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Development and Validation of Partial Pressure of Carbon Dioxide Algorithm in the Southwest Bay of Bengal

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Abstract

The primary productivity in the upper ocean is also a key factor associated with the surface CO_2. Therefore, there is a potential to remotely sense the surface pCO_2 using satellite data based on its correlation with SST and chlorophyll *a*. Hence, the *in-situ* SST and chlorophyll datasets have been regressed with the calculated pCO_2 three dimensionally for four different functions suchas plane, paraboloid, Gaussian and Lorentzian. Among four functions parabolic function found to be better fit than other functions for postmonsoon with a R^2 of 0.783 and minimum standard error estimate (SEE) of ± 24.052 µatm. Thus, the postmonsoon parabolic algorithm was used to generate the pCO_2 image. The validation of MODIS-Aqua derived SST and chlorophyll based pCO_2 map showed better agreement with calculated pCO_2 with R^2 of 0.755 and SEE of ± 23.609µatm. The better regression between pCO_2, SST and chlorophyll suggest that the effects of biological activities on the spatial and temporal changes in pCO_2 of the southwest Bay of Bengal cannot be ignored. However, the RMSE (± 27.156µatm) of present pCO_2 algorithm is appreciably high due to inbound errors in MODIS derived SST and chlorophyll data products. Hence, improvement in sensor technology and retrieval algorithm would definitely improve the retrieval of input parameters (SST and Chlorophyll a) which in turn useful in estimating pCO_2 and air-sea CO_2 flux precisely in the Bay of Bengal at large spatial and temporal scales.

Keywords: SST, chlorophyll, pCO_2, regression, RMSE, SEE, paraboloid

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1. INTRODUCTION

In the recent years, researchers are more and more interested in understanding the global carbon cycle in the changing global climate. As one of the most important reservoir of the earth's carbon, oceans play a vital role in regulating global atmospheric CO_2 concentration. By using accurate estimates of global sea surface partial pressure of CO_2 (pCO_2), the ratio of net CO_2 uptake of global ocean can be measured, which can provide a support for further research of global carbon cycle[1]. The Indian Ocean has been shown to be a net sink of atmospheric CO_2, although the north Indian Ocean is richer in CO_2 than the atmosphere[2]. Studies from the north Indian Ocean indicated that the Arabian Sea is a perennial source of atmospheric CO_2[3,4,5], while the Bay of Bengal act as a seasonal sink[6]. Due to strong upwelling during the southwest monsoon, surface waters of the coastal region in the Arabian Sea show a substantial increase in dissolved inorganic carbon (DIC) accompanied by very high pCO_2[7].

Generally, the solubility of CO_2 in seawater is temperature dependent; hence the variation in the pCO_2 is mainly driven by thermodynamics. In a parcel of seawater with constant chemical composition, pCO_2 would increase by 4% when the water is warmed about 1°C[8,9]. Bay of Bengal is much warmer than the Arabian Sea and is consistent with Levitus climatology[10] indicating a possibility of stronger stratification in the Bay of Bengal which make it as sink of atmospheric CO_2. The exchange of CO_2 directly with the atmosphere at the mixed-layer waters is affected primarily by temperature (SST), dissolved inorganic carbon (DIC) levels and total alkalinity (TA), where SST is influenced by physical processes like mixing of water masses, DIC and TA are influenced by the biological processes (photosynthesis and respiration)[11]. The DIC in the surface ocean varies from an average value of 2150 μmol kg^{-1} in Polar Regions to 1850 $\mu molkg^{-1}$ in the tropics as a result of biological processes and reduce pCO_2 by 4%[12]. Therefore, the effect of biological drawdown and temperature on surface water pCO_2 is similar but the two effects are often compensating. Hence, the spatial and temporal distribution of pCO_2 in surface waters and CO_2 flux is largely governed by a balance between the changes in seawater temperature, net biological utilization of CO_2 and the upwelling flux of CO_2 rich waters.

Satellite observations are more useful in distinguishing spatial-temporal variations of geophysical parameters over the global oceans from intra-seasonal to inter-annual time scales. In addition to the change of atmospheric CO_2 accumulation, pCO_2 is also essential to study the changes in ocean biogeochemistry. As the temperature and upwelling process can well be recorded in SST and the biological utilization can be derived in terms of chlorophyll *a* concentration. Both these parameters are effectively been recorded from space which can result in retrieval of pCO_2 through empirical algorithms. Various algorithms have been derived for different areas at varied spatial scales. Initially, Stephens et al.[8] produced the statistical relationship between pCO_2

and SST in the north Pacific and concluded that the relation is sufficient to estimate pCO_2 using satellite SST over the oligotrophic waters but not over the eutrophic waters with significant primary production. Likewise, many algorithms that relate SST to pCO_2 followed, in the Arabian Sea[13], in the Sargasso Sea[14], in the equatorial Pacific[15], in the north Pacific[16,17], in the Bay of Biscay[18] and in the northern south China Sea[8], but their applicability is limited by geographical region, season and time scale based on the data used to develop the relationship between variables.

