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Assessment of the summer-autumn bloom in the Bohai Sea using satellite images to identify the roles of wind mixing and light conditions

Feifei Liu\textsuperscript{a,b}, Jian Su\textsuperscript{b,c}, Andreas Moll\textsuperscript{c}, Hajo Krasemann\textsuperscript{b}, Xueen Chen\textsuperscript{a}, Thomas Pohlmann\textsuperscript{c}, Kai Wirtz\textsuperscript{b}

\textsuperscript{a}College of Physical and Environmental Oceanography, Ocean University of China, Songling Road. 238, 266100 Qingdao, China
\textsuperscript{b}Institute for Coastal Research, Helmholtz-Zentrum Geesthacht Centre for Materials and Coastal Research, Max-Planck-Str. 1, 21502 Geesthacht, Germany
\textsuperscript{c}Institute of Oceanography, Institute of Oceanography, Bundesstr. 53, 20146 Hamburg, Germany

Abstract

In shallow coastal ecosystems, summer-autumn phytoplankton blooms require thorough investigation because of their large variability in space and time. This variability results primarily from the complex interplay of different governing factors, e.g., wind mixing and light availability. To identify the effects of these governing factors on the summer-autumn blooms in the Bohai Sea, we first established a statistical approach to define the biological variables that characterize summer-autumn blooms, i.e., the bloom onset time (denoted as bloom onset), the bloom magnitude, and the rate of chlorophyll-a (Chl-a) increase during the bloom period (denoted as Chl-a increase rate). These variables were quantified using daily Medium Resolu-
tion Imaging Spectrometer (MERIS) satellite scenes from 2003 to 2009. We observed a remarkable onshore-offshore gradient in all three biological variables. For example, bloom onsets were delayed in coastal areas compared to deep offshore waters. Spatially, the bloom onset exhibited a high correlation with wind mixing prior to the bloom period ($R > 0.6$), whereas the Chl-a increase rate and bloom magnitude were highly correlated to the distribution of the light attenuation coefficient ($K_{d(min)}$, $R = -0.65$ and $R = 0.69$, respectively). Furthermore, the empirical orthogonal function (EOF) analysis revealed similar interannual variability in the $K_{d(min)}$, bloom onset and Chl-a increase rate. We also observed similar interannual trends in the bloom magnitude and wind mixing during the bloom period. From the analysis above, we believe that light is a crucial limiting factor for summer-autumn phytoplankton dynamics in the Bohai Sea. Wind influenced Chl-a dynamics in many ways and at various scales. Spatially, weak wind speeds prior to bloom events tended to provide favorable light conditions for the development of blooms. Over the long-term, however, enhanced wind mixing tended to supply the surface layer with nutrients more effectively and thus promoted a higher bloom intensity.

Keywords: Bohai Sea; MERIS Data; phytoplankton bloom; wind mixing;
1. Introduction

The summer-autumn phytoplankton bloom dynamics in coastal waters have been poorly investigated in the past, mostly because of the lack of measurements with sufficiently high resolution in space and time (Cloern, 2001). In recent years, a unique means of studying the spatio-temporal distribution of coastal phytoplankton has been provided by high-resolution ocean color sensors (e.g., Brickley and Thomas, 2004; Tang et al., 2003a). Satellite-based studies have clearly identified a strong variability in chlorophyll-a (Chl-a) concentration over different spatio-temporal scales (Iida and Saitoh, 2007; Navarro and Ruiz, 2006; Sackmann et al., 2004). Although many studies have focused on spring blooms (e.g., Tian et al., 2009; Wiltshire et al., 2008), satellite-based data can also help to quantify variability in summer-autumn blooms and, thereby, start pinpointing the mechanisms behind that variability (Kim et al., 2007; Ueyama and Monger, 2005). In addition, not only can the growing number of satellite images constrain parameterizations of ecological models (Gohin et al., 2005), multi-scale correlations between biological and environmental variables will help to improve functional representations within the models.
The Bohai Sea is a semi-enclosed sea in northeast China (Fig. 1) with an area of approximately 77,000 km$^2$. It is a typical shallow water body with a mean depth of 18.7 m and maximum depth of approximately 70 m located near the northern coast of the Bohai Strait. The Bohai Sea experiences low water exchange capacity because the Bohai Strait with a width of $\sim$ 150 km is the only connection to the Yellow Sea (Zhao and Shi, 1993). The Yellow River, the second largest river in China, drains into the Bohai Sea. The run-off shows a very strong seasonal variability reaching over 10,000 m$^3$/s in summer with an annual mean value of only 1,400 m$^3$/s. Connected to this freshwater inflow is a strongly variable input of sediments and nutrients (Martin et al., 1993). The wind field of the Bohai Sea is dominated by the East Asia Monsoon, which is characterized by strong northwesterly winds with a mean speed of 6-7 m/s in winter and weak southeasterly winds with a mean speed of less than 4-6 m/s in summer, both of which are superimposed by stochastically short-period changes on the weather scale and an interannual variability dominated by the ENSO signal (Feng et al., 1999). Tides in the Bohai Sea are dominantly semi-diurnal and relatively strong with a tidal range of more than 4 m and maximum tidal velocity of around 2 m/s. Due to the combined effect of tide, wind stress and seasonal stratification, the resid-
ual circulation in the Bohai Sea shows a complex pattern (e.g., Hainbacher et al., 2004; Huang et al., 1999; Zhao and Shi, 1993; Sündermann and Feng, 2004). These complex and strongly variable conditions thereby result in an additional complication of the ecosystem dynamics.

In temperate coastal ecosystems, phytoplankton dynamics reflect a tight balance between nutrient supply and light limitation (Smetacek et al., 1991; Walsh, 1988). It is thought that primary production is primarily controlled by light during spring and by nutrient availability during summer (Colijn and Cadée, 2003; Gomes et al., 2000; Hatcher, 2006; Rousseaux et al., 2012; Yin et al., 1997). In summer and autumn, nutrient concentrations in the upper layer are generally depleted by intense spring blooms, and strong stratification may inhibit the supply of nutrients from deeper waters or the sea floor (Chen, 2009; Kim et al., 2007; Yin et al., 1997). However, summer-autumn nutrient limitation may weaken in eutrophic waters such as the Bohai Sea.

