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Research Article

An Empirical Algorithm using Derivative Difference for Estimating Chlorophyll-A in Case-II Water

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Abstract Water quality management includes measurement of quantity and quality. The abundance of phytoplankton in water body represents the physical condition and chemical constituents. As Chlorophyll-a exists in all types of phytoplankton, naturally the choice for water quality measurement is estimation of Chl-a concentration. The Chl-a concentration is estimated using various spectral reflectance algorithms such as single band regression, band ratio, three-band ratio, four-band ratio etc have been developed and is being used. Subsequently, the first order derivative ratio and second order derivative ratio methods are also used in some studies. Though such algorithms provide water quality measures, new algorithms are being introduced to improve estimation accuracy. In this paper, a new algorithm 'Derivative Difference' is proposed. It is based on the Chlorophyll concentration variation with shape of reflectance spectrum. The derivative data represents the slope of the reflectance data at different wavelength. The difference in derivative values at selected two different wavelengths were correlated with measured values to estimate Chl-a concentration. Obtained results were compared with the values obtained from band ratio method and derivative ratio methods. The algorithm is found to be better in some conditions.

Keywords *Remote sensing; Chlorophyll-a; Derivative; Spectroradiometer; Hyperspectral*

1. Introduction

The deterioration of water quality of inland water bodies is a serious ecological and social problem as they are the water resources for drinking, domestic, agricultural and industrial purposes. Management of quality of water bodies is essential to provide water to the ever increasing population and changing lifestyle. Water management activities usually include protecting water bodies from polluting elements, saving water and distributing it without wastage, i.e. managing the quality and quantity of water. While quantity management is maintaining capacity of water body by preventing encroachment and sedimentation, quality management is controlling the physical, chemical and bio-objects within the specified limit to enable usability of the water.

As the abundance of Chl-a content represents the physical and chemical characteristics of the water, Chlorophyll-a (Chl-a) concentration is a major indicator of eutrophic status and water quality (Moses et al., 2009). In case of ocean water (Case-I), the reflectance is dominated by the chlorophyll and the variation of reflectance can be attributed to the Phytoplankton abundance variation only. In contrast, the reflectance of in-land water (Case-II) is considerably affected by the optical properties of inorganic suspended matter and Colored Dissolved Organic Matter (CDOM). Hence the algorithms with blue-green bands used in case-I water is not suitable to case-II water. As CDOM absorption and particulate scattering decrease with increase in wavelength and become negligible in Red-infrared region, Red and Near Infrared (NIR) spectral region is extensively used to estimate Chl-a in Case-II water (Yu et al., 2014). As the physical and chemical components vary from lake to lake, the spectral bands suitable to measure the Chl-a for a particular lake may not suit to another lake. For every lake, suitable spectral bands are to be selected by comparing the estimated values from spectral bands combinations with laboratory-measured values.

The conventional method of quantifying Chl-a measurement is collecting samples from different locations of water body and measuring the chlorophyll-a concentration using spectrophotometer. This method needs field sampling, usage of chemical etc, which are time consuming, so difficult to perform for large area water bodies. Measuring certain optical properties like reflectance in different wavelength provides the concentration of the chlorophyll instantly. The spectral reflectance methods are used to estimate Chl-a in Aerial, Satellite and in situ measurements. The aerial surveys collect the spectral reflectance of the water bodies of small area and study the relation between reflectance spectrum with the chlorophyll-a. The satellite remote sensing provides a near real time, large scale and spatially continuous data in fixed time frequency, at less cost.

Many algorithms are developed to estimate the abundance of these constituents in water bodies like ocean, coastal, lakes and rivers based on spectral reflectance. The Chl-a estimation algorithms can be divided into two different categories: (i) Multiband models in the forms of ratios of different band combinations which utilizes the absorption bands of Chl-a in the red and NIR spectral region (Ruddick et al., 2001); and (ii) algorithms that use the Chl-a fluorescence emission around 685 nm (Gower et al., 1999).

The first group of algorithms are based on multispectral imaging. In this group, many algorithms have been developed using Red and NIR region spectral bands to estimate Chl-a concentration in eutrophic and turbid case II waters (Huang et al., 2014; Han et al., 2014). It covers single band, band ratio model (Hoge et al., 1987), three band models (Sathyendranath et al., 1989; Chen et al., 2013; Duan et al., 2010a, Tian et al., 2014), four band model (Le et al., 2009), five band model (Gohin et al., 2002), normalised differential chlorophyll index (NDCI) (Mishra and Mishra, 2012) etc. Some band ratio algorithms developed for the Chlorophyll estimation in terrestrial vegetation have also demonstrated in estimating Chl-a in water (Dall’Demo et al., 2003). As multispectral imageries are collected with less number of wide spectral bands, they cannot reflect minute variations like intensity variation in particular wavelength, intensity maximum shifting from wavelength to wavelength. As their output is integrated reflectance, change in reflectance with respect to narrow spectral bands is submerged in wider band.

The second group of algorithms are mainly based on Hyperspectral data, which provides almost continuous spectral measurements with hundreds of narrow spectral bands. They are: peak position near 700 nm (Gitelson, 1992); peak magnitude above baseline; area above baseline; first order derivative (Rundquist et al., 1996), second order derivative (Shi et al., 2007) and derivative ratio model (Tsai and Philpot, 1998) etc. Artificial neural network based algorithm (Chauhan et al., 2005), spectral decomposition method (Zhang et al., 2014), weighted algorithm (Yi, 2013), Spectral Vector Machine (SVM) based model (Sun et al., 2009) and three-band reflectance difference model (Duan et al., 2010b) are also used to estimate the chlorophyll-a concentration.

