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

Water IOPs
- Absorb
- Scatter

Solar location

Sensor location

Wind Speed

x 2000

CHL
SM
CDOM

CHL
SM
CDOM

x 2000

Wind Speed
Modeling the Constituent Retrieval Process: At the Sensor

Resample | Add Noise | Quantize

AVIRIS

ETM+

OLI
Modeling the Constituent Retrieval Process: CRA

<table>
<thead>
<tr>
<th>CHL (µg/L)</th>
<th>SM (mg/L)</th>
<th>CDOM</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>0.5</td>
<td>0.5</td>
<td>0.5</td>
</tr>
<tr>
<td>1</td>
<td>1</td>
<td>0.75</td>
</tr>
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<td>24</td>
<td>14</td>
<td>10</td>
</tr>
<tr>
<td>46</td>
<td>20</td>
<td>12</td>
</tr>
<tr>
<td>68</td>
<td>24</td>
<td>14</td>
</tr>
</tbody>
</table>

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
SNR Margins
Results
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

\[ \rho_{t}(\lambda) = \rho_{r}(\lambda) + \rho_{a}(\lambda) + \rho_{ar}(\lambda) + T(\lambda)\rho_{w}(\lambda) \]

- Image
- Atmosphere
- Water
OLI Approach
Case 2 Waters

\[ \rho_i(\lambda) = \rho_r(\lambda) + \rho_a(\lambda) + \rho_{ar}(\lambda) + T(\lambda) \rho_w(\lambda) \]

- Image
- Atmosphere
- Dark Water
Incorporate dark water component into an atmospheric LUT.

\[ \rho_t(\lambda) = \rho_r(\lambda) + \rho_a(\lambda) + \rho_{ar}(\lambda) + T(\lambda)\rho_w(\lambda) \]

- Atmosphere
- Dark Water

- Mid-latitude Summer profile.
- Standard gases
- Rural aerosols
  - Varied visibility between 5 and 60 kilometers.
OLI Approach
Case 2 Waters

- Incorporate dark water constant into an atmospheric LUT.

\[ \rho_t(\lambda) = \rho_r(\lambda) + \rho_a(\lambda) + \rho_{ar}(\lambda) + T(\lambda)\rho_w(\lambda) \]

Atmosphere  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.
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.
OLI Atmospheric Compensation
Experiment 2: Simulated Scene

Percent Error

Lake Ontario | Braddock Bay | Cranberry Pond | Long Pond | Genesee River Plume | Irondequoit Bay

- Band Ratio Method
- Blue Band Method

- Chlorophyll
- Suspended Materials
- CDOM

46 vs. 68 units of chlorophyll
Ongoing

• Develop tool to spatially sharpen TIRS data With OLI
  – Done

• Use TIRS thermal data to calibrate flow field of hydrodynamic model.
  – ALGE output 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.
Back up
AVIRIS data (May 20th, 1999) spectrally sampled to OLI’s sensor response function.
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.
• 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

Cranberry Pond

Long Pond

Compensated Data

Retrieved Reflectances

Expected Reflectances

Spectral Average: Long Pond ROI
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

Retrieved Reflectances: Biased
Retrieved Reflectances: Bias Corrected
Expected Reflectances

Cranberry Pond

Long Pond
Objective 3:

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

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Landsat 5: July 13th, 2009
Hydrodynamic Modeling: Steady State

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

Start Model

July 2\textsuperscript{nd}, 2009

Stop Model

Landsat 5: July 13\textsuperscript{th}, 2009

July 13\textsuperscript{th}, 2009
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.

<table>
<thead>
<tr>
<th>Wind Speed(%)</th>
<th>Wind Direction(deg.)</th>
<th>River Rate(%)</th>
<th>River Temp.(C)</th>
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<tbody>
<tr>
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<td>50</td>
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<tr>
<td>-</td>
<td>50</td>
<td>150</td>
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</tbody>
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Hydrodynamic Modeling: Calibration

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

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</tr>
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</table>

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

<table>
<thead>
<tr>
<th></th>
<th>Expected</th>
<th>Optimized</th>
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</thead>
<tbody>
<tr>
<td>Wind Speed</td>
<td>100%</td>
<td>88.9%</td>
</tr>
<tr>
<td>Wind Direction</td>
<td>0.0°</td>
<td>6.1°</td>
</tr>
<tr>
<td>Flow speed</td>
<td>100%</td>
<td>61.8%</td>
</tr>
<tr>
<td>River Temperature</td>
<td>19°C</td>
<td>19.5°C</td>
</tr>
</tbody>
</table>

- 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.
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• Trisha