ABSTRACT
In the recent past, the Satellite authenticated synoptic instrument has been used to retrieve the water quality variables like chlorophyll, suspended materials and the pigmented dissolved organic matter. However, the use of chlorophyll phytoplankton endeavors acts as a proxy and strongly overestimates the contribution to the annual pelagic carbon flows from spring production. Further, Remote Sensing assisted Sparse Statistical Modelling (RSSSM) has been proposed to determine the chlorophyll-a concentration seasonal variations and spatial/temporal structure in the Hailing Bay. It provides high correlation information between the water surface environment and organic matter. Besides, it provides the highest possible correlation coefficient value and gives a more practical representation at a clear water reference site using a lab-scale simulation setup. Thus in considering the coastal system, the seasonal variation in chlorophyll ratios has been reviewed and outcomes has been analyzed using effective experimental validation at lab scale.

Introduction
In recent decades, increased nutrient loadings, driven by the development of industrial, growth of human population and variations in land utilization, have resulted in eutrophication and improved phytoplankton concentration in Hailing Bay, South China Sea (SCS) (Gong et al., 2003). A major part of the global marine ecosystem is the coastal ocean. Another big physical factor that influences coastal ecosystems is ocean dynamic forcing (Gong et al., 2000). The rise in chlorophyll-a concentration suggests eutrophication in the sea which has low biodiversity and therefore adequate ecosystem services are deprived of the aquatic environment. Chl-a is reviewed as one of the key components of the aquatic environment turbidity (Muslim & Jones, 2003) which defines aquatic environment water quality (Gao & Li, 2009). Therefore, turbidity is damaging to the local community’s livelihood, which relies primarily on fish and tourism revenue profits (Sheikh et al., 2017). The renewal of ecosystem functions and services, therefore, needs an understanding of the complexities of turbidity, to decide on informed management (Guerrero-Galván et al., 1998). The understanding of temporal/Spatio turbidity dynamics needs frequent turbidity monitoring features such as Chl-a (Guo et al., 2011). However, with high time and cost, it is hard to obtain such data via routine terrain dimensions (Wu et al., 2016). Remote sensing technology will present synoptic Chl-a concentration in the ocean (Odate & Imai, 2003). The total number of observations of chlorophyll-a concentration is still inadequate, and it is complex to grasp the spatial and temporal variations (Zhang, 2001). Satellite sensors have increased ocean understanding and satellite observations have shown, for example, that the marine ecosystem is not as diverse as once believed (Atici & Obali, 2006). Ocean color sensors are commonly used in various fields of research to help understand different environmental processes. Phytoplankton are photosynthesis, the trophic base of the pelagic food web, of the marinated organisms which grow in the oceanic euphotic area (Zhang et al., 2009). A concentration of chlorophyll (Chl-a) could be employed as a phytoplankton biomass indicator (Pérez et al., 2005). Figure 1 shows the study area of the Hailing Bay and the South China Sea.

Satellite Remote sensing technology has been extensively used in recent decades to study the biogeochemical processes of the global ocean (Bresciani et al., 2011). A field sampling and laboratory analysis has been typically used to track the sediment (Moses et al., 2012). The findings of the study can be far from fact as the measurements are confidential on spatial and temporal scales (Harvey et al., 2015). The sample collection is complex as well (Yamada et al., 2004). Satellite remote sensing is commonly used with the capability of synoptic observation to track water quality utilizing a bio-optical model that describes the connection between water and apparent optical properties components (Catts et al., 1985). The seasonal variations found in sea surface Chlorophyll-a and the surface thermal conditions are
perceived in other biological conditions. Early observations in the Hailing Bay indicated the presence of a considerable degree of seasonal variation in primary production (Ndungu et al., 2013). Therefore, it is crucial to monitor, detect, and predict the development and movement of vegetation using more detailed and efficient techniques to moderate the impacts of algal warnings and blooms. The use of remote satellite and airborne sensing has shown in some coastal and sea waters to allows more consistent temporal/spatial data on the quality of water and the extent of cyanobacterial blooming than traditional monitoring (Darecki et al., 2003).

