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1	Seasonal to interannual variability of Chlorophyll-a and sea surface
2	temperature in the Yellow Sea using MODIS satellite datasets
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Abstract: The spatial and temporal variability of Chlorophyll-a concentration (CHL) 16 17 and sea surface temperature (SST) in the Yellow Sea (YS) were examined using Empirical Orthogonal Function (EOF) analysis, which was based on the monthly, 18 cloud-free Data INterpolating Empirical Orthogonal Function (DINEOF) 19 20 reconstruction datasets for 2003-2015. The variability and oscillation periods on an inter-annual timescale were also confirmed using the Morlet wavelet transform and 21 22 wavelet coherence analyses. At a seasonal time scale, the CHL EOF1 mode was 23 dominated by a seasonal cycle of a spring and a fall bloom, with a spatial distribution 24 that was modified by the strong mixing of the water column of the Yellow Sea Cold Warm Mass (YSCWM) that facilitated nutrient delivery from the ocean bottom. The 25 EOF2 mode was likely associated with a winter bloom in the southern region, where 26 27 it was affected by the Yellow Sea Warm Current (YSWC) that moved from southeast 28 to north in winter. The SST EOF1 explained 99 % of the variance in total variabilities, which was dominated by an obvious seasonal cycle (in response to net surface heat 29 flux) that was inversely proportional to the water depth. At the inter-annual scale, the 30 31 wavelet power spectrum and global power spectrum of CHL and SST showed significant similar periods of variations. The dominant periods for both spectra were 32 2-4 years during 2003-2015. A significant negative cross-correlation existed between 33 CHL and SST, with the largest correlation coefficient at time lags of 4 months. The 34 35 wavelet coherence further identified a negative relationship that was significant statistically between CHL and SST during 2008–2015, with periods of 1.5–3 years. 36 These results provided insight into how CHL might vary with SST in the future. 37





- 38 Key words: Empirical orthogonal function analysis; Continuous wavelet transform;
- 39 Wavelet coherency analysis; Sea surface temperature; Chlorophyll-a
- 40

41 **1. Introduction**

42 Chlorophyll-a concentrations (CHL), as an index of phytoplankton pigment, are considered an important indicator of eutrophication in marine ecosystems, which is a 43 44 process that may affect human life (Smith, 2006; Werdell et al., 2009). Additionally, 45 it can be used to analyze the comprehensive dynamics of phytoplankton biomass 46 (Muller-Karger et al., 2005). On the other hand, sea surface temperature (SST) anomalies indicate stratification of the water column, which is related closely to light 47 and to nutrient loads of CHL (He et al., 2010). Certain studies have reported the 48 49 spatio-temporal variability and relationship between CHL and SST (Gregg et al., 2005; 50 Behrenfeld et al., 2006; Boyce et al., 2010). In the open ocean, Wilson and Coles (2005) analyzed global scale relationships between CHL and the monthly SST. 51 Similarly, the spatio-temporal variability of regional CHL and SST in the South 52 53 Atlantic Bight and the Mediterranean Sea have been investigated using long-term satellite datasets (Miles and He, 2010; Volpe et al., 2012). Gao et al. (2013) examined 54 the spatio-temporal distribution of CHL that was associated with SST in the western 55 South China Sea using the Sea-viewing Wide Field-of-View Sensor (SeaWiFS) and 56 57 National Oceanic and Atmospheric Administration Advanced Very High Resolution Radiometer (AVHRR) data. For coastal waters, Li and He (2014) examined 58 spatio-temporal distribution of CHL that was associated with SST in the Gulf of 59





Maine (GOM) using daily MODIS data. Moradi and Kabiri (2015) examined the spatio-temporal variability of CHL and SST in the Persian Gulf using MODIS Level-2 products. These studies found region-specific relationships between climate-driven SST and CHL. These findings also indicated that knowledge of the spatio-temporal variability in CHL and SST can assist scientists in developing a more comprehensive perspective of biological and physical oceanography of marine ecosystems in the global scale.