In this paper, a new algorithm called Derivative difference is introduced to estimate the Chl-a in Case-II water. The effectiveness of this algorithm in case-II water bodies is demonstrated using spectroradiometer data.

2. Materials and Methods

2.1. Methods

Among many factors affect the reflectance values of water, atmospheric absorption, CDOM, Organic Substance Sediments (OSS) are important. When we calculate the derivative values from reflectance, the effect of slowly changing factors with respect to wavelength such as atmosphere and CDOM are eliminated (Philpot, 1991). The derivative values provide the slope of reflective spectrum. These derivative values and derivative ratio values are used to estimate chlorophyll in many studies.

In the present study, as a new measure, the difference of derivative values at two different wavelengths has been used to estimate the chlorophyll-a. Obtained results are compared with the estimated values from both band ratio and derivative ratio methods. The estimated values obtained using this algorithm using spectroradiometer data were verified with measured values as well. Method, study area and results are described in following sections.

2.2. Study Area

The study area selected for this purpose is the Halasuru Lake, which is located at the heart of Bangalore city, India spread over the latitudes of 12° 58’ 41” N and 12° 59’ 15” N and longitudes of 77° 36’ 57” E and 77° 37’ 22” E, respectively. The area of the lake is approximately 125 Acres and is 930 m above the sea level. The depth of the lake varies from 3 m to 15 m and average depth of the lake is 5m. The main source of water to this lake is rainwater. It also receives direct industrial and domestic wastewaters from the surrounding area after aerated. The increased settlements near the lake is the cause for the pollution of the Lake. The satellite view of Halasuru Lake is shown in Figure 1.

Figure 1: *View of Halasuru Lake, Bangalore*

2.3. *In-situ* Reflectance Measurement using Spectroradiometer

In-situ measurements were carried out with spectro-radiometer at different locations of the lake. Sacchi disk measurement was also carried out to measure the Sacchi depth to avoid bathymetry radiation. The depth of lake at sample collection locations was much more than the Sacchi depth. The specular reflection from the water was avoided by carrying out the fieldwork between 9.30 AM and 11.00 AM local time. The locations of sample collection in Halasuru Lake are marked and shown in Figure 1.

Hyperspectral reflectance was measured using Analytical Spectral Devices, Field spec Pro spectro-radiometer with a spectral resolution of one nm and the spectral range from 350 nm to 1800 nm. During the measurement, the instrument was held 0.6 m above the water surface manually, 0.5 m away from the boat and the probe was directed vertically down towards water. During the measurement at each location, sampling of the radiance was carried out for 25 times and the final output is produced after averaging these values. Five such outputs were collected at each location. The radiance plots from those outputs from same locations were compared and the datasets with large errors were rejected. Good data sets were averaged to generate final radiance data. This procedure was followed for measurement of water radiance and reference plate (Lambertian reflector) radiance as well. When radiance of reference plate was measured, the reference plate was kept parallel to the water surface in sun light and the measurement probe was held normal to the surface. The Latitude and Longitude of sample collection location were recorded from a GPS system output.

The remote sensing reflectance spectra $R_{rs}(\lambda)$, were calculated as (Rundquist 1996; Han, 1997).

$$\mathrm{R_{rs}}(\lambda)_{\mathrm{meas}} = \frac{L_w(\lambda)}{L_{cal}(\lambda)} * R_{cal}(\lambda)\mathrm{x}\ 100 \ldots (1)$$

Where $L_w(\lambda)$ water leaving radiance, $L_{cal}(\lambda)$ scattered by reference plate and $R_{cal}(\lambda)$ reflectance of reference panel. At each sampling location, both water leaving radiance and reference radiance were measured without time gap.

2.4. Laboratory Measurements

Water samples were collected at a depth of 10 to 15 cm below the surface immediately after the reflectance measurements. Chl-a in the water was measured using the laboratory method (Jeffrey and Humbprey, 1975; Arar, 1997).

3. Analysis

3.1. Reflectance Spectra Analysis

As the reflectance variation due to Chl-a concentration is found to be between 350 to 800 nm and the absorption of radiation by water is more beyond 800 nm, hence spectro-radiometer data with wavelength between 350 and 800 nm was selected for study. The spectral reflectance of the samples collected from different locations is shown in Figure 2.

The reflectance spectra magnitudes in the region of 350 to 450 nm are low due to the high absorption of water in this region. The maximum absorption is seen at 440 nm. The reflectance spectra show a clear reflectance peak in the green region between 550 nm and 570 nm. After 570 nm the reflectance comes down steadily upto 630 nm and at 640 nm, an inflection is observed. The red absorption is peak around 670 nm. This is due to the combined effect of absorption of chlorophyll and water. After this, the reflection steadily increases up to the region around 705 nm (NIR) and this high reflectance is due to the fluorescence of chlorophyll-a (Neville and Gower, 1997). After this, the reflection decreases to the lowest level due to the absorption of water. Also, around 760 nm a small peak is seen in reflection spectra.