In this paper, satellite remote sensing technology has been established remarkably and sea color sensors evaluate the Chlorophyll-a spatial distribution by estimating the spectra of radiance from the sea surface. The benefit of remote satellite sensing is that data from large areas are obtainable with high resolution and high frequency. The first experimental phytoplankton pigment produced by the Coastal Zone Color Scanner (CZCS). The satellite-derived data to discover the seasonal variability in phytoplankton in the Hailing Bay and evaluate whether the seasonal equatorial upwelling does change the productivity and phytoplankton standing. The water rising along the equator from about 200 m to the surface is called equator upwelling. In spite of the presence of high chl-a concentration in the upwelling area, both the higher amount of shortwave radiation captured in the surface layer.

The main contributions of this paper are,

- To propose the Remote Sensing assisted Sparse Statistical Modelling (RSSSM) to determine the chlorophyll-a concentration seasonal variations and spatial structure in the Hailing Bay.
- Designing the shape prior and model function to determine the seasonal changes and Chl-a algorithm has been proposed.
- The experimental results show the high accuracy in determining the chlorophyll-a concentration in the Hailing Bay.

The rest of the paper discussed as follows: section 1 and section 2 discussed the chlorophyll-a concentration seasonal variation in the ocean and existing methods. In section 3 the Remote Sensing assisted Sparse
Statistical Modelling (RSSSM) has been proposed to determine the chlorophyll-a concentration seasonal variations in the Hailing Bay. In section 4 the experimental results has been demonstrated. Finally, section 5 concludes the research article.

**Literature survey**

Ali Ben Abbes et al. (2018) proposed the multi-resolution analysis wavelet transform (MRA-WT) for satellite image time series decomposition to measure the performance in modeling, detecting and monitoring land cover modification with marked seasonal variations from pretending normal variant vegetation index time series. The model designated have proved their capabilities, along with various physical processes that lead to the dynamics of vegetation, to classify non-stationary vegetation. Their results show that BFAST is the most precise tool of the RMSE dataset, while MRA-WT has great potential for multi-level vegetation dynamics extraction. In terms of the performance of computation, both MRA and STL surpassed BFAST.

Yi Zhong et al. (2018) suggested the Wireless Sensor Network based Device-free sensing (WSN-DFS) for identifying the influences of seasonal variations on the Foliage penetration test. Two specific performance enhancement measures are taken in this approach. It is one example of using a higher-order cumulant (HOC) algorithm to minimize the effect of unintended clutter on detection accuracy. The next is the estimation utilizing a flower pollination algorithm of the optimum classifier parameters. Accordingly, negative impacts on detection precision can be accommodated over four seasons due to changes in weather conditions. Related to the experimental outcomes, the average accuracy of classification the method depicted can be enhanced with guaranteed robustness by at least 22% in all seasons.

Guangming Zheng and DiGiacomo (2017) introduced the Generalized stacked constraint model (GSCM) for remote sensing of Chl-a in coastal waters based on the light absorption coefficient of phytoplankton. Remote sensing of chlorophyll-a concentration in [Chl-a] coastal waters like the Chesapeake Bay has been difficult because of terrestrial substances of optic significance, not phytoplankton. The performance highlights the importance of enhancing the allocation of the total phytoplankton and non-algal light absorption factor in coastal waters for bio-optical remote sensing. A strong absorption partition algorithm is supported to obtain data on phytoplankton when data quality is regarded as a priority in respect of typical water conditions in the Chesapeake Bay and probably the majority of coastal waters.

Patrick M. Olsen et al. (2015) initialized the Integrated Traditional Ecological Knowledge (ITEK) for evolving theoretical marine habitat correctness models from remotely sensed information. In the sense of observer knowledge gained from the Western scientific field surveys on marine mammal observations, this method utilizes the generational and lifetime experience of ecosystems hunters and their harvest results. TEK information was converted to seal presence/pseudo-absence for the period mid-June through October and was used for the training Classification Tree Environmental predictor parameter to determine the correct habitat for barded seals in the Bering area of the Bay Strait. Predictor variables extracted from a variety of distance sensing devices transformed and aggregated with trend analysis techniques, terrestrial, oceanic and atmospheric. For habitat classifications, a Kappa of 0.883 was obtained. The TEKs used are spatially limited, provide a replicable, viable information source that can substitute or accompany the scientific observational knowledge of Western countries.

