Impacts of Atmospheric Corrections on Algal Bloom Detection Techniques

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Abstract

Bio-optical retrieval algorithms based on blue-green reflectance ratios suffer severely in the coastal waters due to imperfect atmospheric corrections and spectral interferences from organic and inorganic components in the water, which furthermore, don't necessarily correlate with chlorophyll in the coastal waters. Standard near-infrared (NIR) atmospheric correction algorithms often fails in the coastal waters because of higher turbidities which result in increased elastic reflectance and significant radiance contributions in NIR bands. Recently, an atmospheric correction algorithm using the short-wave infrared (SWIR) bands has been applied to turbid coastal waters. In this study we examine the performance of our recently proposed bloom detection technique called red band difference (RBD) and toxic dinoflagellate *Karenia brevis* (*K. brevis*) bloom classification technique called *K. brevis* bloom index (KBBI) for use with Moderate Resolution Imaging Spectroradiometer (MODIS) data, corrected for the atmosphere, using NIR and SWIR atmospheric correction algorithms. Our analysis shows that both atmospheric correction algorithms are unsatisfactory, giving negative normalized water-leaving signals at the 412nm band for the bloomed area, which is an indication of a failure of atmospheric correction. Standard reflectance band ratio algorithms applied to this inappropriately atmospherically corrected signal give different and inaccurate results with either atmospheric correction algorithm. However, the RBD values retrieved from either atmospherically corrected data give nearly the same results ($r^2 = 0.99$) for the bloomed region while the KBBI values retrieved from either atmospherically corrected data seems to be less correlated ($r^2 = 0.64$).

1. Introduction

The fundamental measurement in ocean color remote sensing is the water-leaving radiance or the upwelling spectral distribution of the radiance from the ocean. Geophysical parameters such as chlorophyll concentrations can be retrieved from this water-leaving signal since it contains information about the water columns. Only about 10% of the total signal measured by the ocean color sensors contains information about the waters and the rest represents scattering from aerosols and air molecules. The goal of the atmospheric corrections over the ocean is to remove contributions from atmosphere and reflection from the sea surface.

Gordon and Wang (1994) developed an atmospheric correction scheme for the Open Ocean where the aerosol contribution was estimated using TOA radiance/reflectance signals obtained from near infrared (NIR) bands (for MODIS 748-869nm). This approach assumes that ocean is optically black in the NIR bands due to the strong water absorption in this region of the spectrum. Although this technique works well in the Open Ocean, it breaks down in optically complex coastal waters, since black pixel approximation no longer holds true due to strong reflections from organic and inorganic particulate matters. If water-leaving radiance is not negligible in the NIR bands then the retrieved aerosol loading will be overestimated, resulting in underestimated water-leaving radiances.

To avoid this problem, another atmospheric correction approach for coastal water was proposed by Wang and Shi (2005) which uses different short wave infrared (SWIR) bands (i.e., MODIS 1240nm and 2130nm). This approach is based on the fact that ocean water absorbs strongly in this spectral region, and the contributions of the in-water constituents are negligible and can safely be considered dark. However, at these long wavelengths the atmospheric reflectance itself is significantly weaker and spectral features, due to absorbing aerosols or fine urban modes, are particularly difficult to resolve.

Retrieved ocean products in the coastal waters are often inaccurate due to inappropriate atmospheric correction on top of many other contaminations such as CDOM and inorganic particulate matters. Although atmospheric correction algorithms are improving, it still remains a challenge to correct for the atmosphere particularly over the turbid waters. So, it is important to develop techniques that are less sensitive to the atmospheric correction algorithms. The main objective of this paper is to analyze impacts of atmospheric correction algorithms on our recently proposed bloom detection technique called red band difference (RBD) and *Karenia brevis* (*K. brevis*) bloom classification technique called *K. brevis* bloom index (KBBI).

2. Backgrounds

a. Atmospheric corrections

The signal received at the TOA by an ocean color satellite sensor can be expressed as Siegel et al., (2000)

$$L_t(\lambda) = L_r(\lambda) + L_A(\lambda) + t_u(\lambda)L_{wc}(\lambda) + T_u(\lambda)L_g(\lambda) + t_u(\lambda)L_w(\lambda) \qquad (1)$$

where $L_r(\lambda)$, $L_A(\lambda)$, $L_{wc}(\lambda)$, $L_g(\lambda)$, and $L_w(\lambda)$ are the contributions due to molecular scattering (Rayleigh), aerosol and Rayleigh-aerosol scattering, whitecaps, sun glint, and ocean water, respectively. Here $T_u(\lambda)$ and $t_u(\lambda)$ are the direct and diffuse upwelling transmittances of the atmosphere. The radiance, L, can be converted to reflectance, ρ, using the relation $\rho = \pi L / (F_0 \cos\theta_0)$, where F_0 is the extraterrestrial solar irradiance, and θ_0 is the solar zenith angle.

