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SATELLITE OCEAN COLOR DATA FOR ALGAL BLOOM MONITORING IN SOUTHEAST ASIAN WATERS

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ABSTRACT

Algal blooms occur regularly in many different parts of South East Asia. Some of the bloom species are known to be harmful or even toxic. Besides the health effects, algal blooms can result in economic loss to the fishery industry. Traditional monitoring programmes by in situ point measurements are expensive, time consuming and inadequate since they do not have sufficient spatial and temporal coverage to monitor the complex dynamic phenomena occurring during a red tide episode. Satellite remote sensing measurement of ocean colour provides a complementary tool for red tide monitoring. Currently, ocean color data are available from SeaWiFS on board the Orbview2 satellite and the recently launched MODIS on board the NASA's Terra satellite. Future planned ocean color sensors include the NASDA's ADEOS2-GLI and ESA's ENVISAT-MERIS. With the availability of these ocean color satellites, it is foreseeable that satellite ocean color data will play an increasingly important role in the monitoring of algal blooms. In this paper, we describe the works done in developing algorithms for algal bloom detection and classifications using satellite ocean color data in Southeast Asian waters.

1. INTRODUCTION

Phytoplantons (or algae) are microscopic photosynthetic organisms occurring in natural waters. They constitute the base of the marine food web. However, algal blooms may cause harm by shading other aquatic life and depleting the dissolved oxygen content. In situation whereby a bloom is dominated by toxic algal species, toxins can be accumulated in the food chain and eventually be consumed by humans to cause paralytic or diarrhetic shellfish poisoning (Richardson 1997). There have been incidences of harmful algal blooms reported in the East and Southeast Asian waters.

Traditionally, algal blooms are monitored by in-situ sea water sampling and toxicity test of the harvested seafood. Satellite remote sensing measurement of ocean color provides a potential tool complementary to in-situ sea-truth measurements for algal bloom monitoring. As the individual phytoplankton pigments are characterized by their unique light absorption features, this property allows detection and identification of algal blooms by ocean color remote sensing technique (Cullen et al. 1997, Kahru and Mitchell 1998, Sathyendranath et al. 1994),

In 1997, a research project to investigate the application of ocean color data for red tide monitoring has been initiated at the Centre for Remote Imaging, Sensing and Processing (CRISP), with partial funding from NASDA/UN-ESCAP. During the two-year (1997-98) project period, regular sea truth water sampling field trips were conducted in Singapore waters. Sea water reflectance spectra were acquired using a handheld spectrometer together with measurements of water quality parameters (Lin et al. 1999, Liew et al. 1999, 2000). The sea-truth water sampling field trips were continued in 1999.

Several algal blooms were observed during some of the field trips. Spectral signatures of several types of algal blooms have been measured in Singapore waters and in the Manila Bay. In order to assess the capabilities of the various satellite ocean color sensors for algal bloom monitoring, the in-situ spectral signatures of the algal bloom types measured using the handheld spectrometer were used to simulate the spectral response of the satellite ocean color sensors. In this paper, we describe a method of detecting and classifying algal bloom types based on the singular value decomposition technique. The satellite sensors tested are SeaWiFS, MERIS and GLI.

2. OCEAN COLOR SATELLITE SENSORS

Currently, the SeaWiFS sensor on board the Orbview 2 satellite (launched October 1997) provides ocean color data with about 1-km resolution. It has six bands in the visible region and two in the near-infrared region. Each band has a 20-nm bandwidth. The recently launched MODIS sensor on board the NASA's Terra satellite has eight ocean color bands in the visible spectral region, with 10 nm bandwidth. The other recent sensor was the OCTS onboard the Japan's ADEOS satellite launched in August 1996. ADEOS ceased operation in June 1997 when the ADEOS satellite stops its operation. It was the first second-generation ocean color sensor after the 10 years gap since NASA's CZCS. Future planned ocean color sensors include the NASDA's ADEOS2-GLI and ESA's ENVISAT-MERIS. These future sensors have more wavelength bands, all with about 10 nm bandwidths. A summary of the spectral bands present in these satellite sensors are tabulated in Table 1. With the availability of these ocean color satellites, it is foreseeable that satellite ocean color data will play an increasingly important role in the monitoring of algal blooms. Algorithms for algal bloom detection and for classification of algal bloom types will be required.