Na Zhao et al. (2019) suggested the Generalized Additive Model (GAM) for chlorophyll-a of environmental factors in the yellow sea and Bohai sea. In the meantime, the Chlorophyll-a has gradually increased scope and focus, and modes have taken out by the neural network have efficiently elucidated the Chlorophyll-a pattern in seasonal, inter annual and spatial variation, from simple modes to high, low, and medium-content modes. The improvements in Chlorophyll-a, which had significant impacts on Chl-a transition, accounted for 47.9%. Sea Surface Temperature can better explain the Chl-a transition compared with average wave direction, wind speed, and substantial wave height. Increased human activity and wind direction (for example, drainage of rivers) have played a key role in shifting the Yellow Sea and Bohai Sea Chlorophyll-a distribution.

To overcome these issues, in this paper, Remote Sensing assisted Sparse Statistical Modelling (RSSSM) has been proposed to determine the chlorophyll-a concentration seasonal variations and spatial structure in the Hailing Bay. The spatial and temporal variations of Chl-a concentration in the SCS Hailing Bay have been observed and examined between 2019 September and 2019 October. Nutrient, light and other factors regulate the phytoplankton biomass. Some of the most recent cruises have primary productivity data available. The relationship between Chl-a and primary productivity has been developed to assess primary productivity more effectively in the study area, which has allowed us to estimate the lack of primary productivity data. Therefore, the primary productivity data set for the South China Sea Hailing Bay covering three seasons and three regions with different water characteristics has been collected on a temporal and spatial variation.

**Remote sensing assisted sparse statistical modelling method**

In this paper, the Remote Sensing assisted Sparse Statistical Modelling (RSSSM) has been proposed to
determine the chlorophyll-a concentration seasonal variations and spatial structure in the Hailing Bay. For an accurate evaluation of the concentration of chlorophyll a (Chl-a) and correct recognition using remote sensing is very effective when compared to conventional methods. The dataset is taken from https://neo.sci.gsfc.nasa.gov/analysis/index.php to examine the Chl-a concentration in the region of Hailing Bay. This article applies a coastal upwelling index to quantify the upwelling intensity. A common oceanographic phenomenon is upwelling that brings deeper water to a surface or sub-surface layer. Upwelling can cause seawater to change its biological and physical properties. Since coastal upwelling carries nutrients from the deeper to the upper layer, it supports primary producers’ production, including phytoplankton. This can have an indirect impact on the evolution and distribution in coastal areas. Sea Surface Height Anomaly (SSHA) information is utilized to examine the connection between the upwelling and eddy kinetic energy (EKE) in our training region.

**Case 1: mathematical model on seasonal variability**

**Solution 1:** The Ekman Transport is stated as the force of Coriolis causes the transport of the water from the surface wind to the right. The Ekman transport drives or wind-driven upwelling is known as the surface water away from the coast, deep water rich in nutrients are bought to the surface. Preassuming a steady, horizontal and homogeneous flow with friction on earth rotating, Ekman transport can be calculated in Cartesian directs as,

\[
\begin{align*}
N_x &= \frac{\sigma_w}{\sigma_0} \tau_x \\
N_y &= -\frac{\sigma_w}{\sigma_0} \tau_y
\end{align*}
\]  

(1)

As inferred from Equation (1) where \( \tau \) is the wind stress vector, \( f \) is the Coriolis parameter and \( (y, x) \) denotes the matches in the northward and eastward direction, correspondingly. The seawater density is \( \sigma_w = 1026 \text{kg/m}^3 \). The offshore element of Ekman transport \( N_e \) can be calculated as,

\[
N_e = N_y \sin \varphi - N_x \cos \varphi = \frac{\tau_x}{\sigma_w} \sin \varphi + \frac{\tau_y}{\sigma_w} \cos \varphi
\]

(2)

