Regional-scale Measurement of Colored Dissolved Organic Matter in Freshwater Lakes by Satellite Imagery Leif G. Olmanson, Patrick L. Brezonik, Jacques C. Finlay & Marvin E. Bauer **UNIVERSITY OF MINNESOTA**





Colored dissolved organic matter (CDOM) is the most abundant DOM fraction in many natural waters, especially in forested watersheds with wetlands. CDOM has major effects on physical, chemical, and biological processes. It regulates heat transfer to water and controls lake temperature and stratification. By reducing light, it suppresses primary productivity. CDOM mediates transfer of contaminants into food webs. Although not directly harmful to human health, CDOM affects production of safe drinking water negatively by increasing treatment chemical use, reacting with chlorine to form harmful disinfection byproducts, and fouling membranes.

Introduction

Few water management agencies include CDOM in their monitoring programs, and the paucity of CDOM data limits our understanding its dynamics in surface waters. CDOM data also are needed for global-scale models of carbon cycling. Satellite imagery has the potential to fill this void and improve our understanding of CDOM distribution and the factors that affect its levels in surface waters. We are measuring CDOM in optically complex waters in Minnesota, Wisconsin, and Michigan (USA) by satellite remote sensing. To support these efforts we have been collecting data on related water quality variables and *in situ* optical reflectance measurements (Fig. 1). Sites are selected to obtain wide concentration ranges of CDOM, chlorophyll, and suspended sediment, the primary factors affecting reflectance. Our goal is to develop robust CDOM algorithms applicable to optically complex waters across large geographic regions.

Here we present results comparing Landsat 7 Enhanced Thematic Mapper Plus (ETM+) to Landsat 8 Operational Land Imager (OLI) data for regional measurements of CDOM and describe a method for image normalization to surface reflectance using radiometric rectification that was used on a series of overlapping Landsat 8 imagery. Data extracted from the normalized images were then used to develop a common CDOM model that was used to create the first Minnesota state-wide CDOM map even when calibration data were sparse for some of the images.

Comparison of Algorithms for Landsat 7 & 8

We used clear Landsat 7 and 8 images for northern Minnesota from September 9 and 16, 2013 to compare the capabilities of the respective ETM+ and OLI sensors to retrieve CDOM data. We examined various band and band-ratio models and found that the two-variable model using the green/red and red/NIR bands worked well for both Landsat 8 OLI (R² = 0.76, Fig. 2) and Landsat 7 ETM+ (R² = 0.74, Fig. 3). and represented the lakes with high CDOM and high mineral suspended solids well. The common green/red model¹ had a poor fit for both sensors (R² = 0.24, 0.25), and five sites with high mineral suspended solids (MSS) were clear outliers. Exclusion of these sites yielded a subset of 20 less optically complex lakes for both images. Strong models were found for this subset for many equation forms, including the green/red model ($R^2 = 0.79$ for ETM+ and $R^2 = 0.81$ for OLI). The less optically complex subset may explain why the green/red model has worked well in other areas.²





Fig. 1. Representative reflectance spectra showing some of the optical complexity (dominant optical properties indicated) of water bodies in Minnesota.



Minnesota statewide CDOM measurements using Landsat 8

Fig. 2. Distribution of lake CDOM levels in northern MN near Ely based on part of the September 16, 2013 Landsat 8 OLI image.

Fig. 3. Distribution of lake CDOM levels in northern MN near Ely based on part of the September 9, 2013 Landsat 7 ETM+ image.

Five clear Landsat 8 images were found for 2015 that cover most of the state. Calibration data were fairly sparse, however, and not well distributed for three of the images. Analysis of intra-seasonal variability of 2015 CDOM levels in Minnesota lakes (Brezonik et al., unpublished ms) showed that one month (± 4 weeks) is an acceptable window for CDOM calibration data in most Minnesota water bodies. Because the sparseness of data limited mapping of CDOM using traditional empirical methods (which need calibration data for each image), we used a longstanding image normalization technique, radiometric rectification (RR) to analyze the five images. RR corrects for differences between images due to atmospheric moisture, haze, sun angle, and other factors that affect radiance values of spectral bands by using pseudo-invariant targets (features with stable reflectance over time). This normalizes images to a consistent absolute surface reflectance so they appear to have been collected by the same sensor under the same illumination and atmospheric conditions.^{3,4}

To radiometrically correct the imagery we used a linear regression technique similar to that introduced elsewhere^{3,4} using pseudo-invariant landscape elements within the overlap areas of adjoining paths of Landsat 8 imagery. Pseudo-invariant features included dark features (clear water lakes), intermediate features (conifer forests) and bright features (high density developed areas) that were consistent between the base and target images. Using linear regression analysis, we developed models to correct each band from each image to a base Landsat 8 OLI image from path 27 November 9, 2015 that had been corrected to surface reflectance using the EROS USGS provisional Landsat 8 surface reflectance product. Relationships between the base and target images (path 26 Aug., 14, 2105, path 28 Sept., 29, 2015) were strong ($r^2 = > 0.99$ for each band and image). The remaining path 29 images (Nov., 7, 2015, Sept., 20, 2015) were corrected to the RR-corrected path 28 image with $r^2 = > 0.99$. To visually compare the RR corrected images we clipped adjacent strips from each image and combined them into a mosaic (composite) image (Fig. 4). Phenology differences can be seen in the later September images, as expected, but otherwise the images have consistent radiometric responses.



Fig. 4. Mosaic of Landsat images corrected to surface reflectance using radiometric regression with the 8/22/13 Landsat OLI image as the reference image the other images were normalized to.

With the RR-normalized imagery we developed relationships using field CDOM data for paths 26, 27 and 28. The combined CDOM data (63 sites) had a strong relationship with the imagery reflectance data ($r^2 =$ 0.79) using the common green/red model (Fig. 5) and $r^2 = 0.87$ for a two-variable model (green/red + ln(red/NIR), Fig. 6). The two-variable model appears to have a better fit with high CDOM lakes. The combined model was applied to each image, including the path 29 images that did not have calibration data, to produce maps. All of the maps have similar CDOM conditions with some variations due to temporal changes in CDOM for some lakes between the images. The combined maps provide the first map for CDOM in lakes across Minnesota Fig. 7.



≥11



Fig. 5. a440 in situ vs. a440 predicted with the green/red model using Landsat 8 data from multiple dates normalized to surface reflectance using radiometric rectification.

Fig. 6. a440 in situ vs. a440 predicted with the twovariable model (green/red + In(red/NIR)) using Landsat 8 data from multiple dates normalized to surface

reflectance using radiometric rectification.

Discussion/Conclusion

The radiometric rectification approach is easily transferable to other areas and has the potential to significantly improve the usefulness of satellite monitoring of inland lakes. In the future we will extend it to additional Midwest states and other variables to further evaluate the approach. Once robust water quality models are developed for an area they can be applied to similarly radiometrically-corrected images without the need for calibration data. This should allow for use of historical images lacking corresponding water quality data to develop water quality maps and time-trend analyses. The method also could be used for newly acquired imagery without the need to wait for lab water quality data, thus allowing for near-real time water quality monitoring.

References

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