67 The Yellow Sea (YS) has an average water depth of only 44 m, and it is marginal 68 seas surrounded by China, and Korea (Fig. 1a). It responds quickly to atmospheric climate change and, in turn, the YS influences local climate variability as a result of 69 the air-sea feedback process. The Yellow Sea Warm Current (YSWC) moves from 70 71 southeast to north in winter (Fig.1b) (Teague and Jacobs, 2000; Lie et al., 2009; Yu et 72 al., 2010), and the Yellow Sea Cold Water Mass (YSCWM; 122–125 °E, 33–37 °N) is entrenched at the bottom in summer (Fig. 1c) (Zhang et al., 2008). These water 73 masses represent the two most important physical oceanographic features in the YS. 74 75 In addition, a southward coastal flow is present in winter along the eastern and western sides of the YS, which corresponds to the northward YSWC in the central sea 76 area (Wei et al., 2016; Xu et al., 2016). These features affect the physical properties, 77 water mass and circulation in the YS, and they are complicated both spatially and 78 79 temporally (Chu et al., 2005).

To date, the importance of SST variability and the associated features such as
thermal or tidal fronts, coastal waters, and currents in the YS have been addressed by

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82	numerous satellite-based studies (Tseng et al., 2000; Lin et al., 2005; Wei et al., 2010;
83	Yeh and Kim, 2010; Shi and Wang, 2012), and the long term CHL trends and
84	seasonal variations have been studied as well (Shi and Wang, 2012; Yamaguchi, et al.,
85	2012; Liu and Wang, 2013). In recent years, warming signals of SST in the YS were
86	reported by Yeh and Kim (2010) and Park et al. (2015), but few researchers have paid
87	attention to how has the increasing SST affected the spatio-temporal pattern of CHL
88	in the YS? What is the region-specific relationship between climate-driven SST and
89	CHL?

90 To answer these questions, we combined remote sensing datasets and statistical analysis to investigate the patterns of variability of CHL and SST over seasonal and 91 inter-annual periods at temporal scales during 2003-2015 in the YS. The present work 92 93 provides a comprehensive description of the phytoplankton biomass and the physical conditions using 13 years of satellite-derived datasets. The objectives of the study 94 were (i) to identify the seasonal spatial and temporal patterns of CHL and SST with 95 the empirical orthogonal function (EOF) statistical model in the YS, (ii) to investigate 96 the inter-annual trends of CHL and SST in a long-term time series with the continuous 97 wavelet transform (CWT) analysis, and (iii) to explore the temporal correlations 98 between CHL and SST using wavelet coherency analysis at a regional scale. 99

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Fig. 1. (a) Bathymetric and geographic map of the study area in the Yellow Sea,
China. (b) Major currents in the study region during winter. (c) Major currents in the
study region during summer: Yellow Sea Coastal Current (YSCC), Yellow Sea Warm
Current (YSWC), Yellow Sea Cold Water Mass (YSCWM).

105 2. Data and Methodology

106 2.1 Data

107 The monthly MODIS-Aqua data for CHL and SST during January 108 2003-December 2015 were used in this study. The CHL and SST data were level 3 109 fields provided by the NASA ocean color web page (http://oceancolor.gsfc.nasa.gov). 110 The standard CHL product that was derived from the OC3Mv5 algorithm (OC3M





- updated version after the 2009 reprocessing) and the daytime SST 11 μm product
 (which uses the 11 and 12 μm bands) were obtained. The level 3 product was
 collected in a 4 km spatial resolution from 30–40 °N in latitude and 118–126 °E in
 longitude for the YS region.
- 115 **2.2. Methodology**

116 2.2.1 DINEOF

117 Due to the cloud coverage of the MODIS images over the YS, MODIS pixel 118 values were missing for some months. The EOF and wavelet analyses generally 119 require a complete time series of input maps without data voids. Therefore, a method to reconstruct missing data based on the Data Interpolating Empirical Orthogonal 120 Functions (DINEOF) decomposition was applied to obtain complete CHL and SST 121 122 data (Beckers and Rixen, 2003; Beckers et al. 2006). It is a self-consistent, 123 parameter-free technique for gappy data reconstruction. Recently, DINEOF has been used widely to reconstruct SST (Miles and He, 2010; Huynh et al., 2016), CHL and 124 winds (Miles and He, 2010; Volpe et al., 2012; Liu and Wang, 2013; Liu et al., 2014), 125 126 total suspended matter (Sirjacobs et al., 2011; Alvera-Azcarate et al., 2015), and sea surface salinity (Alvera-Azcarate et al., 2016). This technique presents some 127 advantages over more classical approaches (such as optimal interpolation), especially 128 when working on CHL and SST datasets (Miles and He, 2010; Volpe et al., 2012). 129 130 CHL and SST are characterized by different scales of variability in coastal or open ocean areas. This method identifies dominant spatial and temporal patterns in CHL 131 and SST datasets, and it fills in missing data. Thus, DINEOF was applied to 132





