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MODIS-Aqua Data based Detection and Classification of Algal Blooms along the Coast of India using RLS Classifier

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Abstract

In the field of marine biology, researches reveal that there exists a constant increase in Algal bloom (AB) count, along the coast of India. This work aims at detecting and classifying six most frequently appearing algal blooms in this region (viz.:*Trichodesmium erythraeum, Noctiluca scintillans/miliaris, Cocholodinium ploykrikoides, Chattonella marina* and *Karenia mikimotoi* blooms). The uniqueness of ocean's optical properties such as remote sensing reflectance (R_{rs}) and normalized water leaving radiance (nL_w) during bloom period serve as the underlying features on whose grounds classification is performed. These parameters are acquired from Aqua/MODIS sensor measurements and Regularized least squares classifier is used in GURLS library for classification. An overall classification accuracy of 94.37% is obtained using both R_{rs} and nL_w features, which is superior to the previously conducted studies for monitoring ABs using optical properties of water. Given a MODIS image, a map is developed wherein the pixels with ABs are highlighted and the causative species is recognized. A MODIS image is available every two days and hence frequent generation of AB moitoring maps is possible, which is of great significance in the fisheries industry.

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Keywords: Algal bloom; R_{rs}; L_w; MODIS Aqua; RLS classifier; India

1. Introduction

Studies in marine biology indicate a growth in frequency of occurrence of Algal Blooms (AB) along the coast of India[4]. Though not all these blooms are harmful, their decomposition consumes dissolved oxygen in water resulting in a hypoxic condition that poses as a threat to marine life. Hence several studies are focused on detecting and classifying ABs, introducing vast variety of algorithms for the same, especially with the availability of large number of ocean related satellite data. Advances in research based on remote sensing techniques overcome the bottleneck that arises in traditional methods and allows more frequent study across wide geographies.

Over the past decades, a number of remote sensing technique based algorithms have been introduced to detect and monitor ABs. One of the common approaches include detection using optical methods which comprises of

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examining water discoloration, concentration of chlorophyll and absorption spectra [12]. In case I water (where optical properties are solely determined by phytoplankton), optical methods such as water discoloration is effective, however in case of turbid water (case II water), discoloration is dependent on the interaction between backscattering of light by phytoplankton and that by sediments. But in the case of cyanobacterial blooms, water discoloration is adequate even in turbid water [10]. A second approach involves monitoring ecological parameters such as sea surface temperature and density [12] associated with ABs. For example, in temperate zones, transient upwelling actions exists which may lead to the development of SST patterns that initiate blooms. Several algorithms based on these techniques are developed for remote identification of blooms. *Shanmugam et al.* [9] proposes an algorithm to accurately compute the chlorophyll a (Chl-a) values based on the ratios of water leaving radiance (L_w) along with ABI (algal bloom index) using three bands in the visible region. Algorithm is generated using data from SeaWiFS sensor and is later fine-tuned to be applied to MODIS data. In another work, [5] reflectance signatures of several blooms were recorded using a hand-held spectrometer. Reflectance values for SeaWiFS and MERIS sensors were simulated using the collected data and the types of blooms were classified based on the SVD algorithm. When compared to the classification accuracies obtained using SeaWiFS and MERIS sensor reflectance values, this technique proved to be superior. *Park et al.* [7] developed a threshold map which is compared to MERIS and MODIS Chl-a data to detect bloom occurrences. Compute RedTide Index that can pin point regions of HAB from SeaWiFS image. The optical properties of water is used by *Amin et al.* [2], a technique for detection of blooms with low backscattering characteristics known as RBD is introduced. A multi-algorithm technique for classification of bloom and no-bloom regions based on an Empirical Approach and a Bio-optical Technique is proposed by *Carvalho et al.* [3]. Uniqueness of the spectral signatures of different blooms are exploited to generate a band ratio algorithm for classification of four species of algae by *Simon et al.* [11].