Later, the inclusion of chlorophyll *a* along with SST was done in North Pacific[16] and South China Sea[8]. Sarma et al.[17] further developed a remote-sensing algorithm for pCO_2, by including SST, chlorophyll *a* and climatological salinity. Lohrenz and Cai[19] added chromophoric dissolved organic matter (CDOM) to derive sea surface salinity as a parameter in their remote-sensing algorithm for pCO_2. Recently, Zui et al.[20] and Qin et al.[1] proposed a regression equation for pCO_2 with SST and chlorophyll *a* with a RMSE of 13.45 μatm and 21.46 μatm with the satellite derived pCO_2 respectively. Similar such studies that relate SST and chlorophyll with pCO_2 through empirical relation are scanty in the Bay of Bengal. Hence, the present study is attempted to develop a regional pCO_2 algorithm using the relationships between *in-situ* SST, chlorophyll and calculated pCO_2 and the best fit algorithm has been validated with the calculated pCO_2 measurements for remote sensing applications.

2. MATERIALS AND METHODS

The present study was carried out along the Tamilnadu coast falling along the southwest Bay of Bengal region. Four sampling station covering the longitude and latitude viz. Chennai (80°23.9E-13°07.9N), Cuddalore (79°48.5E – 11°42.4N), Parangipettai (79°51.7E – 11°30.6N) and Karaikal (79°55.5E – 10°54.8N) (Fig.1) were fixed and regular monthly samplings were made from January 2013 to March 2017. The entire study period was classified into four seasons namely postmonsoon (January to March), summer (April to June) and premonsoon (south west monsoon - July to September) and monsoon (October –December) classified based on northeast monsoon prevails in the region. Northeast monsoon is an actual monsoon in the southwest Bay of Bengal which brings more rainfall over Tamilnadu coast with northeast monsoon winds. Whereas, during southwest monsoon, the strong southwesterly winds play vital role in the surface waters resulting the turbulence at surface and wind driven vertical mixing of water column but rainfall was very minimum in the southwest Bay of Bengal.

