Satellite based Monitoring of Interactions between Chl-a and SST in the Arabian Sea and Persian Gulf area: a useful tool to identify ocean productive zones

Faisal Ahmed Khan*, Tariq Masood Ali Khan, Muhammad Ghayas Uddin

Abstract— **This study aims to employ remote sensing as a means to ascertain the marine productive zones through the correlative relationship between Sea Surface Temperature (SST) and Chlorophyll-a (Chl-a) concentration. We used monthly data sets of SST and Chl-a concentrations at 4 km resolution, obtained from Terra-Moderate Resolution Imaging Spectroradiometer (MODIS) from the year 2001 to 2017. The study of Chl-a enrichment in certain parts of Arabian Sea and the Persian Gulf is generally associated with the variability of SST. This study demonstrates the usability of satellite data which can be greatly enhanced by the use of Data Interpolating Empirical Orthogonal Functions (DINEOF) method, which in turn has proven a reliable tool for finding the missing data due to cloud covers especially in the months of SW monsoon in the region under study. Monitoring of Spatial and temporal distributions of SST and Chl-a concentration in different seasons indicated that most of the study area (96%) exhibited negative correlation between SST and Chl-a. Just a few regions (4%) including some coastlines and Persian Gulf show positive correlation, indicating the impact of some oil spills and human interaction with seawater quality. Marine productivity has a pivotal character to play in the socio-economic development of countries, located around the Arabian sea and this study could be beneficial to find the spatial association of SST and Chl-a with marine productive zones.**

Index Terms— **Arabian Sea, Monitoring of marine productive zones, Persian Gulf, Satellite derived measurements.**

I. Introduction

Remote sensing and Geographic Information Systems (GIS) are providing advantageous sustainable source to monitor different oceanographic parameters world widely [1], [2], [3]. Large Spatial and temporal coverage of oceanographic satellite data can be used to monitor the interaction between Sea Surface Temperature (SST) and surface Chlorophyll-a (Chl-a) concentration. In a marine ecosystem the regions with low SST and high Chl-a concentration is considered to be significant in terms of ocean productivity [4].

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To evaluate the persistency of such productive regions in the sea, it is required to understand the association between SST, Chl-a and related physical processes [5], [6]. In-depth Information about the seasonal variability of SST and Chl-a assists in the proper identification of marine productivity hotspots in a region [6], [4].

Arabian Sea located below 25°N, demonstrates the coastal impact on its oceanography [6]. The sea is famous for the reversing of winds in the South-West (SW) and North-East (NE) monsoon season [7]. The variation of land and sea temperature, in summer and winter seasons, is the main cause of the wind reversal. This reversing of wind, in two monsoon seasons, affects the spatial distribution of Chl-a concentration in the region [5], [8], where SST variability is associated with the upward vertical movement, upwelling, of the water column. The upwelled cold and nutrient-dense water increases the Chl-a concentration at the sea surface [9].

The Persian Gulf, which is deep from 250m to 400m, is much shallower than open Arabian Sea. The gulf is famous for its high values of salinity and high evaporation rates of about 1.5-2 meters per year [10]. Being partially enclosed water mass, wind and outflows from surrounding coastlines play an important role to control the oceanography of the gulf. The gulf waters, surrounded by oil and gas-related industrial countries, are under marked influence of dissolved hydrocarbons [11]. Seasonal variations of SST and Chl-a concentrations in the gulf are different than that of Arabian sea [12].

Due to very less availability of ground data and the missing values in satellite data, because of cloud covers in some specific seasons, studies of interaction between SST and Chl-a were limited to some particular regions and seasons [5], [13]. In previous studies mostly in situ data, which is very limited to time and having limited spatial distributions, is used [6]. In the present study, MODIS data from 2001 to 2017 are used and reconstructed using the Data Interpolating Empirical Orthogonal Functions (DINEOF) method for missing values. In many other regions worldwide, DINEOF method has been found to be very useful in re-construction of missing satellite data [14], [15], [16]. Use of Ocean color satellite data sets after reconstruction of missing data, providing vibrant means for long term analytical studies in the field of oceanography [14], [15], [16], [17]. DINEOF method has proven a stronger and superior mathematical tool than other methods for interpolation of missing spatially distributed data [18].

In the present study, we selected an area with latitude 10◦N to 30°N and longitude 50°E to 75°E (Fig. 1) to evaluate the correlative relationship between SST and Chl-a concentration. Our study area, around 3.28 million km^2, covers most of the Arabian Sea and Persian Gulf with 164007 sea surface data points.

