

Declined trends of chlorophyll *a* in the South China Sea over 2005–2019 from remote sensing reconstruction

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Abstract

Chlorophyll *a* concentration (CHL) is an important proxy of the marine ecological environment and phytoplankton production. Long-term trends in CHL of the South China Sea (SCS) reflect the changes in the ecosystem's productivity and functionality in the regional carbon cycle. In this study, we applied a previously reconstructed 15-a (2005–2019) CHL product, which has a complete coverage at 4 km and daily resolutions, to analyze the long-term trends of CHL in the SCS. Quantile regression was used to elaborate on the long-term trends of high, median, and low CHL values, as an extended method of conventional linear regression. The results showed downward trends of the SCS CHL for the 75th, 50th, and 25th quantile in the past 15 a, which were $-0.0040 \text{ mg}/(\text{m}^3 \cdot \text{a})$ (-1.62% per year), $-0.0023 \text{ mg}/(\text{m}^3 \cdot \text{a})$ (-1.10% per year), and $-0.0019 \text{ mg}/(\text{m}^3 \cdot \text{a})$ (-1.01% per year). The negative trends in winter (November to March) were more prominent than those in summer (May to September). In terms of spatial distribution, the downward trend was more significant in regions with higher CHL. These led to a reduced standard deviation of CHL over time and space. We further explored the influence of various dynamic factors on CHL trends for the entire SCS and two typical systems (winter Luzon Strait (LZ) and summer Vietnam Upwelling System (SV)) with single-variate linear regression and multivariate Random Forest analysis. The multivariate analysis suggested the CHL trend pattern can be best explained by the trends of wind speed and mixed-layer depth. The divergent importance of controlling factors for LZ and SV can explain the different CHL trends for the two systems. This study expanded our understanding of the long-term changes of CHL in the SCS and provided a reference for investigating changes in the marine ecosystem.

Key words: chlorophyll *a* concentration, quantile trends, remote sensing reconstruction, South China Sea

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1 Introduction

Phytoplankton is the basis of the food chain in the ocean. It affects sea-surface carbon dioxide through photosynthesis. Chlorophyll *a* concentration (CHL) is one of the most important indicators of the phytoplankton biomass (Behrenfeld and Falkowski, 1997), and is often used to represent primary productivity. CHL also serves as a tracer of the physical dynamics of the ocean (Lévy et al., 2018). Studying CHL variability not only helps understand the energy flow (Longhurst et al., 1995) and material cycles in the marine ecosystem (Keiner and Yan, 1998; Aumont et al., 2002), but also promotes the research of carbon cycles (Boon and Duineveld, 1998) and supports the estimation of CO₂ concentration (Chen et al., 2011). The long-term variabilities and trends of CHL are key components of climate studies, such as the studies of the El Niño–Southern Oscillation (Feng and Zhu, 2012), sea-level rise (Wilson and Adamec, 2001), and other global issues (Huynh et al., 2020; Grémillet et al., 2008; Kouketsu et al., 2016).

The South China Sea (SCS) is the largest marginal sea in the western Pacific Ocean. The topography of the SCS varies greatly, with broad shelves and a deep basin larger than 5 000 m. The SCS is a semi-enclosed sea basin that connects to the Pacific Ocean and the Indian Ocean through Luzon Strait and the Malacca Strait, respectively. In addition to the water exchange with the open ocean, there is also abundant runoff input into the SCS (Liu et al., 2010, 2013). The SCS has distinct biogeochemical regimes consisting of an oligotrophic basin and river-dominated shelves (Dai et al., 2022). As a representative marginal sea and a weak source of CO₂ to the atmosphere (Dai et al., 2013), the ecosystem of the SCS has been paid broad attention. The changes in the SCS ecosystem can lead to changes in the capacity of carbon pumps (Lu et al., 2018a), altering the regional carbon cycle (Wang et al., 2021a) and other ecosystem functionalities. With the development of satellite remote sensing (Carder et al., 1999; Doney et al., 2009), opportunities were provided to reveal multi-scale variabilities, trends, and the controlling mechanism of CHL in the SCS

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(Tang and Liu, 2020).

In this study, we focus on long-term trends of CHL in the SCS. Many investigations reported the trends over the past decades. Boyce et al. (2010) analyzed the trend of global CHL over the past century (1899–2009) based on measurements and satellite observation data and concluded that the global CHL had been declining at a rate of ~1% per year. But in a small portion of marginal seas including the SCS, CHL had been rising. Temporally, the sign and magnitude of CHL trends depended on the time periods taken. Tang and Liu (2020) found different signs of CHL trends, decreasing in 1980–2000 and increasing in 2000–2012, in the SCS. Spatially, the CHL trends were also heterogeneous. For example, CHL increased along the coast of China and Vietnam from 2002 to 2017, but decreased in the basin (Yu et al., 2019). Besides linear trends, Palacz et al. (2011) applied an Ensemble Empirical Mode Decomposition to analyze the trends of CHL and winds. They found that CHL increased by ~12% between 1997 and 2003, and then decreased in 2010. This type of nonlinear trend, however, could still be different when different techniques were applied (Zhao et al., 2019).

Furthermore, many physical factors including sea surface temperature (SST), monsoon, and upwelling are also changing, which can affect CHL trends in marginal seas (Chen et al., 2004; Gan et al., 2010; Zhao and Tang, 2007; Yu et al., 2020; Boyce et al., 2010; Dunstan et al., 2018). For instance, Boyce et al. (2010) found that the SST in the SCS increased by 0.5 °C from 1899 to 2009, which led to the positive CHL trend. The increase of SST is often accompanied by a decline in CHL in the open ocean (Boyce et al., 2010; Dunstan et al., 2018), but this relationship in the marginal sea can be modified by other factors such as increased wind-induced mixing (Tang and Liu, 2020). Besides, the signs of SST trends can be different depending on the time span chosen for analysis (Chen et al., 2020), further complicating the trends. Except for regional processes, there are local dynamics, such as the submesoscale activity (Guo et al., 2017), that can also contribute to the CHL variabilities and trends (Liu and Levine, 2016). The submesoscale activity can induce intensive upwelling (Guo et al., 2017), and can be quantified with SST fronts (SSTF).

In summary, focusing on SCS, most previous studies investigated CHL trends from the classic least square perspective, which only reflected the mean CHL trend. Recently, the Quantile Regression (QR) approach was drawn broad attention (Lee et al., 2013; Gao and Franzke, 2017; Fan and Chen, 2016; Beniston, 2009; Barbosa, 2008), which can fully reflect the linear trends by using quantile statistics. Using QR, Gao et al. (2020) found that the CHL of the Zhujiang River Estuary, the northern SCS, declined from 1998 to 2018. QR analysis requires a fully covered data set, which was previously unavailable, especially for optical remote sensing data that is vulnerable to cloud contamination. Yet, our recent effort (Wang et al., 2021b) has published a full-coverage CHL data set (details in Section 2.1.1), which provides the opportunity for such analysis. Applying this data set, we will focus on the CHL trends in the recent 15 a (2005–2019) and discuss the main factors. The data set and methods will be described in Section 2, while Section 3 will show the results and analyze the controlling factors of the CHL trends. Summary and conclusions are provided in Section 4.

2 Data and methods

2.1 Data

2.1.1 CHL data set

In our previous study, we used a discrete cosine transform

(Wang et al., 2021b) method to fill the data gaps in the remotely sensed CHL product, Ocean Color Climate Change Initiative version 4.2 (OC-CCI v4.2) near the Luzon Strait in the northern SCS. The data set was validated favorably with observational data (Xiao et al., 2018). In this study, we further applied the same reconstruction procedure to obtain a complete CHL dataset from 2005–2019 for the entire SCS (termed SCS DCT data). The SCS DCT data have the size of 5 478×600×576 (days×longitude×latitude) and can be accessed in the Science Data Bank at <https://www.scidb.cn/en/detail?dataSetId=1387ffe83af54f0fb574d60e97b206b2>.

For the entire SCS, the accuracy of SCS DCT is briefly validated here. The spatial distribution of Root Mean Square Error (RMSE) between the cross-validation subset (5% of the data points) of OC-CCI and SCS DCT is shown in Fig. 1. The overall RMSE for $\ln[\text{CHL} (\text{mg}/\text{m}^3)]$ is 0.106 7. Compared with the observation from Xiao et al. (2018), SCS DCT has an RMSE of 0.129 4 mg/m^3 for CHL and R^2 of 0.54 (Fig. 2). By comparing the original OC-CCI (i.e., those not masked by clouds) and *in-situ* data, the RMSE is 0.096 4 mg/m^3 for CHL and the R^2 is 0.66, which is the upper limit of the reconstruction. Because the reconstruction error is large for the coastal ocean, the area shallower than 50 m was masked. After this process, the range of CHL is 0.002 9–93.0 mg/m^3 . Statistically, compared with the cross-validation set, the accuracy of SCS DCT for the entire SCS was close to that in the adjacent Luzon Strait. When compared with *in-situ* data, the performance was even higher for the whole SCS region (see Fig. 5 and Fig. 6 in Wang et al. (2021b)). So, we can confidently apply it to the following analysis.