The reflectance contributed by whitecaps is estimated from the surface wind and subtracted from measured reflectance/radiance. The surface atmospheric pressure and wind speed are used to compute the Rayleigh scattering which is then subtracted from the whitecap corrected reflectance/radiance. The algorithm then selects from a family of aerosol models using signals from NIR or SWIR bands and estimates the aerosol contribution in each of the visible wavelength bands. After subtraction of the aerosol contribution, the water-leaving reflectance/radiance is obtained in each of the visible bands by dividing by the diffuse atmospheric transmittance.

b. Detection algorithm

The bloom detection algorithm or the RBD technique was introduced in Amin et al., (2008a, 2008b) and can be expressed as follows:

$$RBD = nLw(678) - nLw(667) \quad (2)$$

Where the $nLw(\lambda)$ is the normalized water-leaving radiance which is defined as the upwelling radiance just above the sea surface, in the absence of an atmosphere, and with sun directly overhead. The RBD technique was achieved based on the principle that organisms such as *K. brevis* absorbs strongly around 675nm which causes $nLw(\lambda)$ to have a trough around this band. But because of the contribution of chlorophyll fluorescence emission centered at 685nm and the known lower backscattering efficiency of *K. brevis,* this trough is shifted toward shorter wavelengths around 667nm or below depending on the concentrations of chlorophyll and the quantum yield of chlorophyll fluorescence. The signal at 678nm band, which falls in the shoulder of the red-NIR water-leaving radiance peak, has higher values than the signal at 667nm band due to the chlorophyll fluorescence contribution on top of reflectance due to the total inverse absorption (phytoplankton and sea water) spectra. Simulation shows that the positive RBD values ($>1 mg/m^3$ of Chlorophyll) are primarily due to the fluorescence signal which correlates strongly with the chlorophyll concentration of the *K. brevis* bloom conditions and open water conditions. Because of the strong correlation between RBD and *K. brevis* chlorophyll concentration found in simulation, it may be possible to quantify *K. brevis* blooms in terms of the chlorophyll concentrations more accurately than the standard band ratio algorithm by developing some empirical relationship between the RBD and *K. brevis* bloom chlorophyll using in situ data. However, the RBD technique may also detect blooms of other species as well particularly when high concentrations chlorophyll is present in the bloom. To distinguish between *K. brevis* and other blooms, we developed a *K. brevis* classification technique to discriminate *K. brevis* blooms from other blooms and bloom like features such as CDOM plumes, sediment plumes and bottom reflectance.

c. Classification algorithm

This classification technique was introduced in Amin et al., (2008a, 2008b) and can be expressed as follows:

$$KBBI = \frac{nLw(678) - nLw(667)}{nLw(678) + nLw(667)} \quad (3)$$

The KBBI technique was developed based on the total particulate backscattering associated with *K. brevis* and non-*K. brevis* blooms. *K. brevis* bloom water is known to have lower total particulate backscattering than the non-*K. brevis* bloom waters. So the water-leaving radiance signal is much lower for *K. brevis* bloom than the non-*K. brevis* bloom waters since radiance signal is proportional to the backscattering. As a consequence, the sum of the two red bands of MODIS (band 13 and band 14) has much higher values for non-*K. brevis* blooms than the *K. brevis* bloom. At the same time, the differences between the two red bands or the RBD for non-*K. brevis* blooms is usually lower (and even negative for low chlorophyll) than the difference for *K. brevis* bloom with the same chlorophyll concentration. Therefore, when the smaller (negative for low chlorophyll) difference of non-*K. brevis* bloom is divided by a larger sum, the KBBI value becomes very small (negative for low chlorophyll) while for *K. brevis* bloom it magnifies because the numerator and denominator are larger and smaller respectively compared to the non-*K. brevis* bloom with the same chlorophyll concentrations.