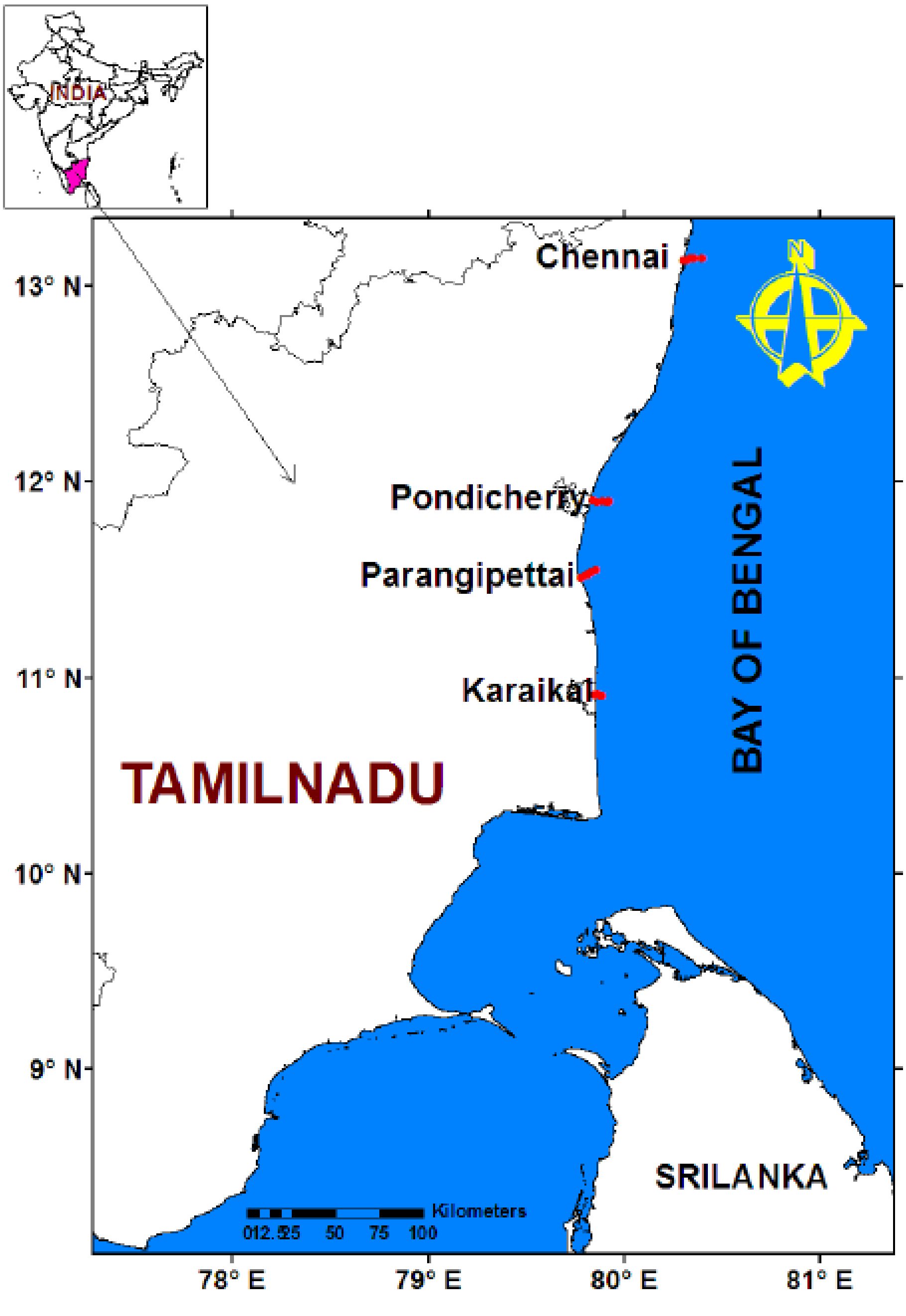

Fig. 1. Map showing the study area

In-situ data

In-situ SST was measured using digital multi-stem thermometer of 0.1° C accuracy. Water samples were collected using 5-litre Niskin water sampler and stored in polypropylene bottles (Tarson) in dark ice box and transported to laboratory. Chlorophyll *a* concentration was measured by following the method described by INCOIS[21] using spectrophotometer (Shimadzu- UV 2450) and it was calibrated with standard chlorophyll *a* (Sigma C6144) using 90% acetone within 24 hours.

Salinity was measured using a hand held refractometer (Atago hand refractometer, Japan) and the pH was measured using a pH meter (EUTECH - cyberscan pH meter) with the accuracy of ± 1‰ and ± 0.002 respectively. Total alkalinity (TA) was measured using an automated titrator (905 potentiometric Titrando, Metrohm, Switzerland) by following the Gran titration method[22]. 0.1N stock solution of HCl was standardized by preparing standard solution of known alkalinity with analytical grade Na_2CO_3. DIC and pCO_2 were computed based on measured SST, salinity, pH and TA using CO_2CALC program[23] by using the CO_2 dissociation constants (k1 and k2) given by Lueker et al.[24].

SST and chlorophyll a based pCO_2 retrieval algorithm

In-situ SST, chlorophyll *a* and calculated pCO_2 concentrations (595 data points) were obtained by monthly coastal samplings carried out at four sampling stations from January 2013 to March 2017 in the southwest Bay of Bengal region. The data points (15) matching with the date of satellite derived chlorophyll and SST data were treated separately for validation purposes. Finally, 580 points were taken for regression analysis accounting for ~97% of the total data.

The primary productivity in the upper ocean is also a key factor associated with the surface CO_2. Therefore, there is a potential to remotely sense the surface pCO_2 using satellite data based on its correlation with SST and chlorophyll *a*. Hence, the *in-situ* SST and chlorophyll datasets have been regressed with the pCO_2 three dimensionally for four different functions such as plane, paraboloid, Gaussian, and Lorentzian (Table 1).

Table 1. Results of regression analysis between *in-situ* SST, chlorophyll and calculated pCO_2

	N	Plane		Paraboloid		Gaussian		Lorentzian	
		R^2	**SEE(±)**	**R^2**	**SEE(±)**	**R^2**	**SEE(±)**	**R^2**	**SEE (±)**
Entire	580	0.804	76.174	0.809	75.266	0.815	74.104	0.811	74.811
Postmonsoon	165	0.778	24.154	**0.783**	**24.052**	0.637	31.090	0.632	31.298
Summer	120	0.690	42.870	0.700	42.370	0.535	52.781	0.522	53.486
Premonsoon	150	0.725	48.102	0.749	46.224	0.746	45.517	0.751	46.071
Monsoon	145	0.721	120.086	0.750	114.307	0.747	121.960	0.696	126.124

Parabolic function found to be better fit than other functions from the entire regression analysis with a R^2 of 0.783 and minimum standard error estimate of ± 24.052 µatm. The derived pCO_2 algorithm was used to generate the pCO_2 image. The pCO_2 algorithm implies the following equation:

$$pco_2 = 1025.6820 - 7.7794 * SST + 6.0874 * Chl - 0.5777 * SST^2 + 19.9015 * Chl^2$$

Where, pCO_2 = Partial pressure of carbon dioxide, SST = Sea surface temperature

Chl = Chlorophyll concentration, N = Number of points

Satellite data

To generate remotely sensed pCO_2 image, satellite derived SST and chlorophyll *a* data were required. For remote sensing measurements in the southwest Bay of Bengal, February to May is good period for getting cloud free data, on the other part of the year only rare and sporadic data sets alone available because of the influence of both southwest and northeast monsoons which makes southern Bay of Bengal as more cloud prone area in the northern Indian Ocean region. Hence, MODIS-Aqua derived Level-2a SST and chlorophyll data products for the date 11th February 2017 with a spatial resolution of 1km were acquired from the http://modis.gsfc.nasa.gov. The data were processed to generate SST and chlorophyll image using ERDAS IMAGINE (ver. 9.2.), SeaDAS (Ver. 7.3.2.) and ENVI (ver.4.7.) software. The datasets were applied to geometric correction to remove the image distortion and bring them to a standard geographic projection (Lat/Lon) with modified Everest Datum.