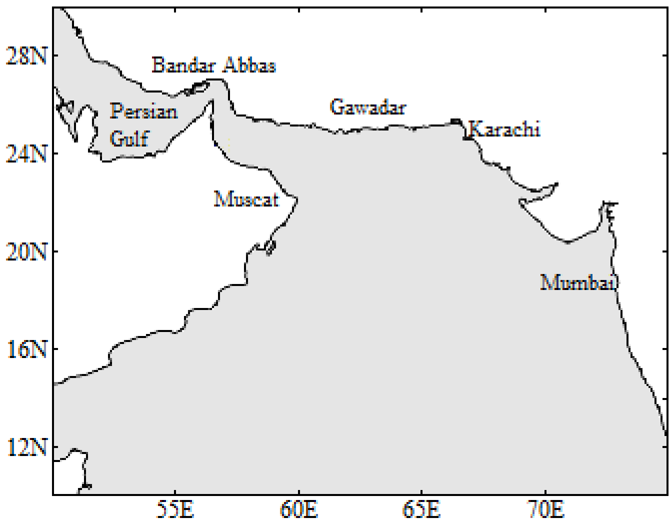

Fig. 1. Study area with grey color, about 3278090 km^2 sea surface area (10-30◦N and 50-75◦E)

II. DATA AND METHODS

204 Monthly data sets and monthly climatologies of SST and Chl-a concentrations each from January 2001 to December 2017 at 4 km resolution are obtained from NASA Goddard Space Flight Center, Ocean Ecology Laboratory, Ocean Biology Processing Group, USA (https://oceandata.sci.gsfc.nasa.gov). We use Moderate Resolution Imaging Spectroradiometer (MODIS)-Terra, level-3 monthly data in NetCDF format [19]. Global data files are cropped for the study area of our interest (Fig.2, Fig. 3). For data handling and analysis MATLAB R2014a of MathWorks, Inc. and Climate Data Operators CDO 1.7.2 in Ubuntu 14.04 environment is used.

In order to have a better understanding of the interaction between SST and Chl-a concentration in the region, it is required to have larger time series of cloud-free satellite data sets.

To eliminate the issue of cloud cover in satellite data, we used the DINEOF method, which was evolved by Belgian scientists Beckers and Rixen in the year 2003 [20]. DINEOF method is extensively used to reconstruct the oceanographic satellite data that is missing due to cloud cover and demonstrates reliable results [16], [15].

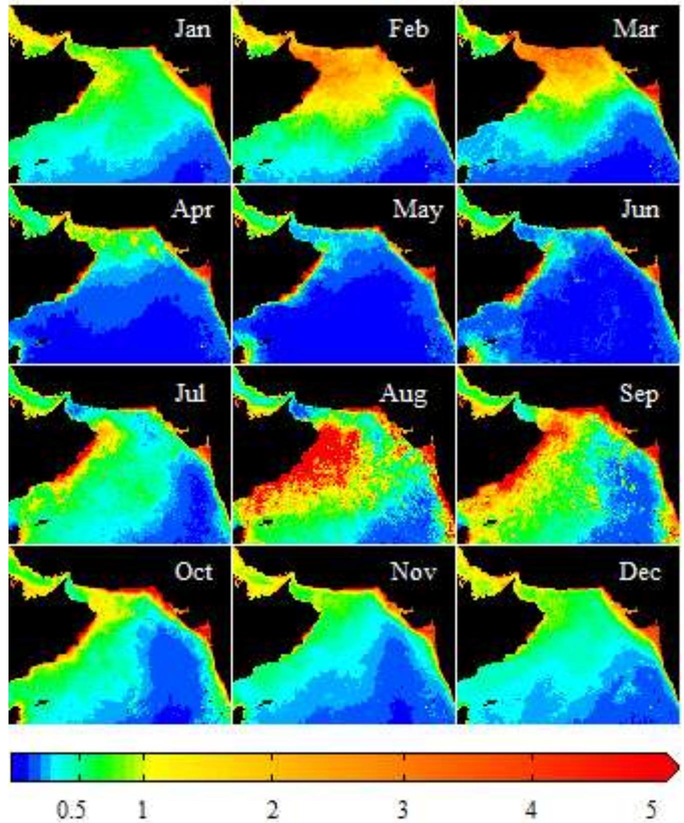

Fig. 2. Chlorophyll-a concentration (mg/m^3) monthly climatology from year 2001 to 2017