The spectral reflectance curve for each species of phytoplankton is unique, and with adequate information of the L_w values (and thereby the remote sensing reflectance values) over different wavelengths in the visible and near infra-red region, it is possible to study a pattern in the reflectance curves pertaining to each species. The technique for detection and classification of ABs presented here is based on this observation. Monitoring of blooms is based on data obtained from MODIS/Aqua images in waters of the Arabian sea and Bay of Bengal. Regularized least squares (RLS) algorithm is utilized for classification with the aid of GULRS library.

The remainder of this paper proceedes in the following structure: Section 2 states the importance of the selected study area and explains the technique through which the data set is acquired. The significance of the features upon which classification is based is justified in Section 3. The classifier used and the proposed methodology is also mentioned in this section. The classification results obtained along with the AB monitoring maps is presented in Section 4 and discussed in Section 5. The work is concluded in Section 6.

2. Materials

An explanation for why this study focuses on the bloom occurrences along the coastline of India is given in this section. The basis on which the six specific algae species are considered for classification are mentioned and the source of the data products are stated.

2.1. Region of Study

AB usually tend to occur in regions with high nutrient content like stagnant waters, generally in land-locked seas. But, despite the exposure to winds and currents of the Indian Ocean, AB reports reveal bloom dominance along the coast of India, especially along the south west coast. AB counts reach their peak values during the pre-monsoon and withdrawal of the south−west monsoon periods. Figure 1 shows the AB count in waters around India recorded for over a century, which was documented by *D'Silva et al.* [4]. The two types of phytoplankton that dominate blooms in this water, dinoflagellate and cyanobacteria are considered in this figure. An analysis of the ABs reported in the last five decades reveal that the most commonly occurring species of phytoplankton along the coast of India are *Trichodesmium erythraeum, Noctiluca scintillans/miliaris, Cocholodinium ploykrikoides, Chattonella marina* and *Karenia mikimotoi* [4].

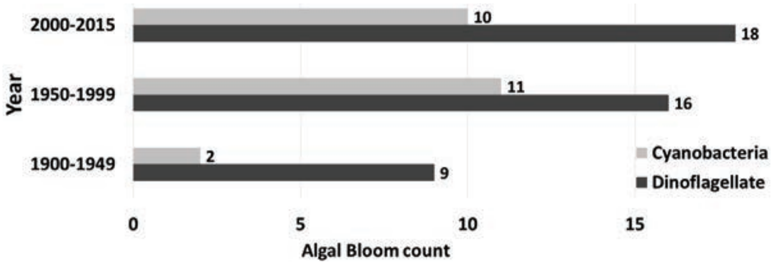


Fig. 1: Algal bloom count along the coast of India

2.2. Dataset

The work proposed in this paper is implemented using the images obtained from Moderate Resolution Imaging Spectroradiometer (MODIS) sensor onboard the Aqua spacecraft. Level zero MODIS images are procured from NASA Goddard Space Flight Center[1] and then processed using SeaDAS software (v 7.2) to obtain the required ocean features provided by the sensor. Among the several data products acquired from MODIS sensor observations, the chl-a, R_{rs} and nL_w (normalized water leaving radiance) are the products of prime interest in this work.

The MODIS images employed in this work, are date and location specific images corresponding to bloom occurrences contributed by either of the six species stated in[4]. The pixels pertaining to the bloom regions (mentioned in section 5) are extracted and the required information from each pixel such as latitude, longitude, chl-a, R_{rs} and nL_w values are saved in a spreadsheet. A combination of similar data from different images for a single species bloom (for eg:, *Trichodesmium erythraeum*), are clubbed to develop a dataset for that class of algae and is assigned a particular class label (for eg:, class label 1). Similarly the dataset is generated for all the six species and a certain percentage of the entire data is randomly chosen as training data and the remaining data is used for testing.

3. Methods

The ocean features exploited in this work along with their significance in terms of classification of blooms is justified in this section. The procedure undertaken by the RLS classifier is briefly explained along with the attempted work methodology.