On one hand, the Bohai Sea experiences low nutrient exchange with the outer open seas because of limited water exchange through the Bohai Strait (Zhao and Shi, 1993). On the other hand, the Bohai Sea is heavily affected by nutrient-enriched anthropogenic inputs and exhibits a strong water-sediment exchange (Liu et al., 2011), which can alleviate the nutrient limitation in
summer and autumn. The Bohai Sea is dominated by a high concentration of suspended particular matter (SPM), owing mostly to large SPM loads from the Yellow River (Jiang et al., 2004; Saito et al., 2001), which significantly decreases light availability in the water column. Therefore, the impacts on phytoplankton growth posed by enhanced nutrient availability and more limited light conditions in the Bohai Sea might be of similar magnitude during the summer-autumn period.

In shallow waters, another critical physical factor for biological dynamics is wind mixing. Wind influences bloom development both positively and negatively, as it changes the relationship between the mixed layer depth and the critical optical depth for growth (Sverdrup, 1953). Wind-related alterations in vertical mixing, destratification, and upwelling can enhance nutrient supply to the upper layers (Findlay et al., 2006; Roegner et al., 2002; Tang et al., 2003a; Wilkerson et al., 2006). Meanwhile, strengthened vertical mixing can limit depth-averaged light availability and entrain phytoplankton below the critical depth (Ueyama and Monger, 2005), which can therefore suppress the initiation of blooms in the upper layers. In the Bohai Sea, wind of high variability with different scales leads to complicated local processes and modulates water stability together with tidal mixing, wave mixing and
the buoyancy input (Sündermann and Feng, 2004). Therefore, for the Bohai Sea, the role of wind mixing in modulating the spatial and temporal features of summer-autumn blooms requires further analysis.

A synoptic overview of the spatial and temporal features of summer-autumn blooms has not been yet achieved for the Bohai Sea. The spatial Chl-a concentration distribution in summer-autumn, derived from the Medium Resolution Imaging Spectrometer (MERIS) product from 2003 to 2009, exhibits an obvious onshore-offshore gradient (Fig. 2a). However, this gradient could not be easily explained by wind mixing (spatially $R<0.1$, Fig. 2a-b).

The spatial pattern of total suspended matter (TSM) derived from MERIS indicates complex and variable light conditions, which may in principle critically affect summer-autumn blooms (Fig. 2c). In this paper, we investigated the spatio-temporal distribution of three biological variables derived from MERIS data to describe phytoplankton blooms in summer and autumn: the summer-autumn bloom onset time (denoted as bloom onset), the normalized bloom magnitude during the bloom period (denoted as bloom magnitude) and the Chl-a increase rate during the bloom period (denoted as Chl-a increase rate). By quantifying the major features of the summer-autumn blooms in the Bohai Sea, we aim to identify the possible underlying mecha-
nisms (i.e., wind mixing and light conditions) behind the observed variability in summer-autumn blooms.

2. Dataset and Method

2.1. MERIS Data

MERIS was developed with the aim of analyzing not only the open ocean but also coastal waters (Doerffer et al., 1999). This ability was supported by the European Space Agency (ESA) in supplying special variables for Case-2 waters in standard products. These are, specifically, a Case-2 Chl-a value, a value for TSM, and a measure of absorption due to dissolved and particulate organic matter, called gelbstoff (or colored dissolved organic matter, CDOM).

The underlying algorithm for the Case-2 ESA-standard variables was further developed and is also available in several versions as a separate tool, the Case-2 regional processor (Doerffer and Schiller, 2007), including a specific coupled atmospheric correction. Many studies have supported the strength of this concept (e.g., Cui et al., 2010; Martinez-Vicente et al., 2004; Ruddick et al., 2008). MERIS level-1 scenes were processed by the Case-2 regional processor in version 1.4.1 (R. Doerffer, personal communication, May 16, 2011) to retrieve a daily level-2 product. These data were further subsampled
over the study area (37-41 °N and 117.5-122.8 °E) at a reduced resolution of
\[ \sim 1200 \text{ m}. \] Because our analysis in this paper is focused on summer-autumn
phytoplankton bloom dynamics, we selected MERIS data collected from May
to November between 2003 and 2009 for the subsequent analysis.

The number of available data for each grid point is weather and trajectory
coverage dependent. MERIS collects data every 3 days at the equator and
more often at higher latitudes. However, clouds, contrails and sun glint can
prevent the observation of the underlying surface. When the satellite passes
by, it sometimes captures only part of the Bohai Sea because of the contrail
coverage. Therefore, for a large number of days each year, the data were
not usable. Fig. 2d presents the number of valid retrievals at individual grid
point gathered for the summer-autumn period from 2003 to 2009. There is
visibly a weak statistical bias towards the western part of the sea.

2.2. Statistical approach used to derive biological variables

2.2.1. Bloom period

In shallow coastal waters, a bloom is generally defined as a rapid growth
of phytoplankton that leads to a significant increase in biomass (Richardson,
1997). Our definition of the summer-autumn bloom was based on the cu-
mulative variance of Chl-a concentration (Ueyama and Monger, 2005). The
succession of phytoplankton bloom in summer-autumn is influenced by many factors (e.g., grazing and nutrient supply), which complicates the story. However, the environmental factors are presumably identical in space and time before the occurrence of the summer-autumn blooms. Therefore, we focused on the first bloom during summer-autumn period as the beginning of the seasonal succession in each year.

