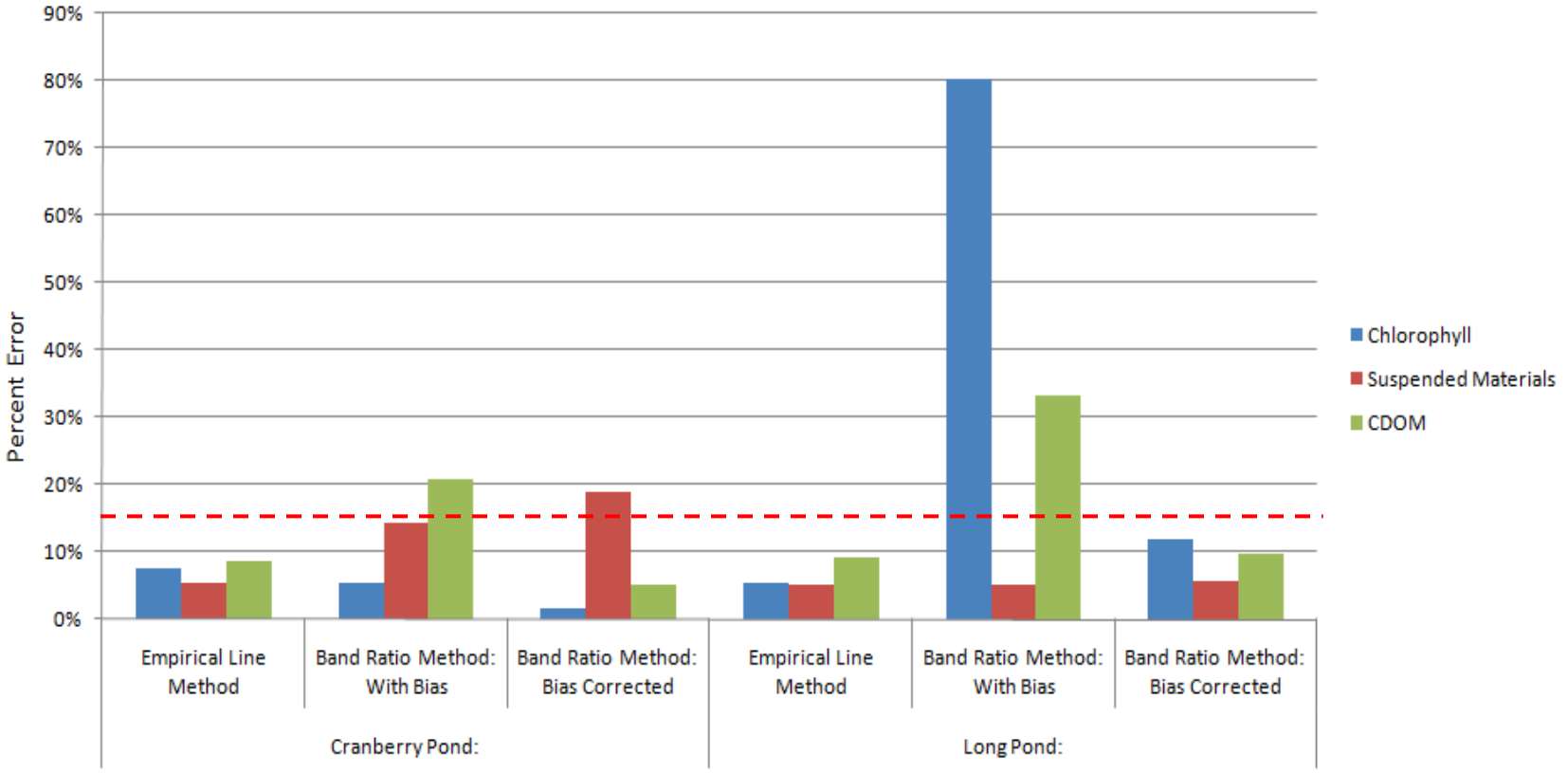
Experiment 3: Real Data



OLI Atmospheric Compensation

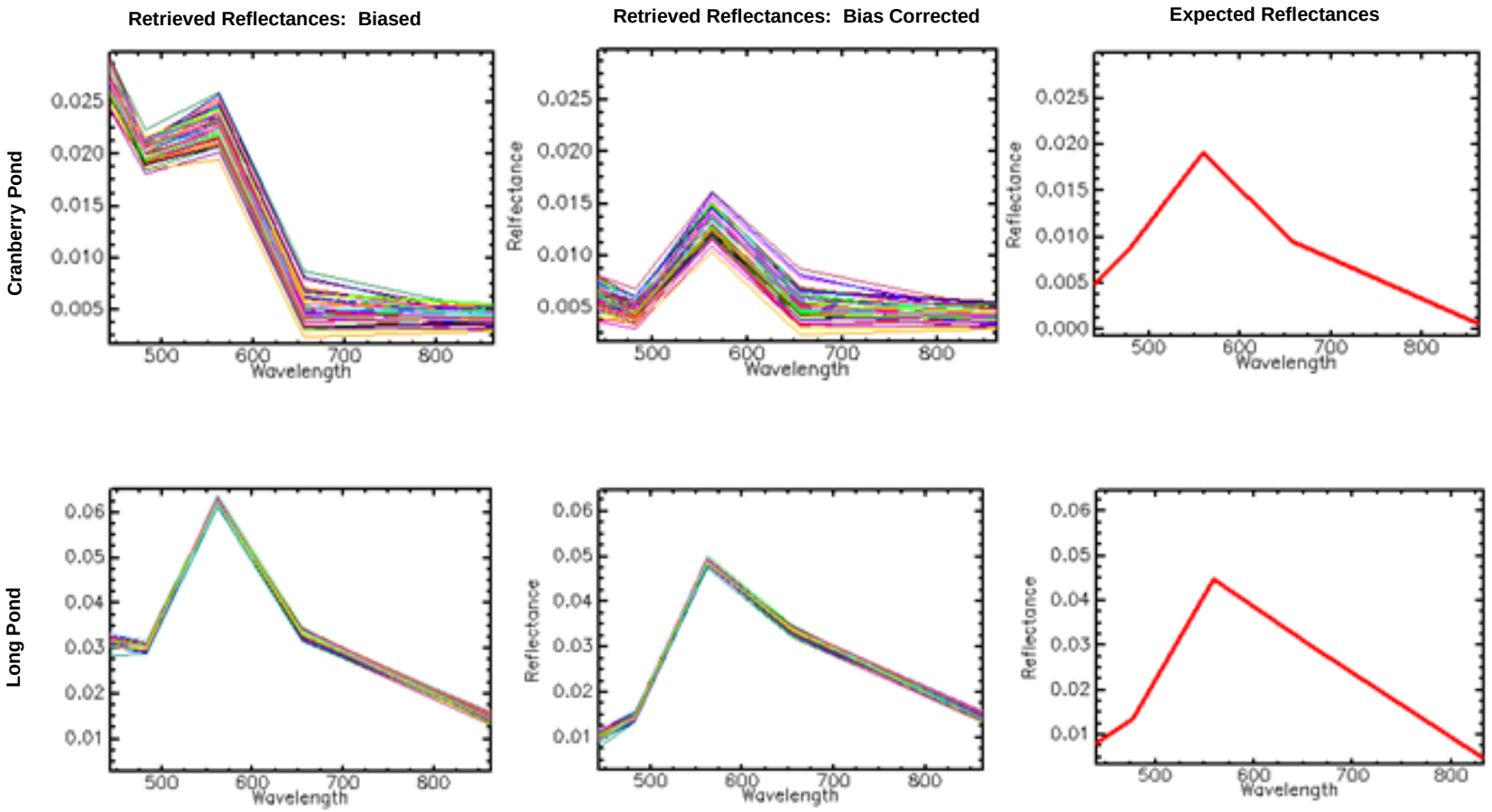
Experiment 3: Real Data

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



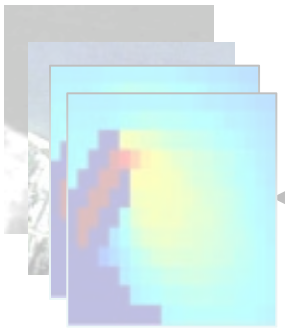
OLI Atmospheric Compensation

Experiment 3: Real Data