As described from the above Equation (2) where \( \varphi \) is the coastline tilt angle. Moreover, the wind-drag and wind-shear equations utilized to evaluate the wind stress at sea level is expressed as

\[
\tau = \sigma_w D_e |\vec{u}| \vec{u}
\]

(3)

As shown in Equation (3) where \( \vec{u} \) are the wind vector and the atmospheric density \( \sigma_0 = 1.23 \text{kg/m}^3 \) from cross calibrated multi-platform. The drag coefficient \( D_e \) is a

\[
\begin{align*}
D_e &= 1.2 \cdot 10^{-3} & 4 \leq |\vec{u}| < 11 \text{m/s} \\
D_e &= (0.49 + 0.065 |\vec{u}| \cdot 10^{-3}) & 11 \leq |\vec{u}| < 25 \text{m/s}
\end{align*}
\]

(4)

To utilizing the Equation (4) the wind speed is set as > 4 m/s as 4 m/s and larger than 25 m/s as 25 m/s. To calculate the offshore element of the Ekman transport utilizing geostrophic wind speeds determined from the mean pressure area, which then utilized to state the upwelling index. Since, the association between these factors is expressed as,

\[
N_e \cdot K_x = \omega_e \cdot K_y \cdot K_x
\]

(5)

As inferred from Equation (5) where \( K_x, K_y \) are the width and length and correspondingly. The upwelling velocity can be calculated as,

\[
\omega_e = \frac{N_e}{K_y}
\]

(6)

The real coastal upwelling response width has asimilar scale as the radius of deformation, so \( K_y \) is equivalent to the first radius.

The geostrophic approximation and Sea Surface Height Anomaly data to evaluate the eddy kinetic energy from the geostrophic velocity anomalies \( (v', u') \),

\[
\text{EKE} = \frac{1}{2} \left( v'^2 + u'^2 \right)
\]

(7)

where

\[
\begin{align*}
v' &= -h \left( \frac{\partial \sigma'}{\partial y} \right) \\
u' &= h \left( \frac{\partial \sigma'}{\partial y} \right)
\end{align*}
\]

(8)

In the above Equation (8) where \( g' \) is the Sea Surface Height Anomaly and \( h \) is the gravitational acceleration.

The Chl-a concentration world map shows where the sea is made up of small floating organisms. These images are taken from https://neo.sci.gsfc.nasa.gov/analysis/index.php to examine the Chl-a concentration in the region of Hailing Bay. Figure 2 shows chlorophyll-a Concentration from satellite view and (a) Step 1-September month 2019 Chl-a concentration (b) Step 2-October month 2019 Chl-a concentration (a) Step 3-August month 2019 Chl-a concentration. Such plants are called phytoplankton because many animals, such as small fish and whales, feed on it. They are an important part of the oceanic food chain. Through looking at where and when phytoplankton grows in large numbers. Scientists use satellites to measure the degree to which phytoplankton develops in the sea by looking at the light color, reflected in the shallow waters. Phytoplankton produces a pigment called chlorophyll photosynthesis, which gives them a greenish color. These map showing where and how
much phytoplankton developed on a given day or over days from the satellite observations. The black areas show that phytoplankton can not be measured by the satellite.

Case 2: Model function and shape prior

Solution 2: Our approach is based on the assumption that when there is less information or a lack there should be an optimum adjustment method based on an earlier seasonal process, which is here described as an average or climatological seasonal time-conscious. This method is particularly helpful when the values are imputed during missing periods of data, for example, when linear interpolation can lead to incorrect results. The idea of providing support from a pixel environment has already proven to be helpful. The model function $x_n$ is a sum over $m$ basis functions, one for each season,

$$x_n = d_0 + \sum_{j=1}^{m} d_j a(y, t)$$  \hspace{1cm} (9)

As basis functions, a double logistic function has been taken, although other functions like asymmetric functions are possible.

$$a(y, t) = \frac{1}{1 + \exp\left(\frac{y - y_1}{y_2}\right)} - \frac{1}{1 + \exp\left(\frac{y - y_4}{y_3}\right)}$$  \hspace{1cm} (10)

In the above Equation (9) the $d_0$ variable identifies the base level and linear parameter $d_1, \ldots, d_m$ states the amplitude for seasons. The non-linear parameter $y_1$ and $y_2$ measures the left and right inflexion points for season $j$, whereas $y_3$ and $y_4$ measure the period of increase and decrease correspondingly. The model function based on the base level, $m$ linear parameter and $4 \times m$ non-linear parameter and is flexible enough to encompass interannual seasonal shifts and variations. Assuming that season has the same amplitude, equal rise time, the same fall cycle and turning points adjusted by 365 days. Figure 3 shows the Flow Chart of the process to determine Chlorophyll-a concentration maps.

