

# Influence of sea surface temperature and chlorophyll-a on the distribution of particulate organic carbon in the southwest Bay of Bengal

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Abstract: Particulate Organic Carbon (POC) plays a vital role in the ocean carbon cycle. POC is responsible for large fluxes of carbon and is linked to many important ocean biogeochemical processes. Nowadays, improved ocean colour sensor provides better understanding of the Sea Surface Temperature (SST), chlorophyll-a and POC distribution in the oceans with good spatial resolution. Better retrieval of POC from satellite data is envisaged to improve our ability to study the ocean biogeochemical cycle. In this context, the present study was carried out to understand the spatial and temporal changes of POC in the year 2017. Validation of VIIRS derived SST, chlorophyll-a and POC with in-situ measurements showed the better correlation of SST ( $R^2 = 0.77$ , Mean Normalized Bias (MNB) = ±0.004, Root Mean Square Error (RMSE) =  $\pm 0.23$  and Standard Error of Estimate (SEE) =  $\pm 0.42$ ), chlorophyll-a (R<sup>2</sup> = 0.74, MNB =  $\pm 0.035$ , RMSE =  $\pm 0.13$ , and SEE = $\pm 0.23$ ) and POC (R<sup>2</sup> =0.73, MNB =  $\pm 0.011$ , RMSE = $\pm 89.42$ , and SEE = $\pm 29.53$ ) in the southwest Bay of Bengal respectively. The basin average of monthly composited VIIRS data showed the maximum chlorophyll-a (0.54 µgl-1) and POC (108.72 mgCm<sup>-3</sup>) during monsoon in the month of November and minimum chlorophyll-a (0.25 µgl-1) and POC (62.60 mgCm<sup>-3</sup>) observed during summer in the month of May. In contrast, monthly composite SST showed the minimum basin average (27.77°C) during monsoon in the month of December and the maximum (30.76°C) during summer in the month of May due to increased incoming solar radiation with cloud free sky compare to monsoon which experienced dense cloud cover with decreased light intensity at the surface of the ocean. The multiple regression analysis between POC, SST and chlorophyll-a demonstrated the better agreement between the variable with  $R^2$  of 0.66 POC = 195.040 - 5.310 (SST) + 110.059(chl a) and suggested the strong positive influence of chlorophyll-a on the distribution of POC while the SST acted in a reverse manner in the southwest Bay of Bengal. The observed positive relationship between chlorophyll-a and POC in multiple linear regression analysis suggesting the influence of monsoon inputs and primary production on the distribution of POC. However, the negative relationship between SST and POC in MLR depicted that the increased SST hindered the primary production rate due to the strong stratification at the surface layers which results the unavailability of nutrients at the surface waters.

Keywords:SST, Chlorophyll-a, POC, validation, regression, southwest Bay of Bengal

# 1. Introduction

The exchange of carbon dioxide  $(CO_2)$  between the atmosphere and ocean is a critical component of the global carbon cycle and climate system (Sabine et al., 2004; Gruber et al., 2009). The ocean plays an important role in the global carbon cycle as it is a sink for about half of the anthropogenic carbon production (Sabine et al., 2004). An improved knowledge of the Particulate Organic Carbon (POC) reservoir is of interest to research on ocean biogeochemical cycles, ocean ecosystems, and climate studies relating to the ocean carbon cycle (Houghton, 2007).

POC plays a vital role in the ocean carbon cycle. The POC is responsible for large fluxes and is linked to many important ocean biogeochemical processes. The satellite ocean-color signal is influenced by particle composition, size and concentration and provides a way to observe variability in the POC pool at a range of temporal and spatial scales. There are many studies on the distribution of POC in the Pacific and Atlantic Ocean (Romankevich, 1984; Gordon and Cranford 1985; Yoro et al., 1997). However, little information is available on the distribution of POC (Bhosle et al., 1988) in the Indian Ocean in general, and in the Bay of Bengal in particular (Radhakrishna et al., 1978; Bhattathiri et al., 1980; Nandakumar et al., 1987).

Sea Surface Temperature (SST) is a fundamental variable at the ocean-atmosphere interface (Donlon et al., 2009). It affects the complex interactions between atmosphere and ocean at a variety of scales. Thus, SST datasets with high quality are needed for many applications, such as operational monitoring, numerical weather, and ocean forecasting, climate change research, and so on (Tu et al., 2015). SST data are often used in combination with chlorophyll-a to relate bloom events to mixed layer depths (Villareal et al., 2012) or upwelling zones (Thomas et al., 2012; Shi and Wang, 2007). Moreover, they are an important factor in marine carbon cycling and energy fluxes (Hedges, 2002; Hoikkala et al., 2015; Kuliński et al., 2014).