Evaluation criteria

The evaluation process was made by 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), Standard Error of Estimate (SEE) and Root Mean Square Error (RMSE) were analyzed to test the performance of the algorithms. 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.

3. RESULTS AND DISCUSSION

The oceanic partial pressure of CO_2 (pCO_2) is highly variable and it is difficult to assess spatial and temporal variability because of the paucity of measurements. In general, pCO_2 is strongly correlated with sea surface temperature (SST). Even in oceanic regions where physical and biological factors are significant, the pCO_2 remain be strongly correlated with SST. SST has a dual impact on pCO_2. On one hand, the equilibrium of carbonate system in seawater would alter due to the influence of SST in the absence of external exchange. Thereby pCO_2 will be enhanced as temperature rises[25]. On the other hand, the solubility of carbon dioxide in seawater decreases as temperature increases, which leads to a decrease of pCO_2[1]. The chlorophyll is capable of altering the carbonic acid cycle with its primary productivity and respiration. Hence, the three dimensional approach of SST, chlorophyll and pCO_2 regression fits are attempted to understand the role of SST and chlorophyll on pCO_2 in the southwest Bay of Bengal coastal waters.

Development of pCO$_2$ algorithm based on in-situ SST and chlorophyll *a*

The regression analysis between *in-situ* SST, chlorophyll *a* and calculated pCO_2 was carried out for four different three dimensional functions viz. plane, paraboloid, Gaussian and Lorentzian. The regression equations are given below:

Entire dataset (N=580)

$$pCO_2 = 1659.9047 - 46.7099 * SST + 59.7721 * Chl \rightarrow (1) Plane$$

$$pCO_2 = 3378.7004 - 162.7676 * SST + 46.6872 * Chl + 1.9715 * SST^2 + 1.3970 * Chl^2 \rightarrow (2) Paraboloid$$

$$pCO_2 = 1482.9996 * \exp(-0.5 * ((SST - 21.8135)/(-7.3584))^2 + ((Chl - 15.8418)/10.9075)^2) \rightarrow (3) Guassian$$

$$pCO_2 = 1314.3895/((1 + ((SST - 23.9130)/6.8894)^2) * (1 + ((Chl - 12.4741)/9.9683)^2)) \rightarrow (4) Lorentzian$$

Postmonsoon (N=165)

$$pCO_2 = 1447.4029 - 39.6711 * SST + 46.5801 * Chl \rightarrow (5) Plane$$

$$pCO_2 = 1025.6820 - 7.7794 * SST + 6.0874 * Chl - 0.5777 * SST^2 + 19.9015 * Chl^2 \rightarrow (6) Paraboloid$$

$$pCO_2 = 3315.3998 * \exp(-0.5 * ((SST + 1750771883.6265)/1078697778.5464)^2 + ((Chl - 6.8488)/4.584)^2) \rightarrow (7) Guassian$$

$$pCO_2 = 522.4279/((1 + ((SST + 42.4186)/(-211512.256)^2) * (1 + ((Chl - 2.954)/2.9575)^2)) \rightarrow (8) Lorentzian$$

Summer (N=120)

$$pCO_2 = 1776.7438 - 50.6222 * SST + 63.1597 * Chl \rightarrow (9) Plane$$

$$pCO_2 = 3796.4168 - 174.7775 * SST - 1.17778 * Chl + 1.9237 * SST^2 + 27.3216 * Chl^2 \rightarrow (10) Paraboloid$$

$$pCO_2 = 502.2731 * \exp(-0.5*((SST-109275.1995)/197788508.4115)^2 + ((Chl-2.499)/1.9359)^2) \rightarrow (11) Guassian$$

$$pCO_2 = 502.2731/((1+((SST+119216.007)/(-60993449.624))^2)*(1+((Chl-2.7029)/2.3569)^2)) \rightarrow (12) Lorentzian$$

Premonsoon (N=150)

$$pCO_2 = 2449.5745 - 71.5094 * SST + 16.8118 * Chl \rightarrow (13) Plane$$

$$pCO_2 = 16901.2522 - 1056.7893 * SST + 18.8756 * Chl + 16.7786 * SST^2 - 0.6697 * Chl^2 \rightarrow (14) Paraboloid$$

$$pCO_2 = 17301.9896 * \exp(-0.5*((SST+2.0725)/12.5839)^2 + ((Chl-39.1642)/31.2197)^2) \rightarrow (15) Guassian$$

$$pCO_2 = 2390.7451/((1+((SST-21.0947)/4.0488)^2)*(1+((Chl-12.2996)/21.0347)^2)) \rightarrow (16) Lorentzian$$