reconstruct the missing CHL and SST data in this study. Because the satellite CHL 133 values spanned three orders of magnitude and CHL retrievals are often distributed 134 log-normally (Campbell, 1995), raw data were log-transformed prior to reconstruction 135 to homogenize the variance and to yield a near-normal distribution (Fig. 2). These 136 137 images show clearly the utility of the DINEOF method in reconstructing monthly, high-resolution imagery from datasets with large amounts of cloud cover. For 138 139 example, in the CHL, DINEOF gives a low concentration of CHL in the southeast regions of the YS (Fig. 2b). 140



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142 Fig. 2. The spatial pattern of CHL in Jan 2011. (a) cloud-covered and (b) DINEOF

143 reconstructed CHL; the spatial pattern of SST in Jan 2011. (c) cloud-covered and (d)

¹⁴⁴ DINEOF reconstructed SST.





145 2.2.2 Empirical Orthogonal Function (EOF) analysis

146 After DINEOF reconstruction, cloud free CHL values were log-transformed before we included them in figures and before statistical analysis. In Section 4, to 147 better discern the spatial heterogeneity and the degree of coherence and temporal 148 evolution of the CHL and SST fields, a traditional EOF analysis was applied further 149 to the monthly, cloud-free DINEOF CHL and SST datasets, which is an approach that 150 151 is also used widely in other disciplines (Hu and Si, 2016a). Each data set was 152 organized in an M×N matrix, where M and N represented the spatial and temporal 153 elements, respectively. Taking CHL for instance, the matrix I(x,t) can be represented by $I(x,t) = \sum_{n=1}^{N} an(t)Fn(x)$, where an(t) are the temporal evolution 154 functions and Fn(x, y) are the spatial eigen-functions for each EOF mode. Prior to 155 EOF analysis, the temporal means of each pixel were removed from the original data 156 using: $I'(x,t) = I(x,t) - 1/N \sum_{j=1}^{N} I(x,t_j)$, where I'(x,t) are the resulting residuals 157 (anomalies). The first two modes were decomposed to analyze the major variability in 158 CHL and SST. 159

To assess the significance of the EOF modes, we followed the methods described by North et al. (1982). The error produced in a given EOF (e_j) was calculated as: $e_j = \lambda_j (2/n)^{0.5}$, where λ is the eigenvalue of that EOF, and n is the degrees of freedom. When the difference between neighboring eigenvalues satisfied $\lambda_j - \lambda_{j+1} \ge e_j$, then the EOF modes represented by these two eigenvalues were significant statistically.

166 2.2.3 The continuous wavelet transform (CWT)





167	The continuous wavelet transform (CWT) was used to determine the
168	inter-annual scales of variability and the oscillation periods of DINEOF CHL and SST.
169	Prior to the CWT analysis, the seasonal variation of each pixel was removed from the
170	original data. The CWT is a tool for decomposing the non-stationary time series at
171	different spatial or time scales into the time-frequency space by translation of the
172	mother wavelet and by analyzing localized variations of power (Messi é and Chavez,
173	2011). The mother wavelets used in this study were the "Morlet" wavelets, which is
174	used commonly in geophysics, because it provides a good balance between time and
175	frequency localization (Grinsted et al., 2004; Hu and Si, 2016b; She et al., 2016). The
176	CWT can localize the signal in both the time and frequency domains, but the classical
177	Fourier transform was able to localize the signal only in the frequency domain with no
178	localization in time (Olita et al., 2011). In addition, cross-correlation functions
179	(Venables and Ripley, 2002) were used to determine the degree of temporal
180	correspondence between the CHL and SST time series datasets, after we removed the
181	seasonal variations. Then, the wavelet coherence was used to show the local
182	correlation between CHL and SST in time-frequency space (Ng and Chan, 2012) that
183	was based on the cross-correlation result. We used the wavelet software provided by
184	Grinsted et al. (2004) (http://noc.ac.uk/usingscience/cross
185	wavelet-wavelet-coherence).