In many coastal regions, the resuspension of sediments is also an important source of POC. Bottom POC concentration in a shallow sea can rise up to three times under the influence of resuspension when the wind speed increases (Hung et al., 2000). Furthermore, physical mechanisms constitute important control factors for POC distribution. For example, convective mixing induced by decreasing temperature is the main reason for POC to

exhibit a uniform vertical profile in the water column (Zhao et al., 2003). Most importantly, evidence of sinking particles carrying POC out of the euphotic zone, a potential strategy to sequester CO<sub>2</sub> from the atmosphere, is still poorly understood. Bay of Bengal receives large influx of fresh water that decreases the sea-surface salinity. Moreover, the presence of weak winds (<10 m s -1) and warm sea-surface temperature (>28°C) results in strong stratification of the surface of the ocean and hence laver. shallowing the mixed SST and sea surface salinity (SSS) are directly related to surface heat and freshwaterfluxes. More importantly, these surface values are linked to atmospheric circulation, and their inter-annual variability, could have implications for larger-scale climate. As a result, low or no nutrients are injected into the surface waters thereby, influencing biological production (Kumar et al., 2007). However, the efficiency of the biological carbon pump to sequester atmospheric CO<sub>2</sub> and export particulate organic carbon from the surface is not well known. Nowadays, the availability of satellite derived ocean color products such as chlorophyll-a and POC has been the focus of numerous studies in the ocean observations at a large extent.

Although, the spatial distribution and seasonality of POC have been described in several reports (Gustafsson et al., 2014; Hoikkala et al., 2015; Kulinski et al., 2011; Maciejewska and Pempkowiak, 2014), only few studies are available in the validation of POC (Haeentjens et al., 2017; Szymczycha et al., 2017; Swirgon and Stamska, 2015). Similar such works are scanty in the Bay of Bengal that pertained on the POC distribution of and spatio-temporal variability. Hence our present study aimed to assess the spatial and temporal variability of POC and its interrelationship with SST and chlorophyll-a in the coastal waters of the southwest Bay of Bengal.

#### 2. Materials and Methods

The Bay of Bengal is north-eastern part of the Indian Ocean, extended between the latitude 5°N to 30°N and longitude 80°E to 105°E (Figure 1). This is a semi enclosed basin alike the Arabian Sea, bounded by India on the west, by Bangladesh, Myanmar, and part of India on the north, and Burma and Malaysia in the east. The present study was carried out along the Tamilnadu coast falling in the southwest Bay of Bengal viz., transect of our study area are in Chennai, Cuddalore, Parangipettai and Nagapattinam, which are major prominent coastal stations in the east coast of Bay of Bengal.

### 1.1. In-situ measurements

In-situ SST,chlorophyll-a and POC were measured at five fixed sampling stations along the southwest coast of Bay of Bengal from 2nd February to 4th February 2018. On 2nd February Nagapattinam station was covered, 3rd February Parangipettai and Cuddalore stations were covered and 4th February Chennai station was covered. The stations were fixed with the help of Global Positioning System (GPS) at 5 km from shore and at an interval of 1 km between sampling point.Water samples were collected at the surface waters by using a Niskin water sampler. Sea Surface Temperature (SST) was measured using a digital multisensor of  $\pm 0.01^{\circ}$ C accuracy (Merck Millipore-Multi 3420). The SST measurements were carried out using handeld multisensor temperature probe in the surface waters and the data was transmitted through USB interface. Chlorophyll-a concentration was measured by following the method of UNESCO (1994) using UV-VIS spectrophotometer (Shimadzu- UV 2450), calibrated previously with standard chlorophyll-a (Sigma – C6144), using 90% acetone. POC concentrations were determined by combustion of sample filters through pre treated 47mm Whatman GF/F filters and samples were treated with chromic acid fumes to remove the inorganic carbon and estimation were done by following the standard methods described by Parsons et al. (1984).



#### 2.2. Remote sensing observations

Satellite measurements greatly increases the spatial and temporal extent of observations available for characterizing SST, Chlorophyll-a and POC dynamics and their relations to various dominant physical forcings to the surface ocean specifically POC from satellite images to understand the dynamics and cycling of carbon in the ocean. The Suomi National Polar-orbiting Partnership (SNPP) satellite Visible Infrared Imaging Radiometer Suite (VIIRS) derived 1 km SST, chlorophyll-a and POC image were acquired from the Ocean colour web for 3rd February 2018. The satellite derived images were processed by using SeaDAS 7.4 ver. software for interpretation and analysis. Validation of satellite derived SST, chlorophyll-a and POC products were done by using concurrent in-situ measured SST, chlorophyll-a and POC data in the southwest Bay of Bengal.

#### 2.3.Statistical analysis

The evaluation process involved comparing satellite derived values with the field measurements. Statistical fitting was applied to these data using SigmaPlot (Ver.12.0) statistical software. Mean Normalized Bias (MNB), Root Mean Square Error (RMSE) and Standard Error of the Estimate (SEE) were analyzed to test the performance between insitu and satellite. Standard error of the estimate (SEE) has been used to provide a numerical index in between satellite and insitu data performance and graphical criteria such as regression plots provide indication of the linear behavior of the fit.Mean normalized bias is a measure of the over or underestimation of the true values. Root mean square error provides a good measure of data scatter for normally distributed variables and gives useful information of the accuracy between satellite and in-situ data. These errors are defined as follows,

$$SEE = \sqrt{\frac{\sum(X-X^{1})^{2}}{N}}$$
(1)  
$$RMSE = \frac{1}{N} \sum \sqrt{(X-X^{1})^{2}} - - - (2)$$
$$MNB = \frac{1}{N} \sum \frac{(X-X^{1})}{N} - - - (3)$$

Where X = insitu data,  $X^1 = satellite data and N = number of points.$ 

Multiple Linear Regression (MLR), is the simplest and most analogues to the bivariate techniques commonly used and thus provide the most readily interpretable results. It was carried out to calculate the values of a dependent variable, given a set of predicted variables which was used to determine the extent to how the variables contributed to the POC concentration.