We used a least-squares fit curve analysis to determine the bloom period at each $0.025^\circ \times 0.025^\circ$ grid point and for each year (2003-2009). First, we conducted quality control. After filtering extreme values, the data were run through a nine-point spatial median filter. For each year, grid points with more than 10 data points between May and November were then chosen for further analysis. For each grid point, the annual cycle of Chl-a concentration was normalized (hence $\mu = 0$ and $\sigma = 1$) by subtracting the temporal mean and dividing by the standard deviation. Missing values in the time series were filled using linear interpolation (Fig. 3, green line). Second, we robustly defined a bloom event as occurring when there was more than one day with a normalized Chl-a concentration higher than 1.5 (Appendix A). If the time interval between two days with Chl-a concentration (normalized) higher than 1.5 was more than 15 days (Appendix B), these days were attributed to two
different bloom events. For this case, we defined it multiple blooms, otherwise
single bloom (Fig. 3) so that the first bloom can be separated from the later
bloom succession (See the reasoning in Appendix B). Third, we derived the
Chl-a variance time series. For each day, the variance was computed over
a 15-day period (analogous to running mean, 7 day window). Fourth, we
adjusted the Chl-a variance time series (Fig. 3, magenta line). To obtain
an ideal “S” curve of the cumulative variance (Fig. 3, red line) focused on
the first bloom period, the disturbance related to later blooms should be
excluded, and the largest Chl-a variance during the first bloom period should
be centered in the variance time series (denoted as the central day) with equal
time distances forward and backward (Ueyama and Monger, 2005). The time
distance was defined as the minimum of the three time intervals, i.e., from
1 May to the central day, from the central day to 30 November and from
the central day to the second possible bloom event (for the case of multiple
blooms only, otherwise, this time interval was ignored). Fifth, a time series of
the cumulative variance was created by generating a cumulative sum of the
daily variance corresponding to the new Chl-a variance time series (Fig. 3,
red line). Sixth, based on this cumulative variance time series, a logistic
curve was fitted using a nonlinear least-squares method (Fig. 3, black cross)
The logistic function

\[ f(t) = \frac{C_1}{1.0 + \exp(C_2 - C_3 t)} + C_4 \]  

contains the time index \( t \) and fitted shape constants \( C_i \). Finally, the bloom onset and bloom end time were functionally defined where the slope of the fitted-curve equaled one-tenth of its maximum slope. Typical examples of procedure defining the bloom-period (multiple blooms and single bloom, separately) are illustrated in Fig. 3a-b. At each grid point in the Bohai Sea, this procedure was repeated for each year, from which a 7-year averaged bloom onset was calculated.

2.2.2. Bloom magnitude

The magnitude of the summer-autumn bloom was expressed as the index of bloom intensity. We used the normalized index instead of the absolute magnitude so that the relative variation would not be overwhelmed by the large variability in areas of high Chl-a concentration over the whole year. The bloom magnitude was computed by averaging the normalized Chl-a concentration over the bloom period (Fig. 3). This procedure was repeated at each grid point for each year, and the averaged bloom magnitude for the 7 years was also calculated.
2.2.3. *Chl-a increase rate*

During the bloom period, absolute Chl-a concentrations were used to calculate the Chl-a increase rate. For each grid point, as the Chl-a concentration measurements were rather sparse, we selected two measurements between the bloom onset and the peak day of the bloom to calculate the Chl-a concentration difference (Fig. 3). Then, the Chl-a increase rate was computed through dividing the difference by the time interval between the two measurements.

2.2.4. *Light conditions and CDOM during the bloom period*

A high correlation between Secchi depth (SD) and diffuse light attenuation coefficient $K_d$ has been found both in the ambient waters of the Bohai Sea, e.g., the Yellow Sea (Son et al., 2005), and other coastal waters that exhibit remarkable similarities in hydrography with the Bohai Sea, e.g., the North Sea (Tian et al., 2009; Sündermann and Feng, 2004). Therefore, we used the MERIS-derived diffuse light attenuation coefficient $K_{d(min)}$ to represent the light conditions. $K_{d(min)}$ is the minimum $K_d$ of all available wavelength-bands of MERIS (Doerffer and Schiller, 2007). We calculated the averaged $K_{d(min)}$ during the bloom period for each grid point for each year. The climatologically averaged $K_{d(min)}$ was also computed by averaging the yearly $K_{d(min)}$ during the bloom period over the 7 years.
The CDOM data were retrieved as "Yellow Substance" by the Case-2 regional processor as well as by the MERIS standard processor. We averaged it over the bloom period for each grid point for each year as well as for the average over 7 years.

2.3. QuikSCAT wind data and wind mixing

QuikSCAT Level 3 daily wind speed data at a $0.25^\circ \times 0.25^\circ$ resolution were obtained from the NASA/DAAC dataset (ftp://podaac-ftp.jpl.nasa.gov/) from 2003 to 2009 and further interpolated to a $0.025^\circ \times 0.025^\circ$ grid (Fig. 2b). To evaluate wind mixing, we parameterized it as the cube of the surface wind speed and assumed the bulk aerodynamic constant ($\alpha$ in the following equation) to be 1.0. Similar processing methods have also adopted to study the mixing caused by the surface wind forcing (Brickley and Thomas, 2004; Ueyama and Monger, 2005).

In addition to the averaged wind mixing during the bloom period, we obtained the wind mixing preceding and following the bloom to find the lag correlation with the biological variables. Because of missing values, the wind mixing in parts of the Bohai Sea was omitted from the analysis (Fig. 2b).

The formula is as follows:
\[ M_{\text{wind}} = \frac{\sum_{n=T_b-i}^{T_e-i} (\alpha \mu_n^3_i)}{(T_e - T_b)} \]  

where \( M_{\text{wind}} \) is wind mixing, \( T_b \) and \( T_e \) present the bloom onset time and the bloom end time, which are calculated as in Section 2.2.1. \( \alpha \) is the bulk aerodynamic constant which is set to be 1.0 in this study. \( \mu \) is wind speed derived from the QuikSCAT product. \( i \) represents the number of days preceding (positive value) or following (negative value) the bloom when calculating the period-averaged wind mixing.

