Correcting Bidirectional Effects in Remote Sensing Reflectance from Coastal Waters

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Motivation

Understanding bidirectional effects including sunglint is important for GEO-CAPE for several reasons: (i) correct interpretation of ocean color data; (ii) comparing consistency of spectral data radiance from space observations with a single instrument for a variety of illumination and viewing conditions; (iii) merging data collected by different instruments operating simultaneously. We present a new neural network (NN) method to correct bidirectional effects in water-leaving radiance for both Case 1 and Case 2 waters. We also discuss a new BRDF and 2D sunglint model that was validated by comparing simulated surface reflectances with Cloud Absorption Radiometer (CAR) data. Finally, we present an extension of our bio-optical model to the UV range that accounts for the marine dependence of the inherent optical properties (IOPs).

The Neural Network Method

The bidirectional effect or the Bidirectional Reflectance Distribution Function (BRDF) has been studied extensively in the past few decades. The standard correction method developed by Morel et al. in 2002 (MAG02) is based on the Case 1 assumption making it unsuitable for application to coastal (Case 2) waters. We introduce a neural network (NN) method that can be applied to both Case 1 and Case 2 waters.

Figure 1 shows 5 cases of simulated remote sensing reflectances. The differences between Case 1 and Case 2 waters is significant, but for each case, the difference is small between nadir-viewing remote sensing reflectance $R_{rs}$ ($\theta_n, \theta_i$) and angle-dependent remote sensing reflectance $R_{rs}$ ($\lambda, \theta_n, \phi, \Delta \phi$). We found that a Radial Basis Function Neural Network (RBF-NN) can establish a direct connection between $R_{rs}$ ($\lambda, \theta_i$) and $R_{rs}$ ($\lambda, \theta_n, \theta_i, \phi, \Delta \phi$). We simulated 30,000 cases with different sun-sensor geometries and different water and atmospheric IOPs to include both Case 1 and Case 2 water conditions. Then we trained a neural network to derive the nadir-viewing $R_{rs}$ ($\lambda, \theta_n$) from the angle-dependent $R_{rs}$ ($\lambda, \theta_n, \theta_i, \phi, \Delta \phi$) directly.

Figure 2 shows the comparison between our BRDF and 2D sunglint model simulated surface reflectances (blue) and CAR measured surface reflectances (red). From left to right, each column shows the comparison of a limited data extracted from the principal plane, and the bottom panel shows the comparison of the entire surface reflectance, the middle panel shows a comparison of a limited data extracted from the principal plane, and the bottom panel shows the comparison of the entire surface reflectance.

Summary and Further Work

- A new neural network (NN) method to correct bidirectional effects in remote sensing reflectance ($R_{rs}$) has been developed and validated by in-situ data (Fan et al. 2015).
- The new NN method shows a similar performance as the standard MAG02 algorithm in Case 1 water, but a significant improvement in Case 2 water.
- The bio-optical model was extended to the UV range and in UV factor was introduced to account for seasonal dependence.
- A BRDF and 2D sunglint model (see another poster) was developed, and validated using Cloud Absorption Radiometer (CAR) BRDF data showed very good agreement.
- Future work: Several anisotropy correction tab les will be provided for the ocean color community, including sunglint correction for both Case 1 and Case 2 water.

References


Marine Bio-Optical Model - CCRR

In the CCHR (Coast Color Round Bobin) model, we assume that algal particles (CHL) and non-algal particles (MIN), in addition to detrital and dissolved organic matter (CDOM) are present in the water so that it can be used to represent both algal-dominated (Case 1) water and Case 2 coastal water. The IOPs are parameterized as:

$$ac_{CHL} = A(x) \times CHL^{0.04},$$

$$ac_{MIN} = 0.03 \times MIN \times \exp[-0.012(\lambda - 443)],$$

$$ac_{CDOM} = CDOM \times \exp[-0.0176(\lambda - 443)],$$

where $A(\lambda)$ and $E(\lambda)$ are from the paper of Brichard et al. (1998), $\nu = 0.5 \times \log_{10}(CHL - 0.3)$, when $CHL < 2.0$, and $\nu = 0$ when $CHL \geq 2.0$. The model has been extended to UV range (300-400 nm) based on the papers by Morsman and Nelson (2004), and Vaulina et al. (2005). In the UV range, the absorption coefficient of algal particles varies with season (absorption is higher in summer than in winter). We introduced a UV factor that can be used to describe the seasonal dependence.

Anisotropy Correction: Synthetic Data Study and Validation of NN Method

We first analyzed a synthetic dataset to demonstrate the importance of the BRDF correction. We simulated 80,000 remote sensing reflectances for different sun-sensor geometries and water IOPs using AccuRT, which is a RTM for the coupled atmosphere-ocean system. The correlation and distribution of the marine parameters: CHL, CDOM and MIN are shown in Fig. 3. We computed the percentage error between the nadir viewing $R_{rs}(\theta_n)$ and the angle-dependent $R_{rs}(\theta_n, \theta_i, \Delta \phi)$, which can be used as an indicator of anisotropy. The error distribution is shown in Fig. 4. We found that for Case 1 water, the error incurred by the BRDF effect can go up to 25% with an average of 2.8%-5.5% for different wavelengths. For Case 2 water, the error can go up to 50%, and the average error increases to 9%-11%. We also found that the anisotropy in $R_{rs}$ depends strongly on sensor viewing angle, whereas the dependence on solar angle and relative azimuthal angle is relatively weak.

Validation of the BRDF and 2D Sun Glint Model with CAR Data

We developed a BRDF model and 2D sunglint model. Validation using surface reflectance data measured by the Cloud Absorption Radiometer (CAR) in July 18, 2001 over Chesapeake Bay shows good agreement (Fig. 5).

Figure 1. Simulated remote sensing reflectances.

Figure 2. Extended $A(\lambda)$ and $E(\lambda)$ coefficient from 380nm to 1080nm.

Figure 3. Covariance and distribution of the marine parameters: CHL, CDOM and MIN.

Figure 4. Statistics of BRDF anisotropic distribution. Panel 1 shows percentage difference between the viewing angle-dependent $R_{rs}(\theta_n, \theta_i, \Delta \phi)$ and the nadir viewing $R_{rs}(\theta_n)$ for 80,000 simulation data, panel 2 shows the distribution of the difference for Case 1 and Case 2 waters, and panel 3 shows the dependence on sun-sensor geometry.

Figure 5. Comparison of the percentage error distribution of the BRDF derived from the NN and MAG02 algorithms.