3. Results

a. Impacts of atmospheric correction on RBD

Fig. 1a shows two normalized water leaving radiance spectra averaged over 3 by 3 pixels taken from the same bloomed region but atmospherically corrected using standard NIR and SWIR algorithms. The negative signal at 412nm band shown with an orange circle in Fig. 1a is an indication of the atmospheric correction failure meaning that the signal is over corrected for the atmosphere which is often the case in bloomed and coastal waters. Although SWIR seems to do little bit better than NIR in the bloomed region (Fig 1a), they both give negative signal at blue band, an indication of the limitations of both algorithms. We also confirm that the errors in the atmospheric correction scheme are clearly strongest for shorter wavelengths. Clearly, blue-green band ratio algorithms applied to the inappropriately corrected for atmosphere signal can result in inaccurate and different results with different atmospheric correction algorithms. The spike at the 678nm band, shown with a red circle in Fig. 1a is caused by chlorophyll fluorescence and the RBD technique takes advantage of this fluorescence signal.

Fig. 1b demonstrates the sensitivity of the RBD technique on NIR and SWIR atmospheric correction algorithms. The data for Fig 1b are taken from MODIS Aqua sensor image containing data from the region between (25.9ºN - 25.5ºN) and (81.9ºW - 82.3ºW) for 13 Nov 2004 when a *K. brevis* bloom was documented by Hu et al., (2005). This region includes *K. brevis* bloomed areas as well as neighboring pixels which may or may not contain *K. brevis* cells. However, in our previous study (Amin et al., (2008b)) we concluded that these neighboring pixels may have *K. brevis* cells but in low concentrations since the satellite data followed the same trend as the simulated data. Our analysis shows that the RBD values are nearly the same with either atmospheric correction algorithm (Fig 1b) for the bloomed regions. This is due to the fact that we are calculating difference between the two bands which doesn't change if the spectrum is shifted up or down by different atmospheric correction schemes as oppose to the ratios which changes significantly even with a small shift in the spectrum.

a. Impacts of atmospheric correction on KBBI

Sensitivity of the *K. brevis* classification technique on NIR and SWIR atmospheric correction is demonstrated Fig. 2. The data is taken from the same region as the RBD data in Fig 1b. The correlation between NIR and SWIR KBBI data is somewhat reduced mainly because of the normalization while the RBD which retains its strong correlations. Although the numerator (same as the RBD) remains nearly the same, the sum of the two red bands (denominator of the KBBI) changes when the spectrum is shifted up or down with different atmospheric correction algorithms. Because of the changes in the denominator of Eq.3 with the atmospheric corrections the KBBI values changes somewhat, but still give reasonable enough correlations ($r^2 = 0.64$) compared to traditional band ratio algorithms, such as standard chlorophyll retrieval.

4. Discussions

Our analysis shows that both atmospheric correction algorithms are unsatisfactory over the bloomed region, giving negative normalized water-leaving signals at blue-green bands. These negative $nLw(\lambda)$ values are primarily due to the fact that waters containing large accumulations of *K. brevis* species have a relatively strong water-leaving radiance in the near-infrared bands, while at the same time are absorbing strongly in the blue-green region, which leads to possible errors in the atmospheric correction and underestimation of $nLw(\lambda)$ in the blue and green bands of MODIS. Reflectance band ratio algorithms applied to this inappropriately atmospherically corrected signal gives different and inaccurate results with either atmospheric correction algorithm. Results for the RBD bloom detection technique are found to be similar with either atmospheric correction algorithm. This is due to the fact that for this technique we are using the difference in magnitude of the water-leaving radiance signal at two adjacent red bands, and since these two bands are relatively close spectrally, 667nm and 678nm, the magnitude of the optical impact of the atmosphere will be very nearly the same on either band, and also when we calculate the difference of the two bands it remains nearly the same regardless of the shift the whole spectrum. This is in marked contrast to the impact of the atmosphere on the ratio of signal magnitudes at these bands. In our previous study Amin et al., (2008b), simulations for *K. brevis*, which is known to be characterized by weak backscatter, both because its own backscatter is low due to its low index of refraction, and also due to the typically low cohort submicron particulate concentrations typically associated with it, show that the *K. brevis* chlorophyll concentration strongly correlates with the RBD values for high chlorophyll ($>1mg/m^3$). It should be possible to evolve empirically based relationships between RBD and *K. brevis* chlorophyll concentrations using in situ data. The nearly insensitivity of the RBD technique to atmospheric corrections in addition to the less sensitivity to CDOM Amin et al., (2008b) may enable us to retrieve chlorophyll more accurately than the blue-green reflectance ratio algorithms for low backscattering blooms such as *K. brevis* that blooms regularly in the Gulf of Mexico particularly in the West Florida Shelf.