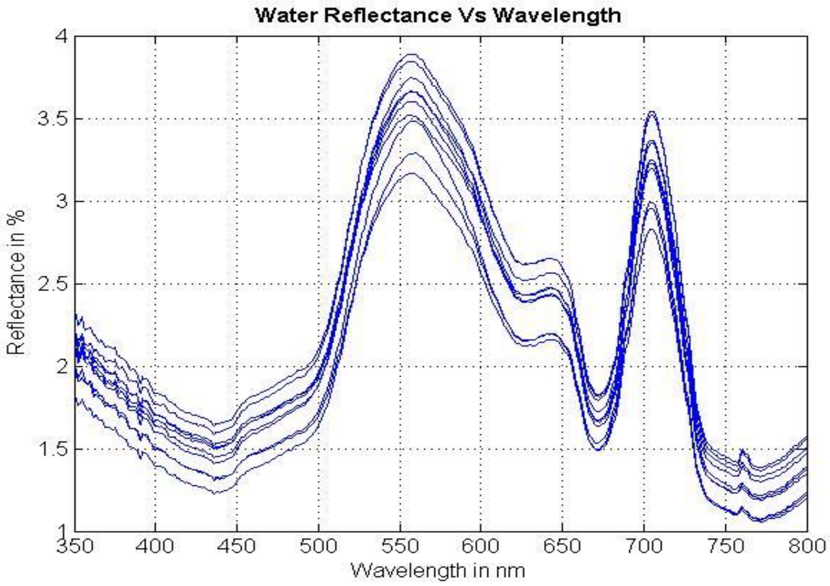

Figure 2: *Reflectance spectra of all samples*

3.2. Reflectance Band Ratio Methods

As the reflectivity in the NIR region R_{NIR} is due to the fluorescence of chlorophyll and is directly proportional to chlorophyll contents and the dip in reflectance in Red region R_{Red} is due to the absorption of Chl-a, and inversely proportional to reflectance in Red region, the Ratio R_{NIR}/R_{Red} will be directly proportional to the chlorophyll concentration. Hence, the ratio of NIR to Red reflectance will represent the chlorophyll-a concentration.

Table 1: *Top ten-correlation values obtained using the reflectance band ratio method*

	WL_1	WL_2	R^2
1	637	705	0.9042
2	637	703	0.9025
3	638	705	0.9017
4	637	702	09002
5	623	705	0.8995
6	637	706	0.8993
7	638	703	0.8981
8	629	709	0.8979
9	637	701	0.897
10	643	704	0.8957

3.3. First Order Derivative Values

The derivative values are calculated using following equation:

$$\text{Where, } R'_{\lambda n} = \frac{R_{\lambda n+1} - R_{\lambda n-1}}{\lambda(n+1) - \lambda(n-1)} \ldots (2)$$

Where $R_{\lambda n+1}$, $R_{\lambda n-1}$ are the reflectance at λn+1 and λn-1. These values provide the change in reflection with respect to small change in wavelength (1 or 2 nm).

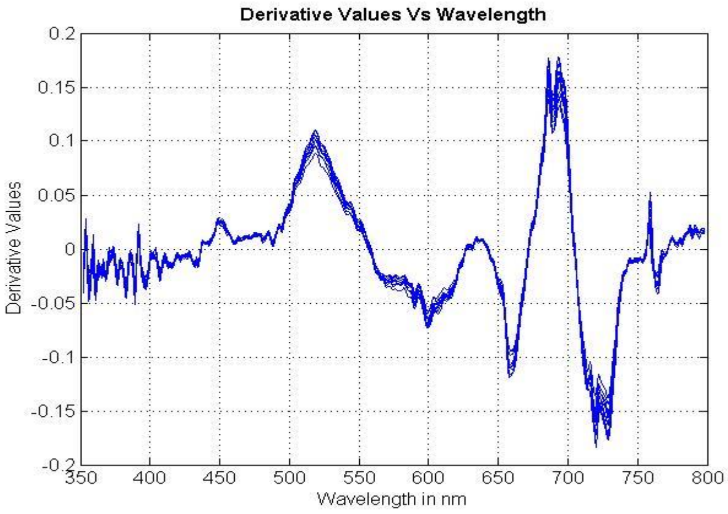

Figure 3: *First order derivative data*

Regression Analysis between Derivative Values and Chl-a

The derivative values of reflectance spectrums are correlated with measured chlorophyll values to estimate Chlorophyll-a (Huang et al., 2010). In this study, the derivative values are smoothened to reduce the noise and correlated with Chl-a values. The maximum correlation value 0.69 was found at wavelength of 678 nm. Smoothening was done with linear running mean filter with different window size. Following figure shows the derivative values smoothened by different window sizes.

Table 2: *Top ten-correlation values obtained using derivative values*

	Not smoothened		Smoothened with 1 x 3 windows		Smoothened with 1 x 5 windows		Smoothened with 1 x 7 windows	
	Wl (nm)	R^2	Wl (nm)	R^2	Wl (nm)	R^2	Wl (nm)	R^2
1	678	0.69	356	0.70	350	0.66	678	0.64
2	612	0.63	678	0.66	637	0.64	677	0.61
3	392	0.62	392	0.63	678	0.64	383	0.59
4	385	0.61	677	0.62	677	0.62	679	0.58
5	552	0.60	679	0.61	679	0.61	544	0.57
6	460	0.59	545	0.59	392	0.59	545	0.56
7	545	0.58	546	0.58	545	0.58	676	0.55
8	680	0.57	552	0.57	421	0.58	543	0.55
9	551	0.57	680	0.57	544	0.57	550	0.54
10	624	0.56	551	0.56	546	0.56	551	0.54

The maximum correlation value was achieved at 356 nm with 1 x 3 window smoothening. Many bands have shown better correlation in 678, 676nm range and 550-552 range. The R2 values are varying with the smoothening window size.

3.4. The First Order Derivative Ratio Method

The derivative ratio method combines the benefits of the ratio and derivative methods. In this method the ratio of first derivative at two different wavelengths is correlated with measured values of chlorophyll-a.