Case 3: Chl-a algorithm

To determine the satellite-derived data Chl-a algorithm has been utilized. In regions with $nLw_{555} > 2mW.cm^{-2}.\mu m^{-1}.sr^{-1}$, the regionally tuned algorithm has been utilized.

$$\log(Chl - a) = -0.167 - 2.518\log_{10}(T) + 9.345\log_{10}(T)$$  \hspace{1cm} (11)

$$T = \left[(T_{rs443}/T_{rs555})(T_{rs412}/T_{rs490})\right]^{-0.463}$$  \hspace{1cm} (12)

Under the low range of $nLw_{555}(< 2mW.cm^{-2}.\mu m^{-1}.sr^{-1})$, the regionally tuned algorithm has been utilized,
\[
\log(Chl - a) = 0.247 - 2.702T + 1.695T^2 - 1.764T^3 + 1.092T^4
\]  
(13)

As inferred from the above equation where \( T \) is a spectra value function and \( T_{\alpha}(\lambda) \) is the reflectance value of remote sensing at a given wavelength. The daily Chlorophyll-a data has been controlled into monthly averages to equal the sea surface temperature and photosynthetically available radiation datasets.

To evaluate the efficiency of the Chlorophyll-a retrieval algorithm, the coefficient of identification \( (T^2) \), RMSE and MAPE has been measured between satellite-derived Chlorophyll-a and calculated values as,

\[
T = \log[\max(T_{\alpha443}/T_{\alpha555})/T_{\alpha490}/T_{\alpha555}]
\]  
(14)

\[
RMSE = \frac{1}{m} \sqrt{\sum_{j=1}^{m} \left[ (Y_{j,\text{derived}} - Y_{j,\text{field}})/Y_{j,\text{field}} \right]^2}
\]  
(15)

\[
MAPE = \frac{1}{m} \sum_{j=1}^{m} \left| (Y_{j,\text{derived}} - Y_{j,\text{field}})/Y_{j,\text{field}} \right| \times 100\%
\]  
(16)

As shown in the above equation where \( m \) is the number of samples and \( Y_{j,\text{derived}} \) and \( Y_{j,\text{field}} \) indicates satellite-derived and Chlorophyll-a data for \( j \)-th sample correspondingly.

The similarity of the various parameters is often found using the Pearson correlation study. However, statistical correlations between parameters are not explored. In that analysis, we used an information flow mathematical method (IF), which can analyze the relationship between cause and effect between time series quantitatively. The procedure has been described as

\[
R_{2\rightarrow1} = \left( B_{11} \times B_{12} \times B_{2,sl} - B_{12}^2 \times B_{1,sl} \right) / B_{11}^2 \times B_{22} - B_{11} \times B_{12}^2
\]  
(17)

\[
s_1 = (Y_{1,m+1} - Y_{1,m})/\Delta t
\]  
(18)

As inferred from the above equation where \( R_{2\rightarrow1} \) is the information flowing rate from \( Y_2 \) to \( Y_1 \), \( B_{ji} \) is the covariance between \( Y_j \) and \( s_i \), and \( B_{ij} \) is the sample covariance between \( Y_i \) and \( Y_j \).

Figure 4 shows the Remote Sensing and GIS. Remote sensing refers to the use of satellites or aircraft for gathering earth’s surface information. Remote sensing
Satellites aid to remotely sensing valuable object information. The proposed statistical model based on remote sensing technology will increase the accuracy in predicting the chlorophyll-a concentration in the Hailing bay. The satellite-derived data is a very efficient and robust solution and determined the seasonal variability.