2.1.2 SST and frontal intensity

The Multi-scale Ultra-high Resolution (MUR) SST, which merged the Advanced Microwave Scanning Radiometer, the Advanced Very High Resolution Radiometer, and the Moderate Resolution Imaging Spectroradiometer data, is available from June 1 2002 to the present. The product is available in daily maps gridded at 1-km resolution, which can be acquired at <https://podaac.jpl.nasa.gov/MEASURES-MUR?sections=data>. To quantify the role of submesoscale fronts that were reported to be important (Guo et al., 2017), we further calculated the SSTF from MUR SST, based on gradient analysis following the method of ocean front detection (Belkin and O'Reilly, 2009).

2.1.3 Mixed layer depth (MLD)

The MLD product was obtained from the Oregon State University Ocean Productivity (<http://orca.science.oregonstate.edu/data/1x2/8day/mld125.hycom/hdf/>), which was derived from a numerical model (HYCOM). The spatial resolution was (1/12)° and the temporal resolution was 8 d.

2.1.4 Along-track sea level anomaly (SLA)

We used Centre of Topography of the Oceans and the Hydro-sphere (CTOH) Along-Track Sea Level Anomalies regional products (X-TRACK) over 2005–2019 from Archiving, Validation, and Interpretation of Satellite Oceanographic data (AVISO) (<https://www.aviso.altimetry.fr/en/data/products/sea-surface-height-products/region-al/x-track-sla.html>). The CTOH database provided additional elevation corrections for the elevation data. The distance between each adjacent spatial point is 6–7 km the time interval is ~1 s (Birol et al., 2017).

2.1.5 Gridded absolute dynamic height (ADT)

The ADT is derived from a merge of multiple altimeters, processed by the AVISO project and distributed by the Copernicus Service at <https://resources.marine.copernicus.eu/?option=>

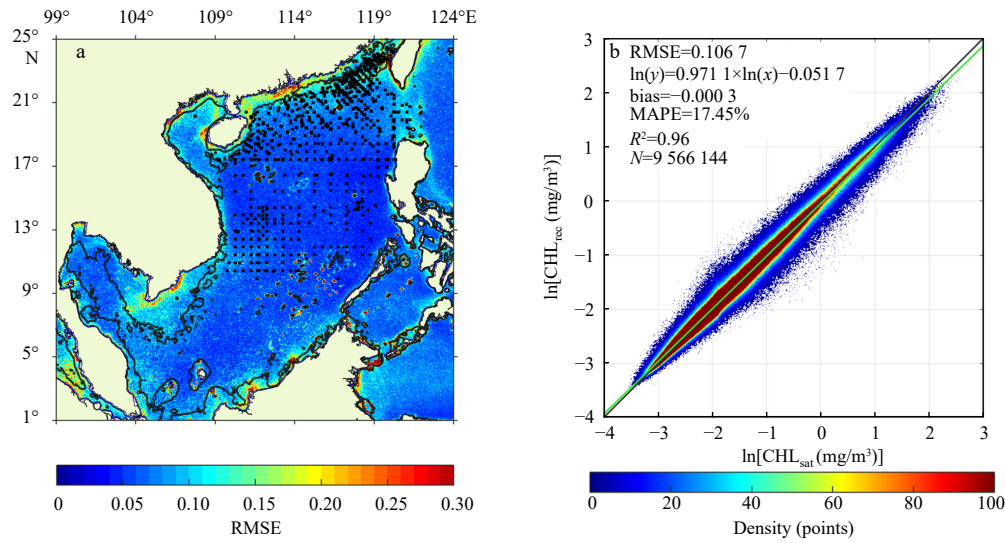


Fig. 1. The cross-validation errors of SCSDCT. a. The spatial distribution of RMSE for $\ln[\text{CHL}_{\text{rec}} (\text{mg}/\text{m}^3)]$; b. the density plot between OC-CCI and SCSDCT. The black dots and solid lines in a represent observation sites from Xiao et al. (2018) and the 50-m isobath. The black line in b is the 1:1 line, and the green one is the linear least-squared fit of scatters. MAPE: Mean Absolute Percentage Error. N is the number of points. The subscript rec represents reconstruction; sat, cross-validation set from satellite data set.

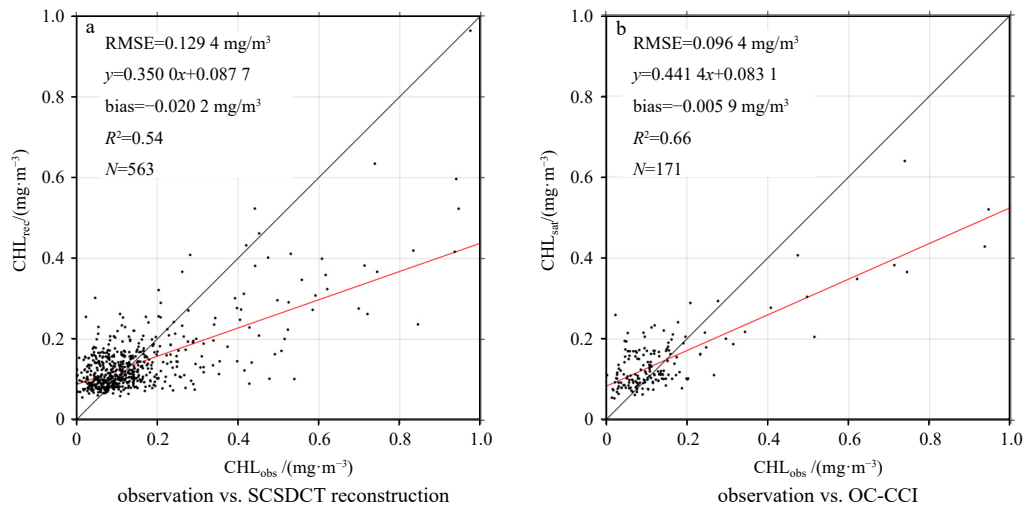


Fig. 2. Scatter plots of *in-situ* observation versus CHL_{obs} reconstruction (a) and observation versus original OC-CCI (b). The solid black lines represent $x=y$ lines, and the red lines represent the regression lines. The subscript rec represents reconstruction; sat, cross-validation set from satellite data set; obs, *in situ* observations. N is the number of points.

[com_csw&view=details&product_id=SEALEVEL_GLO_PHY_L4_REP_OBSERVATIONS_008_047](#). The ADT product has a spatial resolution of $0.25^\circ \times 0.25^\circ$, covering 1993–present. Moreover, to focus on the steric height (SH) changes due to temperature and salinity changes, we have removed the mass-induced volumetric changes using the Gravity Recovery and Climate Experiment (GRACE) and GRACE Follow On (GRACE-FO) observations following Feng et al. (2012). GRACE/GRACE-FO missions are twin satellites that are able to sense the variations in the earth's gravity field, which can then be related to the mass changes at the earth's surface (Wahr et al., 1998). For the ocean, it measures the total water column thickness, which can reflect the changes in seawater volume. For convenience, global surface mass change (level-3 data) in terms of equivalent water thickness is now provided at NASA's Jet Propulsion Laboratory (<https://podaac-tools.jpl.nasa.gov/drive/files/allData/tellus/L3/mascon/RL06/JPL/v02/CRI/netcdf>). Note that the GRACE/GRACE-FO product is

provided on a monthly basis and the native resolution is around 300–500 km (corresponding to a grid size of 3°) (Wiese et al., 2016, 2018; Watkins et al., 2015; Landerer et al., 2020). Therefore, we have interpolated the data set both temporally and spatially for consistency.

2.1.6 Wind product

To analyze the trends of winds, the fifth generation of European Center for Medium-Range Weather Forecasts atmospheric reanalysis of the global climate (ERA5) data were adopted from Copernicus Climate Change Service (<https://cds.climate.copernicus.eu/>) (Hersbach et al., 2020). The ERA5 product has a spatial resolution of a quarter degree. Atmospheric changes are much faster than the ocean, so we smoothed the wind with a 365-days moving mean before the regression analysis. This procedure only affected the statistical significance, while the trend itself was insensitive to the smoothing as we tested.

2.2 Methods

2.2.1 QR

QR can be seen as an extension of the classic least-square regression, which was developed in economics firstly (Bassett and Koenker, 1978). The trends obtained by the classic least squares model (LSM) only reflect the least-square fit to the data, i.e., the average of trends, while QR can calculate trends for individual quantiles of the population. Mathematically, in LSM, the dependent variable represented by y is linearly related to time t , then the simplest form is $y=kt+b$. So, we can express y_i as $f(k, b, t_i)$ point by point.