3.1. Data Products: R_{rs} and L_w

In general, to study the optical properties of the ocean, the concept of albedo is taken into account. It is defined as the ratio of upwelling irradiance to downwelling irradiance, also known as irradiance reflectance[6], which is given by

$$R_{irr} = {}^{E_u}\!/_{E_d} \tag{1}$$

Where E_u is the upwelling irradiance and E_d is the downwelling irradiance at surface depth. But in the case of observation by a sensor onboard a satellite, it is not the isotropic incident radiance that is measured but rather a directional component. Hence we deal with the term *remote sensing reflectance*, which is defined as

$$R_{rs} = {}^{L_w}\!/_{E_d} \tag{2}$$

Where L_w is the water leaving radiance. It is the light that passes through the ocean and it is affected by the absorption and scattering of components present in the water. It is eventually scattered in an upward direction, where it leaves the sea surface and is captured by the sensor[6]. The L_w value contains information regarding the water column. Hence, these two parameters are considered for a range of wavelength values and the spectral reflectance patterns obtained for bloom and no bloom conditions are analyzed and form the basis on which classification is performed. The R_{rs} values taken in this work correspond to ten wavelength values in the visible region (412, 443, 469, 488, 531, 547, 555, 645, 667 and 678nm) and the L_w values correspond to sixteen wavelength values in the visible and near-infra red regions (412, 443, 469, 488, 531, 547, 555, 645, 667, 678, 748, 859, 869, 1240, 1640 and 2130nm).

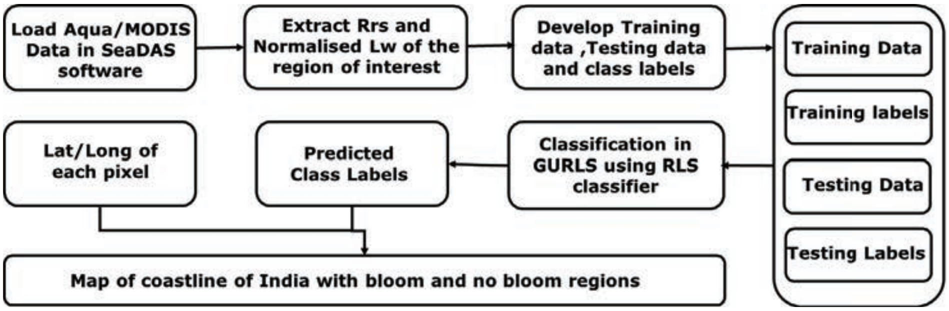


Fig. 2: Block diagram of the proposed AB monitoring method

3.2. RLS Classifier

Each data point essentially comprises of the R_{rs} and L_w features and hence can be thought of as $a_i \in R^N$, where $i \in Z_K = \{1, 2, ..., K\}$, K is the total number of data points and $N, K \in Z^+$. The labels representing each class belongs to set $Z_L = \{1, 2, ..., L\}$, where L is the number of classes. A supervised classification technique based on the RLS algorithm is employed in this case[8]. Consider a matrix of the data points $A = [a_1, a_2, ..., a_K]$ and let the class lables corresponding a_i be $b_i \in Z_L$. Consider the function $f : Z_L \to \mathbb{R}^M$ where $M \in \mathbb{N}^+$ such that $f(b_i) \neq f(b_j)$ when $b_i \neq b_j$ where $j \in Z_K$ then corresponding class label′s matrix is constructed as $B = [f(b_1), f(b_2), \ldots, f(b_K)]$. The principal idea behind the RLS algorithm[8] is to find an optimum weight matrix W for the optimization problem

$$\min_W ||B - WA||_F^2 + ||W||_F^2 . \tag{3}$$

Where $||.||_F$ stands for forbenious norm.

GURLS is a software library used in MATLAB for quick and efficient classification and regression operations. RLS algorithm based classification is implemented using GURLS library as a platform.