186 **3. Results**

187 3.1 Monthly Climatology of CHL and SST

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The CHL monthly means during 2003-2015 followed a similar pattern from





month to month, with more CHL in the shallow coastal waters and a decreased in the 189 190 seaward direction (Fig. 3). Although the maximum CHL appeared to be fairly consistent seasonally, the spatial extent of blooms had significant seasonal 191 fluctuations. Monthly mean imagery showed the largest spatial coverage of CHL in 192 193 YS was in spring and the smallest coverage was in summer. The CHL in coastal waters was relatively high in spring during every year. Some portions of 194 195 phytoplankton blooms occurred only in subsurface waters, which made it impossible 196 to see using satellite imagery. Overall, the CHL was the greatest in coastal waters in 197 spring or in regions with greater diluted water, such as near the Yangtze River, where the CHL was characterized by a long-lasting summer CHL maximum that started in 198 April and ended in September. 199

200 The seasonal cycle was more evident in the SST field (Fig. 4). SST showed a 201 sinusoidal seasonal cycle, with a persistent, seasonal, warming trend from winter (February) to summer (August). The SST in the YS during December-April were 202 below 12 °C, increased to 15 °C in May, reached a maximum above 25 °C in August, 203 204 and then decreased again in September-October. From December to May, there was a drastic temperature difference between northern waters and southern waters, but the 205 SST during summer months was nearly uniform over the entire YS. Spatially, 206 isotherms were generally parallel to the isobaths. There was a clear temperature 207 208 contrast between coastal waters and offshore waters in winter and spring. Similarly, the thermal front in southeast waters was more visible during winter and spring. The 209 thermal difference reached as high as ~4 $\,$ °C between northern and southern regions in 210





211 February.



212 Fig. 3. Long-term CHL monthly mean climatology computed from monthly DINEOF

²¹³ CHL during 2003–2015 in the YS.







215 Fig. 4. Long-term SST monthly mean climatology computed from monthly DINEOF

- 216 SST during 2003–2015 in the YS.
- 217 3.2 Annual Climatology of CHL and SST





218 Spatial variation in the annual mean CHL during 2003-2015 resembled that of the monthly mean CHL (Fig. 5). CHL was relatively low in offshore waters in the YS 219 and it was higher in the narrow band along the coast, where CHL was stable, except 220 for areas near the Yangtze River. Inter-annual variation of CHL was relatively subtle 221 in the YS, and mean annual values ranged from 2.65 to 3.28 mg m^{-3} . The maximum 222 CHL occurred in 2011, and the minimum CHL were observed in 2003. In summary, 223 the CHL was stable and revealed the stationary level of CHL in the YS irrespective of 224 monthly or annual cycles. 225



226 Fig. 5. CHL annual mean climatology computed from monthly DINEOF CHL during

^{227 2003–2015} in the YS.







Fig. 6. SST annual mean climatology computed from monthly DINEOF SST during
2003–2015 in the YS.

For each year during 2003–2015, the annual isotherms of SST generally ran parallel to the isobaths (Fig. 6). There was a clear temperature contrast between northern and southern waters. Similarly, the thermal front in southeast waters was visible each year. The thermal difference reached as high as ~ 5 °C between northern and southern waters in 2011. Inter-annual variation of the SST was relatively minor, and ranged from 15.17 to 16.88 °C. The maximum SST occurred in 2015, and the minimum SST was in 2011.

238 3.3 Monthly mean and temporal variability of CHL and SST

239 The spatial patterns of CHL and SST concentration were produced by the





240	temporal means of monthly data during 2003-2015 (Fig. 7a and c) and variability
241	associated with the standard deviations (STD) of monthly mean temporal values (Fig.
242	7b and d). One general evident spatial pattern was that mean CHL showed a sharp
243	decrease from coastal waters to offshore regions (Fig. 7a). In our study, the highest
244	CHL values (~ 6 mg m^-3) and the lowest STD (~ 0.02 mg m^-3) were observed in
245	coastal waters (Fig. 7b) that were adjacent to the mouth of the Yangtze River where
246	the water depth was less than 20 m. Compared with the coastal waters and the sea
247	adjacent to large river mouths, central YS waters had lower CHL, but they displayed
248	greater variability. In these regions, strong water mixing could make more deep-ocean
249	nutrients available for utilization by phytoplankton in some months. The
250	spatially-averaged time series showed clear inter-annual variability that was
251	superimposed on the seasonal spring (April) and fall (August) blooms (Fig. 7e). A
252	noticeable scenario was the increasing trend in CHL of ~ 0.03 mg $m^{-3} \mbox{ year}^{-1}$
253	throughout the YS during 2003-2015; this phenomenon would require more
254	observations of subsurface nutrients to understand the underlying mechanisms.