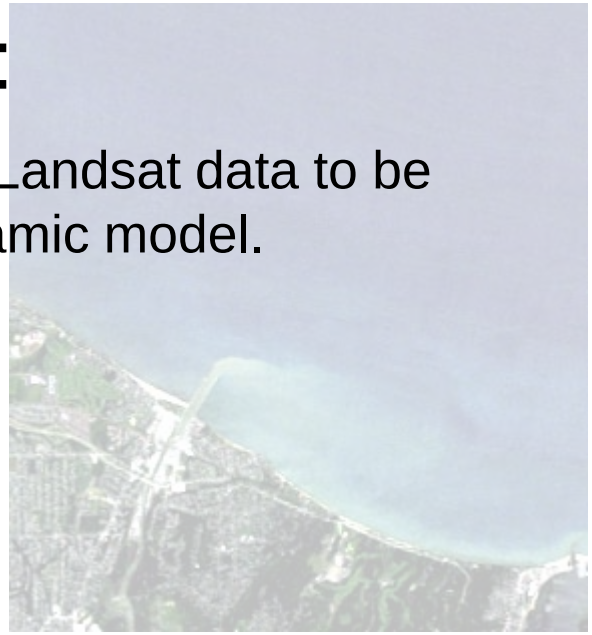


Objective 3:

Develop techniques that will enable Landsat data to be used to calibrate a hydrodynamic model.



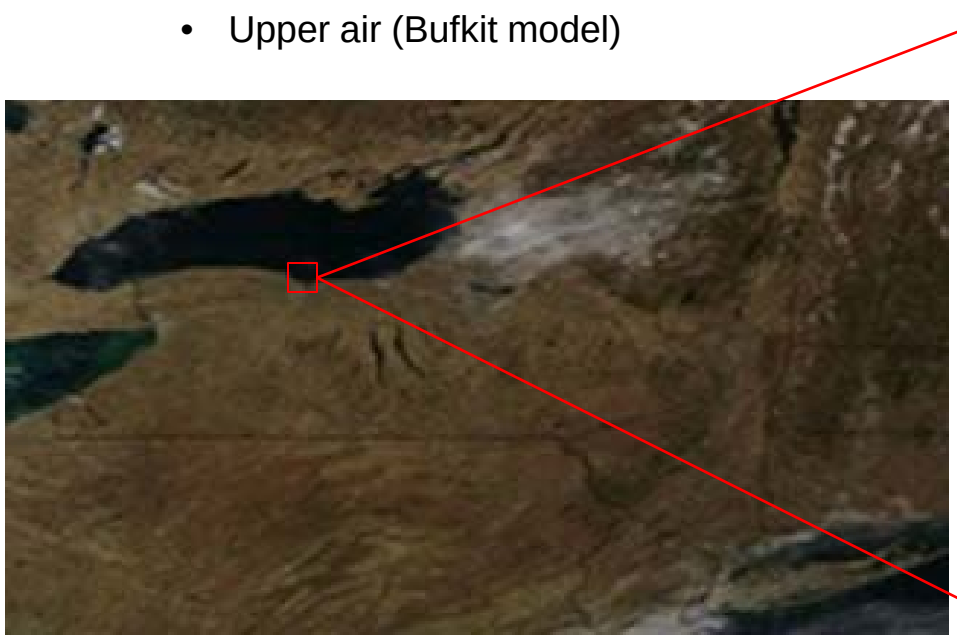
ALGE Hydrodynamic Model



Landsat 5: July 13th, 2009

Hydrodynamic Modeling: Inputs

- To model the Genesee River plume, ALGE requires information from the scene of interest…
  - Static: Land/Water, latitude/longitude, bathymetry, voxel size, DOY, etc.
  - Dynamic: Environmental Measurements (hourly)
    - River data (flow rate, initial temperature)
    - Surface data (Pier / Rochester airport)
    - Upper air (Bufkit model)