#### 3. Results and Discussion

The satellite images of SNPP-VIIRS derived SST, chlorophyll-a and POC were retrieved on 3<sup>rd</sup> February 2018 covering the southwest Bay of Bengal (Figure 2-4).

#### 3.1. Validation of VIIRS derived SST

VIIRS derived SST data was validated with in-situ data to evaluate the performance of VIIRS and exhibited the good agreement with significant correlation co-efficient of  $R^2 = 0.77$  with Standard Error of Estimation (SEE) of ±0.42, Mean Normalized Bias (MNB) of 0.004 and Root Mean Square Error (RMSE) of ±0.23 (Figure 2). The data points fall outside of the 95% confidence band suggests that the satellite derived values were higher or lower than they should be in natural waters. The relationship between the in-situ and VIIRS derived SST showed a highly significant relationship. Tu et al., (2015) investigated comparison between the VIIRS SST and insitu SST, based on the overall comparison result showed that all types of in situ SST have very high correlation with the VIIRS SST. Similarly, our study also showed good correlation between in situ SST and VIIRS SST.

#### 3.2. Validation of VIIRS derived chlorophyll-a

VIIRS derived chlorophyll-a data was validated with insitu data to evaluate the performance of VIIRS and exhibited the good agreement with significant correlation co-efficient (R2) of 0.74 with SEE of  $\pm$ 0.24, MNB of 0.038 and RMSE of  $\pm$ 0.13 (Figure 3). The relationship between in-situ and VIIRS derived chlorophyll-a showed very less significant relationship due to uncertainties. VIIRS shows higher spatial coverage and detection accuracy than MODIS, after coefficient improvement. VIIRS is also able to predict chlorophyll-a with 53% accuracy (Zeng et al., 2016). Validation of the VIIRS ocean color products by inter-comparison with in situ observations, confirming good matchup of the water, leaving radiance between ship and VIIRS data (Arnone et al., 2012).

# 3.3 Validation of VIIRS derived POC

Validation of VIIRS derived POC showed good agreement with insitu estimations of POC (R<sup>2</sup>=0.73, SEE  $= \pm 29.50$ , MNB  $= \pm 0.01$  and RMSE  $= \pm 89.42$ ). Recently (Everskings et al., 2017) five different POC empirical algorithms were validated with in situ data. Among the five algorithms, Stramski et al., (2008) found the better algorithm for the better retrieval of POC. It is therefore important to continue the validation work to improve the reliability of in-situ and satellite POC determinations. Haeentjens et al., (2017) validated the float POC with VIIRS and MODIS derived POC. Float-based POC estimates agree well with NASA's algorithm, but also exhibit a large spread (relativelylow prediction capability) in matchups. The uncertainty of the POC for both sensors(MODIS  $R^2 = 0.44$  and VIIRS  $R^2 = 0.40$ ) is very close to the one from the algorithm used (Stramski et al., 2008) which has Root mean square differences (RMSD) =21.3 mg m-3, Root mean square relative deviation (RMSRD) =21.7%, R<sup>2</sup>=0.87, for N=53 suggesting the POC derived from VIIRS agrees well with the float POC within uncertainty specified



Figure 2: a) SNPP-VIIRS derived (3<sup>rd</sup> February 2018) image of SST; b) Regression plot of *in-situ* SST Vs VIIRS derived SST



Figure 3: a) SNPP-VIIRS derived (3<sup>rd</sup> February 2018) image of chlorophyll-a; b) Regression plot of *in-situ* chlorophyll-a Vs VIIRS derived Chlorophyll-a



Figure 4: a) SNPP-VIIRS derived (3<sup>rd</sup> February 2018) image of POC; b) Regression plot of in-situ POC Vs VIIRS derived POC

# 3.4. Seasonal variability of SST

Seasonal variability of SST in the southwest Bay of Bengal was studied from the monthly composite images of VIIRS derived SST (Figure 5). The SST concentration has been varied from 26.7 to 31.1°C in the southwest Bay of Bengal and registered its highest concentration (31.1°C) at Nagapattinam during the Summer season and the lowest concentration observed during the Post monsoon (26.7°C) at Nagapattinam coastal waters.