2.4. EOF analysis

Empirical orthogonal function (EOF) analysis was used to examine the spatio-temporal variability of the variables. In this study, the principal components (PCs) represented the interannual variability, whereas the resultant spatial eigenfunctions represented spatial patterns that varied with the corresponding PCs. Data sets were prepared in two steps before applying the EOF analysis. First, the original data were converted to anomaly data by subtracting the temporal mean at each grid point. Second, if a given grid point contained missing data in any year during the 2003-2009 period, the data for that grid point were omitted from the EOF analysis. EOF analyses were performed separately on each variable (the bloom onset, the bloom...
magnitude, Chl-a increase rate, the wind mixing, $K_d(\text{min})$ and CDOM during the bloom). Considering that only 7 years of data were available for the analysis, the EOF images were expected to be rather noisy. The temporal and spatial patterns of the second mode and subsequent modes were less coherent and difficult to interpret in terms of possible physical forcing mechanisms. Therefore, we concentrated on the results of the first EOF mode for each variable.

3. Results

3.1. Long-term averaged spatial pattern

Fig. 4 displays a synoptic overview of the 7-year averaged spatial distribution of the biological variables (left panels) and the possible governing factors (right panels). The bloom onset distribution clearly illustrated an onshore-offshore gradient (Fig. 4a), i.e., later blooms (after August) always occurred in the nearshore coastal areas, whereas earlier blooms occurred in the offshore Central Bohai Sea. The wind mixing exhibited a significant spatial gradient as well (Fig. 4b). Strong wind mixing was observed in the nearshore areas, which corresponded with the areas of late blooms. Across the southwest-northeast direction in the Central Bohai Sea, the water was
dominated by weak wind mixing, indicating that weak wind facilitated the enhancement of early summer-autumn blooms. Spatially, the wind mixing distribution was highly correlated with the bloom onset, with a correlation coefficient as high as 0.69 (Table 1, Exp.1). However, neither the bloom onset nor the wind mixing displayed a good correlation with bathymetry, with correlation coefficients of -0.26 and -0.33, respectively (Fig. 4a-b).

The spatial distribution of Chl-a increase rate exhibited a skewed pattern, i.e., the Chl-a increase rate was low in the Laizhou Bay, the Bohai Bay and the northwestern marginal areas of the Central Bohai Sea (Fig. 4c), whereas the eastern part of the Central Bohai Sea was characterized by high rates of Chl-a accumulation. For the distribution of $K_{d(min)}$ (Fig. 4d), the spatial variation displayed the opposite pattern. Low $K_{d(min)}$ values were observed in the Central Bohai Sea, whereas high $K_{d(min)}$ dominated in the Laizhou Bay and the Bohai Bay, which was consistent with the locations of low Chl-a increase rates. However, the northern Liaodong Bay, characterized by high $K_{d(min)}$, did not exhibit the expected low Chl-a increase rate. The spatial correlation coefficient between the Chl-a increase rate and $K_{d(min)}$ was moderate (Table 1, Exp.1, $R = -0.65$).

The distribution of bloom magnitude also displayed the opposite pattern
to that of the Chl-a increase rate (Fig. 4e). The three bays were characterized by high bloom magnitude, whereas the southwest of the Liaodong Bay and the Bohai Strait were dominated by low bloom magnitudes. This spatial pattern resembled that of $K_{d(min)}$, with a spatial correlation coefficient as high as 0.69 (Table 1, Exp.1). For the spatial pattern of CDOM, high values were concentrated only in the narrow marginal areas and the estuaries, indicating that the land and riverine inputs were the main sources of CDOM.

In coastal waters, CDOM interferes with the algorithm to obtain Chl-a concentration in ocean color remote sensing, influencing the accurate estimation of Chl-a concentration (Van Der Woerd and Pasterkamp, 2008). Therefore, it is necessary to evaluate the perturbation caused by CDOM in our analysis. We performed an experiment, excluding pixels of high CDOM concentration ($>0.8 \text{ mg m}^{-3}$) when calculating the six variables, and found no significant difference either for the spatial patterns (figures not shown) or for the correlation coefficients (Table 1, Exp.1 and Exp.2) between the two cases. Therefore, we confirmed that CDOM has little influence on the estimation of biological variables, and the analysis was acceptable without considering the influence of CDOM.
3.2. Interannual variability

The spatial eigenfunctions of the first EOF mode for the bloom onset illustrate high coherence (Fig. 5a). For most parts of the Bohai Sea, the spatial eigenfunctions are positive. The corresponding temporal pattern indicates significant increases in 2003 and 2006 (Fig. 6a), implying that in most parts of the Bohai Sea, the summer-autumn blooms were delayed in those years.

For wind mixing, the first EOF mode accounted for approximately 26.5% of the total variance. Significant negative signals occurred in the eastern part of the Bohai Sea and the three bays (Fig. 5b), whereas positive signals were observed in the northern and western part of the Central Bohai Sea. For the temporal pattern, there was a strong negative amplitude in 2003 (Fig. 6b), implying weak wind mixing in that year.

Spatially, positive eigenfunctions were found in the Bohai Bay, the Laizhou Bay and the western Central Bohai Sea for Chl-a increase rate (Fig. 5c). For \( K_{d(min)} \), the most significant interannual variability occurred in the southeastern Central Bohai Sea and the northern Liaodong Bay (Fig. 5d). The temporal patterns of Chl-a increase rate and \( K_{d(min)} \) were remarkably similar to that of bloom onset, with positive values in 2003, 2006 and the opposite
in 2004, 2005, 2008 and 2009 (Fig. 6c-d). Combined with the corresponding spatial patterns, the positive values revealed a high Chl-a increase rate and high $K_{d(m)}$ situation in 2003 and 2006.