3.3. Methodology

The level zero image file obtained from MODIS sensor is processed in SeaDAS to include the desired ocean features such as Rrs and Lw. As can be studied from figure 2, once the pixels of the bloom regions are isolated (using the information stated in section 5) and assigned their respective class labels, they are grouped as training and testing data. About 40% of data points from each class are randomly chosen and set aside as testing data, while the remaining data is used as testing data. RBF kernel is used in GURLS library for classification, to which the training data, training label, testing data and testing label are given as input. Result of the classifier is an optimized weight matrix with which the predicted class labels are obtained. Having known the latitude and longitude values of each tested data points, the predicted class labels are used to generate a map showing no bloom and bloom regions (in case there is more than one species contributing to the bloom, the type of bloom can be inferred from the assigned class labels).

4. Results

Over three hundred thousand data points were used in this study, where each class had evenly distributed number of data points. The predicted class labels are compared with the original testing label to compute the accuracy of classification. When different optical features of water were considered separately for classification, good overall accuracies were obtained (as shown in table 1), probably owing to the large number of data points. The class-wise accuracies when both, Rrs and Lw features were taken into account is given in table 2.

Owing to the unavailabilty of MODIS images with more than one causative species for algal bloom, testing is performed on images with atmost one kind of algal bloom. The classifier is designed in such a way that it analyses the image pixelwise, independent of the neighbouring pixels. Thus it is capable of classifying images having one and more than one algal blooms with same accuracy. The generated maps for monitoring ABs is presented in figure 3. The

Table 1: Overall accuracies using different optical features.

R_{rs} and L_w	R_{rs}	L_w
94.37%	94.05%	94.28%

Table 2: Class-wise accuracy using R_{rs} and L_w values.

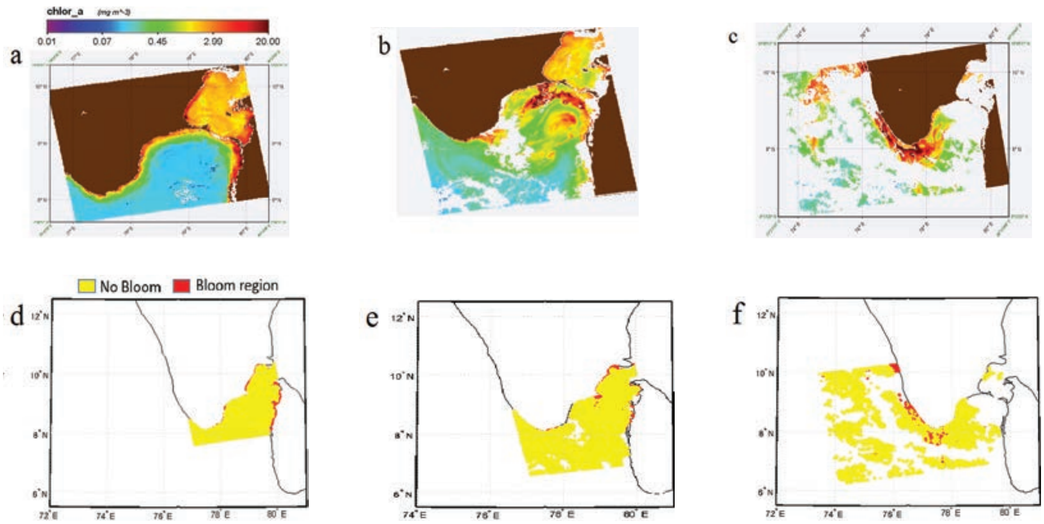
Class 1	Class 2	Class 3	Class 4	Class 5	Class 6	No Bloom
96.09%	99.38%	95.82%	98.61%	93.88%	95.89%	74.96%

subfigures 3a, 3b, 3c, 3g, 3h and 3i present chl-a maps computed from MODIS data procured from GSFC (NASA). While, the subfigures 3d, 3e, 3f, 3j, 3k and 3l are the generated maps, where each map has a bloom occurrence due to one of the six species of algae considered in this work. The maps given in figure 3 are not to scale.