The basin scale averages of SST in the southwest Bay of Bengal clearly indicate the seasonal pattern of SST with the maximum SST in the month of May  $(30.76^{\circ}C)$  (Figure 6) during summer season. The minimum SST concentration was observed during December  $(27.06^{\circ}C)$  month of monsoon followed by January  $(27.08^{\circ}C)$ ,

February (27.25<sup>o</sup>C) during the postmonsoon season. As SST increases in summer there is a concurrent thermal stratification of the water column in the vertical dimension and the thermocline (the strongest gradient of temperature) progressively deepens. In contradictory, SST decreases during monsoon and early postmonsoon of January and February vertical mixing is enhanced and thermal stratification reduced until well mixed conditions are reached in monsoon again. During the premonsoon season SST was moderately present in July, August and September around 29<sup>o</sup>C. This process explains SST patterns at large latitudinal gradients depending on seasonal variation in atmospheric temperatures. This clearly depicted the well-known bi-modal distribution of surface temperature (Colborn, 1975) in the Bay of Bengal



Figure 5: SNPP-VIIRS monthly composite of SST from January to December in the year 2017



Figure 6: Seasonal variation of basin averaged SNPP-VIIRS derived Sea surface temperature in the southwest Bay of Bengal

#### 3.5 Seasonal variability of chlorophyll-a

Seasonal variability of chlorophyll-a in the southwest Bay of Bengal was studied from the monthly composite images of VIIRS derived chlorophyll-a (Figure 7). The chlorophyll-a concentration has been measured as a representative of the phytoplankton biomass varied from 0.13 to 2.31  $\mu$ gl<sup>-1</sup> in the southwest Bay of Bengal and registered its highest concentration (2.31  $\mu$ gl<sup>-1</sup>) at Nagapattinam during monsoon season and the lowest concentration observed during the summer (0.13  $\mu$ gl<sup>-1</sup>) at Cuddalore coastal waters. However, the chlorophyll-a concentration was high in Palk Bay region throughout th year.

Monthly means of chlorophyll-a concentrations (Figure 8) shows clear seasonal pattern with the highest concentration  $(0.60 \mu gl-1)$ during premonsoon (September) followed by monsoon and the lowest value (0.25 µgl-1) was recorded during summer (May). Hence the annual variability indicated that the southwest Bay of Bengal was productive during premonsoon and monsoon seasons rather than the postmonsoon and summer seasons.Higher chlorophyll-a concentration is found during the premonsoon and monsoon due to windinduced upwelling in the north Indian Ocean compared to other oceans (Yoder, 2001), and also the runoff from southern rivers could explain the enhanced level of nutrients and associated elevated chlorophyll-a (Kumar et al., 2010). During summer, the chlorophyll-a distribution was less due to the incoming solar radiation was higher because of cloud absence combining with low winds, resulting in highly stratified mixed layer depth. This inhibited any vertical mixing, and hence there was no input of nutrients from the subsurface to the upper ocean (Kumar et al., 2010).

# 3.6. Seasonal variability of POC

Seasonal variability of POC in the southwest Bay of Bengal was studied from the monthly composite images of VIIRS derived POC (Figure 9). The satellite derived POC concentration varied from 50.59 to 304.19 mgCm<sup>-3</sup> in the southwest Bay of Bengal. The POC level was found highest (304.19 mgCm<sup>-3</sup>) during the monsoon season at Nagapattinam coastal waters, whereas the lowest POC concentration (50.59mgCm<sup>-3</sup>) observed during summer season at Cuddalore coastal waters.

The mean values of POC obtained from spatial and temporal distribution pattern (Figure 10) shows moderate seasonal variation in Southwest Bay of Bengal. The highest POC value (111.163 mgCm<sup>-3</sup>) is observed during early postmonsoon season is January 2017 followed by monsoon season (November 108.721 mgCm<sup>-3</sup>). The distribution of POC was found minimum during summer season in May (62.599 mgCm<sup>-3</sup>). During the premonsoon season POC concentration was moderate (90 - 100 mgCm<sup>-3</sup>). Similar such distribution pattern was observed for chlorophyll-a also in Southwest Bay of Bengal, which clearly suggested the interrelationship between chlorophyll-a and POC.

The spatial distribution of the surface POC concentration in the ocean is generally governed by both the biological processes specifically in primary production and physical process particularly vertical mixing and advection (Stramska, 2014). The significance of the different processes can vary in time and space. Higher values were in fact present in monsoon season because surface primary production is high in the Bay of Bengal during monsoon (Qasim, 1977). Moreover large amount of suspended matter containing high organic matter is introduced into the Bay by major rivers flowing through the various geological formations of the Indian subcontinent (Rao, 1985). Probably this high amount of organic matter and primary production are responsible for the higher values of POC observed during monsoon season. In summer typically have low POC concentration because significant away from the source of nutrients, that the lower primary production might be inhibited due to water stratification (Huang et al., 2013). Accordingly, the POC concentrations are low during May and June, when the values of spatially averaged POC concentrations was 62.599 mgCm-3. By November and December, POC concentrations in the Southwest Bay of Bengal are more often greater than 111.163 mgCm<sup>-3</sup>



Figure 7: SNPP-VIIRS monthly composite of chlorophyll-a from January to December in the year 2017



Figure 8: Seasonal variation of basin averaged SNPP-VIIRS derived Chlorophyll-a in the southwest Bay of Bengal



Figure 9: SNPP-VIIRS monthly distribution of POC from January to December in the year 2017



Figure 10: Seasonal variation of basin averaged SNPP-VIIRS derived Particular Organic Carbon in the southwest Bay of Bengal

# 3.7. Relationship between SST, chlorophyll-a and POC

The pixel/data points falling in the box of concurrent latitude 7.8-14.5N/longitude 77.2 to 82.5E covering the entire southwest Bay of Bengal was taken from the entire image. This was used to generate the mean value of monthly images of SST, chlorophyll-a and POC by using SeaDAS software. Monthly mean value for each dataset were plotted as bar plots to understand the variability in respective timescale and seasons in the figure 6, 8, 10. The resultant mean values of SST, chlorophyll-a and POC in the year of 2017 were analyzed by linear regression of variance on ranks using SigmaPlot (ver. 11) software to distinguish the effects of variables (Figure 11). The differences in the mean values among the different seasons was observed in the year of 2017. There was a statistically significant difference (P =<0.001) between seasons in the distribution of SST, chlorophyll-a and POC.