The KBBI technique is somewhat sensitive to the atmospheric corrections. However, it is still possible using either atmospheric correction scheme to identify *K. brevis* bloomed areas. While in general, the KBBI technique could identify potential *K. brevis* bloomed area using data corrected with either atmospheric correction, the SWIR algorithm does more poorly in the offshore pixels and often gives noise values of KBBI (positive and negative false bloom alarm in nearby pixels). This is because the MODIS SWIR bands are designed for the land and have substantially lower signal-to-noise ratio (SNR) values. So the signals received in the SWIR bands in offshore pixels are low, and often within the noise level. Thus the overall performance of NIR algorithm is found to be better for use with KBBI than the SWIR algorithm, with the exception that NIR gives more false positive bloom alarms at the cloud edge pixels and spurious results for the stripe regions at the ends scan lines. Probably a combined NIR-SWIR atmospheric correction approach would be the best approach for the KBBI technique although it still needs to be verified.

5. Conclusion

Our results show that both NIR and SWIR atmospheric correction approach fail in the bloomed regions which can lead to poor retrieval results particularly when band ratio algorithms are used to retrieve geophysical parameters such as chlorophyll which is often used to quantify blooms. We have shown that our bloom detection technique performs equally well with MODIS standard NIR and SWIR algorithms unlike the traditional band ratio algorithms such as standard chlorophyll retrievals. Our classification technique also performs reasonably well with the either atmospheric correction scheme for the bloomed regions.

Acknowledgments.

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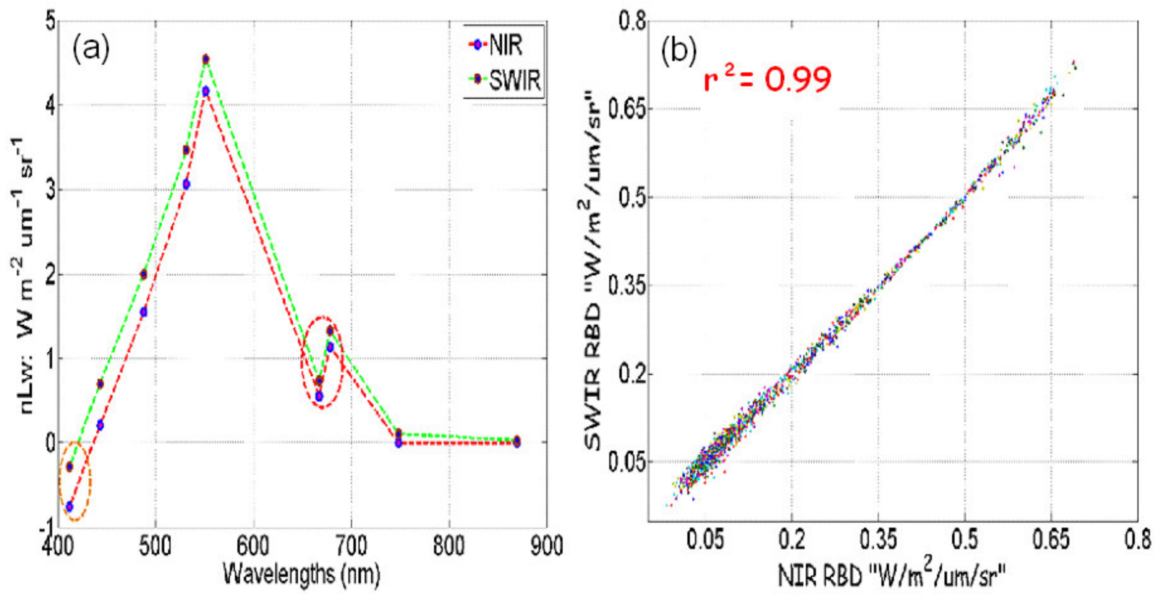
FIG. 1. (a) Normalized-water leaving radiance spectra of K. brevis bloom taken from the same bloomed region but atmospherically corrected using NIR and SWIR atmospheric correction Algorithms. Both algorithms fail in the bloomed region although SWIR seems to give smaller negative values in blue bands. (b) RBD data corrected with NIR and SWIR atmospheric correction and they are nearly the same.

FIG. 2. 13 Nov 2004 MODIS RBD images: (a) Data corrected for atmosphere using standard NIR atmospheric correction algorithm and (b) Data corrected for atmosphere using SWIR atmospheric correction algorithm. Both atmospheric corrections give nearly the same values of RBD. The white regions are clouds and lands while the warm regions are the bloomed areas. The bright pixels next to the white regions are contamination from the cloud at the cloud edge pixels.