The spatial eigenfunction of the bloom magnitude indicates inverse phases between the southeastern Bohai Sea and other areas (Fig. 5e). The temporal pattern remarkably resembles that of wind mixing, with a strong negative amplitude in 2003 (Fig. 6e) indicating that weaker summer-autumn blooms occurred in the coastal areas of the three bays and the southern part of the Central Bohai Sea whereas at the same time there were intensified blooms in the other parts of the Bohai Sea (Fig. 5e). The positive values in the temporal pattern in combination with the corresponding spatial eigenfunction depict an inverse distribution of the bloom magnitude in the other years.

For the spatial eigenfunctions of CDOM, there was high interannual variability in the Bohai Bay with the lowest CDOM concentration in 2009 (Fig. 5f and Fig. 6f). However, in the northern part of the Liaodong Bay and the Yellow River mouth, there existed opposite interannual variations that were characterized by maximum CDOM concentration in 2009. For the other parts of the Bohai Sea, the spatial pattern exhibits strong coherence with slight positive values, implying a weak interannual variability.
4. Discussion

4.1. Is the effect of tidal stirring significant?

The timing of a phytoplankton bloom is regulated by the balance between phytoplankton production and losses, which is sensitive to the rate of vertical mixing in the water column (Cloern, 1991). In shallow coastal waters, vertical mixing is manipulated by tidal stresses applied at the bottom and wind stresses on the water surface (Cloern, 1996; Simpson et al., 1991). The tide is strong in the Bohai Sea (Huang et al., 1999), and tidal mixing might have an important influence on phytoplankton dynamics there. However, semi-diurnal and diurnal tides are filtered out in the work because the employed observational data do also not resolve the tidal scale explicitly. According to Cloern (1991, 1996), in shallow coastal ecosystems such as the South San Francisco Bay, phytoplankton blooms with short timescale might be regulated by the neap-spring tidal effect, as the phytoplankton biomass increases during periods of weak tidal mixing (neap tides) and declines during spring tides (strong tidal mixing). We selected the year 2008 for a primary analysis (Appendix C). Fig. C.2 shows that in 2008, summer-autumn blooms developed during both neap and spring tide periods, and the Chl-a increase rate had no obvious correlation with tidal energy. This suggests that the effect of
the neap-spring tidal effect might be overwhelmed by other processes.

From another aspect, in this paper, the first bloom in summer-autumn can be referred to as “the seasonal initiation of summer-autumn bloom succession”. To the first order, tides are sub-daily periodic phenomena, we cannot explain the generation of seasonal signals as resulting from the short periodic physical forcing of tides. Therefore, we ignored the influence of tidal stirring and focused our concentration on the influence of wind mixing.

4.2. Is light a limiting factor in summer and autumn in the Bohai Sea?

The light attenuation coefficient is a good indicator of light availability for photosynthesis. For the 7-year average, the $K_{d(min)}$ value was higher than 0.2 m$^{-1}$, implying high turbidity and rather limited light availability in summer-autumn all over the Bohai Sea, which was consistent with the observed conditions in 1982-1983 (Fei, 1986). In our analysis, the Chl-a increase rate and bloom magnitude exhibited the strongest correlations with $K_{d(min)}$ among the three potential governing factors, revealing that the light condition played an important role in modulating the spatial variability of Chl-a during the bloom period. This conclusion was similar to previous findings for the spring blooms in temperate coastal regions (Cloern, 1999; Dore et al., 2002; Yoder et al., 1993). Guo (1994) also drew the conclusion that
the spring bloom in the Bohai Sea occurs when the light input and water
temperature increase under calm water conditions. However, the traditional
views about the triggers of summer-autumn blooms are concentrated on nu-
trient replenishment assuming that light availability is sufficient to sustain
photosynthesis (Guo, 1994; Iida and Saitoh, 2007; Wei et al., 2004). To fur-
thar characterize the role of light limitation in summer-autumn blooms, more
in situ measurements concerning water condition and nutrient limitation are
required.

4.3. How does wind influence the spatial pattern of summer-autumn blooms in the Bohai Sea?

The spatial coherence between wind mixing and bloom onset (Fig. 4a-b)
suggests that weak wind over offshore waters stimulates the occurrence of
summer-autumn blooms, whereas in coastal areas, strong wind suppresses
the blooms. These results differed from previous findings that wind mixing
promotes summer-autumn blooms via the nutrient replenishment resulting
from vertical-mixing-induced entrainment or the upwelling of nutrient-rich
bottom water (Carstensen et al., 2004; Kim et al., 2007; Ueyama and Monger,
2005).

Phytoplankton growth is affected by light and nutrient limitation (Ben-
nett et al., 1986). However, Liu et al. (2011) and Sun et al. (2002) reported that, based on observations, in summer-autumn the Bohai Sea is enriched by a high concentration of nutrients from river discharge, sewage discharge, regeneration from sediments, and subsurface groundwater discharge. These observational data imply that in most parts of the Bohai Sea, nutrients might not be the most significant limiting factor in summer-autumn. On the contrary, the analysis of light limitation confirmed that light availability still influences phytoplankton growth in summer-autumn. Wind stirring had a negative effect on the development of summer-autumn blooms. Concerning the various mechanisms that relate to wind mixing, the time lag between wind mixing and bloom onset varies. The lag correlation analysis (Fig. 7a) illustrates a high correlation between wind mixing 0-10 days prior to the bloom and the bloom onset but an independence of the bloom onset from wind mixing after the bloom initiation. The time series data of Chl-a concentration and the corresponding wind mixing at two grid points also indicated weak wind conditions within 10 days before the bloom onset (Fig. 7b-c). This result confirmed that weak wind conditions preceding blooms created a favorable environment for bloom initiation. This conclusion implies that wind mixing played the same role in triggering both the spring blooms and the
summer-autumn blooms, indicating that in the Bohai Sea, there were similar
water conditions in spring and in summer-autumn, which were characterized
by high turbidity and relatively rich nutrients. This condition in summer is
possibly caused by eutrophication.