The spatial distribution of the 13-year averaged SST in the YS showed the mean SST with a smooth transition from colder water along the coast to warmer water in offshore areas (Fig. 7c). Similarly, SST in the northern YS was colder compared to that in the southern YS. In contrast, the STD calculated from the 13-year time series of SST also revealed a high spatial distinction between the northern and southern regions (Fig. 7d). In the northern region, the STD reached its highest values in excess of 8 %, in contrast to the STD of the southeastern YSWC region, which were





relatively small. Similarly, the zonal distribution of the variability demonstrated that the western region contained a much higher variability greater than 6.5 °C, which contrasted with the relatively small variability in the eastern region. The spatial mean of SST anomalies was superimposed by synoptic and inter-annual variability signals, which showed a positive trend of ~ 0.02 °C year⁻¹ during 2003–2015 (Fig. 7f).



Fig. 7. Long-term temporal mean and standard deviation maps of DINEOF CHL during 2003–2015 in the YS. (a) spatial pattern of temporal mean and (b) standard deviation map. Long-term temporal mean and standard deviation maps of DINEOF SST during 2003–2015 in the YS; (c) spatial pattern of temporal mean and (d)





- 271 standard deviation map. Time series of mean anomalies for DINEOF values during
- 272 2003–2015 in the YS. The blue lines are least-square linear fits; (e) CHL anomaly and
- 273 (f) SST anomaly.
- 274 4. Discussion
- 275 4.1 Modes of the variability in CHL and SST
- 276 4.1.1 The dominant CHL EOF mode

277 The first EOF (EOF1) and second EOF (EOF2) modes accounted for 40 % of 278 the total CHL variability in this study (Fig. 8), which are similar to those observed in 279 previous studies on the regional and global CHL (Messi é and Radenac, 2006; Thomas et al., 2012). The CHL EOF1 mode explained 34 % of the total variance. The 280 anomalies were not distributed uniformly throughout the entire study area (Fig. 8a). 281 282 One of the centers of CHL anomalies was located in an area with the geographical 283 coordinates of about 35–37 °N and 122–126 °E, which was affected mainly by the YSCWM in the central waters of the YS (Teague and Jacobs, 2000; Lie et al., 2009; 284 Yu et al., 2010). In that location, the stronger mixing of the water column brought the 285 286 deeper nutrients upward, in turn favoring a phytoplankton bloom (Liu and Wang, 2013). Another CHL positive center was in the southeast waters close to the YSWC, 287 which indicated that the EOF1 mode could be explained by the influences of the 288 currents in the YS. As such, EOF1 mode is a good representation of differences in the 289 290 timing of the blooms. The temporal amplitude showed positive values from winter to spring (November to April) but negative values from summer and autumn (June to 291 October) (Fig. 8b). The result was related to the seasonal cycles, with a high CHL 292





293 during winter-spring in offshore waters and a high CHL in summer in coastal waters. 294 In addition, we postulate that this mode is likely associated with nutrient supply from the deep and warm current. The subsurface slope water is nutrient rich and, therefore, 295 offers important nutrients from the subsurface (Townsend et al., 2010). The CHL 296 297 EOF2 mode, which accounted for 6 % of total variance, showed an annual cycle that was different from the EOF1 mode. The spatial pattern showed a remarkable positive 298 299 signal in the southeast waters of the YS, but the negative signal dominated in the northern YS (Fig. 8c). This distribution was different with previous studies conducted 300 301 in the YS (Liu and Wang, 2013), in which a remarkable positive signal was found in 302 the central YS. The temporal amplitude of this mode exhibited a positive signal in spring (March-May), but it was negative in other months (Fig. 8d). 303







- Fig. 8. The first two prominent EOF modes for CHL variability using DINEOF CHL anomaly data during 2003–2015 in the YS. (a) spatial pattern and (b) temporal amplitude from EOF1 mode; (c) spatial pattern and (d) temporal amplitude from EOF2 mode.
- 308 4.1.2 The dominant SST EOF mode