The ratio of first derivative can be computed as $P_{\lambda mn} = R'_{\lambda m}/R'_{\lambda n}$ … (3)

Where, $R'_{\lambda n} = \frac{R_{\lambda n+1} - R_{\lambda n-1}}{\lambda(n+1) - \lambda(n-1)}$

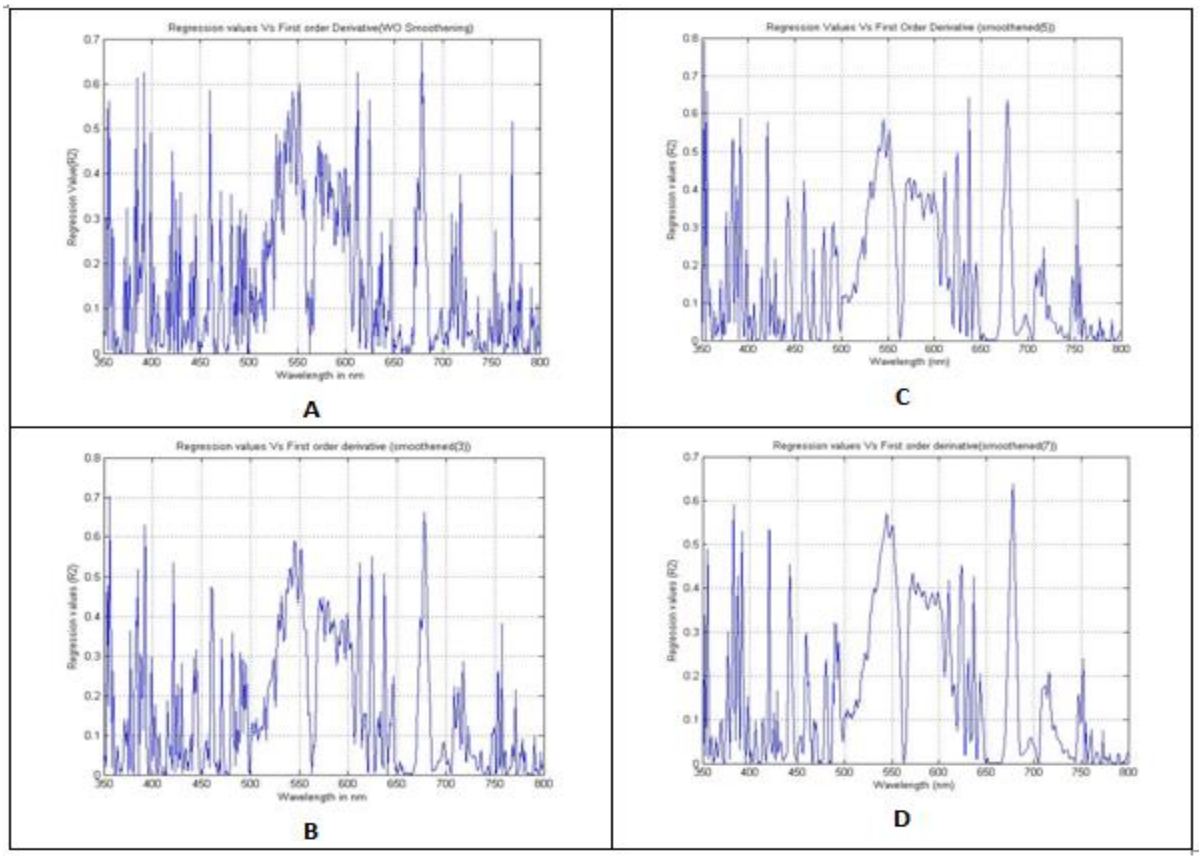

Figure 4: *Correlation between first order derivative values and measured Chl-a values at different wavelengths: A-without smoothening; B, C & D are smoothened with 1 x 3, 1 x 5 and 1 x 7 window running linear mean filter*

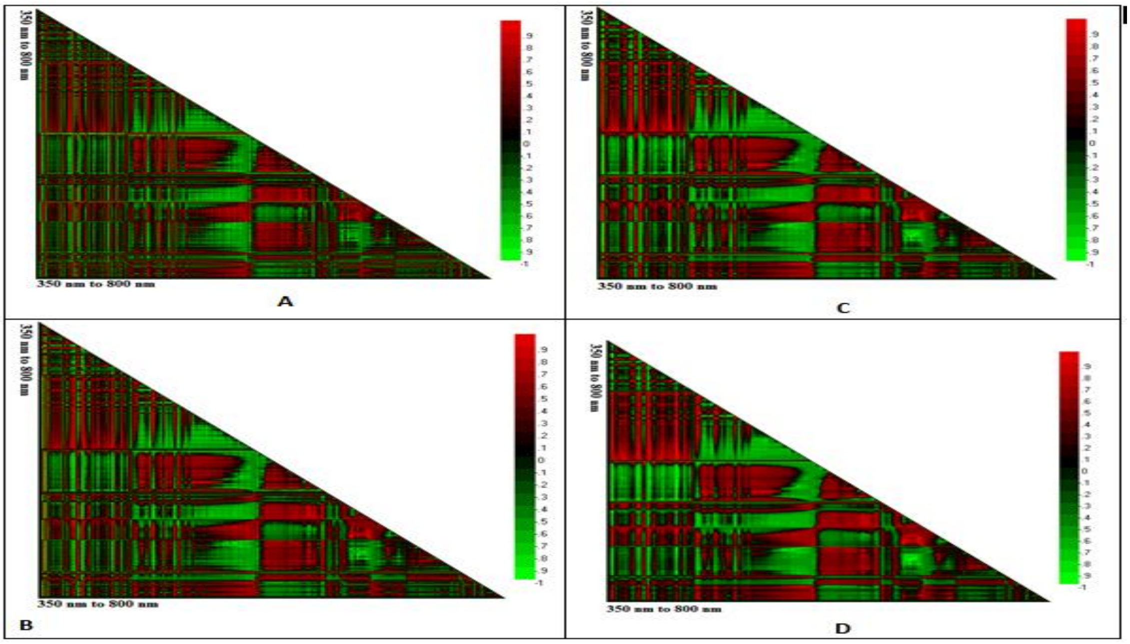

Figure 5: *The correlation of ratio of first order derivative values with measured Chl-values at different wavelengths: A-without smoothening; B, C& D are smoothened with 3, 5 and 7 window running average algorithm*

$P_{\lambda mn}$ is the ratio of first derivative, $R'_{\lambda n}$ is the derivative at λ_n and $R'_{\lambda m}$ is the derivative at λ_m. Computation of derivative, derivative ratio and regression between derivative ratio and the Chl-values were implemented in software. The correlation was calculated for all possible band combinations and results are presented in the Figure 5.