SST measurements are based on the quantification of infrared radiation leaving the ocean surface (Njoku, 1990) within the spectral range of 650–1200 nm. Water vapor is the largest source of uncertainty in space-borne SST measurements. In Bay of Bengal, (Poornima et al., 2018) stated there is no clear interannual variation in the SST and chlorophyll-a over the decade with the consistent seasonal pattern.

In this study an attempt was made to find the linear relationship between SST, chlorophyll-a and POC. The relationship was found inversely proportional to the SST and chlorophyll-a observed with the  $R^2 = 0.54$ , SEE =  $\pm 1.03$ . Similary, SST and POC also found a negative correlation of the  $R^2 = 0.54$ , SEE =  $\pm 1.03$ .The better agreement between chlorophyll-a and POC observed with the  $R^2=0.58$ , SEE =  $\pm 1.02$  relationship was found positive suggesting that the POC distribution in the southwest Bay of Bengal was highly dependent on the distribution of phytoplankton biomass rather than other physical parameter.



Figure 11: a) Regression analysis of Sea Surface Temperature and Chlorophyll-a, b) Regression analysis of Sea Surface Temperature and Particular organic carbon and c) Regression analysis of Chlorophyll-a and Particular Organic Carbon

3.7. 1. Regression analysis of SST and Chlorophyll-a In this study an attempt was made to find the linear relationship between SST and chlorophyll-a observed the  $R^2 = 0.54$ , SEE =  $\pm 1.03$  and the relationship was found inversely proportional to the SST and chlorophyll-a. Analysis of relationship between SST and chlorophyll-a increases our understanding of the productivity of the ocean. Satellite images provide reliable important oceanographic information on conditions and simultaneously support marine environmental monitoring and assessment (Nurdin et al., 2014). The present study showed the relationship between the SST and Chlorophyll-a was good around 29°C. When SST was high chlorophyll-a productivity is less. A similar relationship has earlier been reported from the Indian Ocean (Goes et al., 2005).

# 3.7.2. Regression analysis of Particulate Organic Carbon and SST

The regression analysis between SST and POC was found inversely correlated to the  $R^2 = 0.55$ ,  $SST = \pm 1.03$ . The observed higher POC formation rate at low temperatures is in a good agreement with observations of (Kang and Cleasby 1995). The POC was less in summer obviously chlorophyll-a also less due to high temperature. Chlorophyll-a showed a fairly good significant positive co-relationship with POC (Fernandes et al., 2009). However, SST was a negative correlation with POC and Chlorophyll-a. Further more, physical mechanisms constitute important control factors for POC distribution. For example, convective mixing induced by decreasing temperature is the main reason for POC to exhibit a uniform vertical profilein the water column (Zhao et al., 2003; Delu et al., 2015).

# 3.7.3. Regression analysis of Particulate Organic Carbon and Chlorophyll-a

Chlorophyll-a and POC shows the significant relationship of R<sup>2</sup>=0.52 and SEE=±0.07. This suggests that an important portion of the POC is composed of marine diatoms, dinoflagellates and/or brown algae which contain chlorophyll-a (Dougherty et al., 1970). Many studies have focused on the relationship between POC and Chlorophyll-a concentration (Morel, 1988; Buck et al., 1996; Legendre and Michaud 1999; Morel et al., 2006) and found the strong correlation between in-situ data with satellite data. They noted that, since chlorophyll-a is readily estimated from satellite data, such relationships provide a simple avenue for estimating POC from satellite data. They also pointed out the importance of POC in ecosystem models as the food source for zooplankton. Linear regression of POC on chlorophyll-a has been used to derive the phytoplankton fraction of the carbon from the slope of the fit, on the assumption that there is a back-ground of POC at sea that is not associated with phyto-plankton (Steele & Baird 1961, Townsend & Thomas 2002, Behrenfeld et al., 2005). The variability observed in the relationship between total carbon and chlorophyll-a arises from 2 main sources, variability in the proportion of non phytoplanktonic particulate carbon and variability in the phytoplankton carbon. The former type of variability is related to the status of the ecosystem as a whole, whereas the latter may be associated with changes in the phytoplankton community itself or with its acclimation to the light or nutrient regime.

#### 3.8. Multiple Linear Regression (MLR)

Multiple regression was employed in order to ascertain the influence of SST and chlorophyll*a* with the dependent variable of POC.