Table 1: The spectral bands of satellite ocean color sensors in the visible band (400 to 760 nm)

CZCS												
BC	-	443	-	-	520	550	-	-	670	-	-	-
BW	-	20	-	-	20	20	-	-	20	-	-	-
OCTS												
BC	412	443	-	490	520	-	565	-	665	-	-	-
BW	20	20	-	20	20	-	20	-	20	-	-	-
SeaWiFS												
BC	412	443	-	490	510	-	555	-	670	-	-	-
BW	20	20	-	20	20	-	20	-	20	-	-	-
MODIS												
BC	412.5	443	-	488	531	-	551	-	667	678	-	748
BW	15	10	-	10	10	-	10	-	10	10	-	10
MERIS												
BC	412.5	442.5	-	490	510	-	560	620	665	681.25	705	753.75
BW	10	10	-	10	10	-	10	10	10	7.5	10	7.5
GLI												
BC	412	443	460	490	520	549	565	625	666	680	718	749
BW	10	10	10	10	10	10	10	10	10	10	10	10

(Note: BC = Band Center in nm; BW = Bandwidth in nm)

3. ALGAL BLOOM CLASSES

Sea-truth water sampling campaigns were carried out from Dec 1996 to Dec 1999 in coastal waters around Singapore (Lin et al. 1999, Liew et al. 1999, 2000). In-situ reflectance spectra from sea water surface were acquired using a portable spectroradiometer. Several minor algal bloom events were sighted and their characteristic reflectance signatures were collected during this period. The classes of algal blooms observed include: Trichodesmium (a type of cyanobacteria); Chain forming diatoms; Chochlodinium (naked dinoflagellate); Dinoflagellates predominantly Dinophysis caudata; Diatoms (Rhizolenia Sp.); and mixture of chain forming diatoms (Skeletonema type) with some armoured dinoflagellates. Two additional algal bloom classes were collected during two field trips to the Manila Bay. One trip was carried out during the algal bloom episode (mainly Ceratium and Pyrodinium Bahamense) in Aug 1998, and the other in March 2000. Although there was no report of red tide during the later trip, results of water sampling in Manila Bay indicated that there were signs of increasing phytoplankton counts. A class of sea water reference spectra for sea water samples with low chlorophyll and low suspended solids was also collected during the regular water sampling field trips.

Altogether eight algal bloom classes and one reference sea water class are used in the analysis. The nine classes of spectra are tabulated in Table 2.

Table 2: The nine classes of reflectance spectra from algal blooms and reference sea water

Class	Description
1	Clear sea water reference (Singapore)
2	Trichodesmium (Singapore)
3	Chain forming diatoms (Singapore)
4	Cochlodinium (Singapore)
5	Ceratium and Pyrodinium Bahamense (Manila Bay)
6	Dinoflagellates (mainly Dinophysis caudata) (Singapore)
7	Diatoms (Rhizolenia Sp.) (Singapore)
8	Chain forming diatoms (Skeletonema) with some armoured dinoflagellates (Singapore)
9	Protoperidinium and Ceratum (Manila Bay)

4. SPECTRAL REFLECTANCE SIGNATURES OF ALGAL BLOOM CLASSES

Spectral reflectance refers to the ratio of the detected radiance reflected from a target surface to the total incidence irradiance. In this project, a handheld spectrometer (GER 1500) was used to measure the radiance reflected from the sea surface. The detected radiance from the sea surface was normalized by the radiance reflected off the surface of a reference white plate to obtain the reflectance of the sea surface. The spectrometer has 512 wavelength channels covering the wavelength from 350 nm to 1050 nm, with a wavelength resolution of 2 nm.