4.4. Factors driving interannual variability

The large variation in primary productivity is an important characteristic
of coastal ecosystem dynamics. Previous observations for the Bohai Sea and
adjacent ecosystems indicate that decadal variability in productivity is likely
to be modulated by multiple mechanisms (Tang et al., 2003b; Liu et al.,
2013). Although it is impossible to derive a reliable correlation between
phytoplankton dynamics and climate indices within the limited study period
of seven years, the analysis of satellite data can still provide a first explanation
of anomalous years such as 2003 and 2006. The resulting hypotheses can then
guide the analysis once longer-term time-series data can be introduced.

The multiple ways in which Chl-a variation depends on physico-chemical
forcing operate in many ways and at various scales, particularly in a shallow
coastal sea. This effect can be observed in the data from 2003, when a nega-
tive value appeared in the time series for the first EOF mode of wind mixing
and bloom magnitude (Fig. 6b and e), presenting low wind mixing associated
with a small average bloom magnitude. At small spatial scales, wind is here shown to suppress Chl-a accumulation in the Bohai Sea (Table 1, Exp.1 and Section 4.2). At an annual scale, however, on average reduced wind mixing correlated with a smaller bloom magnitude throughout the summer-autumn period but did not display any correlation with Chl-a increase rate (Fig. 6). Given our previous discussion, it can be hypothesized that diminished nutrient availability reduces bloom magnitude in a year with weaker average wind mixing. Although weak winds provided favorable light conditions for a bloom, the wind-mixing-induced nutrient replenishment was low. To conclude, a positive wind influence could be derived at the interannual scale, whereas spatially, bloom development exhibits a negative influence of wind mixing.

The year 2006 was also extreme, with a significantly delayed bloom onset but enhanced Chl-a increase rate. This can be explained first by the extreme light conditions. Enhanced light attenuation and reduced light availability would impede bloom initiation but could stimulate photoacclimation if such conditions occur frequently. This extreme year is also related to El Niño/Southern Oscillation (ENSO). Environmental factors in the Bohai Sea are significantly influenced by ENSO. For example, ENSO events resulted in
a decrease of approximately 51% in water discharge from the Yellow River to the Bohai Sea (Wang et al., 2006). Because 2006 was an El Niño year (Kashino et al., 2009; Logan et al., 2008; McPhaden, 2008), river discharge during the flood season was relatively low in that year (Fan et al., 2009).

Our results may indicate that lower riverine nutrient inputs cause delays in summer-autumn blooms and diminished bloom magnitude but, surprisingly, also increased Chl-a increase rates. The negative correlation between bloom magnitude and Chl-a increase rate might reflect physiological constraints in phytoplankton. Intense short-term variations in Chl-a (Fig. 3) very likely reflect effective photoacclimative responses rather than a pure biomass buildup or loss, respectively. Nevertheless, the driving mechanism of summer phytoplankton blooms could be an interplay of water temperature, nutrients, salinity and hydrodynamic conditions (Peng et al., 2012). To elucidate the governing mechanism of interannual variability, a longer time-series of data should be introduced to the analysis system.

5. Conclusions

In the Bohai Sea, the spatial and interannual characteristics of summer-autumn blooms were studied using satellite data. In contrast to traditional
monthly composite products, in this study, we used daily scenes. A high temporal resolution is a prerequisite for quantifying the statistical relationships between variables that may drive or characterize summer-autumn blooms.

Summer-autumn blooms occurred earlier in the deep offshore waters compared to nearshore areas. The spatial correlation between bloom onset and wind mixing preceding the bloom period were extremely high. Higher Chl-a increase rates with lower bloom magnitudes appeared in the deep offshore waters, which reflected better light conditions but also the ongoing photoacclimation of phytoplankton cells. Light still represented a key factor modulating bloom intensity and growth during the summer-autumn period in the Bohai Sea, indicating a coexistence of light and nutrient limitation. Interestingly, the triggers of the summer-autumn blooms were similar to those of spring blooms, providing new insight into the ecosystem dynamics of a shallow coastal sea with severe eutrophication.

Interannual variability revealed, in part, different trends from the spatial analysis, which is a further indication of the complexity of the coupling of physico-chemical and biological dynamics. At an annual scale, light attenuation $K_{d(min)}$, bloom onset and Chl-a increase rate displayed a clear and positive correlation, which is counterintuitive for $K_{d(min)}$ and the Chl-a in-
crease rate. Also differing from the spatial analysis, annually averaged bloom magnitude and wind mixing exhibited a positive correlation. We found it impossible to apply a single theory to explain the causes of interannual variability in the Bohai Sea ecosystem, as it is likely to be regulated by multiple factors. Hence, we suggest incorporating more MERIS and in situ data in future studies and closely connecting those analyses with integrated and mechanistic modeling.

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Appendix A. The critical Chl-a concentration for quantifying the bloom frequencies

In this paper, we used the threshold criterion described by Tett (1987) to preliminarily quantify bloom frequencies. However, the critical Chl-a concentration for the bloom definition varies from region to region. Therefore,
we applied normalized data to the analysis. We coarsely assume that the
time series of Chl-a concentration at a certain grid point obeys a Gaussian
distribution. When converted to a standard normal distribution (with $\mu = 0$
and $\sigma = 1$), values higher than 1.5 or less than -1.5 accounted for less than
18 percent of the distribution. Therefore, the period with values higher than
1.5 can be treated as the bloom period.

We also performed a series of experiments to determine the optimal criti-
cal value. From Fig. A.1, we can find that the three spatially and temporally
averaged biological variables all increased as the critical value increased. N-
evertheless, the spatial pattern of the biological variables did not reveal a
large difference (not shown). Therefore, we chose the median value (1.5)
as the optimal critical value. Although this criterion is not exact, we can
reasonably use it to define the first summer-autumn bloom for the further
statistical analysis.

Appendix B. The time interval between two blooms

For a certain grid point, if a second summer-autumn bloom occurred, we
performed the analysis based on the first bloom. For these instances, we
resampled the time series of Chl-a variance from the very beginning of the
study period (1 May) to the day before the initiation of the second bloom and then conducted the further statistical analysis. Fig. B.1, a second bloom occurred in early September. For case a), we did the curve fitting before the second bloom and successfully captured the first bloom event and obtained reasonable biological variable estimations (e.g., for bloom onset). For case b), we did the curve fitting without excluding the second bloom. The "S" curve fitting failed to reproduce the first bloom event and therefore resulted in large deviations for the biological variable estimations.