Table 3: *Top ten-correlation values obtained using derivative ratio values*

	Not smoothened			Smoothened with 1 x 3 values			Smoothened with 1 x 5 values			Smoothened with 1 x 7 values		
	B1	**B2**	**R^2**	**B1**	**B2**	**R^2**	**B1**	**B2**	**R^2**	**B1**	**B2**	**R^2**
1	460	473	0.9122	612	714	0.8925	421	460	0.9386	421	544	0.9667
2	460	486	0.8938	653	699	0.8885	356	376	0.9183	421	545	0.9645
3	612	715	0.8849	422	482	0.8823	421	539	0.8962	421	527	0.959
4	356	700	0.8778	356	796	0.8724	421	540	0.8923	420	545	0.959
5	356	703	0.8778	356	732	0.8506	653	696	0.8866	421	525	0.9559
6	612	683	0.8684	356	733	0.8481	421	611	0.8864	421	546	0.9553
7	356	649	0.8608	421	482	0.8398	421	749	0.8808	420	535	0.9495
8	356	758	0.8573	539	710	0.8374	421	543	0.8748	420	538	0.9487
9	356	720	0.8562	651	699	0.8323	355	615	0.8742	421	459	0.9399
10	666	735	0.8501	356	652	0.8317	421	546	0.8742	421	547	0.937

The high correlation was found with the wavelengths of 460 nm and 473 nm.

3.5. The Second Order Derivative Method

The higher order derivative methods for spectral analysis is proposed by Philpot (1991). The second order derivative values were used for chlorophyll estimation in many studies (Shi, 2007). The ratio of Second derivative is computed as

$$P_{\lambda mn} = R''_{\lambda m} / R''_{\lambda n} \ \ldots \ (4)$$

Where, $R''_{\lambda n} = \frac{R'_{\lambda n+1} - R'_{\lambda n-1}}{\lambda(n+1) - \lambda(n-1)}$

$P_{\lambda mn}$ is the ratio of second derivative, $R''_{\lambda n}$ is the second derivative at λn and $R''_{\lambda m}$ is the second derivative at λm. As the second order derivative values have noise and spikes, smoothening is recommended to get better results.