5. Discussions

AB occurrences due to a variety of algae species is recorded by *D'Silva et al.*[4], where all the records have been explained with in-situ reading during the bloom period. These bloom reports provide as validation for this work, with whose knowledge we assign training and testing labels to each data point. It is against these labels that we test our results and compute classification accuracies. A classification map is generated showing bloom (Red pixels) and no bloom (yellow pixels) regions. These maps can be compared with the chl-a map obtained from MODIS data for the same day and location (as shown in figure 3).

Maximum number of ABs reported along the coast of India are due to *Trichodesmium erythraeum*. Amoung the several bloom reports used in this study, a few of these blooms are mentioned here. Along the coast, from Manglore to Kollam (9^o54'N to 12^o59'N and 74^o31'E to 75^o37'E) discoloration of water due to *Trichodesmium erythraeum* bloom was observed from 6th to 20th May 2005. A similar bloom was also studied off Kollam, Kochi and Kannur (8^o59'492"N to 11^o59'891"N and 74^o35'153"E to 75^o59'334"E) from 29th May to 11th June 2009. The AB monitoring map for *Trichodesmium erythraeum* bloom shown in figure 3, is of an AB that occurred in Mandapam and Keelakarai, Tamil Nadu (8^o35'N to 9^o25'N and 78^o08'E to 79^o30'E) that killed several fishes and shellfishes in the October of 2009.



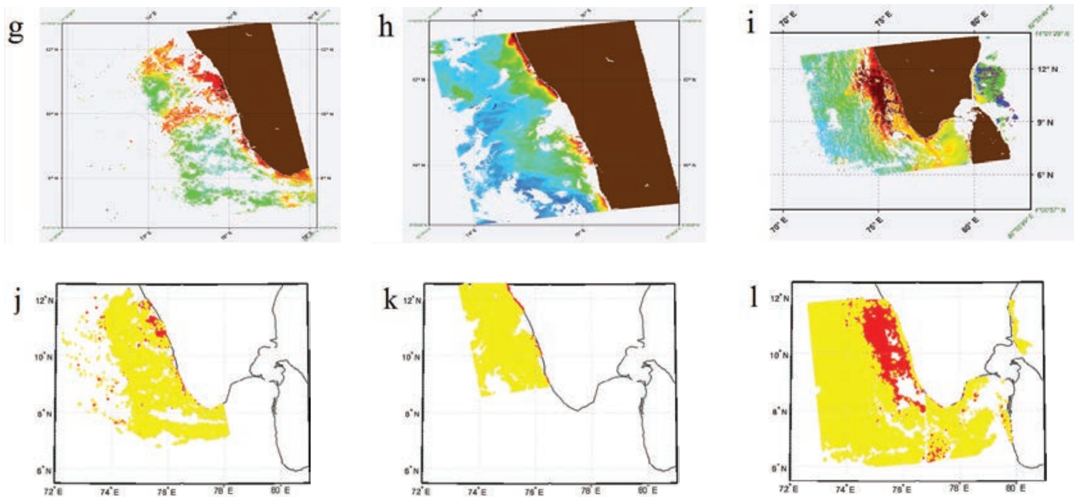


Fig. 3: Comparison of Classification Results with MODIS Chlorophyll-a data (a) Chl-a during *Trichodesmium erythraeum* bloom; (b) Chl-a during *Noctiluca scintillans* bloom; (c) Chl-a during *Noctiluca miliaris* bloom; (d) Classification during *Trichodesmium erythraeum* bloom; (e) Classification during *Noctiluca scintillans* bloom; (f) Classification during *Noctiluca miliaris* bloom; (g) Chl-a during *Cocholodinium polykrikoides* bloom; (h) Chl-a during *Chattonella marina* bloom; (i) Chl-a during*Karenia mikimotoi* bloom; (j) Classification during *Cocholodinium polykrikoides* bloom; (k) Classification during *Chattonella marina* bloom; (l) Classification during *Karenia mikimotoi* bloom.