Then, the slope k and the intercept b are obtained by minimizing the residual (e):

$$e = \sum_i [y_i - f(k, b, t_i)]^2. \quad (1)$$

The expression of the QR method is that there is a tilted absolute value containing the percentile number (τ):

$$e_\tau = \sum_i \rho_\tau[y_i - f(k_\tau, b_\tau, t_i)], \quad (2)$$

where the tilted absolute value function (ρ) is calculated following Koenker and Hallock (2001) by the formula:

$$\rho_\tau = \begin{cases} \tau, & y_i \geq f(k_\tau, b_\tau, t_i) \\ 1 - \tau, & y_i < f(k_\tau, b_\tau, t_i) \end{cases}. \quad (3)$$

In this study, the QR method was used to estimate the temporal trends of CHL and other controlling factors. The “qr_standard” package for QR analysis is from https://github.com/zjph602xtc/Quantile_reg on MatLab. Confidence intervals for the quantile trends were assessed using Wald Test (Goh and Knight, 2009). The advantage of the Wald Test is that it only needs to estimate an unrestricted model, which reduces the computational burden compared with Least Squares Test (Barbosa, 2008). We obtained the trends in quantiles 0.75, 0.50, and 0.25 for all variables, representing low (25th), median (50th), and high (75th) groups respectively.

2.2.2 Random Forest

Since CHL trends can be controlled by various coupling forcings, a full understanding cannot be achieved with the linear model. So, the Random Forest (RF) method was applied. The RF model predicts the LSM trend (represented by $\Delta(\cdot)$ in Eq. (4)) of

CHL from the trends of SST, MLD, wind speed, ADT, SH, and SSTF. Using this method, we can rank the relative importance of these factors.

$$\Delta\text{CHL} = \text{RF}(\Delta\text{SST}, \Delta\text{MLD}, \Delta\text{WS}, \Delta\text{ADT}, \Delta\text{SH}, \Delta\text{SSTF}), \quad (4)$$

where WS is wind speed.

In summary, RF is a regressor based on decision trees proposed by Breiman (2001). It was widely applied in oceanography problems such as subsurface temperature estimation (Lu et al., 2019) and intrusive flow estimation (Casella et al., 2020). The Random Forest algorithm, compared with other regression methods like multivariate linear regression (Lu et al., 2018b), better captures the nonlinear relationship between CHL trends and the controlling factors.

3 Results and discussion

3.1 Quantile and linear trends of CHL

The 2005–2019 annual averaged CHL in the SCS was 0.22 mg/m³ (Fig. 3), higher in winter (0.27 mg/m³) and lower in summer (0.19 mg/m³). Spatially, the nearshore CHL was much higher than offshore where the riverine inputs were less capable to contribute. The spatial patterns of CHL highlighted the high values in winter Luzon Strait (LZ) bloom and summer Vietnam Upwelling Systems (SV) (Lu et al., 2015, 2018b). In the map of CHL trends in Fig. 4a, the LSM trend was generally downward, which was stronger in the western and northern parts of the SCS with an overall rate of -0.0029 mg/(m³·a) (-1.29% per year, divided by the CHL mean of 0.22 mg/m³, Fig. 4a). Then we obtained 75th, 50th, and 25th quantile trends in Figs 4b–d, which were also generally negative. The decreasing trend was -0.0040 mg/(m³·a), -0.0023 mg/(m³·a), and -0.0019 mg/(m³·a), respectively for the 75th, 50th, and 25th quantile. These values are equivalent to 1.62%, 1.10%, and 1.01% declines per year if divided by corresponding quantile thresholds. The 50th quantile trend was very similar to the linear trend, which meant that the median and the mean trends of CHL were close. Apparently, stronger declines occurred for the higher percentiles (Figs 4b–d). These higher percentiles corresponded to the broad region in the northern SCS and the Beibu Gulf (Fig. 3b). In other words, over the spatial domain, higher CHL declined more significantly.

To confirm this finding, we further calculate the trends for the 5th–95th percentiles (Fig. 5). As the percentile increased, the downward trends became larger. The trends lower than the 50th percentile showed little fluctuation, but the downward trend was more severe when the percentile exceeded 60th, which implied a divergent response for lower and higher CHL in the SCS.

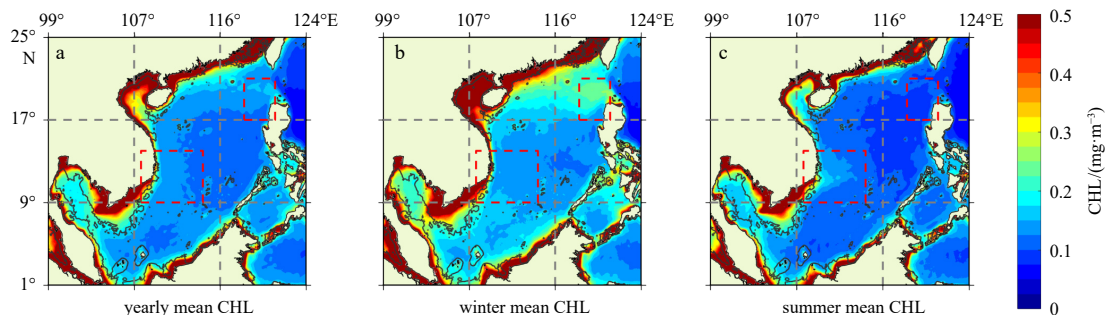


Fig. 3. Yearly- (a), winter- (b), and summer- (c) mean chlorophyll a concentration (CHL) in the South China Sea. The two red boxes represent the region of Vietnam Upwelling Systems (SV) (left) and Luzon Strait (LZ) (right). The black bold line is the 50-m isobath.

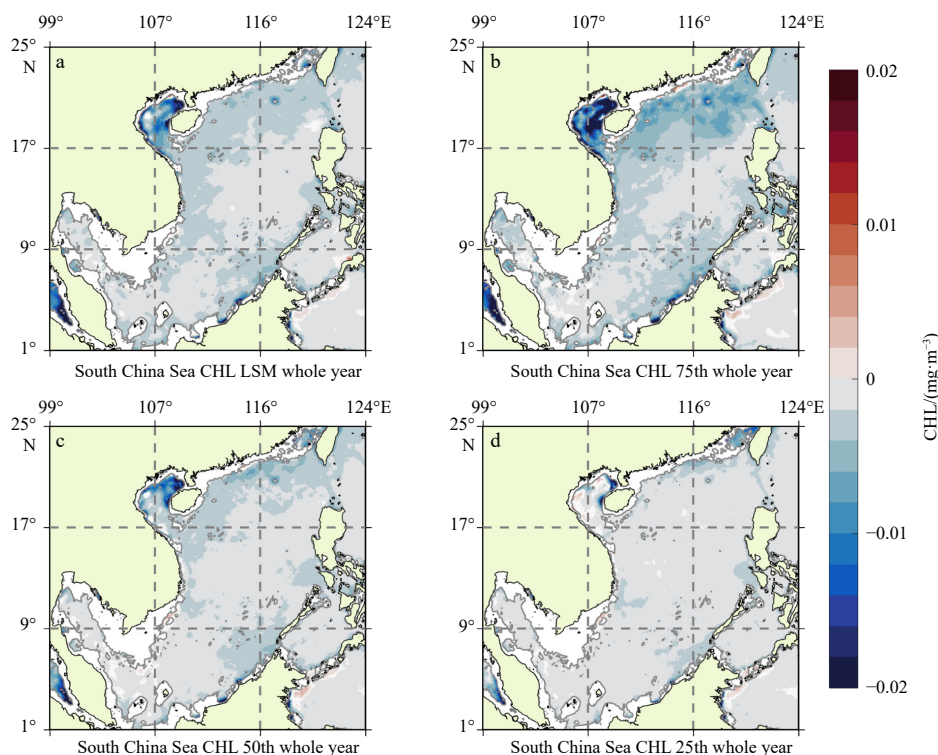


Fig. 4. Trends of chlorophyll *a* concentration (CHL) in the whole year for linear trend (a) of the classic least squares model (LSM), 75th quantile (b), 50th quantile (c), and 25th quantile (d). Points that fail the significance test ($p > 0.05$) are covered by white points.

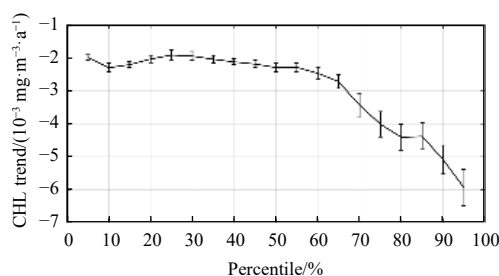


Fig. 5. The chlorophyll *a* concentration (CHL) trends in all quantiles range from 5th to 95th percentages every 5%. The vertical bars are standard errors in each regression.