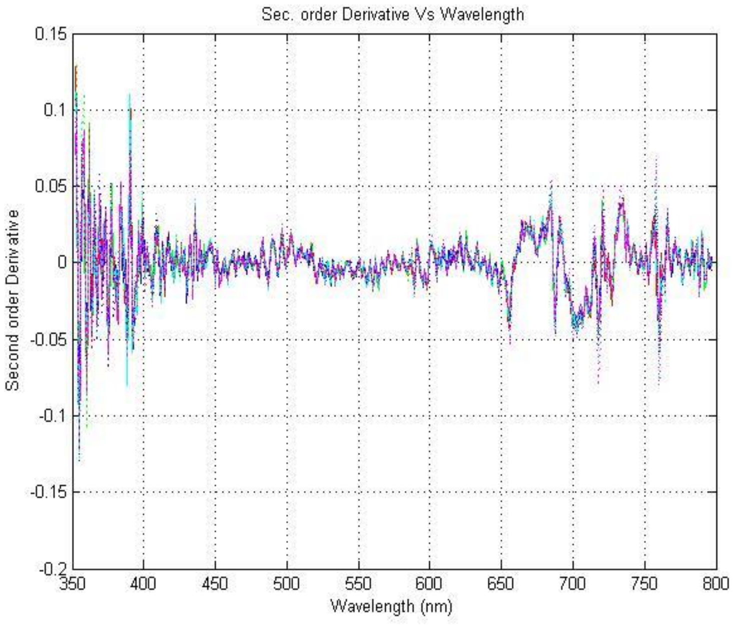

Figure 6: *Second order derivative data*

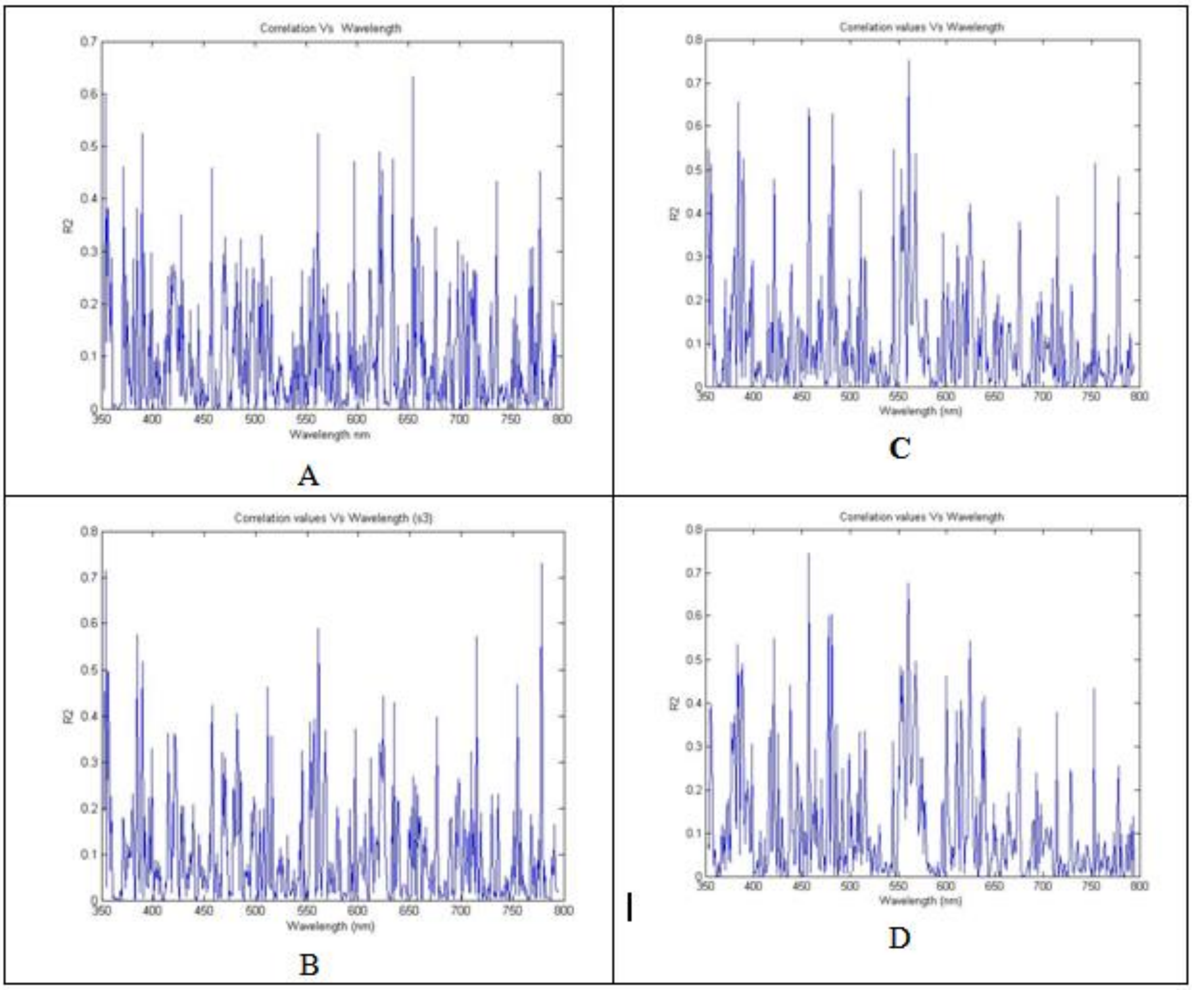

Figure 7: *Correlation between second order derivative values and measured Chl-a values at different wavelengths: A-without smoothening; B, C& D are smoothened with 1 x 3, 1 x 5 and 1 x 7 window running linear mean filter*

Table 4: *The high correlation values with second order derivative values*

	Not smoothened		**Smoothened with 3 windows**		**Smoothened with 5 windows**		**Smoothened with 7 windows**	
	Wl (nm)	**R^2**	**Wl (nm)**	**R^2**	**Wl (nm)**	**R^2**	**Wl (nm)**	**R^2**
1	654	0.6327	778	0.7312	565	0.752	457	0.7434
2	354	0.5963	354	0.7145	384	0.6561	560	0.6757
3	562	0.5246	561	0.5892	457	0.6402	481	0.6054
4	390	0.5243	385	0.5756	482	0.6276	561	0.5985
5	622	0.4892	715	0.5721	458	0.6064	478	0.5985
6	635	0.4750	390	0.5172	560	0.5887	421	0.5475
7	597	0.471	357	0.4966	545	0.5454	624	0.5423
8	372	0.4609	356	0.4952	353	0.5451	383	0.5335
9	458	0.4595	755	0.4683	568	0.5355	383	0.5027
10	624	0.4529	512	0.4614	389	0.5255	477	0.5012

3.6. The Second Order Derivative Ratio Method

The second order ratio method is used to estimate the chl-a Concentration.

The ratio of Second derivative is computed as $P_{\lambda mn} = R''_{\lambda m}/R''_{\lambda n}$ … (5)

Where, $R''_{\lambda n} = \frac{R'_{\lambda n+1} - R'_{\lambda n-1}}{\lambda(n+1) - \lambda(n-1)}$

$P_{\lambda mn}$ is the ratio of second derivative, $R''_{\lambda n}$ is the second derivative at λn and $R''_{\lambda m}$ is the second derivative at λm.