### POC = 195.040 - 5.310 (SST) + 110.059 (chl a) -----(4)

The above multiple regression equation represent the dependent variable of POC the distribution of chlorophyll-a was highly positively correlated and strongly negatively correlated of SST on the distribution of POC while the SST acted in a reverse manner in the southwest Bay of Bengal. Comparsions of VIIRS POC and Modelled POC (Figure 12) provided reasonably good performance on the POC derivations with RMSE =  $\pm$  84.06, Mean Relative Error(MRE) = 45.42 %. in the southwest Bay of Bengal. Moreover, the NASA standard POC algorithm has MRE of ~42% for the open ocean (Swirgon and Stamska, 2015) implies that the performance of present algorithm is acceptable for coastal waters.





450

400

Figure 12: a) Modelled POC image around SW Bay of Bengal b): Comparision between VIIRS Satellite POC and modelled POC

### Conclusion

Ocean colour remote sensing has long been recognized as a powerful means for the study of the world's oceans. The present study has clearly shown that *in-situ* Chlorophyll-a and POC concentration was high during monsoon compared to other seasons (POC= 108.72 mgCm-3 and Chl  $a= 0.54 \mu$ gl-1). In contradictory, SST decreases during monsoon and increases during summer due to vertical mixing is enhanced and thermal stratification reduced until well mixed conditions are reached in monsoon.

The observed positive relationship between chlorophyll-a and POC in multiple linear regression analysis suggesting the influence of monsoon inputs and primary production on the distribution of POC. However, the negative relationship between SST and POC in MLR depicted that the increased SST hindered the primary production rate due to the strong stratification at the surface layers which results the unavailability of nutrients at the surface waters. Moreover, the seasonal distribution of SST, chlorophyll-a and POC in the southwest Bay of Bengal is influenced by the seasonally reversed monsoon winds, especially southwest monsoon winds which play vital role in enhancing the primary productivity in the coastal waters. However, the northeast monsoon winds and seasonal rainfall also take part in enhancing the productivity during monsoon season.

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# References

Arnone, R., G. Fargion, P. Martinolich, S. Ladner, A. Lawson, J. Bowers, M. Ondrusek, G. Zibordi, Z.P. Lee, C. Trees, C. Davis and S. Ahmed (2012). Validation of the VIIRS Ocean Color: SPIE Defense and Security Ocean Sensing and Monitoring IV, Baltimore, MD. 8372 83720G-1. https://doi:10.1117/12.922949.

Behrenfeld, M. J., E. Boss, D. A. Siegel and D. M. Shea (2005). Carbon based ocean productivity and phytoplankton physiology from space, Global Biogeochemical Cycles, 19, 1-14.

Bhattathiri, P.M.A., V.P. Devassy and K. Radhakrishna (1980). Primary production in the Bay of Bengal during southwest monsoon of 1978, Mahasagar-Bull. National. Institute of Oceanography, 13, 315–323.

Bhosle, N.B., V.M. Dhople and A.B. Wagh (1988). Distribution of particulate organic carbon in the central Arabian Sea, Procreeding Indian Academy Science, Earth Planetary Science, 97, 35-47. Buck, K.R., F.P. Chavez and L. Campbell (1996). Basinwide distributions of living carbon components and the inverted trophic pyramid of the central gyre of the North Atlantic Ocean, summer 1993, Aquatic Microbe Ecology, 10, 283–298.

Colborn, J. G., (1975). The upper layer thermal structure of the Indian Ocean, International Indian Ocean Expedition Monograph No. 2 Honolulu: East-West Central Press, University of Hawaii.

Delu, P, L. Qiong and B. Yan (2015). Review and suggestions for estimating particulate organic carbon and dissolved organic carbon inventories in the ocean using remote sensing data. Acta Oceanologica Sinica, 33(1),pp. 1–10.

Donlon, C. J., I. Robinson, K. S. Casey, J. Vazquez-Cuervo, E. Armstrong, O. Arino, C. Gentemann, D. May, P. LeBorgne, J. Piolle, I. Barton1, H Beggs, D. J. S. Poulter, C. J. Merchant, A. Bingham, S. Heinz, A Harris, G. Wick, B. Emery, P. Minnett, R. Evans, D. Llewellyn-Jones, C. Mutlow, R. Reynolds, H. Kawamural and N. Rayner (2009). The Global Ocean Data Assimilation Experiment (GODAE) high Resolution Sea Surface Temperature Pilot Project (GHRSST-PP), Oceangraphy Magazine.

Dougherty, R.C., H.H. Strain and W.A. Svec (1970). The structure, properties, and distribution of Chlorophyll Journal of American Chemical Society, 92(9), 2826–2833.

Eversking, H., V.M. Vicente, R. J. W. Brewin, G. D. Olmo, A. E. Hickman, T. Jackson, T. S. Kostadinov, H. Krasemann, H. Loisel, R. Rottgers, S. Roy, D. Stramski, S. Thomalla, T. Platt and S. Sathyendranath (2017). Validation and intercomparison of ocean color algorithms for estimating particulate organic carbon in the oceans, Frontier Marine Science, 4(251), 1-20.

Goes, J.I., P.G. Thoppil, R. Gomes and J.T. Fasullo (2005). Warming of the Eurasian landmass is making the Arabian Sea more productive, Science, 308(5721), 545–547.