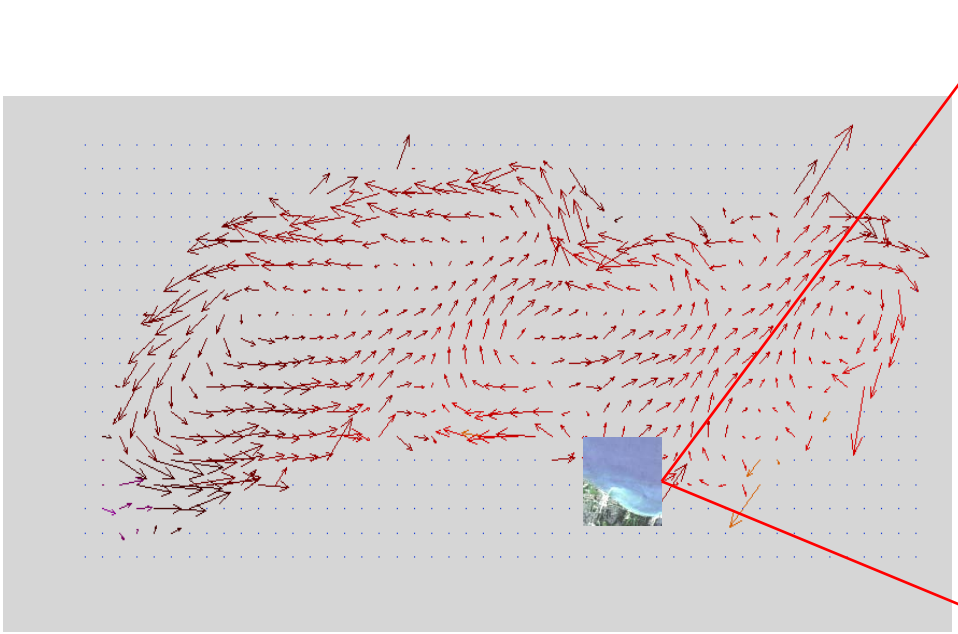


Northeastern United States

Landsat 5: July 13th, 2009

Hydrodynamic Modeling: Inputs

- To model the Genesee River plume, ALGE requires information from the scene of interest…
  - Nudging Vectors (hourly).
    - Whole lake simulation provides nudging vectors for small scale simulation.

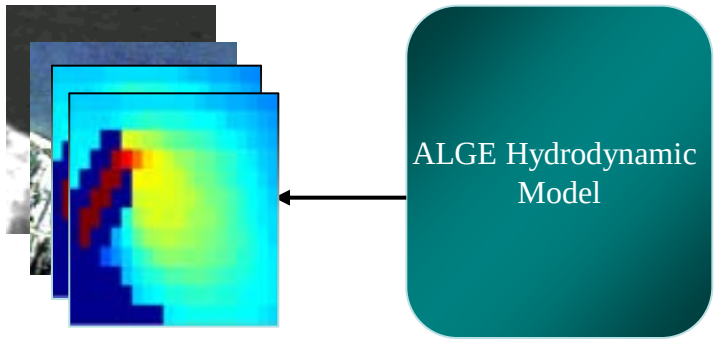


Lake Ontario simulation: Surface Currents

Landsat 5: July 13th, 2009

Hydrodynamic Modeling: Outputs

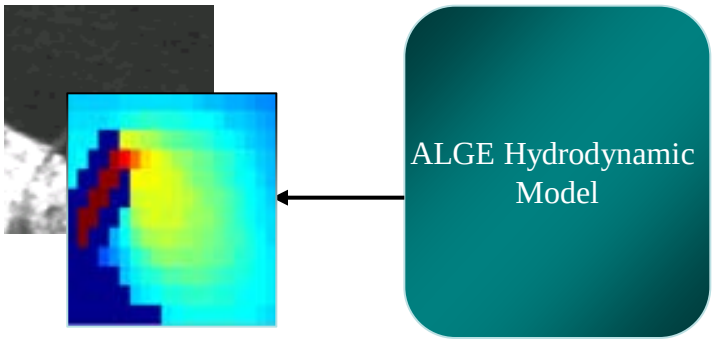
- To model the Genesee River plume, ALGE requires information from the scene of interest…
  - Land/Water, latitude/longitude, bathymetry, voxel size, DOY, etc.
  - Environmental Measurements (hourly)
    - River data (flow rate, initial temperature)
    - Surface data (Pier / Rochester airport)
    - Upper air (Bufkit model)
  - Nudging Vectors (hourly)



Landsat 5: July 13th, 2009

Hydrodynamic Modeling: Outputs

- To model the Genesee River plume, ALGE requires information from the scene of interest…
  - Land/Water, latitude/longitude, bathymetry, voxel size, DOY, etc.
  - Environmental Measurements (hourly)
    - River data (flow rate, initial temperature)
    - Surface data (Pier / Rochester airport)
    - Upper air (Bufkit model)
  - Nudging Vectors (hourly)



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Hydrodynamic Modeling: Steady State

- Run ALGE until model reaches a steady state.
- Satellite data will not match model data…
  - Inaccurate inputs.
  - Model error.