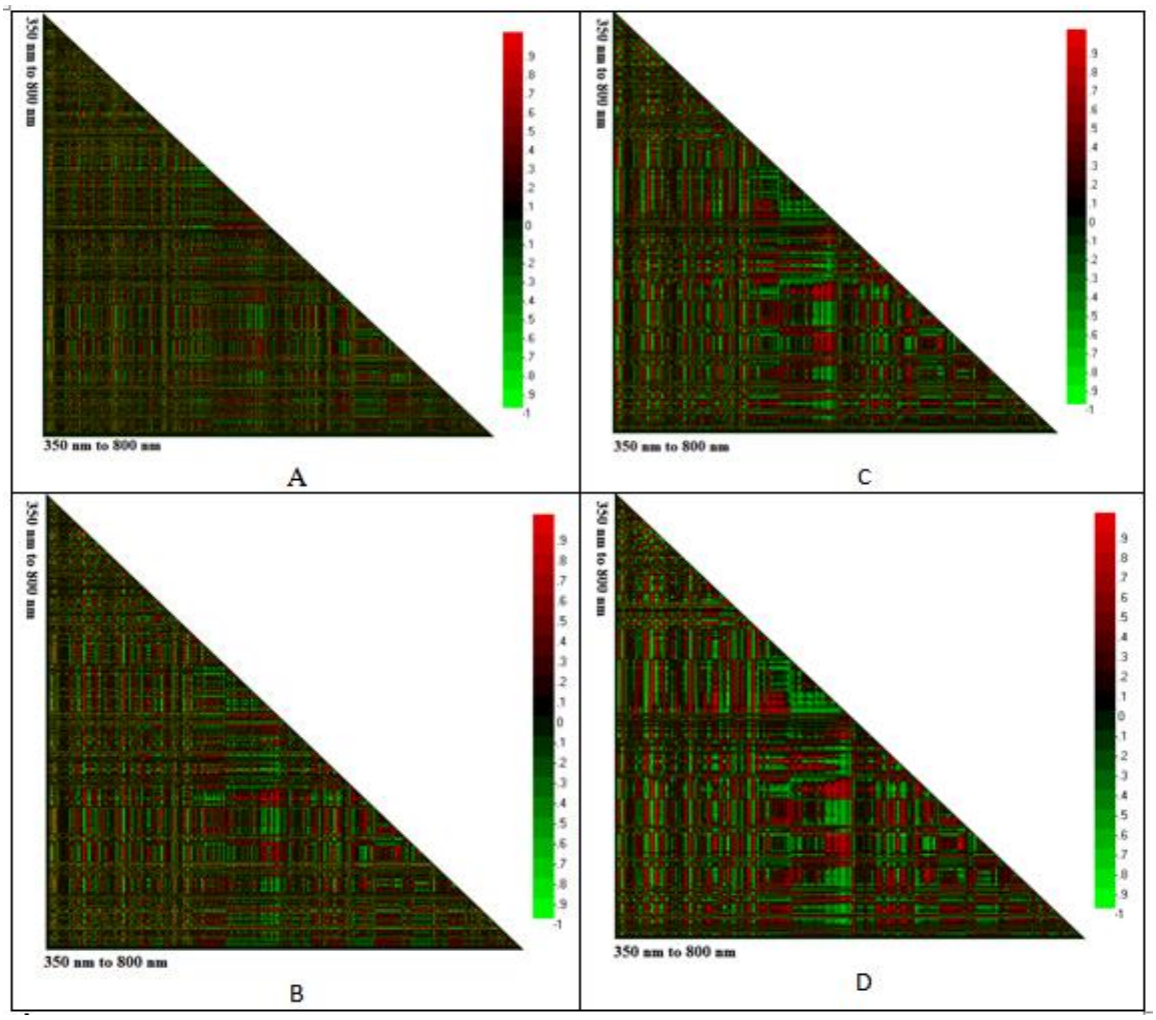

Figure 8: *The Correlation between ratio of second order derivative values and measured Chl-a values at different wavelengths: A-without smoothening; B, C & D are smoothened with 3, 5 and 7 window running average algorithm*

Table 5: *High ten-correlation values obtained using second order derivative ratio values*

2^{nd} rat	Not smoothened			Smoothened with 1 x 3 values			Smoothened with 1 x 5 values			Smoothened with 1 x 7 values		
	WL_1	WL_2	R^2	WL_1	WL_2	R^2	WL_1	WL_2	R^2	WL_1	WL_2	R^2
1	377	413	0.8675	708	735	0.8892	354	519	0.9314	681	709	0.9172
2	704	735	0.8578	355	501	0.8668	354	771	0.9160	399	647	0.8778
3	355	708	0.8490	355	562	0.8647	616	622	0.8997	447	500	0.8603
4	355	655	0.8328	355	677	0.8625	354	687	0.8953	681	708	0.8554
5	357	597	0.8325	386	398	0.8407	354	374	0.8849	399	497	0.8392
6	357	662	0.8286	355	712	0.8348	354	553	0.8819	353	545	0.8336
7	355	691	0.8277	355	704	0.8317	354	445	0.8765	556	696	0.8328
8	355	505	0.8219	386	527	0.8277	354	561	0.8757	497	616	0.8314
9	355	683	0.8098	355	734	0.8185	354	742	0.8696	458	553	0.831
10	424	577	0.8089	355	707	0.8181	459	562	0.8640	458	561	0.8301

3.7. Derivative Difference Method

In this study, a new algorithm called Derivative Difference method is introduced to estimate Chlorophyll-a. In this algorithm the difference between derivative values at different wavelengths were correlated with the measured Chl-a values.

Difference of First Order Derivative

The difference of first order derivative can be computed as $P'_{\lambda mn} = R'_{\lambda m} - R'_{\lambda n}$ … (6)

Where, $R'_{\lambda n} = \frac{R_{\lambda n+1} - R_{\lambda n-1}}{\lambda(n+1) - \lambda(n-1)}$

$P_{\lambda mn}$ is the Difference of first order derivative, $R'_{\lambda n}$ is the derivative at λn and $R'_{\lambda m}$ is the derivative at λm.

Difference of Second Order Derivative

The difference of Second order derivative can be computed as $P''_{\lambda mn} = R''_{\lambda m} - R''_{\lambda n}$ … (7)

Where, $R''_{\lambda n} = \frac{R'_{\lambda n+1} - R'_{\lambda n-1}}{\lambda(n+1) - \lambda(n-1)}$

$P''_{\lambda mn}$ is the difference of second order derivative, $R''_{\lambda n}$ is the second order derivative at λn and $R''_{\lambda m}$ is the second order derivative at λm.