From the collected spectra, SeaWiFS and GLI data are simulated according to the band specifications shown in Table 1. The simulation is done by integrating the spectrometer radiance within each specified wavelength window to obtain the desired radiance for the corresponding SeaWiFS and GLI channels. A flat spectral response curve is assumed for each of the satellite sensor channels. Only the channels in the visible region (400 nm to 760 nm) are considered in the simulation. Hence, 6 bands of the SeaWiFS sensor and 12 bands of the GLI sensor are simulated. The simulated SeaWiFS and GLI spectral reflectance data for the reference sea water and the eight algal bloom classes are shown in Fig. 1. Each spectrum shown in Fig. 1 is the mean of a set of spectra corresponding to the reference sea water and each of the algal bloom classes. The spectra have been normalized so that each of them has a mean value of zero and a variance of one. In this way, the magnitude of reflectance has no influence on the normalized spectra, and the shapes of the spectra can be compared directly.

It can be seen that the GLI spectra of the eight algal bloom classes are quite distinct from each other. For many algal bloom types, the spectra can be differentiated visually from their shapes around the chlorophyll absorption band at 670 nm. In comparison, the SeaWiFS does not have spectral bands beyond 670 nm. Hence, it is expected that SeaWiFS will fare poorer in terms of accuracy in classification of the algal bloom types.