Gordon, D. C. and P.J. Cranford (1985). Detailed distribution of dissolved and particulate organic matter in the Arctic Ocean and comparison with other oceanic regions, Deep Sea Research I, 32, 1221-1232.

Gruber, N., M. Gloor, S.E.M. Fletcher, S. C. Doney, S. Dutkiewicz, M. J. Follows, M. Gerber, A. R. Jacobson, F. Joos, K. Lindsay, D. Menemenlis, A. Mouchet, S. A. Muller, J. L.Sarmiento and T. Takahashi (2009). "Oceanic Sources, Sinks, and Transport of Atmospheric CO<sub>2</sub>." Global Biogeochem. Cycles, 23, 1-21.

Gustafsson, E., Deutsch, B., Gustafsson, B.G., C. Humborg and C. M. Morth (2014). Carbon cycling in the Baltic Sea the fate of allochthonous organic carbon and its impact on air-sea  $CO_2$  exchange. Journal of Marine System, 129, 289-302.

Haeentjens, N., E. Boss, and L. D. Talley (2017). Revisiting ocean color algorithms for chlorophyll-a and particulate organic carbon in the Southern Ocean using biogeochemical floats, Journal of Geophysics Research Oceans, 122, 6583–6593.

Hedges, J.I. (2002). Why dissolved organics matter. In: Hansell, D.A., Carlson, C.A. (Eds.), Biogeochemistry of Marine Dissolved Organic Matter. Elsevier Sci., San Diego, 1-33, http://dx.doi.org/ 10.1016/B978-012323841-2/50003-8.

Hoikkala, L., P. Kortelainen, H. Soinne and H. Kuosa (2015). Dissolved organic matter in the Baltic Sea. Journal of Marine System, 142, 47-61.

Houghton, R. A., (2007). Balancing the global carbon budget, Annual Review of Earth and Planetary Sciences, 35(1), 313–347.

Huang W-J, W.J. Cai, R.M. Castelao, Y. Wang and S.E. Lohrenz (2013). Effects of a wind-driven crossshelf large river plume on biological production and CO2 uptake on the Gulf of Mexico during spring, Limnology and Oceanography, 58(5), 1727–1735.

Hung, C.C., G. T. F. Wong, K.K. Liu, F.K. Shiah, and G.C. Gong (2000). The effects of environmental conditions on the relationship between nitrate reductase activity and NO<sub>3</sub>– uptake, field observations in the East China Sea, Limnology Oceanography, 45, 836–848.

Kang, L.S. and J.L. Cleasby (1995). Temperature effect on flocculation kinetics using Fe(III) coagulant. Journal of Environment Engineering, 121, 893–901.

Kulinski, K., J. She and J. Pempkowiak (2011). Short and medium term dynamics of the carbon exchange between the Baltic Sea and the North Sea, Continental Shelf Research, 31 (15),1611-1619.

Kulinski, K., B. Schneider, K. Hammer, U. Machulik, and D. Schulz-Bull (2014). The influence of dissolved organic matter on the acid-base system of the Baltic Sea, Journal of Marine System, 132, 106-115.

Kumar, S.P., M. Nuncio, N. Ramaiah, S. Sardessai, J. Narvekar, V. Fernandes and J. T. Paul (2007). Eddymediated biological productivity in the Bay of Bengal during fall and spring intermonsoons, Deep Sea Research I, 54(9), 619-1640.

Kumar, S.P., J. Narvekar, M. Nuncio, A. Kumar, N. Ramaiah, S. Sardessai, M. Gauns, V. Fernandes and J. T. Paul (2010). Is the biological productivity in the Bay of Bengal light emitted?, Current Science, 98,1331-1339.

Legendre, L. and J. Michaud (1999). Chlorophyll-a to estimate the particulate organic carbon available as food to large zooplankton in the euphotic zone of oceans, Journal of Plankton Research, 21, 2067–2083.

Maciejewska, A., and J. Pempkowiak (2014). DOC and POC in the water column of the southern Baltic, Part I. Evaluation of factors influencing sources, distribution and concentration dynamics of organic matter, Oceanologia, 56 (3), 523-548.

Journal of Marine Systems, 77,137–147.

Morel, A., 1988. Optical modeling of the upper ocean in relation to its biogenous matter content (case I waters), Journal of Geophysics Research, 93, 10749-10768.

Morel, A., B. Gentili, M. Chami, and J. Ras (2006). Biooptical properties of high chlorophyll Case 1 waters and of yellow-substance-dominated Case 2 waters, Deep-Sea Research, I., 53,1439–1459.

Nandakumar, K., K., Venkat and N.B. Bhosle (1987). Distribution of particulate organic carbon in the central Bay of Bengal, Procreeding Indian Academy Science, (Earth Planetary Science), 96,189–193.

Njoku, E. G. (1990). Satellite remote sensing of sea surface temperature, In G. L. Geernaert & W. J. Plant (Eds.), Surface waves and fluxes, 2, 211–338.