Monsoon (N=145)

$$pCO_2 = 2838.4296 - 83.5165 * SST + 33.3749 * Chl \rightarrow (17) Plane$$

$$pCO_2 = -2546.5231 + 302.3587 * SST - 27.6913 * Chl - 6.7814 * SST^2 + 6.7575 * Chl^2 \rightarrow (18) Paraboloid$$

$$pCO_2 = 1382.6457 * \exp(-0.5*((SST-3999570.0953)/(5335726006.6683))^2 + ((Chl-1602.4147)/768.7063)^2) \rightarrow (19) Guassian$$

$$pCO_2 = 1505.4029/((1+((SST-9356374.863)/286260419.8715)^2) * (1+((Chl-14.6659)/8.581)^2)) \rightarrow (20) Lorentzian$$

The entire dataset was regressed at first without considering seasonal variations which represents the significant relationship between *in-situ* variables of entire dataset for plane (R^2 = 0.804, SEE = ±76.174), paraboloid (R^2 = 0.809, SEE = ±75.266), Gaussian (R^2 = 0.815, SEE = ±74.104) and Lorentzian (R^2 = 0.811, SEE = ±74.811) functions. Though coefficient of determination is found to be significant for all the functions, the standard error of estimate was high. Hence, the regression analysis with seasonal difference was thought off for retrieving $p\mathrm{CO_2}$ fields, because the seasonal change of SST and chlorophyll *a* have obvious effect on the $p\mathrm{CO_2}$ algorithm as these input variables were subject to high seasonal differences in this part of the Bay of Bengal.

In the seasonal regression analysis, the R^2 values obtained for different functions and seasons are summarized in table 1. Among the four functions, the parabolic function found to be better fit for the entire and seasonal datasets. The parabolic function provides the highest determination coefficient (R^2 = 0.809, SEE = ± 75.266) for entire dataset and the lowest R^2 values of 0.700 and 0.749 with the SEE of ± 42.370 and ± 46.224 obtained for summer and premonsoon seasons respectively. During premonsoon, the highest chlorophyll *a* concentrations associated with moderate SST, indicating that both SST and chlorophyll have a mutual control on $p\mathrm{CO_2}$. During summer the biological productivity is low due to the high SST and diminished nutrients, under these conditions the $\mathrm{pCO_2}$ concentration is largely influenced by SST rather than chlorophyll *a.* The low chlorophyll *a* concentrations and high SST suggesting that SST might have a major control on $p\mathrm{CO_2}$ as opinioned by Chierici et al.[26]. Moreover, the stratified nature of the water column observed during postmonsoon leads to the lowest biological activities due to the absence of nutrients at the surface waters[27] hence, the SST has a predominant control over the $p\mathrm{CO_2}$ distribution in the Bay of Bengal. Finding a $p\mathrm{CO_2}$-chlorophyll and $p\mathrm{CO_2}$-SST fit does not mean that only biological or physical mechanisms are at work, but rather a complexity of interactions determines the small scale variations in $p\mathrm{CO_2}$, hence, biological contribution must be included in $p\mathrm{CO_2}$ model as the biological activity tends to be higher in warm water[28].

Though, the entire dataset exhibit the better fit than other seasonal datasets, the regression analysis of postmosoon dataset results the minimum SEE ± 24.052 with significant R^2 (0.783). Hence, the postmonsoon parabolic equation (6) is further utilized for the generation of remotely sensed $p\mathrm{CO_2}$ maps.

Validation of MODIS-Aqua derived SST

MODIS derived SST data (Fig.2a) was validated with *in-situ* SST to evaluate the performance of MODIS-Aqua and exhibited the good agreement with significant correlation co-efficient (R^2) of 0.887 with SEE of ±0.179, MNB of -0.104 and RMSE of 3.168ºC (Fig.2b). The data points fall outside of the 95% confidence band suggest that the satellite derived values were higher or lower than they should be in natural waters. However, the comparison plot of *in-situ* SST with MODIS derived SST showed that the 100% of the *in-situ* data were underestimated by the MODIS-SST

(Fig.2c). However, the regression fit found significant with correlation of R^2 = 0.887 hence, MODIS derived SST data was utilized to generate remotely sensed $p$$CO_2$ map.