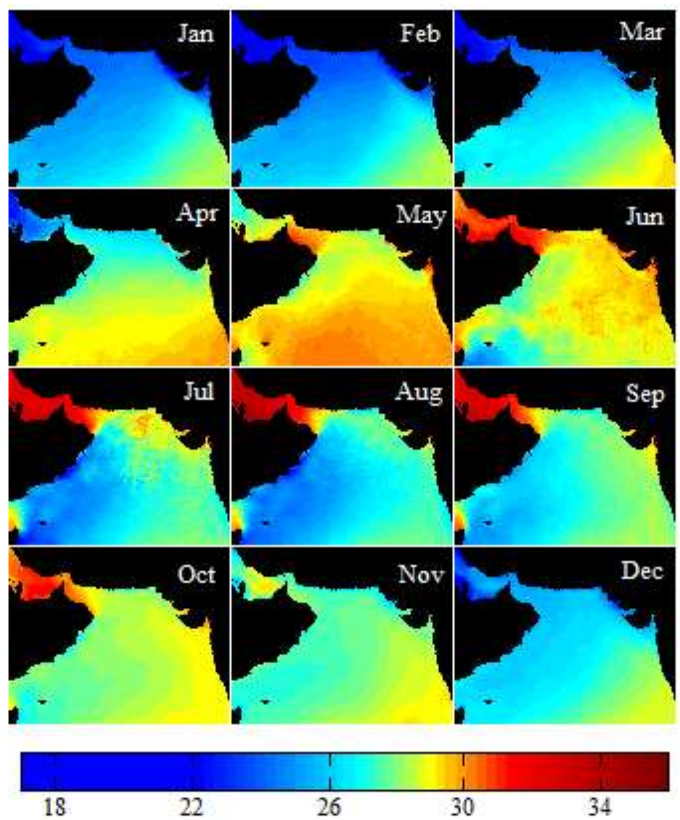

Fig. 3. Sea Surface temperature (◦C) monthly climatology from year 2001 to 2017

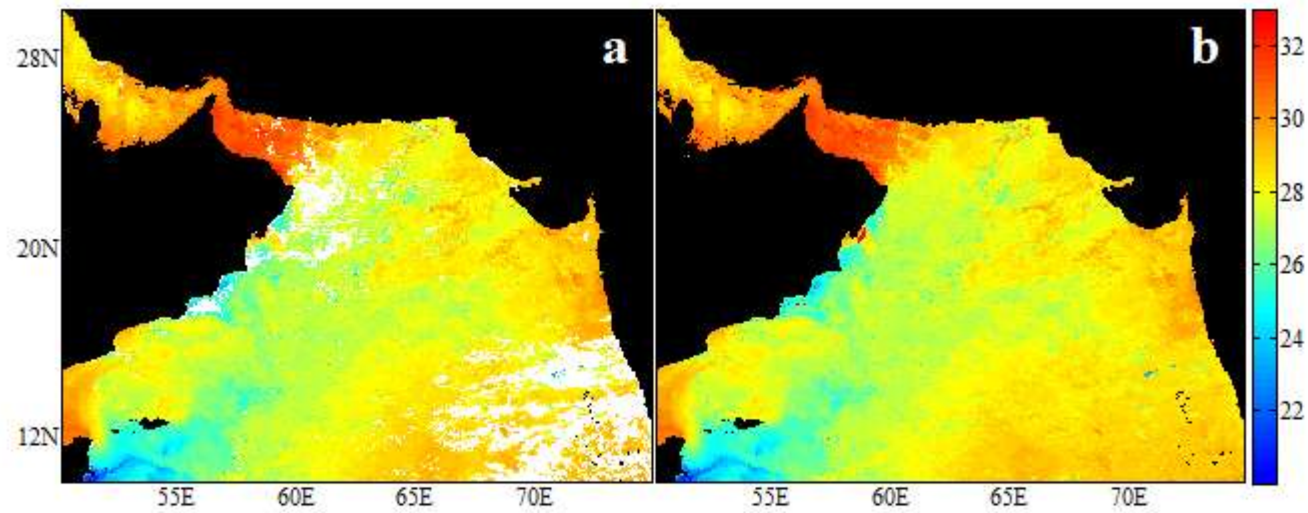

Fig. 4. Sea Surface Temperature (◦C) in the month of June 2001 (a) original cloudy data (b) after reconstruction using DINEOF method.