Combining the information in Figs 3–5, higher CHL tended to have stronger declines both spatially and temporally. Hence, we

calculate the trends of the standard deviation of CHL over both time and space. Figure 6a maps the linear trend of within-month CHL standard deviation (i.e., $N=28, 29, 30$, or 31 depending on the month), with a total of 180 months (15 a). Figure 6b shows the time series of spatial standard deviation ($N=219\ 552$) with the corresponding linear fit. The temporal standard deviation decreased in most parts of the SCS, especially for the western and central SCS (Fig. 6a). And the standard deviation in space decreased significantly with a rate of $-0.028\ 8 \text{ mg}/(\text{m}^3 \cdot \text{a})$. The variabilities of CHL in both space and time decreased. In other words, the SCS CHL declined and became more homogenous over the recent 15 a.

We further analyze the CHL trends for different seasons. We apply QR analysis on CHL in the winter months (November to March) and summer months (May to September). For winter, Fig. 7a shows the LSM trend is $-0.009\ 5 \text{ mg}/(\text{m}^3 \cdot \text{a})$ (-3.54% per

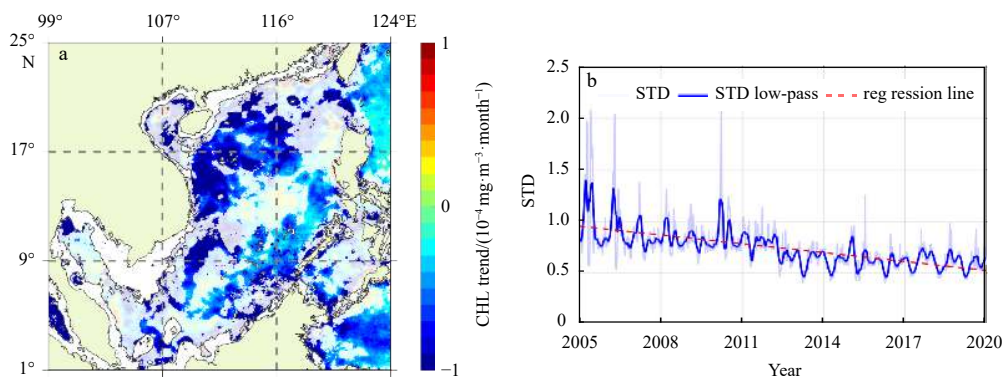


Fig. 6. The chlorophyll *a* concentration (CHL) trend of monthly standard deviation at each point ($N=180$) (a); points that failed the significance test ($p > 0.05$) are covered by white points. Time series of spatial standard deviations (STD) of CHL (light blue, $N=219\ 552$) (b), corresponding 30-days moving mean (thick blue), and the linear fit (dashed red).

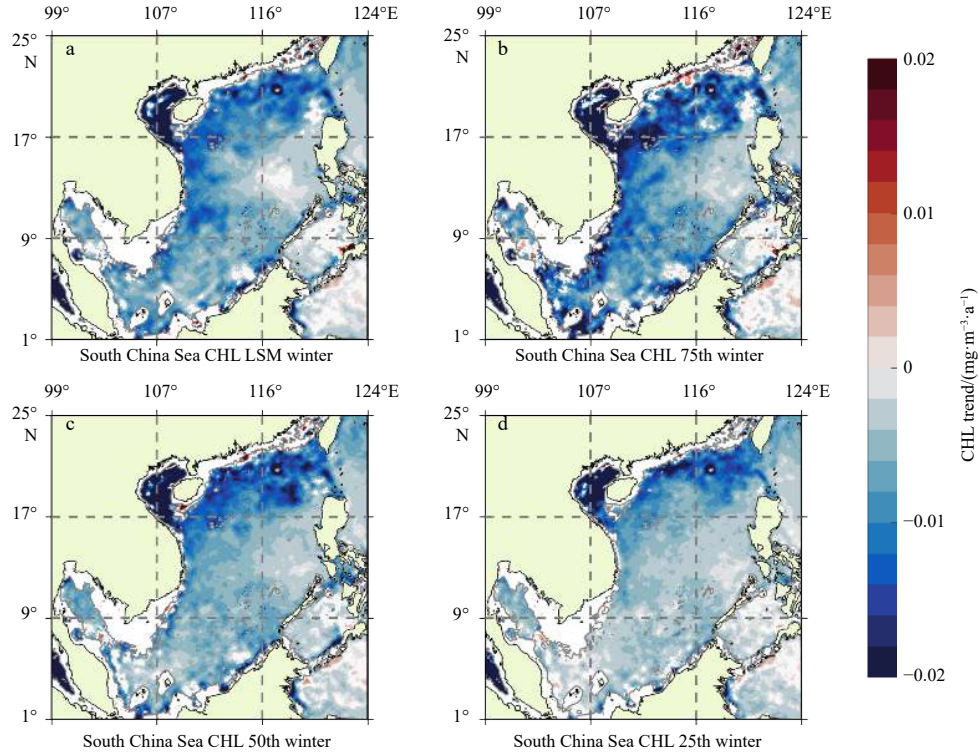


Fig. 7. Trends of chlorophyll *a* concentration (CHL) in winter (November to March of next year) for linear trend of the dassic least squares model (LSM) (a), 75th quantile (b), 50th quantile (c), and 25th quantile (d). Points that fail the significance test ($p > 0.05$) are covered by white points.

year, divided by the mean CHL value of 2.686 mg/m^3), while Figs 7b–d present decreasing trends ($-0.0122 \text{ mg/(m}^3\cdot\text{a)}$, $-0.0097 \text{ mg/(m}^3\cdot\text{a)}$, and $-0.0067 \text{ mg/(m}^3\cdot\text{a)}$) for 75th, 50th, and 25th quantiles, which had stronger decreasing rates in the northern SCS. These trends are equivalent to 4.05%, 3.68%, and 2.96% declines per year, if divided by corresponding quantile thresholds. Given the higher CHL magnitudes in winter, the winter trends were greater than those of the whole year. As well, we calculated the trend of each percentile between 5th–95th (Fig. 8). Combined with the spatial distribution of decreasing trend, “higher CHL decreased faster while lower CHL decreased slower” was still valid in winter. However, the LZ is an exception. The magnitude of decreasing trends became larger in 5th–35th; however, as quantile increases, corresponding trends became smaller (Fig. 8). That implies the LZ bloom events became weaker, but extremely strong events were less affected.

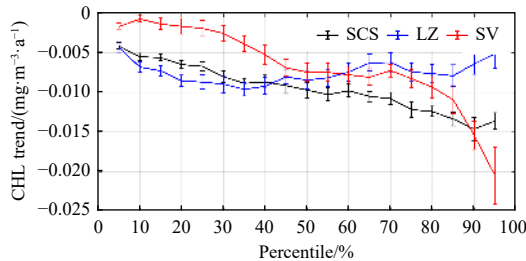


Fig. 8. For the winter South China Sea (SCS) (black), Luzon Strait (LZ) (blue), and Vietnam Upwelling System (SV) (red), the corresponding trends in all quantiles range from 5th to 95th percentiles with an interval of 5%. The vertical bars are standard errors in each regression. CHL: chlorophyll *a* concentration.

For summer, according to Fig. 9a, the LSM trend is $-0.0043 \text{ mg/(m}^3\cdot\text{a)}$ (-2.24% per year), while the quantile trends are shown in Figs 9b–d ($-0.0047 \text{ mg/(m}^3\cdot\text{a)}$, $-0.0033 \text{ mg/(m}^3\cdot\text{a)}$, and $-0.0047 \text{ mg/(m}^3\cdot\text{a)}$ for 75th, 50th, and 25th quantiles, respectively). These are equivalent to 2.29%, 1.71%, and 2.62% per year declines. The declines of CHL in summer was lower than the yearly and winter CHL. Different from the winter and yearly trends, there was a clear increasing area in the western SCS, except for the 25th quantile. The spatial pattern mimic that of the cold jet in summer SV (Li et al., 2014). This will be discussed in the next section. Figure 10 shows the decreasing trends were only at low quantiles, while 30th–95th quantile trends were positive, which implies high CHL were strengthening in SV.

As we mentioned in the Section 1, several studies have investigated the CHL trends in the SCS. In the global study of Boyce et al. (2010), CHL in the SCS increased in the 1988–2009 period. As we found the declined CHL, the sign difference here may be associated with the superimposed climatic variability, presumably the El Niño for the Pacific Ocean (Boyce et al., 2010). ENSO regulated CHL mainly through monsoon intensity in the SCS. This was because the Multivariate ENSO Index (MEI) was highly correlated with wind trend while the wind trend and the CHL trend had a strong correlation at the same time (>0.7) (Palacz et al., 2011). The direct correlation between MEI and CHL trend were relatively weak because the regulation of ENSO on CHL trend was delayed ~ 4 months (Huynh et al., 2020). For the analysis focused on the northern SCS, Gao et al. (2020) found a similar CHL variance decrease. But their analysis did not find significant trends in the basin; this was very likely due to the 8-days data they applied. To prove this deduction, we tested the trends of 8-days averaged CHL, and found the trends of the 8-days average could not pass the significance test ($p > 0.05$) in most of the grids.