Noctiluca scintillans blooms were recorded on 19th August 2008, off Kochi, Kerala (8^{o}52’N and 76^{o}34’26”E). On 20th December 2002, green coloration to water was observed at Minnie bay, PortBlair Andamans (6^{o}45’N to 13^{o}45’N and 92^{o}10’E to 94^{o}15’E) and a bloom that lead to red coloration of water was seen along the Rushikulya river, South Orissa coast (19^{o}22’N and 85^{o}02’E) on the 5th of April, 2005. The bloom studied in figure 3 due to *Noctiluca scintillans* was observed in the Gulf of Mannar (8^{o}55’N to 9^{o}15’N and 78^{o}E to 79^{o}16’E) from 2nd to 12th October 2008. It resulted in a deep green water colour, corals got bleached due to lack of oxygen and large number of fishes and sea animals died.

On March 2007, deep-green coloured water was observed off Gujrat coast (21^{o}00’33”N to 21^{o}50’32”N and 65^{o}01’02”E to 66^{o}09’38”E) due to *Noctiluca miliaris* bloom. Similar bloom occurred off Goa (15^{o}23’53”N and 73^{o}45’03”E) on 8th October 2008. In figure 3, a *Noctiluca miliaris* bloom that occurred off south Thiruvananthapuram, Kerala coast (8^{o}19’N and 76^{o}30’E) on 29th September 2004 is presented.

Gulf of Oman (23^{o}37’72”N and 58^{o}39’003”E) experienced adverse effects on fisheries from October 2008 to mid-January 2009 owing to *Cochlodinium Polykrikoides* bloom in its waters. A bloom due to the same algal species resulted in hospitalization of about 200 children and large scale fish mortality along the coast of Kerala (8^{o}59’492”N to 11^{o}59’891”N and 74^{o}35’153”E to 75^{o}59’334”E) on 17th September 2004. This *Cochlodinium Polykrikoides* bloom is monitored in figure 3.

In September 2002 and September 2003, fishery was affected from Calicut to Tellicherry, Kerala (11^{o}15’28”N and 75^{o}37’28”E) due to *Chattonella marina* bloom. An identical bloom took form in September 2009 off Kochi, Kerala (8^{o}52’N and 76^{o}34’26”E). The *Chattonella marina* bloom studied in figure 3, appeared in waters off Kozhikode, Kerala (11^{o}42’18”N and 75^{o}32’36”E) from 27th October to 1st November 2011.

A sudden discoloration of Karapad lagoon water in Gulf of Mannar (8^{o}46’374”N and 78^{o}09’477”E) was noticed from 2nd to 27th August 2013 due to the *Karenia mikimotoi* bloom in that region. Kochi barmouth, Kerala (9^{o}56’53”N and 76^{o}07’11”E) also had an indentical experience on 21st October 2009. Mass mortality of fish took place along Kerala coast (9^{o}58’N to 10^{o}10’N and 76^{o}10’94”E and 75^{o}56’E) during July to September of 2004 which was monitored in *Karenia mikimotoi* bloom in figure 3.

The classification results can be fine-tuned with in-situ matchups in order to obtain more accurate and validated maps of AB regions. Incorporation of physical ocean parameters such as SST, ocean currents and water density in addition to the optical properties can aid the study of AB monitoring with detailed knowledge of cause of blooms.

6. Conclusion

A large number of bloom occurances owing to one of the six algal species (*Trichodesmium erythraeum, Noctiluca scintillans/miliaris, Cocholodinium ploykrikoides, Chattonella marina* and *Karenia mikimotoi*) are considered for classification using the RLS classifier. The classification results are depicted using a map which monitors AB and no bloom condtions, and in case of a bloom it states the causative species. On a comparitive scale, an impressive overall accuracy of 94.37% was obtained during classification using the R_{rs} and nL_w ocean optical features. A brisk and efficient procedure for classification of ABs is propsed as the GURLS library is used for classification. The training data set can be expanded to include several additional AB occurances to improve the performance of the system. With an examination of physical ocean parameters related to ABs in addition to the optical features, cause of ABs can be studied in detail and frequency of bloom occurances can be reduced upto some extent.

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