The SST EOF1 mode accounted for 99 % of the total variance (Fig. 9a). SST 309 310 anomalies in the EOF1 mode for the entire study area were all positive, but they were 311 not distributed uniformly throughout the entire study area. This indicated that SST 312 exhibited a positive trend, which was consistent with the pattern that was depicted in Fig. 7f. Similar trends were observed by Liu and Wang (2013) and Park (2015) in 313 their analysis of YS SSTs during the period 1997–2011 and 1981–2009, respectively. 314 315 As a result of water depth, the SST spatial EOF1 was highly correlated with the 316 distribution of water depth in the YS. The magnitude of variability of EOF1 in shallow water was larger compared to that in the slope region, which suggested an 317 inverse relationship between the general pattern of CHL and bathymetry (O'Reilly et 318 319 al., 1987). The strong match between the mean CHL and SST patterns throughout the entire YS region can be explained in terms of lower primary production levels that 320 corresponded to stronger stratification of the water column (Behrenfeld et al., 2006; 321 Doney, 2006) and, thus, to warmer surface waters (Wilson and Coles, 2005). This is 322 323 because the variation in SST, in the first order, one-dimensional sense, is inversely proportional to water depth (He and Weisberg, 2003). The shallow ocean waters 324 overall have a larger seasonal cycle. In contrast, SST in the slope region remained 325





fairly consistent especially in winter due to an increase in water depth (heat content) 326 327 and the persistent warm water supply from the southeast water because thermal inertia is linearly proportional to the water column in a shallow ocean (Yan et al., 1990; 328 Chen et al., 1994; Xie et al., 2002; Ichikawa and Beardsley, 2002; Xie et al., 2002; 329 330 Park et al., 2005). The temporal amplitude in SST was dominated strongly by a seasonal periodicity that peaked in summer and winter (Fig. 9b). The influence of 331 332 EOF2 mode on SST variability could be omitted, since it only accounted for 1 % of 333 the total variance (Fig. 9c).



Fig.9. The first two prominent EOF modes for SST variability using DINEOF SST
anomaly data during 2003–2015 in the YS. (a) spatial pattern and (b) temporal
amplitude from EOF1 mode; (c) spatial pattern and (d) temporal amplitude from 21





EOF2 mode.

338 4.2 Scales of variability and oscillation periods on an inter-annual timescale

The CWT were applied to the long-term monthly CHL and SST datasets after 339 removing seasonal variations. The wavelet power spectrum and the global power 340 341 spectrum obtained through the Morlet wavelet transform highlighted the dominant scales of variability and oscillation periods of CHL and SST (Fig. 10). The global 342 343 power spectra showed the multi-period for CHL and SST (right panels of Fig. 10a and 344 b). CHL exhibited dominant and significant periods of ~ 1 year, and insignificant 345 periods of 3-4 years. SST exhibited significant periods of 0.8-1 year (10-12 months), and insignificant periods of 2-3 years. Variations in the frequency of occurrence and 346 amplitude of the CHL anomaly were shown in the wavelet power spectrum (left 347 348 panels of Fig. 10a and b), in which the power varied with time. During 2003-2012, there was a variation period of ~ 2 years for CHL. During 2012-2015, there was a 349 significant period shift to 4 years, but we observed a variation period of ~ 1 year over 350 the entire study period. Overall, the CHL exhibited dominant variations at periods of 1 351 352 year and 3-4 years during the study period. During 2003-2009, there was a significant variation period of 2-3 years for SST, and during 2009-2015, there was a 353 period of 1.5-2 years (Fig. 10b). 354







Fig.10. (a) Wavelets of the amplitudes for DINEOF CHL during 2003–2015 after seasonal variation had been removed. Thin solid lines demarcate the cones of influence and thick solid lines show the 95 % confidence levels; and (b) wavelets of the amplitudes for SST during 2003–2015 after seasonal variation had been removed. The blue dotted lines in the right pannel show the 95% confidence levels.

