A Look-Up-Table Approach to Inverting Remotely Sensed Ocean Color Data

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LONG-TERM GOALS
Remote sensing algorithms for the marine environment have traditionally relied upon semi-empirical approaches to determining water column properties. These algorithms are usually depth-integrals of a proxy of desired information, i.e., chlorophyll algorithms are a proxy for water column autotrophic biomass. The goal of this work is to use the increased spectral resolution of current satellite and aircraft data systems to solve for the depth-dependent optical properties of interest, e.g., absorption and scattering, as well as the depth-dependent distribution of the individual optical constituents, e.g., diatoms, dinoflagellates, cyanobacteria, CDOM, and sediment. This will be accomplished by creating a large dataset of simulated remote sensing reflectance, $R_{rs}$, using a radiative transfer model and developing a look-up-table approach to $R_{rs}$ inversion.

OBJECTIVES
1) Help develop the code to quickly run $>10^7$ calculations of $R_{rs}$.
2) Provide IOPs for individual optical constituents and establish their depth-dependent profiles for simulations.
3) Help develop search optimization schemes to invert satellite and aircraft $R_{rs}$ to depth-dependent optical properties and constituent profiles.

APPROACH
Various ocean color remote sensing instruments are now available or under development. These sensors all measure spectral upwelling radiances which, after atmospheric correction, give the spectral water-leaving radiance $L_w(\lambda)$ or an equivalent remote-sensing reflectance $R_{rs}(\lambda)$; here $\lambda$ is the wavelength. The end goal of ocean color remote sensing is to extract from $L_w$ or $R_{rs}$ useful environmental information such as the absorption and scattering properties of seawater constituents (phytoplankton, dissolved substances, mineral particles, etc), chlorophyll concentration, or bottom bathymetry and bottom type in shallow waters. Currently available algorithms for extracting environmental information generally use empirically derived correlations between the quantity of interest and the ratio of $L_w$ or $R_{rs}$ at two wavelengths. For example, the algorithm for extracting chlorophyll concentrations from SeaWiFS data is based on the ratio $R_{rs}(490 \text{ nm})/R_{rs}(555 \text{ nm})$ (algorithm OC2 in O'Reilly et al., 1998). Such ratio algorithms do not make full use of the available
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spectral data even in the SeaWiFS sensor, nor can they be expected to provide much information about water composition (as opposed to just total absorption or total chlorophyll concentration). Ratio algorithms provide erroneous results if applied to waters outside the range of the empirical data from which they were derived. For example, the OC2 chlorophyll algorithm, which was derived for Case 1 waters, will provide incorrect chlorophyll values if applied to Case 2 waters containing mineral particles or high levels of CDOM (Colored Dissolved Organic Matter).

The Hydrolight radiative transfer numerical model (Mobley, 1994) gives an exact solution of the in-water radiative transfer equation given the water’s inherent optical properties (IOPs, namely the absorption and scattering properties of the water body), the incident sky radiance, and the bottom depth and reflectance (bottom BRDF). The water IOPs can be built up from any number of components, such as various microbes, dissolved substances, organic detritus, mineral particles, or microbubbles. For remote-sensing purposes, the relevant Hydrolight output is the spectral water-leaving radiance. We will first construct a database containing a large number of Hydrolight runs corresponding to different combinations of water composition (different microbial, dissolved, or mineral substances at different concentrations), water depths, bottom types (sea grass, sand, coral, mud, as well as mixtures of these types), sky conditions (different solar angles and atmospheric conditions), sensor viewing directions, and wavelengths. The resulting water-leaving radiances in the database, \( L_{\text{wd}} \), are in principle all different. Given a measured water-leaving radiance \( L_{\text{wm}} \) (obtained from atmospheric correction of an at-sensor radiance), one can then "look up" the \( L_{\text{wd}} \) spectrum that most closely matches \( L_{\text{wm}} \). The water IOPs and bottom conditions in the actual water body are then taken to be the values that were used in Hydrolight to generate the selected \( L_{\text{wd}} \). We thus effect an inversion of the measured spectral signature by the conceptually simple process of spectrum matching and then looking up the answer in the database.

The work is part of a larger project led by C. Mobley of Sequoia Scientific, Inc. (N0001400D01610001).

**WORK COMPLETED**

The optical complexity of the near shore coastal environment has been a challenging area for traditional passive remote sensing systems to accurately classify. Recent advances in passive HyperSpectral Imaging (HSI) have shown it to be a valuable tool in the characterization of these areas. However, the HSI algorithms to map this environment require the simultaneous resolution of water type, bottom type, and depth. While these methods have produced admirable results (Kohler, 2001; Lee et al., 1999; Lyzenga, 1978; Philpot, 1989), better constraining these equations should greatly improve the accuracy of the outcome. Bathymetric LIDAR systems have been demonstrated to reliably produce very accurate estimates of water depth (Guenther, 2001). Thus, the coupling of the two systems should at a minimum produce improved maps of in-water and bottom optical properties by better constraining the passive remote sensing mapping models. In the fall of 2002, the PHILLS2 passive hyperspectral sensor and the SHOALS bathymetric LIDAR were deployed over Looe Key, Florida. While the sensors were flown independently, the data was collected nearly simultaneous to illustrate the merits of a coupled system, as well as provided ground truth data for the HSI/LUT development.

