Visible Derivative Spectroscopy of Multispectral and Hyperspectral Images: A New Approach to Algal and Cyanobacterial Differentiation

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Ortiz et al., (HyspIRI 2017; jortiz@kent.edu)
Water Quality Monitoring by Remote Sensing? The problem...

- Remote sensing of lake color gives information on plant biomass, but...
- Lake water is a complex “organic soup”
  - Various types of algae and cyanobacteria
  - Colored dissolved organic matter
  - Suspended sediment
- Collect Hyperspectral swaths in Western basin of Lake Erie using NASA Glenn HS12
- Apply KSU Spectral decomposition method
  - Varimax-rotated, Principal Component Analysis
  - Eigenvector-eigenvalue decomposition
  - Soft unsupervised classification method

Ortiz et al., (HyspIRI 2017; jortiz@kent.edu)
We apply 4 different variations on the Empirical Line Method (ELM) method to reflectance:

**ELM0** method uses two instruments (HSI2 and ASD HH2) along with mirrors. Ratio HSI2 water pixels to mirror pixels to remove the atm. Then rescale using ASD HH2 data.

**ELM2** method uses two instruments (HSI2 and ASD HH2) surface measurements of reflectance, diffuse to global ratio, and radiative transfer theory to get slope and intercept for water surface and mirror surface pair to go from radiance to reflectance.

The **ELM1** method is **ELM2** with the intercept term removed to test sensitivity of the VPCA to path radiance impact

The **MTRI** (Michigan Technological Research Institute) correction method uses three instruments (HSI2, upward looking ASD HH2, and downward looking HH2) The HSI2 and upward looking ASDHH2 provide at-sensor reflectance and then the downward looking HH2 uses a blacktop reference spectra to reshape the at-sensor reflectance to at-surface reflectance.

Because the Varimax-rotated, Principal Component Analysis (VPCA) method is based on spectral shapes, it should be relatively insensitive to the quality of the atmospheric correction
ELM method
Reflectance and VPCA

• Apply 4 variations of the Empirical Line Method for Atm correction

• How sensitive is the VPCA method to differences in atmospheric correction?

Figure 7
062116 15_MBSP (10nm, SPEARo, smooth9, various reflectance transform, georef) VPCA Pattern A

A) Uncorrected RGB, B) NOAA CI, C) MTRI 6VPCA 1: 56%, D) ELM0 5VPCA 1: 67.1%, E) ELM1 4VPCA -1: 36.9%, F) ELM2 4VPCA -1: 36.9%

Figure 8

G) Pattern A Loadings

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Figure 9

062116 HSI2 Swath 15_MBSP: Pattern B

A) MTRI 6VPCA 2: 16.4%
B) ELM0 5VPCA 2: 15.5%
C) ELM1 4VPCA 3: 26.3%
D) ELM2 4VPCA 3: 26.3%

E) Pattern B Loadings

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Figure 10
062116 HSI2 Swath 15_MBSP: Pattern C
A) MTRI 6VPCA -3: 10%
B) ELM0 5VPCA 3: 7.2%
C) ELM1 4VPCA 2: 26.5%
D) ELM2 4VPCA 2: 26.5%

E) Pattern C Loadings

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Figure 11
062116 HSI2 Swath 15_MBSP: Pattern D
A) MTRI 6VPCA -4: 7.8%  B) ELM0 5VPCA 4: 6.4%  
C) ELM1 4VPCA  D) ELM2 4VPCA

E) Pattern D Loadings

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Figure 13
062116 HSI2 Swath 15_MBSP: Pattern F

A) MTRI 6VPCA 6: 1.3%
B) ELM0 5VPCA 5: 1%
C) ELM1 4VPCA
D) ELM2 4VPCA

E) Pattern F Loadings

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Figure 12
o62116 HSI2 Swath 15_MBSP: Pattern E
A) MTRI 6VPCA 5: 4.4%
B) ELM0 5VPCA
C) ELM1 4VPCA -4: 4.2%
D) ELM2 4VPCA -4: 4.2%

NO Component with Pattern E

E) Pattern E Loadings

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Dealing with Mixed Pixels

Q: How does the amount of information we can extract from Landsat 8 compare with Hyperspectral data sets?