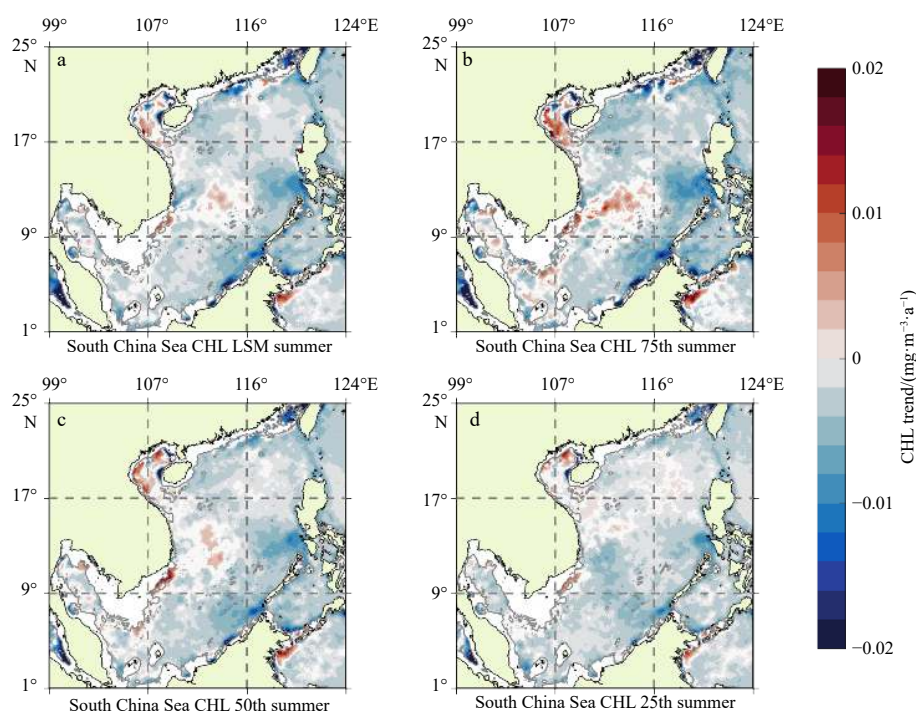


Fig. 9. Trends of chlorophyll *a* concentration (CHL) in summer (May to September) for linear trend of the classic least squares model (LSM) (a), 75th quantile (b), 50th quantile (c), and 25th quantile (d). Points that fail the significance test ($p > 0.05$) are covered by white points.

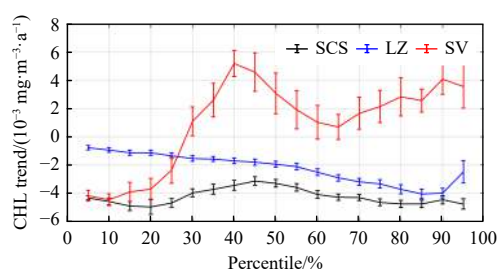


Fig. 10. For the summer South China Sea (SCS) (black), Luzon Strait (LZ) (blue), and Vietnam Upwelling System (SV) (red), the corresponding trends in all quantiles range from 5th to 95th percentages with an interval of 5%. The vertical bars are standard errors in each regression. CHL: chlorophyll *a* concentration.

The analysis of Yu et al. (2019) revealed CHL decreased in the basin from 2002 to 2017, but was significant only for the south-western SCS. This inconsistency is due to different analysis periods and higher missing rate in the optic dataset applied in Yu et al. (2019). Thanks to the daily SCS DCT data applied here, the trends were significant for all seasons in the SCS basin.

3.2 Controlling mechanism

In this section, we analyze the controlling factors of the CHL trends, starting from SST. In the ocean, SST is often tightly linked to CHL since the former reflects the upward motion of cold water and thus the upwelling of nutrients (Dunstan et al., 2018; Boyce et al., 2010; Martinez et al., 2020). So, we first apply the trend analysis to SST. As shown in Fig. 11, there was significant SST increases in the entire SCS regardless of seasons with the global warming, which is consistent with the previous studies (Chen et

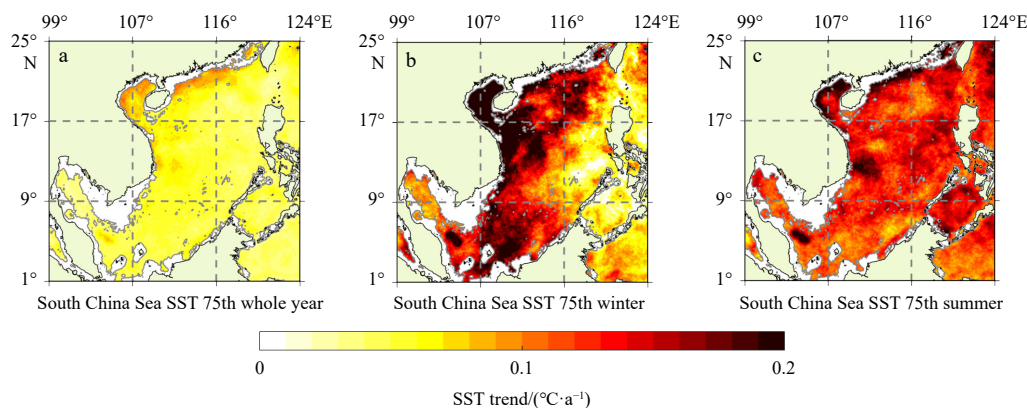


Fig. 11. Sea surface water temperature (SST) trends for 75th quantile in whole year (a), winter (November to March of next year) (b), and summer (May to September) (c). All trends for SST can be found in Fig. S1.

al., 2020; Liao et al., 2015). The SST trends went up with the percentiles in summer (Fig. 12), which implied the high-temperature days got even hotter. In winter, on the other hand, the trends in median percentiles were higher than in low or high percentiles. The overall SST increase of the whole year ($0.051\text{ }^{\circ}\text{C/a}$, 0.18% per year) was lower than that of winter ($0.113\text{ }^{\circ}\text{C/a}$, 0.42% per year) or summer ($0.112\text{ }^{\circ}\text{C/a}$, 0.37% per year). Distinct from the consistent warming trend of SST, until the year 2013, various studies similarly suggested a cooling SST trend in the SCS (Liao et al., 2015; Chen et al., 2020; Li et al., 2021), which was attributed to the global warming hiatus in the period of 1998–2013 (Kosaka and Xie, 2013; Su et al., 2017). This pause in SST warming turned out to be temporary (Yan et al., 2016). For later years, similar to

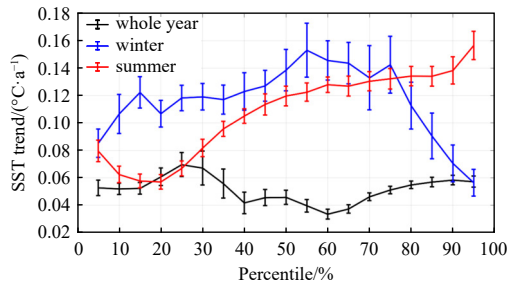


Fig. 12. For yearly sea surface temperature (SST) of the South China Sea (SCS) (black), winter SST (blue), and summer SST (red), the corresponding trends of all quantiles range from 5th to 95th percentages with an interval of 5%. The vertical bars are standard errors in each regression.

the monotonically positive SST in this study, Yu et al. (2019) also found positive SST trends in 2003–2017 of $0.03\text{ }^{\circ}\text{C/a}$. Compared with this rate, the 2005–2019 period was characterized by an even larger rate, suggesting the acceleration of SCS warming.

In winter (Fig. 11b), SST in the western SCS increased more rapidly, which corresponded to a greater decline in CHL in the western and northern SCS (Fig. 7). But in summer, there are major differences between the spatial distributions of SST (Fig. 11c) and CHL trends (Fig. 9). SST increased homogeneously in space, unlike CHL trends. In addition, different from the case of CHL, no big gaps between the increasing magnitudes in winter and summer SST were found, which implies that more physical factors could be involved.

The SCS is forced by strong monsoons, and changes in the intensity of the monsoon would inevitably cause ecological responses (Yang et al., 2012; Gao and Wang, 2008). The wind speed trends in winter and summer were similar (Fig. 13), which cannot explain the seasonal difference in CHL trends. The decreasing region was mostly in the northern and western parts of the SCS, while the increasing region was concentrated in the south-east of the SCS (Fig. 13). Although we cannot obtain clear wind trends that match the distribution of CHL trends, wind speed decreased in more than half of the SCS, and the overall reduction was -0.1 m/s over the 15 a.