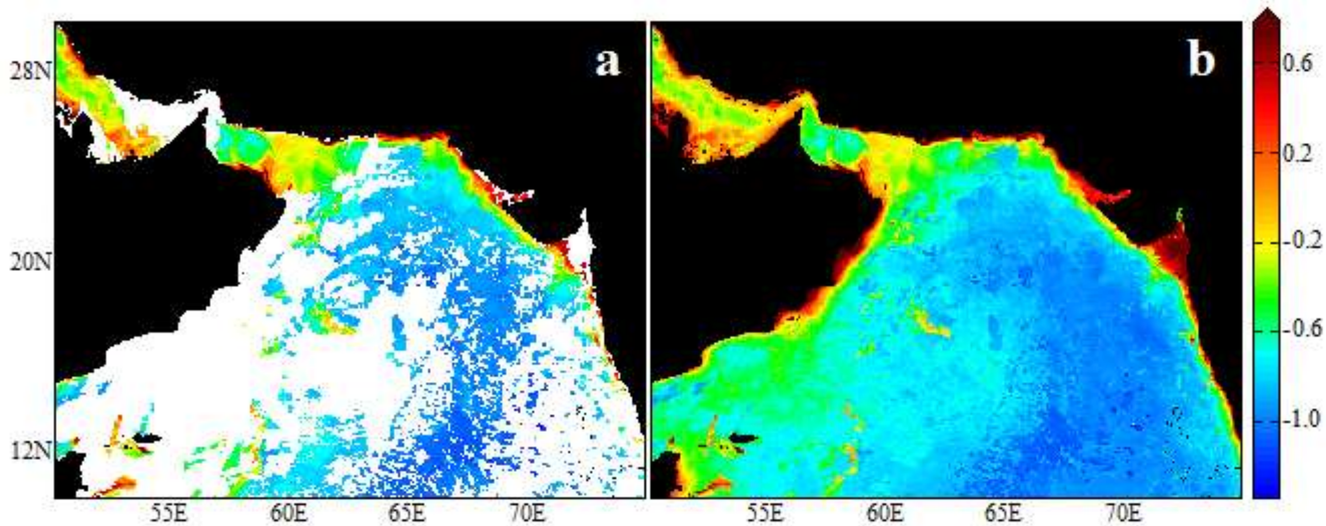

Fig. 5. Log10 Chlorophyll-a concentration (mg/m^3) in month of June 2010 (a) original cloudy data (b) after reconstruction using DINEOF method.

For each oceanographic parameter whole data set combine in a a×b matrix D, where a is the total number of pixels and b is the number of months. In the past, Empirical orthogonal function (EOF) analysis has been widely applied in oceanography and atmospheric sciences. Here EOFs are computed by using singular value decomposition (SVD) (eq. 1) as shown in the following equation [20];

$$\mathbf{D = USV^T} \qquad \textbf{(1)}$$

Here U_p is representing the location related EOF, V_p is representing the time-related EOF and S_p is representing the singular value for pth index.

Repeated computations are done for different values of k starting from 1 to the maximum number of k in order to have the closest estimation of those elements which we missed porously, at the start, for cross-validation [16].

Here U is representing the location EOFs, V is representing the time EOFs and S is representing their singular values.

Then the reconstruction of each missing data point $D_{ij,}$ where i is the location index and j is the time index (eq. 2), is done by computing k modes of EOFs using following computational equation [16];

$$\mathbf{D_{ij}} = \sum_{p=1}^{p=k} S_p \left(U_p\right)_i \left(V_p^T\right)_j \qquad \textbf{(2)}$$

To check the linear dependency of SST and Chl-a concentration, point by point, we used the Pearson correlation coefficient analysis. This statistical tool is widely used to evaluate the linear correlation between variables [14]. Pearson's r values for each location points are calculated using eq. 3[21]. MATLAB function corrcoef() is a statistical computational tool for the calculations of r [22].

$$r = \frac{1}{n-1}\sum_{n}^{i=1}\left(\frac{SST_i - \overline{SST}}{\sigma_{SST}}\right)\left(\frac{Chla_i - \overline{Chla}}{\sigma_{Chla}}\right) \quad \textbf{(3)}$$

Here sample size n is representing the number of months. In the present study n is 204. SST_i and $Chla_i$ are the numerical values of SST and Chl-a for each data point. Value or r varies between -1 to +1, where r from -1 to zero represents negative correlation and r from 0 to +1 represents the positive correlation.