The LUT technique (see Mobley Progress Report, N0001400D01610001 for details of the LUT development) was applied to the atmospherically corrected HSI data (see Bissett Progress Report, N000140010514, and Kohler Progress Report, N000140310626, for details of atmospheric correction).
The LUT results return estimates of water column IOPs, bathymetry, and bottom classification. Comparisons to the bathymetric LIDAR were completed and errors were analyzed. HSI flight data and metadata may be found at http://www.flenvironmental.org/Projectpages/flightlogindex.htm.

RESULTS

Light is attenuated exponentially in water at spectrally different rates. In shallow waters where the bottom can be distinguished with remote sensing techniques, the determination of water depth is critical to retrieving the vertical structure of IOPs, as well as bottom classification. Any remote sensing algorithm that seeks to retrieve these littoral zone properties will have to simultaneously solve for bathymetry. The HSI/LIDAR data set provides a unique opportunity to test an algorithm approach over a statistically significant number of points from an IHO level 1 bathymetric system to provide 1) robust validation, and 2) error analysis. Figure 1 shows an RGB of the atmospherically corrected HSI data from Looe Key. Figure 2 shows the HSI bathymetry estimates. Figure 3 is the RGB with an overlay of ~1.3x10^6 collected LIDAR soundings used for the initial comparisons.

Figure 1: False color composite of the data HSI collected at Looe Key, FL during October, 2002. The area at the bottom is not part of the analysed data as it was collected during aircraft maneuvers resulting in direct sun reflection into the sensor.
Figure 2: LUT estimated bathymetry for Looe Key, FL using HSI data shown in Figure 1. Color contours are in 2 m intervals from dark green to dark blue, as shown by scale on left of image.

Figure 3: SHOALS bathymetric LIDAR coverage for data analysis. Approx. 1.3 million sounding in the area marked in red.
These bathymetric results from the LUT retrieval suggest that the approach is not only reasonable, but statistically significant, particularly in regions where the bottom spectra and classification are well described. Figure 4 shows an enhanced version of the error analysis, highlighted the region of maximum errors, outside of the expected Gaussian distribution if the errors were randomly distributed around zero. The highlighted region of the graph is a substantial underestimation of the bottom depth by the HSI/LUT technique. These errors are from the Hawk Channel region (seen in Figure 1 and 3 as a slightly darker water mass) and seem to a function of an inaccurate bottom spectra or IOP set in the LUT database.

Figure 4: Error analysis of the HSI/LUT estimated bathymetry. The data spanning from the upper left to the lower right of the figure is the sounding overlay seen in Figure 3. The colors highlight the area of maximum error between the HSI/LUT estimated bathymetry and the SHOALS LIDAR bathymetry. The inset figure is the distribution of errors over the combined dataset, (LUT-LIDAR), where the majority of points are centered at zero. The large deviations from the expected Gaussian distribution of errors are highlighted in the inset and correspond to the colored region in the image. The other region outside of the Gaussian curve (at ~1.5 m) appears to correspond to mechanical errors in the SHOALS system.

There is another small region centered around -1.5 meters in error which appears to be the function of mechanical errors in the SHOALS system which caused demonstrated stripping in the bathymetric soundings (data not shown). Outside of these regions, the errors appear to be randomly distributed at zero. Over the whole dataset, 56% of the LUT estimates are ±1 m, and 76% are ±2 m, suggesting that this methodology is a valid approach to retrieving bathymetry, water column IOPs, and bottom classification from hyperspectral imagery.
IMPACT/APPLICATIONS

Full utilization of the hyperspectral data field from aircraft and satellite data streams will provide the mechanism to invert $R_{rs}$ to depth-dependent optical properties such as absorption, scattering, as well as bathymetry and bottom classification. These are critical data streams for performance prediction modeling of in-water acoustic and optical MCM systems, as well as initialization and validation of predictive optical simulations. This program will provide the tools necessary to rapidly invert $R_{rs}$ data into the vertical structure of optical properties.

RELATED PROJECTS

The work is part of a larger proposal being led by C. Mobley of Sequoia Scientific, Inc. (N0001400D01610001), in coordination with the hyperspectral remote sensing program of C. Davis, Code 7212, Naval Research Laboratory.

REFERENCES


PUBLICATIONS


HONORS/AWARDS/PRIZES

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