The anti-phase relationships agreed well with the negative correlation coefficients between CHL and SST, which agreed with other researchers (Hou et al., 2016). In our study, the statistically significant cross-correlation between the monthly CHL and SST datasets after removing seasonal variations (Fig. 11a) also suggested that variability in CHL was slightly negatively correlated with variability in SST in the YS during the study period. The negative correlation was confirmed also by the scatter plot of CHL and SST (Fig. 11b). The cross-correlation between monthly CHL





and SST showed a significant and negative cross-correlation (R = -0.21, p < 0.01) 367 with time lags of 4 months, which suggested that the CHL reached the maximum 368 value 4 months after the SST got the minimum value in the YS. Therefore, to further 369 examine the synchrony between CHL and SST, wavelet coherence analysis was used 370 371 to reveal the coherency between CHL and SST (Fig. 12). The wavelet squared coherence values below the confidence level indicated that there were some randomly 372 373 distributed sections. The vectors indicated the phase difference between CHL and SST at each time and period. The portion of figure 12 with significant correlation showed 374 375 the anti-phase relationship between CHL and SST, with arrows pointing left, which 376 suggested that the two series apparently have negative coherency in the 1.5-3 year band during 2008-2015. 377



Fig. 11. (a) The cross-correlation between DINEOF CHL and SST during 2003–2015.
The blue dashed lines indicate the points that correspond to a 95 % confidence; (b) the
scatter plot of CHL and SST during 2003–2015.







Fig. 12. Wavelet coherency between DINEOF CHL and SST during 2003–2015 in the

YS. Thin solid lines demarcate the cones of influence and thick solid lines show the of solid lines demarcate the cones of influence and thick solid lines show the confidence levels. The color bar indicates strength of correlation, and the direction of arrow show the correlation type with the right pointing arrows being positive and left pointing arrows being negative.

386 5. Concluding remarks

The main purpose of this study was to identify the variability in CHL and SST on both seasonal and inter-annual time scales and its cross relationship based on the long-term, cloud-free, DINEOF CHL and SST datasets. In addition to the EOF, we also applied the wavelet coherency analysis to CHL and SST to determine temporal relations during 2003–2015.

392 Similar with the other middle latitude regions, the CHL variability was 393 dominated generally by a spring bloom with a secondary fall bloom throughout the 394 entire YS region. The EOF1 mode showed stronger seasonal variability in the area





with stronger circulation in the water column. Temporally, the CHL EOF1 mode also 395 396 exhibited a seasonal cycle with a maximum in late winter and early spring and a minimum in summer and early autumn for each year. This could be explained by the 397 influences of the water currents in the YS. The SST EOF1 mode was dominated by a 398 399 seasonal cycle: warmest in summer and coldest in winter. Further analysis showed that the magnitude of the seasonal cycle in different regions was a result of water 400 401 depth and water currents in the YS. There is a strong match between the mean CHL 402 and SST patterns throughout the entire YS region. This relationship can be explained 403 in terms of lower primary production levels that corresponded to stronger stratification of the water column. 404

There were positive trends both for CHL and SST in the inter-annual time scale 405 during 2003-2015. There was a significant negative correlation between CHL and 406 407 SST with time lags of 4 months. Thus, we speculate that CHL reached the maximum value 4 months later than the SST got the minimum value in the YS. Furthermore, the 408 wavelet power spectrum and the global power spectrum for CHL and SST showed 409 410 similar periods of variation, and similar synchronized and corresponding patterns of evolution. The dominant periods were 2-4 years during 2003-2015. CHL was 411 significantly associated with SST in the time-frequency domain, and shared the 412 common variation with the period of 1.5-3 years during 2008-2015, based on the 413 wavelet coherence analysis. The CWT and wavelet coherence analysis extend the 414 discussion on the scales of temporal variability and oscillation periods of CHL and 415 SST, and they provided insights into how CHL might vary with SST in the future. 416





- 417
- 418 Data availability. The SST and CHL datasets used in this study are available
- 419 at <u>http://oceancolor.gsfc.nasa.gov</u>.
- 420
- 421 *Competing interests.* The authors declare that they have no conflict of interest.
- 422
- *Acknowledgements.* This study was supported by the National Science Foundation of
 China (41206166); The Science and Technology Development Plan Project of Weihai
 (2014DXGJ36); The State Key Laboratory of Tropical Oceanography, South China
 Sea Institute of Oceanology, Chinese Academy of Sciences (LTO1608); The National
 Natural Science Foundation of China (41676171); Qingdao National Laboratory for
 Marine Science and Technology of China (2016ASKJ02); The Natural Science
 Foundation of Shandong Province, China (ZR2010DQ019).
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