III. Result and Discussion

North East Arabian Sea (NEAS) is more productive during winter and pre-monsoon seasons. NE monsoon continental winds create strong upwelling areas along the western coast of India. Whereas the irregular shape of the coast along Arabian Peninsula and Pakistan coast also favors wind-driven upwelling at few places of the Northwestern Arabian Sea including the Pakistan coast. Therefore, nutrient-rich upwelled water spreads along the coast and adjacent offshore area. As the winter progresses, the spreading of upwelled water towards the central part of the North Arabian Sea can be seen in the successive months. The higher values of Chl-a up to 6 mg/m^3 depicts strong upwelling in the NEAS and some parts of Pakistan and Arabian coasts. The counterclockwise surface circulation in the Arabian Sea helps the spreading of nutrient-rich water in the central Arabian Sea. In some coastal areas warm mean SST climatology with higher values of Chl a along Pakistan and Arabian coast can only be attributed to the upwelling areas having a positive correlation with the Chl a.

In the North Arabian Sea, the surface Chl-a concentration increases in the winter season from the month of January to March. Besides wind-driven upwelling along the western coast of India, the other cause of this increased surface Chl-a concentration is the contribution of nutrient-rich water of deeper layers through the extended mixed layer depth in the winter season. The upward motion of low temperature nutrient-rich deeper water prompts biological productivity in the region. The present study depicts that the winter monsoon (northeast monsoon) wind-driven upwelling and convicting mixing are responsible for seasonal high productivity in the NEAS.

From January to March, surface Chl-a concentration progressively increases. It is due to the convectional currents carry nutrients, from low levels to high levels of water, as a result of an increase in mixed layer depth which is triggered by very low SST values [7], [23]. Furthermore, the seasonal flow of wind from land to sea causes the enrichments of nutrients in surface waters. The addition of nutrients, to a suitable extent, in surface water can enhance the biological activity to its optimum level and hence identify the highly marine productive zones. So the knowledge of spatial and seasonal distributions of SST and Chl-a concentration, along their temporal persistency can serve as a very useful tool to categorize marine productive areas.

During Southwest Monsoon (June–September) upwelling along the Somalia, Arabia and southwestern of the Indian coast is the dominant process that causes high marine productivity in the Arabian Sea. During summer monsoon, the pressure gradient is created due to the intense heating of landmass, which causes the SW wind to blow in the direction from the sea to the land. During this season strong upwelling brings ample nutrients from the deep ocean to the surface and significantly increases the marine primary productivity. In the previous studies, high marine productivity has also been recorded in the study area and one of the studies showed productivity of about 1700 mgC per m^2 per day [5].

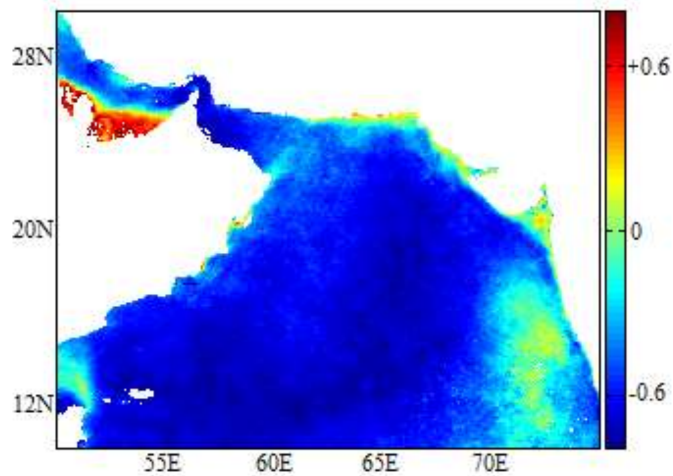

Fig. 6. Spatial Distribution of Pearson's correlation coefficient r between SST and Chl-a, 96% area with blue color showing negative correlation and 4% area with red color showing a positive correlation.

In the recent past, one study [9] has argued that productivity in the western Arabian Sea has increased with the passage of time. The analysis of satellite data showed that Northeastern Arabian Sea (NEAS) has two seasonal peaks of Chl-a, one in winter monsoon (February/March) and the other at the end of summer monsoon (August/September). While the bimodality nature of Chl-a maxima is absent in the Southwest Arabian Sea (SWAS). While comparing results presented in this study with the previous studies, it may be noted that similar pattern is observed. One advantage of present study over the previous studies is that cloudy data received, during SW monsoon for the months from June to August, is processed by DINEOF to have cloud-free data in order to get the maximum accuracy in the analysis [13].