Both the weakened winds and warming SST were linked to phytoplankton growth because they led to shallower MLD. This allowed for fewer nutrient inputs from the lower to the upper layer. In Fig. 14, there was a significant shallowing trend in MLD, and the downward trends were greater in both winter and sum-

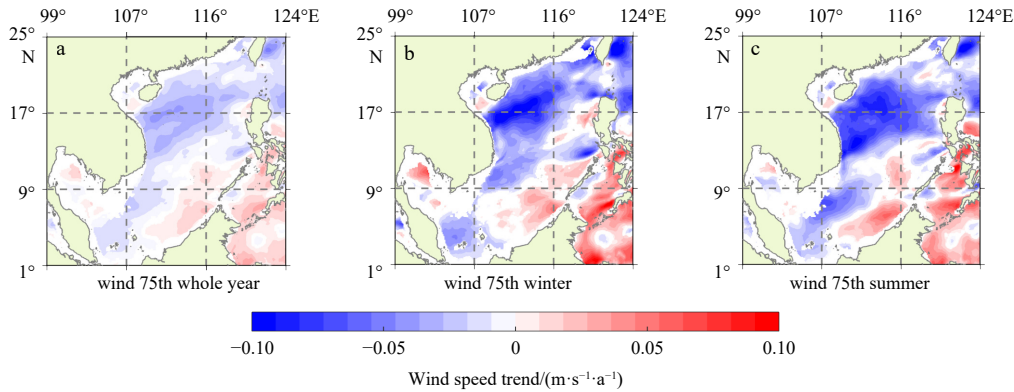


Fig. 13. Wind speed trends for 75th quantile in whole year (a), winter (November to March of next year) (b), and summer (May to September) (c). All trends for the wind can be found in Fig. S2.

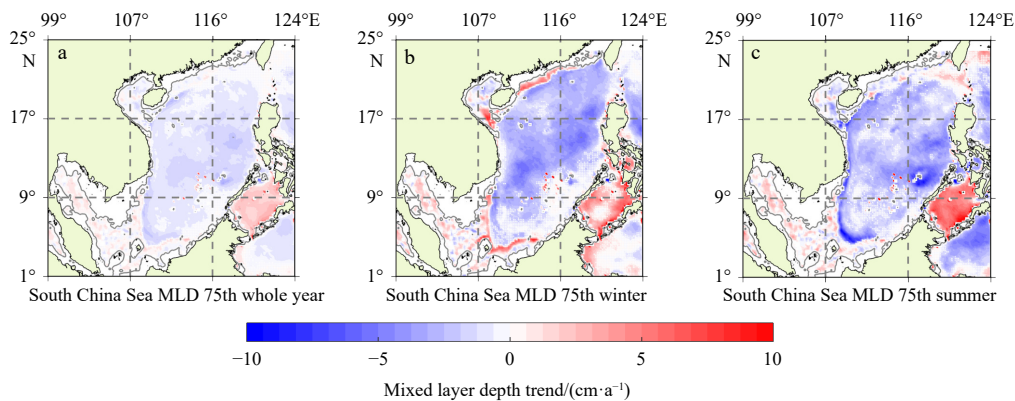


Fig. 14. The mixed layer depth (MLD) trends for 75th quantile in whole year (a), winter (November to March of next year) (b), and summer (May to September) (c). All trends for MLD can be found in Fig. S3.

mer than the yearly average. MLD was generally positively correlated with CHL (Liu et al., 2012; Shen et al., 2020). However, it is noticeable that the MLD data are from the HYCOM model. Although the model can realize near-real-time simulation, cautions should be taken with the data. Also, MLD is controlled by various processes, which can also contribute to the MLD trends. The MLD trends alone cannot explain the different trends in LZ and SV.

In Figs 15 and 16, we further analyze the trends of the surface height. The ADT showed significant increases, especially in SV. The only exception was for the west of Luzon Island. After calculating the trends of the two seasons, the result was still similar. As expected, the trends of the along-track SLA product were larger than the gridded data set, but there was no decisive difference in spatial distribution (Fig. 15). For the SH, after removing mass-induced effects, we found that the rise of SH (the overall rate is 0.260 9 cm/a) was close to the ADT (0.270 4 cm/a), which was consistent with the previous study by Feng et al. (2012) (Fig. 16). This illustrated the sea level mainly was regulated by the steric effect (Jang et al., 2013) and the water budget in the SCS was in rough balance over the 15 a. At the interannual timescales, ADT (lower in winter and higher in summer) and CHL (higher in winter and lower in summer) had an inverse relationship (Gao et al., 2013), thus we anticipated a similar inverse relationship for the trends, i.e., the rising sea level was impeding the growth of phytoplankton. Yet, it is worth noting that the CHL in summer SV showed a clear upward trend (10° – 15° N, 109° – 115° E in Fig. 9). The rising

pattern was similar to that of the jet stream in summer (Xie et al., 2003). Unlike the general case of the SCS, the ADT in SV increased rapidly (0.891 9 cm/a) while the SH did not (0.030 0 cm/a), which suggested the mass-induced change was prominent here. In our previous work (Lu et al., 2018b), we proposed a mechanism that positively linked local productivity and the SV circulation, supporting this co-strengthening in the summer SV.

In recent years, studies have shown that SSTF has a positive effect on CHL (Guo et al., 2017; Ye et al., 2018). SSTF reflects the intensity of submesoscale activity, which contributes to phytoplankton growth significantly because it leads to intense vertical transport of nutrients from subsurface to surface water (Ye et al., 2018). The overall SSTF had been decreasing, but significant increases were found in LZ, the Beibu Gulf, and some other regions (Fig. 17d). Furthermore, the SSTF had similar trends for all these quantiles. In the whole SCS, SSTF increased in winter and decreased in summer (Fig. 17). In summer, the decrease could be linked to the basin-wide SST warming. In winter, when almost all other physical factors had unfavorable effects on CHL, the increase of SSTF moderated the CHL reduction.

To clarify the role of each factor in the CHL trends, the spatial correlation coefficients between the trends of CHL and the six controlling factors were obtained (Table 1). Noting that this trend correlation differs from conventional time-series correlation, with an emphasis on revealing the consistency in the spatial pattern of the trends. CHL often shows a positive correlation with the MLD or SSTF at the seasonal scales (Ye et al., 2018; Ma et al.,

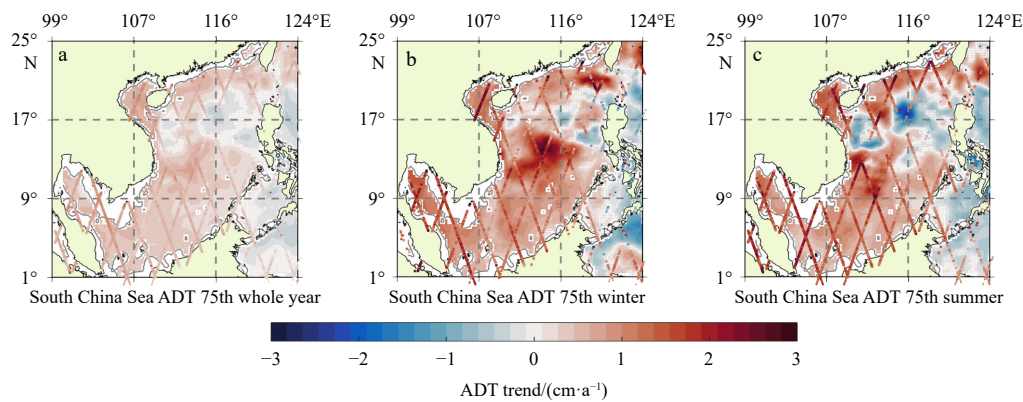


Fig. 15. Gridded absolute dynamic height (ADT) trends for 75th quantile in whole year (a), winter (November to March of next year) (b), and summer (May to September) (c). The colored lines are along-track Sea Level Anomaly, with the same color bar. All trends for ADT can be found in Fig. S4.