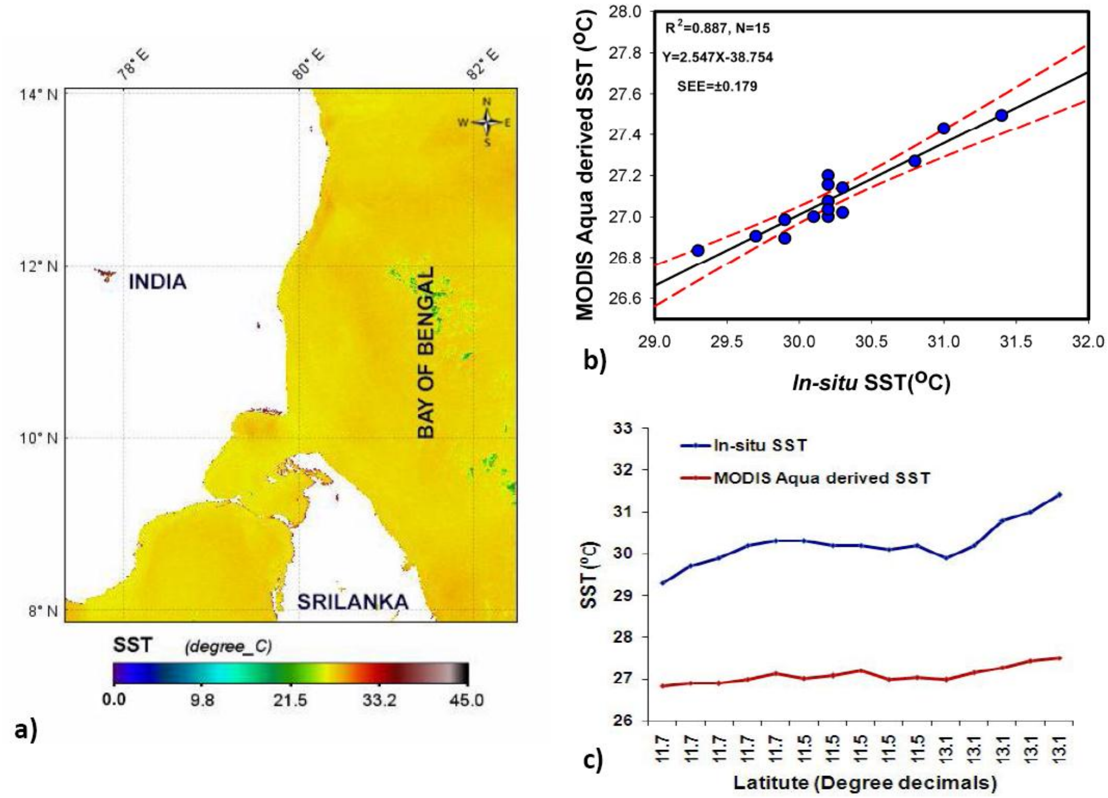

Fig. 2. MODIS-Aqua derived SST image of 11th February 2017 (a) and regression (b) and comparison (c) plots of *in-situ* SST Vs MODIS-Aqua derived SST

Evaluation of MODIS-SST with *in-situ* SST shows the negative bias (MNB = -0.104) with RMSE of ±3.168ºC which is greater than the error (±0.38°C) observed by Gentemann (2014) and could be attributed to possible errors in cloud removal, aerosol contaminated retrievals, or sampling. Moreover, SST measured using infrared radiometers will estimate with high resolution only under cloud free conditions and it has been clearly evident from the regression results (R^2=0.887 and SEE ±0.179ºC). The statistical results obtained in this study are comparable to MODIS SST validation with *in-situ* measurements along the western Pacific coasts[29] with a bias of –0.32°C; western North Pacific[30] with a bias of –0.06°C and RMSE of ±0.81°C, Taiwan coast[31] with a bias of 0.42°C and RMSE of ±0.86°C, San Matías Gulf of Argentina[32] with a R^2 of 0.89 and Bay of Bengal[33] with a bias of 1.80°C and reported the overestimation of the satellite product.

Validation of MODIS-Aqua derived chlorophyll

The relationship between the *in-situ* and MODIS chlorophyll exhibited the fairly good agreement with correlation co-efficient (R^2) of 0.731, SEE of ±0.207µgl^{-1} and RMSE of 0.246µgl^{-1} (Fig. 3a and 3b). MODIS derived chlorophyll shows the 33% underestimation and 67% overestimation of *in-situ* chlorophyll (Fig.3c) which is confirmed by the large positive bias of 0.184. Present algorithm (chlor_a_2) of MODIS overestimates the chlorophyll concentration at low concentrations around <1.0 µgl^{-1} of chlorophyll along the coastal waters. This study agrees with the previous studies of Xiu et al. [35], Montres et al.[36] and Poornima et al.[27] using MODIS data.