Generally, the changes in the physical forcing due to inter-annual variation of SST are controlling the marine productivity in the region. As studied previously, the seasonal variation in data sets of monthly Chl-a concentrations, during the year 1995 to 2005, showed higher values in the eastern Arabian Sea [5]. In our study period (i.e. from 2001 to 2017) the spatial distribution of SST and Chl-a concentrations indicated the significant interactions of both parameters. The seasonal persistent of SST gradient and associated phenomenon of upwelling indicates the higher surface Chl-a concentrations. In winter season, especially in the month of March, peak values of marine productivity are associated with low values of SST. February-March in winter and August-September in summer are observed as most productive months during the study period. In an oceanic ecology, deeper nutrient abundant waters when upwell to surface can be characterized by low SST values and results in high Chl-a concentrations. Some of the regions along the Arabian Sea and Persian Gulf coastlines demonstrate the increasing marine productivity trend with increasing SST values in the region due to the influence of rivers outflow and human activities along the coast.

For DINEOF computation, large global MODIS-terra satellite data sets of SST and Chl-a are cropped and handled using MATLAB R2014a. In the study area cropped D matrix has dimension 164007x204 with 164007 sea surface points for each 204 months. For SST data set missing data points found are 254163 out of 33457428 (0.76%) (Fig. 4) and for Chl-a missing data points found are 7968265 out of 33457428 (23.82%). While using DINEOF method, log transformation provides better results for the estimation of missing values of Chl-a concentration [24], [18]. So before interpolation computations, the log10 transformation is done for each data point of Chl-a data set (Fig. 5).

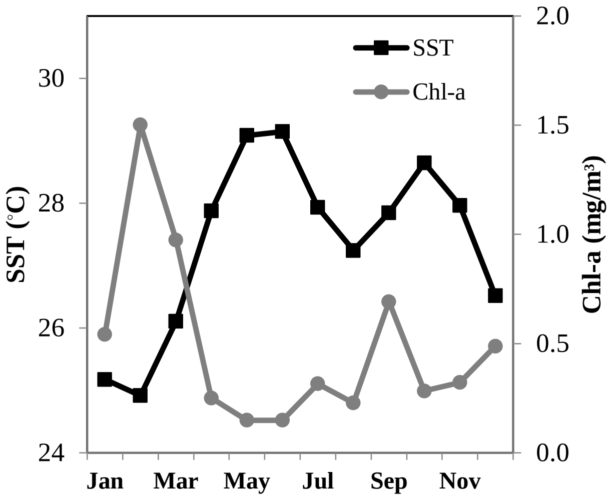

Fig. 7. Monthly averages of Chl-a and SST from the year 2001 to 2017 for a data point (20.8N 66.6E) with negative correlation.

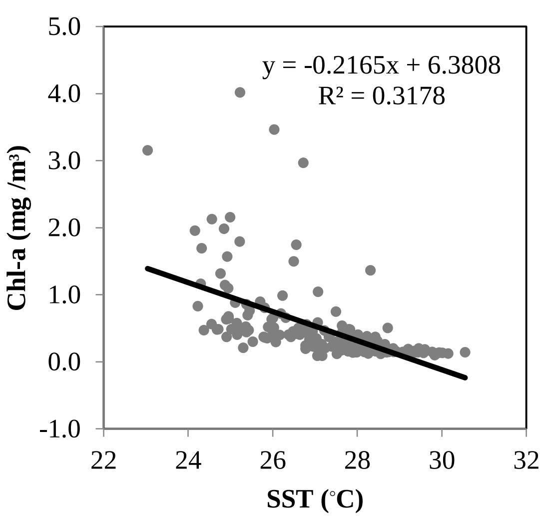

Fig. 8. SST and Chl-a scatter plot with a linear trend line for negatively correlated data point (20.8N 66.6E)

Then the raw data matrices D_{SST} and D_{Chla}, in NetCDF format, are computed for DINEOF separately within the Ubuntu 14.04 platform. In DINEOF computation, for closest estimation with cross-validation, the number of optimal EOF modes is 13 for D_{SST} and 8 for D_{Chla}. An output single file for each SST and Chl-a are then split into monthly files and are plotted in MATLAB (figure-2 and figure-3).