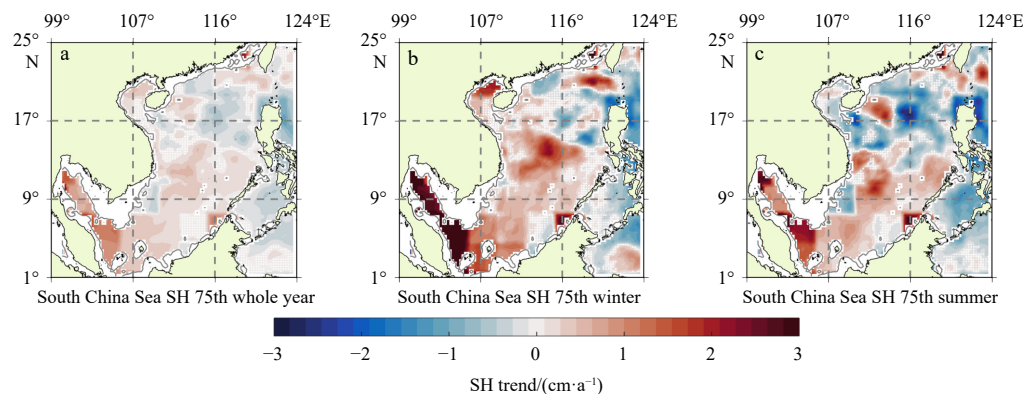


Fig. 16. Steric height (SH) trends for 75th quantile in whole year (a), winter (November to March of next year) (b), and summer (May to September) (c). All trends for SH can be found in Fig. S5.

2012), but here the correlation coefficients are both small in Table 1, albeit significant. For the whole SCS, SST and ADT are the two most important factors for the CHL trends. Higher SST (Fig. 11) and lower ADT (Fig. 15) both contributed to the basin-wide CHL declines. However, the correlation coefficients are not high, explaining only <5% of the CHL trend pattern.

We further examine the two representative systems. For the winter LZ, SST, ADT, and SH all present surprisingly high correlations (greater than -0.5 , >25%), which were similarly negative. Other factors except for SSTF are all important. All factors in this region negatively affected CHL, leading to the strong negative CHL trend of -3.54% per year. This reflected the complexity of dynamics in the LZ. For the summer SV with jet-like CHL increases (Fig. 9), wind speed was the leading factor for the trend pattern ($r=0.42$), while the SST and SSTF were the second ($r=-0.38$) and third ($r=0.28$). The leading role of wind speed and SST is consistent with the previous study (Li et al., 2014). The SSTF's role further highlighted the role of local circulation in the productivities of this region (Lu et al., 2018b), but this modulation cannot be well estimated here since the lack of long-term measurements for the circulation.

3.3 Multivariate analysis

In this section, we present the RF model to understand the nonlinear and multivariate controls, from the six factors, on the spatial pattern of the CHL trend. In Fig. 18, all three RF models can explain a major portion of the spatial pattern of CHL trends (86% for the yearly SCS trend, 98% for the winter LZ trends, and 97% for the summer SV trends). All factors had similar magnitudes of relative importance, suggesting that they all contributed significantly to CHL trends.

For all three cases, MLD and the monsoon are consistently prominent factors. It has been extensively discussed how wind affected phytoplankton growth from wind-induced mixing or the Ekman pumping (Liu et al., 2002). The coupling effects of MLD and the monsoon were the dominant factor of CHL trends (Duan et al., 2012). Surprisingly for the yearly CHL trends, the most relevant factor is SSTF. Since the SSTF's role is distinct from those in Table 1, this implied the submesoscale frontal effects were nonlinear. In fact, high SSTF is not necessarily accompanied by high CHL, such as in the western Pacific region (Guo et al., 2017). But for the SCS, previous studies have revealed that CHL was strongly regulated by submesoscale processes (Zheng et al., 2020; Liu and

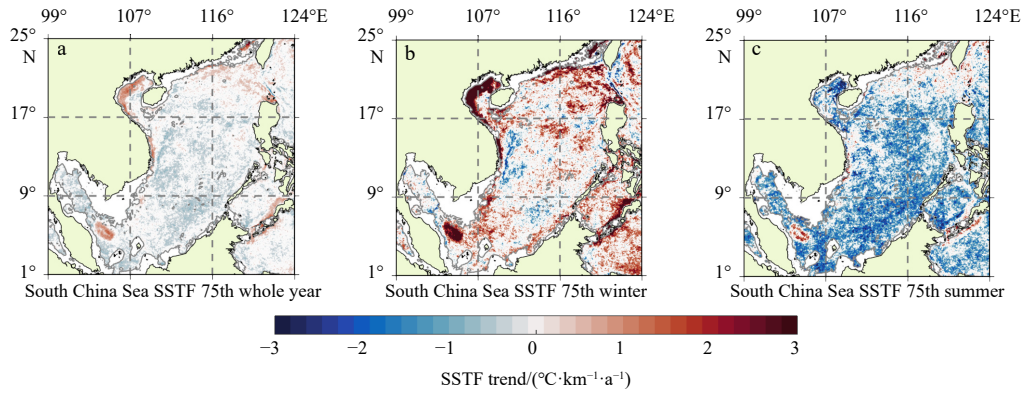


Fig. 17. Sea surface temperature front (SSTF) trends for 75th in whole year (a), winter (November to March of next year) (b), and summer (May to September) (c). All trends for SSTF can be found in Fig. S6.

Table 1. Correlation coefficients between trends of CHL and other factors*

	SST	Wind speed	MLD	ADT	SSTF	SH
Whole year SCS ($N=183\ 393$)	-0.22	0.04	-0.09	-0.18	0.01	-0.06
Winter LZ ($N=6\ 281$)	-0.64	0.24	-0.39	-0.64	0.03	-0.58
Summer SV ($N=13\ 495$)	-0.38	0.42	0.10	0.06	0.28	-0.14

Note: * The $p < 0.01$ for all correlations. SST: sea surface temperature; MLD: mixed layer depth; ADT: gridded absolute dynamic height; SSTF: sea surface temperature front; SH: steric height.

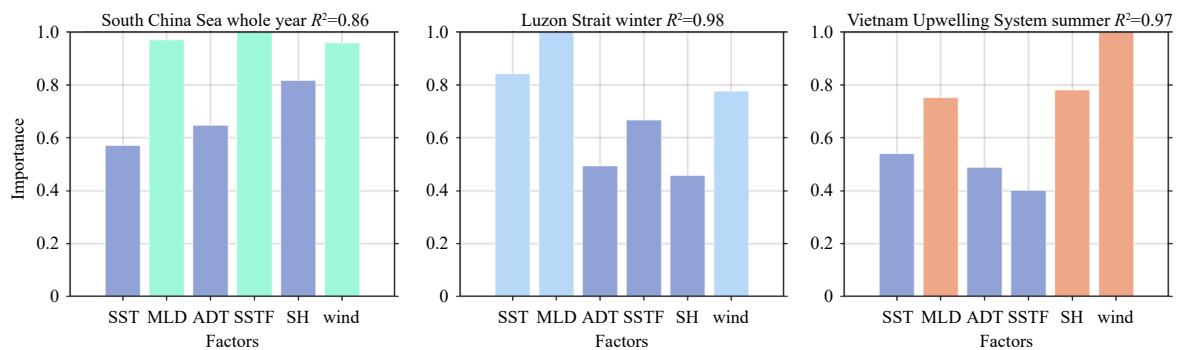


Fig. 18. The relative importance of each factor to Chlorophyll *a* concentration trends by repeating the Random Forest analysis 100 times and taking the averaged importance. SST: sea surface temperature; MLD: mixed layer depth; ADT: gridded absolute dynamic height; SSTF: sea surface temperature front; SH: steric height.

Tang, 2022; Ni et al., 2021; Liu and Levine, 2016). For the winter LZ and summer SV trends, the divergent importance of SST and SH implied different responses of CHL for the two systems. Since the winter LZ trends were also modulated by SST, it is expected that continuous CHL declines could be likely; while for the summer SV, the role of ocean circulation might compensate the wind-induced declines, leading to higher offshore productivities.

4 Conclusions

In summary, we used our recent CHL reconstruction data (namely, SCS DCT) for quantile and linear regression and showed the trends of CHL in the SCS. By using the quantile trend method, we showed a full picture of CHL and related controlling factors' trends during 2005–2019. Generally, the decline of CHL (at 1.10% per year for the median) in the SCS was an indisputable fact in recent years, which was stronger in winter (3.68% per year) and weaker in summer (1.71% per year). The changes also led to a reduced standard deviation of CHL over time and space. And we also focused on two typical systems to further elaborate on the trends. For winter LZ, the intensity of bloom was weakening, but extreme events were less affected. For summer SV, CHL instead increased in the offshore jet region.

Combined with multi-source remote sensing and model data, the reasons for CHL changes were also discussed. The warmed SST, reduced wind speed, and shallowed MLD trends were similar for different seasons. SST increased more significantly in the western SCS, similar to that of CHL, in winter. The SST warming was homogeneously in summer, unlike the summer CHL trends. The wind speed weakened throughout the 15 a. Both higher SST and slower wind speed would intensify the stratification, which can be represented by the shallowed MLD trends. Moreover, through comparisons of ADT and SH, the responses of CHL to ADT were different in different systems.