FIG. 3. The KBBI data corrected with NIR and SWIR atmospheric correction algorithms.



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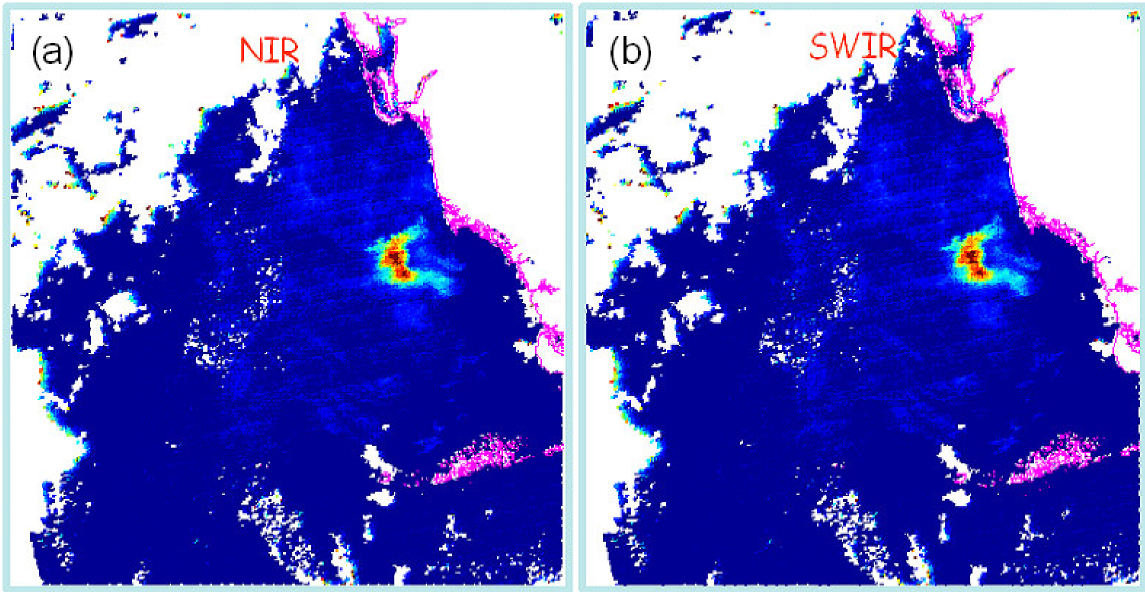

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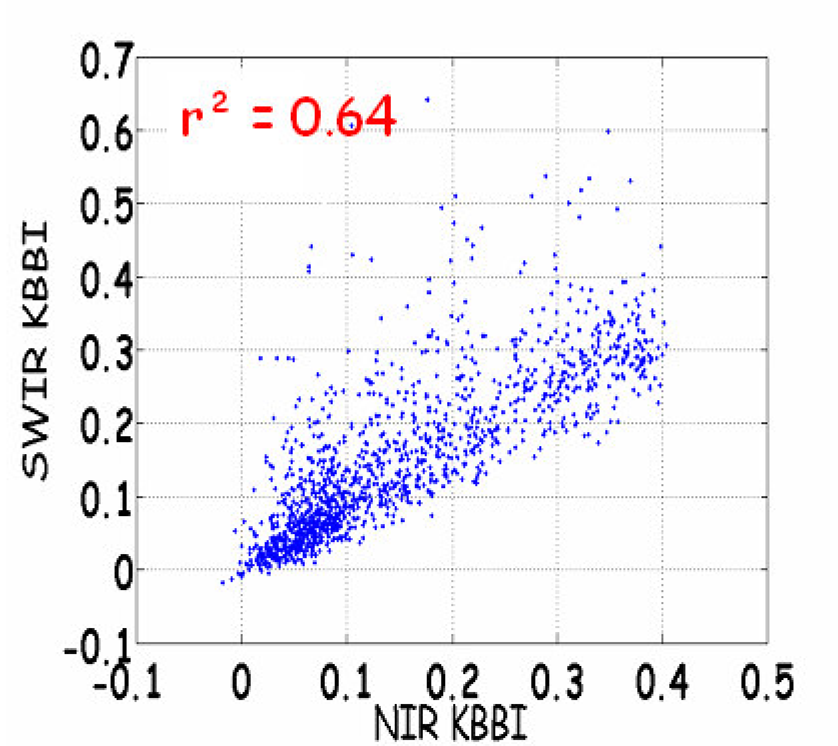

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