We assumed that the time interval between two blooms is no less than 15 days so that we could distinguish the second bloom from the first one. With this assumption, we could constrain the time period used for the subsequent logistic curve fitting to dates before the initiation of the second bloom to avoid disturbances to the fitting result caused by second and subsequent blooms.

Because the time interval between two blooms is highly variable, we cannot select a single interval value that works optimally all of the time. To find the best assignment for the time interval, we chose 5 days, 10 days, 15 days, 20 days and 45 days for the experiments and compared the corresponding results. Fig. B.2 presents the spatial distributions of bloom onset, Chl-a i-
crease rate and bloom magnitude. Fig. B.3 presents the spatial and temporal averages of the three biological variables. Both of the two statistical results indicate inconspicuous differences among the different assignments. Fig. B.3 we can see that the experiment with the interval of 15 days exhibited the smallest bias. Hence, we chose 15 days as the optimal time interval.

Appendix C. The index of neap-spring tide

We obtained hourly sea surface elevation data from the Finite Volume Coastal Ocean Model (FVCOM) model simulation, which is forced by eight major tidal constituents (M2, S2, N2, K2,K1, O1,P1,Q1) from 2007.12.01 to 2008.12.31. For each grid point, we estimated a time series of sea surface elevation from 1 May, 2008 to 30 November, 2008 (Fig. C.1a, blue line). Next, we calculated the daily maximum sea surface elevation (Fig. C.1a, red line). From there, the 2-day running mean was calculated for the time series of daily maximum sea surface elevation (Fig. C.1b, black dashed line). To create the index of neap-spring tide, we constrained the time series within the range of -1 ~ 1 by the following linear formula:

\[ y = \frac{2x}{(a - b)} - \frac{(a + b)}{(a - b)} \] (C.1)
where \( y \) is the index of the neap-spring tides, \( x \) is the daily maximum sea surface elevation (2d running mean), \( a \) is the maximum sea surface elevation during the spring tides (the maximum of the black line in Fig. C.1b) and \( b \) is the minimum of the daily maximum sea surface elevation (the minimum of the black line in Fig. C.1b). For a coarse definition, index values less than 0 could represent neap tides, whereas values greater than 0 could represent spring tides. We followed the same procedure for all of the grid points in the Bohai Sea in 2008. Based on the results, we also calculated the spatial correlation between the index of neap-spring tide and the Chl-a increase rate (Fig. C.2). We found the bloom onset was not regulated by the neap-spring tide because the blooms occurred during both the neap tide period (index < 0) and the spring tide period (index > 0). In addition, there is no remarkable correlation between the neap-spring tide and the Chl-a increase rate.

**Reference**


chlorophyll variability in the Northeast Pacific and Coastal Gulf of Alaska.


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Fei, Z., 1986. Study on the water colour and transparency in the Bohai Sea.


Martinez-Vicente, V., Tilstone, G. H., Blondeau-Patissier, D., Menezes, A., 2004. Validation of MERIS geophysical products in open ocean and coastal


role of the Leeuwin Current and mixed layer depth on the autumn phyto-
plankton bloom off Ningaloo Reef, Western Australia. Cont. Shelf Res. 32,
22–35.

Validation of MERIS water products in the Southern North Sea. In: Pro-
ceedings of the 2nd MERIS -(A)ATSR workshop. Frascati, Spain.

Sackmann, B., Mack, L., Logsdon, M., Perry, M., 2004. Seasonal and inter-
annual variability of SeaWiFS-derived chlorophyll a concentrations in wa-
Res. II 51, 945–965.

Saito, Y., Yang, Z., Hori, K., 2001. The Huanghe (Yellow River) and
Changjiang (Yangtze River) deltas: a review on their characteristics, evo-
lution and sediment discharge during the Holocene. Geomorphology 41,
219–231.

fication induced by freshwater runoff. Estuarine Coastal Shelf Sci. 33 (1),
23–35.

Smetacek, V., Bathmann, U., Nöthig, E., Scharek, R., 1991. Coastal eu-
Son, S., Campbell, J., Dowell, M., Yoo, S., Noh, J., 2005. Primary production in the Yellow Sea determined by ocean color remote sensing. Marine Ecology Progress Series 303, 91–103.


Wang, H., Yang, Z., Saito, Y., Liu, J., Sun, X., 2006. Interannual and season-
al variation of the Huanghe (Yellow River) water discharge over the past 50 years: Connections to impacts from ENSO events and dams. Global Planet Change 50, 212–225.


Yoder, J., McClain, C., Feldman, G., Esaias, W., 1993. Annual cycles of

Table 1. Correlation coefficients between the biological variables and governing factors. Exp.1 is the experiment with the grid points of high CDOM concentration excluded when calculating the variables. Exp.2 is the experiment with the grid points of high CDOM concentration included when performing the same calculations. The red boxes highlight the maximum correlation of each biological variable with the governing factors in Exp.1 and Exp.2, respectively.