Nurdin, S., M.A, Mustapha and T. Lihan (2014). The relationship between sea surface temperature and chlorophyll-a concentration in fisheries aggregation area in the archipelagic waters of spermonde using satellite images, Conference: Universiti-Kebangsaan-Malaysia, Faculty-of-Science-and-Technology. DOI: 10.1063/1.4858699.

Parsons, T.R., Y. Maita and C.M. Lalli (1984). A manual of chemical and biological methods for seawater analysis, 1.7, Determination of Silicate. Pergamon Press,Oxford; New York, 25–27.

Poornima, D., R. Shanthi, L. Senthilnathan, T. Thangaradjou, A. Saravanakumar and R. K. Sarangi (2018). Decadal Pattern of Spatial and Temporal Variability of Nitrate Along the Southwest Bay of Bengal Using Remote Sensing Techniques, Journal of the Indian Society of Remote Sensing. doi.org/10.1007/s12524-018-0915-7(0123456789().,-volV)

Qasim, S. Z. (1977). Biological productivity of the Indian Ocean, Indian Journal of Marine Science, 6, 122-137.

Radhakrishna, K., P.M.A. Bhattathiri, and V.P. Devassy (1978). Primary productivity of the Bay of Bengal during August – September 1976, Indian Journal of Marine Science, 7, 94–98.

Rao, C. H. M., (1985). Distribution of suspended particulate matter in the waters of eastern continental margin of India, Indian Journal of Marine Science, 14, 15-19.

Romankevich, E.A., (1984). Geochemistry of Organic Matter in the Ocean, Springer-Verlag, Berlin, 304-336.

Sabine, C. L., R. A. Feely, N. Gruber, R. M. Key, K. Lee, J. L. Bullister, R. Wanninkhof, C. S. Wong, D.W.R. Wallace, Bronte Tilbrook, F. J., Millero, T.H., Peng, A., Kozyr, T. Ono and A. F. Rios (2004). The oceanic sink for anthropogenic CO2, Science, 305(5682), 367–371.

Shi, W., and M. Wang, (2007). Observations of a Hurricane Katrina-induced phytoplankton bloom in the Gulf of Mexico, Geophysical Research Letters, 34.

Steele, J.H. and I.E. Baird (1961). Relations between primary production, chlorophyll-and particulate carbon, Limnology Oceanography, 6, 68–78.

Stramska, M., (2014). Particulate organic carbon in the surface waters of the North Atlantic, spatial and temporal variability based on satellite ocean colour, International Journal of Remote Sensing, 35(13), 4717–4738.

Stramski, D., Reynolds, R.A., Babin, M., Kaczmarek, S., Lewis, M.R., Rottgers, R., Sciandra, A., Stramska, M., Twardowski, M.S., B.A. Franz, and H. Claustre (2008). Relationship between the surface concentration of particulate organic carbon and optical properties in the eastern South Pacific and eastern Atlantic Oceans, Biogeosciences, 5,171–201.

Swirgon, M., and M. Stramska (2015). Comparison of insitu and satellite ocean color determinations of particulate organic carbon concentration in the global ocean, Oceanologia, 57, 25-31.

Szymczycha, B., A. Winogradow, K. Kulinski, K. Koziorowska and J. Pempkowiak. (2017). Diurnal and seasonal DOC and POC variability in the land-locked sea, Oceanologia., 59, 379-388.

Thomas, A.C., P.T. Strub, R.A.Weatherbee and C.James (2012). Satellite views of Pacific chlorophyll variability:

comparisons to physical variability, local versus nonlocal influences and links to climate indices, Deep Sea Research Part II, Topical Studies in Oceanography, 77(80), 99-196.

Townsend, D.W. and M.Thomas (2002). Spring time nutrient and phytoplankton dynamics on Georges Bank, Marine Ecology Progess Series, 228, 57–74.

Tu, Q., D. Pan, and Hao (2015), Validation of SNPP VIIRS Sea Surface Temperature Retrieved from NAVO, Remote Sensing, 7(12), 17234-17245.

Villareal, T.A. C. G. Brown, M.A. Brzezinski, J. W. Krause and C. Wilson (2012). Summer diatom blooms in the North Pacific Subtropical Gyre, 2008–2009, PLoS One 7, e33109.

Yoder, J.A., J.E.O. Reilly, A.H. Barnard, T.S. Moore and C.M. Ruhsam (2001). Variability in Coastal Zone Color Scanner (CZCS) chlorophyll imagery of ocean margin waters off the US east coast, Continental Shelf Research 21, 1191–1218.

Yoro, S.C., R. Sempere, C.M. Turley, M.A. Unanue, D. Durieu, X. Madron and M. Bianchi (1997). Cross-slope variations of organic carbon and bacteria in the Gulf of Lions in relation to water dynamics (northwestern Mediterranean), Marine Ecology Progress Series, 161, 255–264.

Zeng, C., H. Xu, and A.M. Fischer (2016). Chlorophyll-a estimation around the antarctica peninsula using satellite algorithms: hints from field water leaving reflectance, Sensors, 16, 2075, 1-14.

Zhao, J., H. Ji, and Z. Guo (2003). The vertical distribution of particulate organic carbon in the typical areas of the East China Sea in winter, Marine Sciences, 27(6), 59–63.