This method was used on raw data, first order derivative data and second order derivative data, individually. The results are tabulated and shown below in Table 6-8.

Table 6: *High ten-correlation values obtained using difference method on raw data*

	Not smoothened			Smoothened with 1 x 3 values			Smoothened with 1 x 5 values			Smoothened with 1 x 7 values		
	WL_1	**WL_2**	**R^2**	**WL_1**	**WL_2**	**R^2**	**WL_1**	**WL_2**	**R^2**	**WL_1**	**WL_2**	**R^2**
1	650	693	0.8167	650	693	0.8111	650	693	0.8064	650	693	0.8057
2	651	693	0.8066	651	693	0.8053	651	693	0.8043	648	694	0.8001
3	355	359	0.8032	632	694	0.8005	646	693	0.8005	651	693	0.7976
4	646	694	0.7989	652	693	0.7942	652	693	0.7875	645	693	0.7901
5	650	694	0.7901	642	694	0.7882	633	394	0.7875	649	694	0.788
6	647	693	0.7885	650	694	0.7866	645	693	0.7859	630	695	0.7868
7	652	693	0.7850	634	694	0.7809	650	694	0.7878	628	693	0.7813
8	633	694	0.7834	631	695	0.7799	641	694	0.7813	652	693	0.7806
9	639	695	0.7829	645	693	0.7792	637	694	0.7726	653	692	0.7802
10	642	694	0.7816	631	693	0.7681	632	695	0.7718	650	694	0.7783

Table 7: *High ten-correlation values obtained using difference method on first order derivative data*

	Not smoothened			Smoothened with 1 x 3 values			Smoothened with 1 x 5 values			Smoothened with 1 x 7 values		
	WL$_1$	WL$_2$	R^2	WL$_1$	WL$_2$	R^2	WL$_1$	WL$_2$	R^2	WL$_1$	WL$_2$	R^2
1	422	611	0.9266	475	482	0.9397	648	672	0.9283	379	677	0.9052
2	425	430	0.922	422	612	0.9199	610	671	0.8934	379	678	0.8904
3	392	401	0.9101	436	624	0.9122	611	671	0.8898	610	671	0.8752
4	428	678	0.9021	648	671	0.8949	356	379	0.8774	375	678	0.8591
5	624	678	0.8936	610	671	0.8898	648	673	0.8752	613	671	0.8529
6	399	545	08921	610	672	0.8815	376	678	0.8748	612	671	0.8527
7	666	736	08797	648	673	0.8780	611	672	0.8744	609	670	0.8512
8	476	624	08683	612	671	0.8709	609	671	0.8712	611	671	0.8477
9	385	625	08527	498	681	0.8573	421	749	0.8647	613	670	0.8462
10	356	732	0.8517	356	615	0.8569	427	678	0.8591	426	678	0.8440

Table 8: *High ten-correlation values obtained using difference method on second order derivative data*

	Not smoothened			Smoothened with 1 x 3 values			Smoothened with 1 x 5 values			Smoothened with 1 x 7 values		
	WL$_1$	WL$_2$	R^2	WL$_1$	WL$_2$	R^2	WL$_1$	WL$_2$	R^2	WL$_1$	WL$_2$	R^2
1	517	705	0.8836	512	562	0.9434	354	366	0.9628	433	566	0.8510
2	509	563	0.846	355	396	0.8707	354	397	0.9226	467	561	0.8420
3	609	691	0.8259	355	397	0.856	372	605	0.9101	422	616	0.8347
4	600	716	0.8199	355	385	0.8435	354	603	0.9071	562	778	0.8265
5	655	789	0.8174	505	562	0.8361	354	404	0.8974	458	562	0.8237
6	633	655	0.816	562	636	0.8225	354	604	0.8919	458	553	0.8226
7	459	655	0.815	513	623	0.8183	616	622	0.8879	601	640	0.8201
8	373	417	0.8147	386	626	0.8016	562	779	0.8776	458	482	0.8194
9	517	704	0.8141	355	456	0.7944	354	596	0.8770	459	561	0.8190
10	598	779	0.8104	562	779	0.7937	459	546	0.8739	353	545	0.8131

Table 9 compiles the effectiveness of the derivative difference methods w.r.t to derivative ratio and band ratio methods.

Table 9: *Comparison of the derivative difference results with derivative ratio and band ratio*

	Without Smoothening	Smoothened with 1 x 3 window	Smoothened with 1x 5 window	Smoothened with 1 x 7 window
Raw data Band Ratio	0.9042	0.8987	0.8945	0.8936
Raw data Band Difference	0.8167	0.8111	0.8064	0.8057
1st order derivative ratio	0.9122	0.9139	0.9386	0.9667
1st order Derivative Difference	0.9266	0.9397	0.9283	0.9052
2nd order Derivative Ratio	0.8808	0.8945	0.9314	0.9172
2nd order Derivative Difference	0.8836	0.9434	0.9628	0.8510

4. Conclusion

Chlorophyll concentration was estimated with band ratio, derivative ratio and derivative difference methods. The suitable wavelength sets vary slightly with smoothening window size. From Table 9, it is found the 1 x 5 window provides better correlation values. It is noticed that while proposed band difference method provided a poor correlation with raw data, it provides improved high correlation results with derivative data. The results of proposed difference method on derivative data has provided highest determination coefficient uniformly in 1st order and 2nd order derivative difference methods. It is to be noted from Tables 1-8, the correlation coefficients due to band ratio and derivative methods are poorer and mostly effective for a narrow range of wavelengths; on the other hand the correlation coefficients due to derivative difference methods provide very good measure across all wavelength bands.

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