**Experimental results and discussion**

The leaf color information is a natural qualitative indicator of plant vegetation. In order for potential use in quick and noninvasive Chlorophyll in field crop prediction, an imaging system with color properties capable of recording red, green, and blue (RGB) band information has been highlighted. The proposed RSSSM method has a high prediction ratio in determining the Chl-a concentration in Hailing Bay when compared to conventional methods. Figure 5 shows the Satellite remote sensing display of the globe and small black dots denote the chl-a concentrations.

Satellite dimensions of visible and close-infrared light, reflected in seawater, obtain chlorophyll results. Chlorophyll growth needs a sufficient temperature range, and high sea surface (SST) temperatures are not acceptable to increase chlorophyll. The SST is higher in September & October than in August, which may be in September rather than in October the highest Chlorophyll takes place. Figure 2 shows the Chlorophyll-a Concentration measured in different months. Fluorescence chlorophyll provides a great opportunity to evaluate the photosynthesis of plants at local and regional levels with Earth observation technology. The theory and applications of chlorophyll fluorescence to determine photosynthetic activity are clearly understood. The usable pigments (i.e. chlorophyll) drive fluorescence. Figure 6 shows the scatter plot and histogram plot Chlorophyll-a Concentration prediction with real-time data.

The development of a model that predicts the amount of chlorophyll present at a source of water can pave the way for remote sensing to effectively prevent other water pollutants. This method only involves minor adjustments and redundant measures when additional parameters are calculated using remote sensing. It causes time to be spent on data analysis and not so much on data extraction. The prediction of Chl using a Remote Sensor Model has a limited history of success. The size, the depth, the region and the condition of the water can all affect the performance of the prediction equation. The proposed RSSSM method has a high prediction ratio of chlorophyll concentration in hailing Bay. Figure 7 demonstrates the prediction ratio of the proposed RSSSM method.

An accurate assessment is made by comparing the map generated with a reference map from a specific source of information by means of remote sensing analyses. The consistency of classification can be
Figure 6. (a) Real time data taken from https://neo.sci.gsfc.nasa.gov/view.php?datasetId=MY1DMM_CHLORA. (b) Scatter Plot representation of Chlorophyll-a Concentration. (c) Histogram plot representation of Chlorophyll-a Concentration.
improved by reducing the amount of detail or generalizing it into large classes rather than into very specific classes. One of the main aims of precision measurement and error analysis is to allow objective comparisons of various interpretations. In this case, images identified from different times, categorized by various procedures or generated by different persons can be measured using a pixel-by-pixel point-by-point comparison. Multiple factors, including the choice of data classifier, site-specific features and the collection of training data, affect the accuracy of maps generated from remote sensing methods. The proposed RSSSM method has high accuracy in detecting the chlorophyll concentration. Figure 8(a) shows the accuracy ratio of conventional methods and 8(b) shows the proposed RSSSM method accuracy ratio.

The chlorophyll-a concentration of MSE and RMSE has been derived in Equations (15) and (16). An empiric pattern can not reflect seasonal/temporal variations of chlorophyll-a concentrations that are unique to a specific area of investigation when calibrated utilizing a single date image. The effect of a large time window between the satellite and the locally calculated data set will introduce a major Chl-a concentration error since the temperature of coastal water differs rapidly because of tides and current currents. The models developed in this research have been developed and tested utilizing data from every year. The observed sensitivity of the Chl-a reflectance to the surface (SR) where an SR error of 1% is expected to result in a Chl-a error of 6% indicates a detailed examination of an atmospheric method of correction appropriate for the study area. Furthermore, because of the use of a large number of images and acquisition dates utilized in model creation and validation, the model established should be measured more reliable than previous remote sensors in difficult regions. The proposed RSSSM method has less error rate when compared to other existing methods. Figure 9(a) shows the error rate of the traditional method 9(b) shows the proposed RSSSM method Error rate.