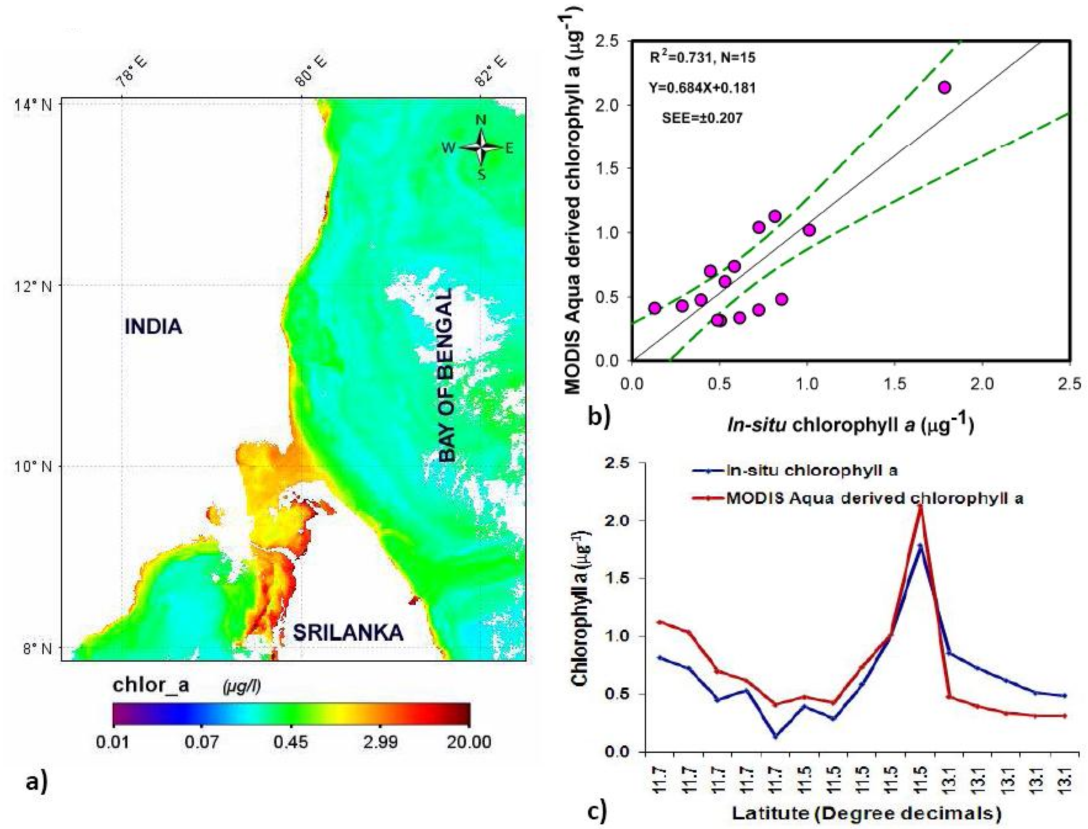

Fig. 3. MODIS-Aqua derived chlorophyll-*a* image of 11th February 2017 (a) and regression (b) and comparison (c) plots of *in-situ* chlorophyll a Vs MODIS-Aqua derived chlorophyll *a*

Possibly, the overestimation of chlorophyll could be due to the interference of suspended sediment and CDOM in the water leaving radiances. Besides this, other possible sources of errors are also identified and are bottom effects[37], the mixtures of organic and inorganic suspensions[38], absorption due to CDOM[39] and turbulent effect of wind agitation. MODIS will probably continue to be executed indiscriminately for all waters of the world's oceans with standard algorithms designed primarily for case 1 waters and at present the NASA adopted OC3M algorithm for the global MODIS processing. Moreover, global algorithms for satellite remote sensing do not always provide reasonable retrievals in all areas of the ocean, because an empirical algorithm is only as good as the data for specific environment or bio-optical provinces where the algorithm is to be applied[40].

Validation of remotely sensed pCO_2

The two parameter (SST and Chlorophyll *a*) parabolic algorithm of pCO_2 showed better agreement with *in-situ* pCO_2 measurements with a R^2 of 0.755 and SEE of ±23.609 (Fig. 4a - c). This suggests that the effects of biological activities on the spatial and temporal changes in pCO_2 of the southwest Bay of Bengal cannot be ignored. Hence, algorithm based on SST and chlorophyll *a* is better fit for the region. However, the RMSE (±27.156µatm) and MNB (0.040) of SST and chlorophyll based algorithm is appreciably higher than RMSE (±14 and ±17µatm) reported by Ono et al.[16] in large areas of subtropical and sub-polar North Pacific Ocean respectively. Similarly, Zhu et al.[9] recorded the improvement of pCO_2 algorithm by the inclusion of chlorophyll *a* with RMSE of ±4.5µatm. On the other hand, Olsen et al.[41] obtained an error of ±9.5µatm from measurements gathered in the Caribbean Sea using different algorithm based on linear relationship between SST and pCO_2 including geographical location. Comparitively higher RMSE in the present study is due to the inbound error in SST and chlorophyll images with higher percentage of cloud cover. The error in SST and chlorophyll estimation reported for the MODIS data would definitely cascade with the pCO_2 measurements.