<table>
<thead>
<tr>
<th>correlation coefficient (R)</th>
<th>Bloom onset</th>
<th>Chl-a increase rate (log)</th>
<th>Bloom magnitude</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Exp.1</td>
<td>Exp.2</td>
<td>Exp.1</td>
</tr>
<tr>
<td>Wind mixing</td>
<td>0.69</td>
<td>0.49</td>
<td>-0.28</td>
</tr>
<tr>
<td>$K_{d(min)}$</td>
<td>0.46</td>
<td>0.10</td>
<td>-0.65</td>
</tr>
<tr>
<td>CDOM</td>
<td>0.44</td>
<td>0.13</td>
<td>-0.47</td>
</tr>
</tbody>
</table>
Fig. 1. Study area with bathymetric contours (m). The Bohai Sea is divided into 4 regions: the Liaodong Bay, the Bohai Bay, the Laizhou Bay and the Central Bohai Sea. The inlet figure in the upper-left shows the location of the Bohai Sea within the China Seas.
Fig. 2. Spatial distribution of a) Chl-a concentration (Chl-a, mg m$^{-3}$), b) wind mixing (m$^3$ s$^{-3}$), c) total suspended matter concentration (TSM, mg m$^{-3}$) averaged over the summer-autumn period (May-November) from 2003 to 2009. Wind mixing intensity was interpolated to a 0.025° × 0.025° grid from the original 0.25° × 0.25° grid (black dots). d) Number of valid pixels from MERIS gathered for the summer-autumn periods from 2003 to 2009.
Fig. 3. Example time series of Chl-a concentration (normalized, green solid line with circle), Chl-a variance (magenta solid line), cumulative variance in Chl-a (solid red line), least-squares fit curve to the cumulative variance (black solid curve with cross), bloom onset (vertical line at X), the bloom period (gray dashed line) and the period used to calculate the Chl-a increase rate during the bloom period (blue solid thin line) during May to November sampled at a) 39.7°N, 120.4°E in 2003 and b) 39.4°N, 119.9°E in 2008, to illustrate the method calculating variables for typical a) multiple blooms and b) a single bloom during the summer-autumn period, respectively. For the condition of multiple blooms a), we derived the variables based on the first bloom.
a) Bloom onset
b) Wind mixing
c) Chl-a increase rate
d) Light attenuation coefficient
e) Bloom magnitude
f) Colored dissolved organic matter

Fig. 4
Fig. 4. Seven year averaged a) bloom onset (month), b) wind mixing during the bloom period (m$^3$ s$^{-3}$) superimposed by the bathymetry, c) Chl-a increase rate (mg Chl m$^{-3}$d$^{-1}$), d) light attenuation coefficient ($K_{d(min)}$, m$^{-1}$), e) bloom magnitude (dimensionless) and f) colored dissolved organic matter (CDOM, mg m$^{-3}$) during the bloom period. Spatial correlations were computed as follows: between bloom onset and wind mixing $R=0.69$ (p<0.001), between CIR (log) and $K_{d(min)}$ $R=-0.65$ (p<0.001), and between bloom magnitude and $K_{d(min)}$ $R=0.69$ (p<0.001). A contour line at 0.8 mg m$^{-3}$ CDOM is overlaid in panel (f) to delineate high CDOM pixels that were excluded from part of our analysis. The spatial correlations of bloom onset and wind mixing with water depth are -0.26 and -0.33, respectively.
a) Bloom onset

b) Wind mixing

c) Chl-a increase rate

d) Light attenuation coefficient

e) Bloom magnitude

f) Colored dissolved organic matter

Fig. 5
Fig. 5. Spatial eigenfunctions for the first EOF mode of a) bloom onset, b) wind mixing, c) Chl-a increase rate, d) light attenuation coefficient ($K_{d(min)}$), e) bloom magnitude, and f) colored dissolved organic matter (CDOM), for the summer-autumn bloom. Each EOF mode accounts for 23.0%, 28.1%, 25.9%, 26.5%, 32.9% and 27.8% of the total variance, respectively.
Fig. 6. Time series for the first EOF mode of a) bloom onset, b) wind mixing, c) Chl-a increase rate, d) light attenuation coefficient \( (K_{d(min)}) \), e) bloom magnitude, and f) colored dissolved organic matter (CDOM) during the summer-autumn bloom period.
Fig. 7
Fig. 7. a) The time lag correlation between the spatial distribution of summer-autumn bloom onset and (i) the light attenuation coefficient $K_{d(min)}$ (black line) and (ii) wind mixing (blue line). Positive time lag values indicate co-variation after the bloom onset. The highest correlation appeared between the bloom onset and wind mixing 0-10 days prior to the bloom event (period between the dashed lines). b) and c) display typical time series of Chl-a concentration and the corresponding wind mixing at certain points sampled in Fig. 3 to illustrate the relationship between wind mixing and bloom onset.
Fig. A.1. The spatially and temporally averaged biological variables with different assigned values of the critical Chl-a concentration that was used as the threshold to determine the occurrence of the bloom.
Fig. B.1. Illustration of the effect of the disturbance caused by a second bloom on the curve fitting results at a certain point sampled in Fig. 3a). In a) the second bloom period was excluded, resulting in a reasonable fitting curve and correct estimation of the timing of bloom onset. In b) the estimations of both the bloom onset and the bloom end time for the first bloom show remarkable inaccuracy because the second bloom had a significant influence on the curve fitting.
Fig. B.2. Spatial distribution of biological variables with different assignments of the time interval between bloom blooms (The same as Fig. 4).
a) Averaged boom onset (day)

b) Averaged Chl−a increase rate (mg Chl m$^{-3}$ d$^{-1}$)

c) Averaged bloom magnitude ($\times 10^{-2}$ dimensionless)

Time interval between two blooms (day)

Fig. B.3. The spatially and temporally averaged biological variables with different assignments of the time interval between two blooms.
Fig. C.1
Fig. C.1. Example for the procedure calculating the index of neap-spring tides at a certain point sampled in Fig. 3b). a) shows the FVCOM simulated hourly sea surface elevation (blue line) and the daily maximum value (red line). b) shows the 2d running mean (dashed black line) and the dimensionless time series (green line). The dashed-dot lines stand for the maximum and minimum values for the 2d running mean time series, respectively. c) shows the time series of the normalized Chl-a concentration (black line with circle) and bloom onset (vertical line at X) in the sampled point.
Fig. C.2. Index of neap-spring tides on the day of bloom onset versus Chl-a increase rate during the bloom period for each grid point in the Bohai Sea. Blooms occurred during both the neap tide period (index < 0) and the spring tide period (index > 0). There is no good correlation between the spatial distribution of index and the Chl-a increase rate.