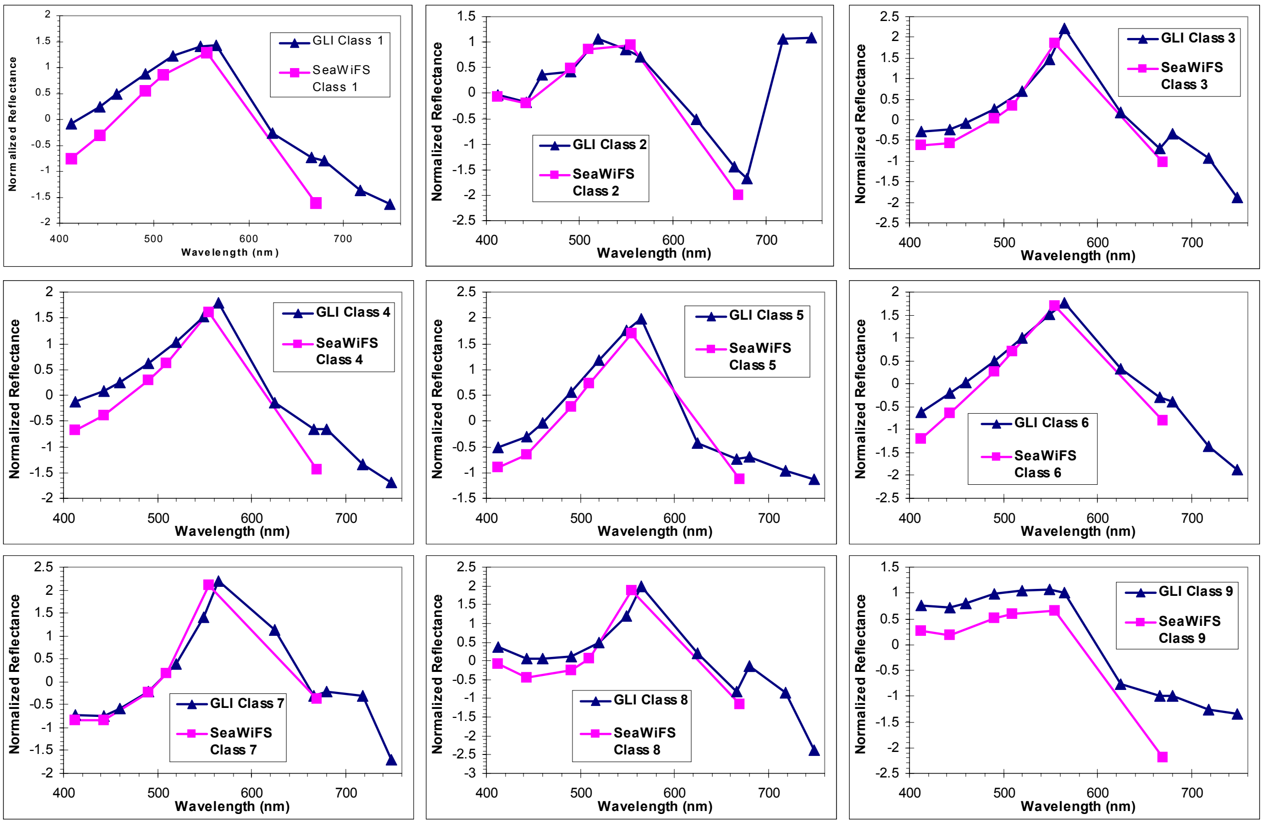

Figure 1: Simulated SeaWiFS and GLI spectra for the reference sea water class (class 1) and the 8 algal boom classes (Class 2 to 9)

5. CLASSIFICATION OF ALGAL BLOOMS FROM REFLECTANCE

An algorithm based on the singular value decomposition (SVD) technique (Danaher and Omongain 1992) has been developed for the detection and classification of algal bloom types from reflectance data. This algorithm is a type of supervised classification technique. In this algorithm, a "key vector" $V_i(\lambda)$ for each algal bloom class labelled by the subscript i is first determined from the reflectance spectra of the algal bloom class of interest measured during the field trips. This key vector acts as a sort of template for this class of algal bloom. A given measured spectrum $R(\lambda)$ to be classified is then "matched" to this key vector using the dot-product operation to give a key value w_i. Mathematically, the dot-product operation is represented by the formula:

$$w_i = \sum_{\lambda} R(\lambda) V_i(\lambda) \qquad (1)$$

Ideally, if the spectrum $R(\lambda)$ belongs to class-i, then w_i=1, otherwise w_i=0. Using a training set of spectra of known classes, the key vector for each of the nine classes (8 algal bloom classes + 1 reference sea water class) are obtained using the singular value decomposition technique. The key vectors are then matched to each of the unknown spectra $R(\lambda)$ to be classified, using the dot-product operation. In this way, each spectrum is transformed into a vector of nine key values. The results of supervised minimum distance classification in the key value space are shown in Tables 3 and 4 for the SeaWiFS and GLI sensors respectively. For comparison, the results of supervised minimum distance classification using normalized spectral values of the respective sensors are shown in Tables 5 and 6.

The accuracy of minimum distance classification using the normalized spectral reflectance values of the SeaWiFS sensors is only 73.8%. With additional bands of the GLI sensor, the accuracy improves to 86.9 % (see Tables 5 and 6). This improvement is expected, as the additional bands are located around the chlorophyll-a absorption band at 670 nm, which helps to discriminate between the algal bloom classes. The transformation of the reflectance spectra into the key value space using a simple matrix multiplication operation improves the classification accuracy to 96.6% and 99.5% for SeaWiFS and GLI respectively (see Tables 3 and 4). It is noted that for both SeaWiFS and GLI sensors, the spectra from eight out of nine classes are correctly classified after transformation into the key values.

6. CONCLUDING REMARKS

We have presented a technique for classification of algal blooms types from remote sensing reflectance. This technique is based on a linear transformation of the normalized reflectance spectra into a "key value" space. The success of this technique depends on the availability of spectral reflectance signatures of known algal bloom classes. The key vectors required for constructing the transformation matrix are derived from this set of reflectance signatures. The present database of algal bloom signatures used in this study have been accumulated during a 3-year period of water sampling in Singapore waters and in the Manila Bay. The classification technique is tested on the simulated data for the current SeaWiFS and future GLI ocean color sensors. The simulated data are constructed from in-situ radiance data measured using a handheld spectrometer. Atmospheric effects are not included in the simulation. Hence, it is assumed that atmospheric correction has been done before the classification technique is applied. This study show that the spectral bands of the current SeaWiFS sensor is sufficient for algal bloom classification, while the GLI sensor provides certain advantages in identifying different algal bloom types.