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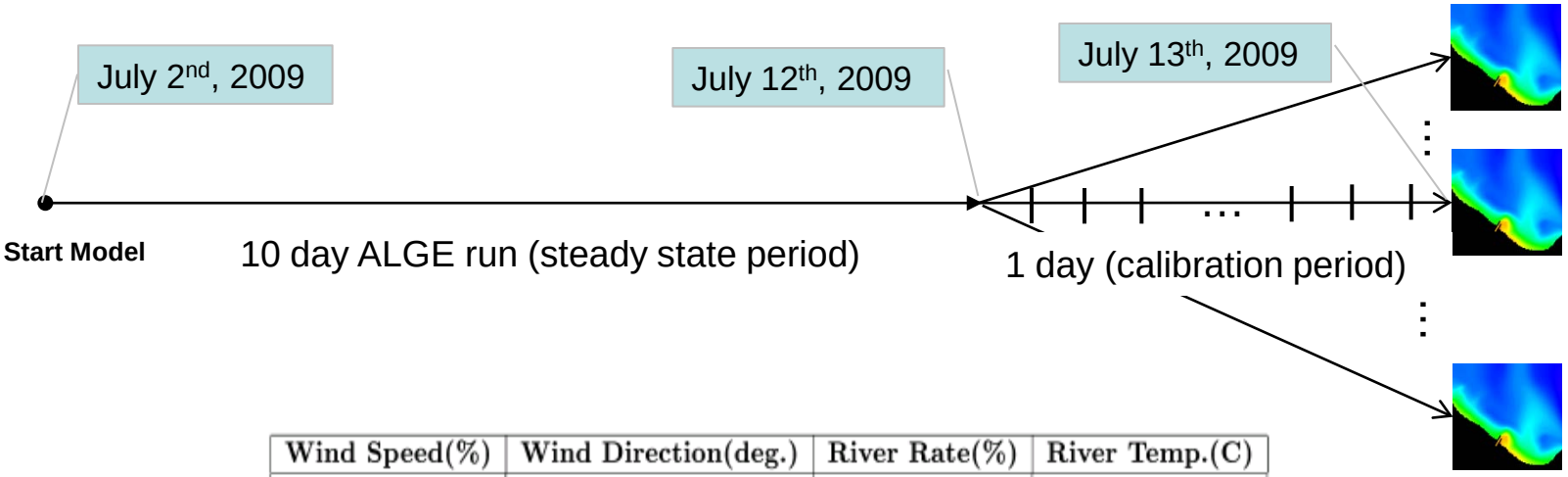
Hydrodynamic Modeling: Calibration

- 24 hours prior to obtaining satellite data, the model is stopped and a calibration LUT created
  - Vary environmental parameters (about their nominal values) that will affect a plume's shape.



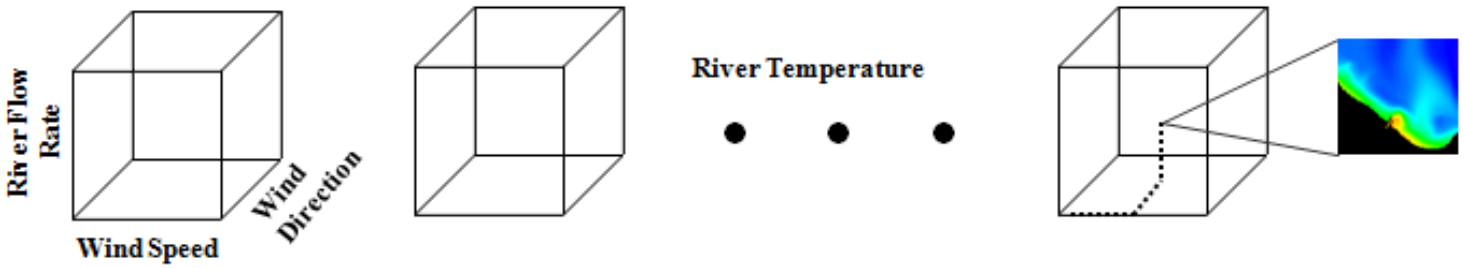
Wind Speed(%)	Wind Direction(deg.)	River Rate(%)	River Temp.(C)
20	-50	50	17
60	-30	70	19
100	-10	90	21
140	10	110	-
180	30	130	-
-	50	150	-

Hydrodynamic Modeling: Calibration

- Develop a calibration LUT whose domain is made up of parameter variations and whose range is made up of ALGE runs.