A: Test w/ KSU Spectral decomposition method

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Figure 14 Z-score Loadings

A) Illite, diatoms & phycoerythrin (R=0.94)

B) Haematite, green algae, - carotene & phycocyanin (R=0.90)

C) Goethite & haematite (R=0.84)

D) Haematite & phycocyanin (R=0.95)

E) Residual aerosol errors (No valid pigment or mineral fit)

F) Cyanophyte accessory pigments & Chl b (R=0.88)

Ortiz et al., (HyspIRI 2017; jortiz@kent.edu)
<table>
<thead>
<tr>
<th>Spectral Placement and Resolution</th>
<th>Spatial Resolution</th>
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<tbody>
<tr>
<td><strong>Landsat 8: Four bands:</strong> 440, 480, 560, 655 @ 20, 60, 60 and 30 nm resolution</td>
<td>30 m (simulated)</td>
</tr>
<tr>
<td><strong>NASA HSI2: 31 Bands 400-700 nm @10nm resolution</strong></td>
<td>30 m (simulated)</td>
</tr>
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Ortiz et al., (HyspIRI 2017; jortiz@kent.edu)
062116 HSI2 swath 15: SPEAR0; MTRicorr; 10nm; 3m – smooth9 pixels: 5VPCA

A) RGB
B) MTRI 6VPCA 1: 55.8%
C) MTRI 6VPCA 2: 24.9%
D) MTRI 6VPCA -3: 11.9%
E) MTRI 6VPCA 4: 3.6%
F) MTRI 6VPCA 5: 1.8%
### KSU Spectral Unmixing Experimental Outcome

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<td></td>
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Ortiz et al., (HyspIRI 2017; jortiz@kent.edu)
Composition:
Illite, diatoms and phycoerythrin (R=0.94)

Ortiz et al., (HyspIRI 2017; jortiz@kent.edu)
Composition:
Haematite, Green algae, -α carotene and phycocyanin (R=0.90)

Ortiz et al., (HyspIRI 2017; jortiz@kent.edu)
Composition: 
- Goethite & Haematite (R=0.84)

And
Hematite & phycocyanin (R=0.95)
Actual L8 Image Decomposition

061916 L8 (surface reflectance product), swath15 subset: VPCA decomposition

Ortiz et al., (HyspIRI 2017; jortiz@kent.edu)
Kent State Univ. Spectral Unmixing: 082317 S3A L2 Lake Erie VPCA Scores (J. Ortiz and D. Avouris)

Ortiz et al., (HyspIRI 2017; jortiz@kent.edu)

Sentinel3A BOA

VPCA 1: 33.6%
+ phycocyanin, -myxoxanthophyll

VPCA 2: 32.4%
+ illite, + accessory pigment

VPCA 3: 19.6%
+ cyanobacteria

VPCA 4: 11%
+ phycocyanin, -fucoxanthin
Sentinel3A Comparison of VPCA to NOAA CI

Figure 1. Cyanobacterial Index from modified Copernicus Sentinel 3 data collc missing data. The estimated threshold for cyanobacteria detection is 20,000 cell

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Conclusions

1. VPCA ties optical assemblages to minerals, phytoplankton and cyanophyta phyla
2. KSU VPCA decomposition method can be applied successfully to Landsat, MODIS, HICO, NASA Glenn HSI\textsubscript{2}
3. VPCA is well suited for application to Sentinel-3, HyspIRI, PACE: Makes use of \textit{all} information present in hyperspectral data
4. The NASA HSI\textsubscript{2} (31 visible bands @ 10nm resolution) collects about twice as many components from a simulated L8 scene (with 4 bands in the visible)
5. Spectral decomposition of an actual L8 image collected within two days of the NASA HSI\textsubscript{2} swath is consistent with the simulated results
6. Increasing spectral resolution doubles the information that can be partitioned in a scene in terms of the number of extractable components
7. Increasing spatial resolution provides more detailed images, but does not help to extract additional spectral components using this method

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Recent Publications

See Water quality webpage at: http://www.personal.kent.edu/~jortiz/home/wqr.html


GS Bullerjahn, et al., Global solutions to regional problems: Collecting global expertise to address the problem of harmful cyanobacterial blooms. A Lake Erie case study, Harmful Algae 54, 223-238, 2016


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