In the present study for the calculation of Pearson's r correlation coefficient the sample size n is 204, representing the number of months in years 2001-2017. The correlation coefficient r is calculated for 164007 data points (Fig. 6). In which 157496 (96%) data points showed negative correlation (Fig. 7 and Fig. 8) and 6511 (4%) data points showed a positive correlation (Fig. 9 and Fig. 10).

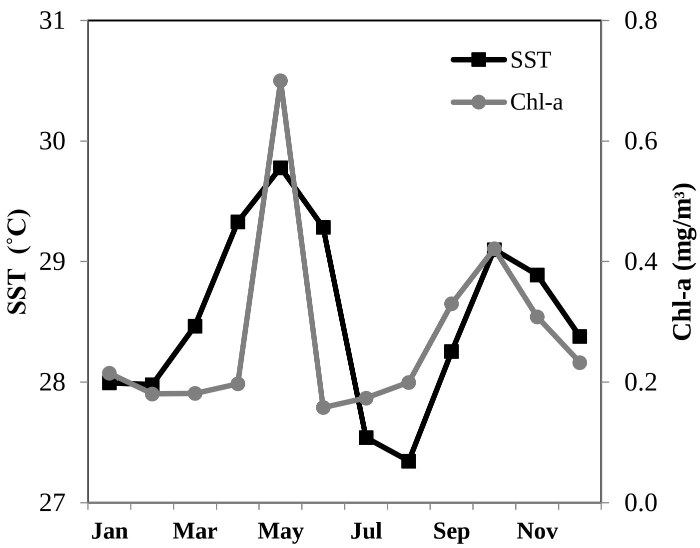

Fig. 9. Monthly averages of Chl-a and SST from the year 2001 to 2017 for a data point (15.1N 72.1E) with positive correlation.

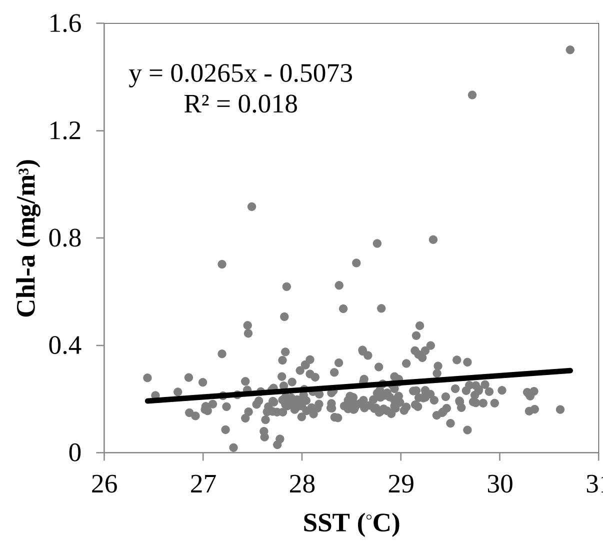

Fig. 10. SST and Chl-a scatter plot with a linear trend line for negatively correlated data point (15.1N 72.1E)

In comparison with the open Arabian Sea, SW monsoon seasonal winds are not much affecting the SST and surface Chl-a concentrations in Persian Gulf. In the NE Monsoon, in the months November-February, the surface Chl-a concentrations are higher. The spatial distribution of SST and Chl-a correlation coefficients (Figure-6) in the region of Persian Gulf, are demonstrating positive values. Higher values of Chl-a concentrations in the gulf waters indicating the presence of high concentrations of dissolved hydrocarbons serve as an evidence of their positive correlation with oil spills [11], [25].

IV. Conclusion

Data Interpolating Empirical Orthogonal Functions (DINEOF) method has proven as a strong statistical tool for coping with the problem of missing pixel values, in terms of SST and Chl-a satellite data. Spatial analysis for the variability of SST and Chl-a provides regional and seasonal descriptions about marine productivity. Zones with persistent high Chl-a concentration and low SST in different seasons are considered as marine productive [4] and are of great significance in terms of fisheries. It is strongly suggested to monitor the oceanography of those productive zones through field data. The findings of this paper will thus contribute to enhancing the socio-economic development of the adjoining regions of the Arabian Sea by assisting marine productivity management. The study may as well create room for researchers to further understand the scope for satellite oceanography in the region.

Acknowledgment

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