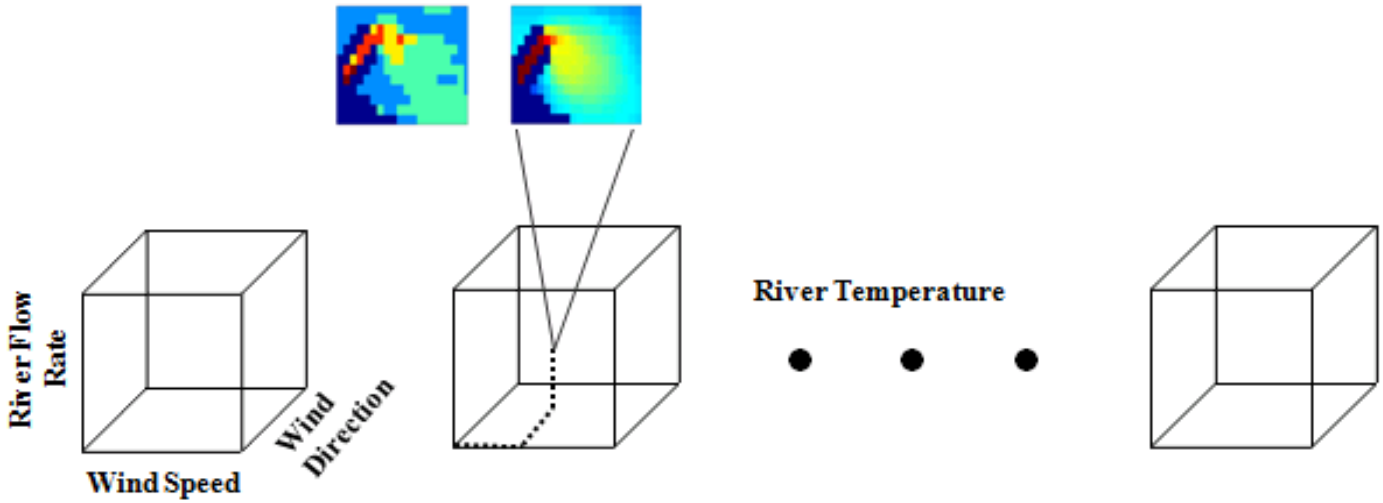
Wind Speed(%)	Wind Direction(deg.)	River Rate(%)	River Temp.(C)
20	-50	50	17
60	-30	70	19
100	-10	90	21
140	10	110	-
180	30	130	-
-	50	150	-

ALGE 4 Parameter LUT

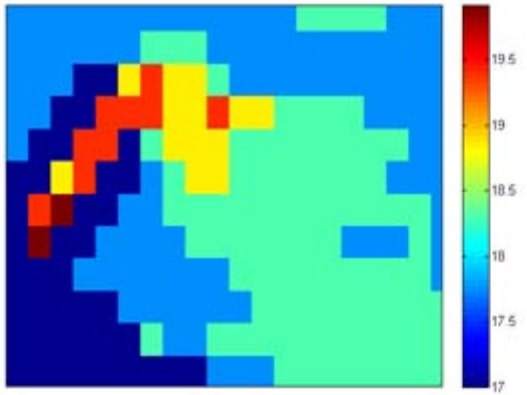


Hydrodynamic Modeling: Calibration

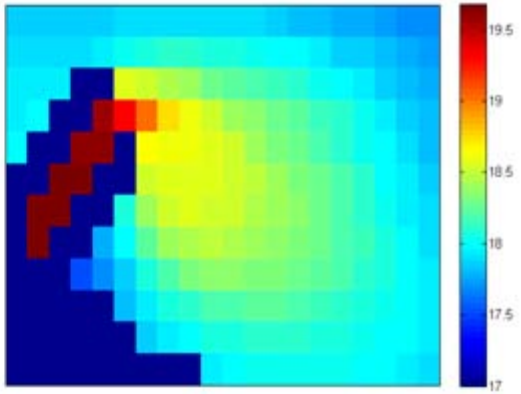
- Nonlinear, least-squares optimizer is used to search the LUT.
  - Landsat data must be registered and atmospherically compensated.
  - The point in space that provides the best match contains the model that best describes the state of the environment.



Hydrodynamic Modeling: Results



Landsat 5: July 13th, 2009



Optimal Model

	Expected	Optimized
Wind Speed	**100%**	**88.9%**
Wind Direction	**0.0°**	**6.1°**
Flow speed	**100%**	**61.8%**
River Temperature	**19°C**	**19.5°C**

– RMS-error of 0.28 Kelvin.

Conclusions

- OLI exhibits enormous potential to be used for monitoring case 2 waters.
- The ability of the OLI atmospheric compensation algorithms were successfully demonstrated on simulated data, a simulated image, and a real image.
  - The sensor must be well calibrated.
  - Adequate SNR must be achieved.

- Techniques were developed which enable Landsat data to be used to calibrate a hydrodynamic model.

Acknowledgements

- Dr. Schott
- My Committee
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