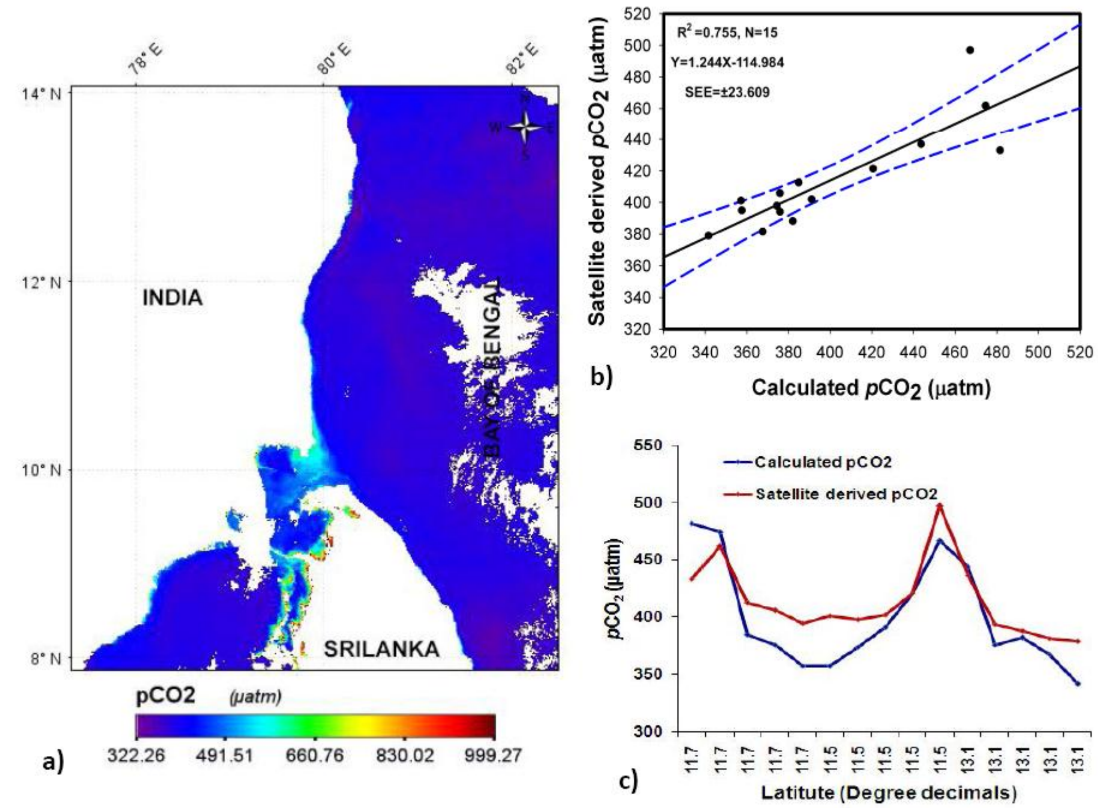

Fig. 4. SST and chlorophyll *a* based satellite derived pCO_2 image of 11th February 2017 (a) and regression (b) and comparison (c) plots of calculated pCO_2 Vs satellite derived pCO_2 using MODIS-Aqua derived SST and chlorophyll

Lohrenz and Cai [19] described *p*CO_2 algorithm using temperature, salinity derived from chromophoric dissolved organic matter (CDOM) and chlorophyll with a R^2= 0.838 of satellite derived *p*CO_2 with shipboard measurements. The *p*CO_2 algorithms developed based on *in-situ* SST, chlorophyll and climatological salinity exhibited the RMSE of 17-20µatm with *in-situ* *p*CO_2 data[17]. Padin et al.[18] applied the empirical algorithm described by Ono et al.[16] for predicting *f*CO_2 measurements in the Bay of Biscay from remotely sensed SST and chlorophyll *a* with a residual error of 0.1±7.5µatm. Similarly, Chierici et al.[26] predicted *f*CO_2 with a standard error of ±13µatm using SST and chlorophyll *a* based algorithm, the SST, chlorophyll *a* and mixed layer depth (MLD) based prediction of *f*CO_2[42] and matched with *in-situ* data (RMSE = ±11µatm) and Zui et al.[20] reported two parameter algorithm and found that the two parameter (SST and chlorophyll) algorithm worked better (RMSE = ±15.82µatm) with the relative error of less than 4.25%. Recently, Qin et al.[1] modified the Ono's equation by removing the second order variable of chlorophyll *a* to obtain a good retrieval of *p*CO_2 in the Yellow Sea and got RMSE of ±16.68µatm.

The seasonal regression analysis showed the significant seasonal variability in the relationship of *p*CO_2 with SST and chlorophyll *a*. The *p*CO_2 and SST had a strong inverse relationship in all the seasons suggesting that increased SST reduce the dissolution of CO_2 in seawater, thereby decreases the *p*CO_2 in seawater. The error in the satellite derived *p*CO_2 map is mainly because of the inbound errors in MODIS derived SST and chlorophyll data products. Hence, improvement in sensor technology and retrieval algorithm would definitely improve the retrieval of input parameters (SST and Chlorophyll *a*) which in turn useful in estimating *p*CO_2 precisely. This would enable us to understand biogeochemical processes behind the variability of CO_2 in the surface waters of the southwest Bay of Bengal

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4. CONCLUSION

The significant agreement between the SST and chlorophyll *a* based algorithm derived *p*CO_2 and calculated *p*CO_2 suggesting that the remote sensing technique is applicable to air-sea CO_2 flux observations in the southwest Bay of Bengal. The collection of more *in-situ* data covering various temporal and spatial scales is necessary in order to improve the algorithm. It should be noted that this work is limited to the preliminary results for the southwest Bay of Bengal in the postmonsoon season. Whether this applicable to other regions of the Bay of Bengal and for other seasons requires further investigation.

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