The remote sensing reflectance is a measure of how much of the down welling radiance in the water’s surface in any direction is gradually restored to a small solid angle centered on a certain direction through the air. This reflection is based on the concept of uniform water-leaving radiance, described as “the radiance which can be measured through a nadir-vision instrument in the absence of any atmospheric loss when the Sun is at the zenith. The incident to reflected radiant flow ratio is the spectral reflectance determined by an object or region on specified wavelengths. Reflectance is an inherent property of an object and is independent of place, time, atmosphere conditions, light intensity, and environment, as opposed by radiance and radiance values. Even though reflectance is a major measurement unit in remote sensing, it is not directly restrained and must instead be derived. Figure 10 shows the Reflectance ratio of the proposed RSSSM method.

The experimental result shows that the proposed RSSSM method has a high prediction ratio in detecting
Chl-a Concentration in Hailing Bay when compared existing method multi-resolution analysis wavelet transform MRA-WT, Wireless Sensor Network based Device-free sensing WSN-DFS, Generalized stacked constraint model GSCM, Integrated Traditional Ecological Knowledge ITEK, and Generalized...
Additive Model GAM prediction model. The proposed Remote Sensing technology with satellite-derived data is a very effective method and robust.

Conclusion
This paper presents the Chlorophyll-a concentration in the Hailing Bay utilizing remote sensing assisted sparse statistical models. In the Hailing sea, the two seasonal peaks performed in September, October of 2019 and maximum Chl-a have been observed in August. These distinctions of Chlorophyll-a could be mainly described by climate change, water column structure, and human activity. The results show a synoptic view of the spatial-temporal variability of the concentration of chlorophyll-a in the water—an extremely turbid tropical sea in China. A significant spatial change occurs in chlorophyll-a concentrations across the sea, as shown on the monthly composite maps, through this analysis. The findings show a large time variability due in part to seasonal factors including climatic (rainfall) and seasonal agricultural practices. The proposed RSSSM method enhances accuracy in predicting chlorophyll-a concentration with a minimum error rate and found the seasonal variation. The important relationship between the trends in chlorophyll and in the sea provides managers and decision-makers with much-needed information in the control.

Disclosure statement
No potential conflict of interest was reported by the authors.

References
Atici, T., & Obali, O. (2006). Seasonal variation of phytoplankton and value of chlorophyll a in the Sarıyar Dam Reservoir (Ankara, Turkey). Turkish Journal of Botany, 30(5), 349–357. http://journals.tubitak.gov.tr/botany/issues/bot-06-30-5/bot-30-5-3-0507-3.pdf
Ben Abbès, A., Bouhou, O., Farah, I. R., de Jong, R., & Martinez, B. (2018). Comparative study of three satellite image time-series decomposition methods for vegetation change detection. European Journal of Remote Sensing, 51(1), 607–615. https://doi.org/10.1080/22797254.2018.1465360
Bresciani, M., Stroppiana, D., Odermatt, D., Morabito, G., & Giardino, C. (2011). Assessing remotely sensed chlorophyll-a for the implementation of the water framework directive in European perialpine lakes. Science of the Total Environment, 409(17), 3083–3091. https://doi.org/10.1016/j.scitotenv.2011.05.001
Catts, G. P., Khorram, S., Cloern, J. E., Knight, A. W., & Degloria, S. D. (1985). Remote sensing of tidal chlorophyll-a variations in estuaries. International Journal of Remote Sensing, 6(11), 1685–1706. https://doi.org/10.1080/01431168508508948318
Darecki, M., Weeks, A., Sagan, S., Kowalczuk, P., & Kaczmarek, S. (2003). Optical characteristics of two contrasting Case 2 waters and their influence on remote sensing algorithms. Continental Shelf Research, 23(3–4), 237–250. https://doi.org/10.1016/S0278-4343(02)00222-4
Gao, S., & Li, Z. Y. (2009). Spatial and seasonal variation of chlorophyll and primary productivity in summer and winter in the Northern Yellow Sea. Periodical of Ocean University of China, 39(4), 604–610. https://doi.org/10.16441/j.cnki.hdzx.2009.04.009
Gong, G. C., Shiah, F. K., Liu, K. K., Wen, Y. H., & Liang, M. H. (2000). Spatial and temporal variation of chlorophyll a, primary productivity and chemical hydrography in the southern East China Sea. Continental Shelf