The results of this study show that it is possible to detect algal blooms satellite ocean color sensors. However, in order to identify the algal bloom types, a library of spectral reflectance signatures for the different algal bloom types must first be acquired. The spectral reflectance signature of a given algal bloom type depends on the species composition present in the bloom. Hence, the acquired spectral library may not be exhaustive to be representative of the diverse species composition of the algal blooms. The problem may be overcome by modelling the spectral signatures of a mixture of different phytoplankton species. The classification algorithm will need to be tested using actual GLI data. It is important to acquire a comprehensive spectral library of various algal bloom types common in the Southeast Asian waters. The cooperation of the many institutions engaged in red tide monitoring and research in the region will be essential in order to establish a system for detecting red tide using satellite ocean color data.

Table 3: Minimum distance classification in the key value space for SeaWiFS

		Assigned Class (%)									
		1	2	3	4	5	6	7	8	9	Total (%)
Actual Class	1	100	0	0	0	0	0	0	0	0	100
	2	0	69.6	0	0	0	0	0	0	30.4	100
	3	0	0	100	0	0	0	0	0	0	100
	4	0	0	0	100	0	0	0	0	0	100
	5	0	0	0	0	100	0	0	0	0	100
	6	0	0	0	0	0	100	0	0	0	100
	7	0	0	0	0	0	0	100	0	0	100
	8	0	0	0	0	0	0	0	100	0	100
	9	0	0	0	0	0	0	0	0	100	100

Average Overall Accuracy **96.6 %**

Table 4: Minimum distance classification in the key value space for GLI

		Assigned Class (%)									
		1	2	3	4	5	6	7	8	9	Total (%)
Actual Class	1	100	0	0	0	0	0	0	0	0	100
	2	0	95.7	0	0	0	0	0	0	4.3	100
	3	0	0	100	0	0	0	0	0	0	100
	4	0	0	0	100	0	0	0	0	0	100
	5	0	0	0	0	100	0	0	0	0	100
	6	0	0	0	0	0	100	0	0	0	100
	7	0	0	0	0	0	0	100	0	0	100
	8	0	0	0	0	0	0	0	100	0	100
	9	0	0	0	0	0	0	0	0	100	100

Average Overall Accuracy **99.5 %**

Table 5: Minimum distance classification in the normalized spectral value space for SeaWiFS

		Assigned Class (%)									
		1	2	3	4	5	6	7	8	9	Total (%)
Actual Class	1	97.5	2.5	0	0	0	0	0	0	0	100
	2	4.35	91.3	0	0	0	0	0	0	4.35	100
	3	0	2.5	42.5	5.0	0	0	37.5	0	12.5	100
	4	0	20	0	50	20	10	0	0	0	100
	5	0	0	0	0	77.8	22.2	0	0	0	100
	6	0	0	0	0	10	90	0	0	0	100
	7	0	0	0	0	0	0	100	0	0	100
	8	0	0	0	0	0	0	50	25	25	100
	9	0	10	0	0	0	0	0	0	90	100

Average Overall Accuracy: **73.8%**

Table 6: Minimum distance classification in the normalized spectral value space for GLI

		Assigned Class (%)									
		1	2	3	4	5	6	7	8	9	Total (%)
Actual Class	1	100	0	0	0	0	0	0	0	0	100
	2	0	69.6	0	0	0	0	0	0	30.4	100
	3	2.5	0	52.5	12.5	0	0	22.5	0	10.0	100
	4	20	0	0	60	0	20	0	0	0	100
	5	0	0	0	0	100	0	0	0	0	100
	6	0	0	0	0	0	100	0	0	0	100
	7	0	0	0	0	0	0	100	0	0	100
	8	0	0	0	0	0	0	0	100	0	100
	9	0	0	0	0	0	0	0	0	100	100

Average Overall Accuracy **86.9%**

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