We further analyze the controlling factors' roles in the CHL trend patterns with single-variate correlation and multivariate RF analysis. Considering the entire SCS, wind speed was the most prominent factor, although the coefficients were not large enough to explain the long-term trends of CHL for the three systems. With the nonlinear multivariate RF importance, it was clear that wind speed and MLD changes were the main prominent physical influencing on CHL trends. For the SCS yearly trends, strong regulation by the SSTF can be found, which emphasized the nonlinear role of submesoscale processes in long-term trends of CHL. For the winter LZ and summer SV, the divergent importance of factors explained the different responses of CHL for the two systems. This study provided a detailed picture of recent trends of the ecosystem in the SCS and can serve as a foundation for future dynamic and mechanism analysis.

References

- Aumont O, Belviso S, Monfray P. 2002. Dimethylsulfoniopropionate (DMSP) and dimethylsulfide (DMS) sea surface distributions simulated from a global three-dimensional ocean carbon cycle model. *Journal of Geophysical Research: Oceans*, 107(C4): 3029, doi: [10.1029/1999JC000111](https://doi.org/10.1029/1999JC000111)
- Barbosa S M. 2008. Quantile trends in Baltic sea level. *Geophysical Research Letters*, 35(22): L22704, doi: [10.1029/2008GL035182](https://doi.org/10.1029/2008GL035182)
- Bassett Jr G, Koenker R. 1978. Regression quantiles. *Econometrica*, 46(1): 33–50, doi: [10.2307/1913643](https://doi.org/10.2307/1913643)
- Behrenfeld M J, Falkowski P G. 1997. Photosynthetic rates derived from satellite-based chlorophyll concentration. *Limnology and Oceanography*, 42(1): 1–20, doi: [10.4319/lo.1997.42.1.0001](https://doi.org/10.4319/lo.1997.42.1.0001)
- Belkin I M, O'Reilly J E. 2009. An algorithm for oceanic front detection in chlorophyll and SST satellite imagery. *Journal of Marine Systems*, 78(3): 319–326, doi: [10.1016/j.jmarsys.2008.11.018](https://doi.org/10.1016/j.jmarsys.2008.11.018)
- Beniston M. 2009. Trends in joint quantiles of temperature and precipitation in Europe since 1901 and projected for 2100. *Geophysical Research Letters*, 36(7): L07707
- Birol F, Fuller N, Lyard F, et al. 2017. Coastal applications from nadir altimetry: example of the X-TRACK regional products. *Advances in Space Research*, 59(4): 936–953, doi: [10.1016/j.asr.2016.11.005](https://doi.org/10.1016/j.asr.2016.11.005)
- Boon A R, Duineveld G C A. 1998. Chlorophyll a as a marker for bioturbation and carbon flux in southern and central North Sea sediments. *Marine Ecology Progress Series*, 162: 33–43, doi: [10.3354/meps162033](https://doi.org/10.3354/meps162033)
- Boyce D G, Lewis M R, Worm B. 2010. Global phytoplankton decline over the past century. *Nature*, 466(7306): 591–596, doi: [10.1038/nature09268](https://doi.org/10.1038/nature09268)
- Breiman L. 2001. Random forests. *Machine Learning*, 45(1): 5–32, doi: [10.1023/A:1010933404324](https://doi.org/10.1023/A:1010933404324)
- Carder K L, Chen F R, Lee Z P, et al. 1999. Semianalytic Moderate-Resolution Imaging Spectrometer algorithms for chlorophyll *a* and absorption with bio-optical domains based on nitrate-depletion temperatures. *Journal of Geophysical Research: Oceans*, 104(C3): 5403–5421, doi: [10.1029/1998JC900082](https://doi.org/10.1029/1998JC900082)
- Casella D, Meloni M, Petrenko A A, et al. 2020. Coastal current intrusions from satellite altimetry. *Remote Sensing*, 12(22): 3686, doi: [10.3390/rs12223686](https://doi.org/10.3390/rs12223686)
- Chen Yuh-ling Lee, Chen Houn-Yung, Karl D M, et al. 2004. Nitrogen modulates phytoplankton growth in spring in the South China Sea. *Continental Shelf Research*, 24(4–5): 527–541
- Chen Liqi, Xu Suqing, Gao Zhongyong, et al. 2011. Estimation of monthly air-sea CO₂ flux in the southern Atlantic and Indian Ocean using *in-situ* and remotely sensed data. *Remote Sensing of Environment*, 115(8): 1935–1941, doi: [10.1016/j.rse.2011.03.016](https://doi.org/10.1016/j.rse.2011.03.016)
- Chen Chen-Tung Arthur, Yu Shujie, Huang Ting-Hsuan, et al. 2020. Changing biogeochemistry in the South China Sea. In: Chen Chen-Tung Arthur, Guo Xinyu, eds. *Changing Asia-Pacific Marginal Seas*. Singapore: Springer, 203–216
- Dai Minhan, Cao Zhimian, Guo Xianghui, et al. 2013. Why are some marginal seas sources of atmospheric CO₂? *Geophysical Research Letters*, 40(10): 2154–2158, doi: [10.1002/grl.50390](https://doi.org/10.1002/grl.50390)
- Dai Minhan, Su Jianzhong, Zhao Yangyang, et al. 2022. Carbon fluxes in the coastal ocean: synthesis, boundary processes, and future trends. *Annual Review of Earth and Planetary Sciences*, 50: 593–626, doi: [10.1146/annurev-earth-032320-090746](https://doi.org/10.1146/annurev-earth-032320-090746)
- Doney S C, Lima I, Moore J K, et al. 2009. Skill metrics for confronting global upper ocean ecosystem-biogeochemistry models against field and remote sensing data. *Journal of Marine Systems*, 76(1–2): 95–112
- Duan Rui, Yang Kunde, Ma Yuanliang, et al. 2012. A study of the mixed layer of the South China Sea based on the multiple linear regression. *Acta Oceanologica Sinica*, 31(6): 19–31, doi: [10.1007/s13131-012-0250-8](https://doi.org/10.1007/s13131-012-0250-8)
- Dunstan P K, Foster S D, King E, et al. 2018. Global patterns of change and variation in sea surface temperature and chlorophyll *a*. *Scientific Reports*, 8(1): 14624, doi: [10.1038/s41598-018-33057-y](https://doi.org/10.1038/s41598-018-33057-y)
- Fan Lijun, Chen Deliang. 2016. Trends in extreme precipitation indices across China detected using quantile regression. *Atmospheric Science Letters*, 17(7): 400–406, doi: [10.1002/asl.671](https://doi.org/10.1002/asl.671)
- Feng Wei, Zhong Min, Xu Houze. 2012. Sea level variations in the South China Sea inferred from satellite gravity, altimetry, and oceanographic data. *Science China: Earth Sciences*, 55(10): 1696–1701, doi: [10.1007/s11430-012-4394-3](https://doi.org/10.1007/s11430-012-4394-3)
- Feng Jianfeng, Zhu Lin. 2012. Changing trends and relationship between global ocean chlorophyll and sea surface temperature. *Procedia Environmental Sciences*, 13: 626–631, doi: [10.1016/j.proenv.2012.01.054](https://doi.org/10.1016/j.proenv.2012.01.054)
- Gan Jianping, Lu Zhongming, Dai Minhan, et al. 2010. Biological response to intensified upwelling and to a river plume in the northeastern South China Sea: a modeling study. *Journal of Geophysical Research: Oceans*, 115(C9): C09001
- Gao Meng, Franzke C L E. 2017. Quantile regression-based spati-

- otemporal analysis of extreme temperature change in China. *Journal of Climate*, 30(24): 9897–9914, doi: [10.1175/JCLI-D-17-0356.1](https://doi.org/10.1175/JCLI-D-17-0356.1)
- Gao Na, Ma Yi, Zhao Mingli, et al. 2020. Quantile analysis of long-term trends of near-surface chlorophyll-*a* in the Pearl River plume. *Water*, 12(6): 1662, doi: [10.3390/w12061662](https://doi.org/10.3390/w12061662)
- Gao Shan, Wang Hui. 2008. Seasonal and spatial distributions of phytoplankton biomass associated with monsoon and oceanic environments in the South China Sea. *Acta Oceanologica Sinica*, 27(6): 17–32
- Gao Shan, Wang Hui, Liu Guimei, et al. 2013. Spatio-temporal variability of chlorophyll *a* and its responses to sea surface temperature, winds and height anomaly in the western South China Sea. *Acta Oceanologica Sinica*, 32(1): 48–58, doi: [10.1007/s13131-013-0266-8](https://doi.org/10.1007/s13131-013-0266-8)
- Goh S C, Knight K. 2009. Nonstandard quantile-regression inference. *Econometric Theory*, 25(5): 1415–1432, doi: [10.1017/S0266466609090719](https://doi.org/10.1017/S0266466609090719)
- Grémillet D, Lewis S, Drapeau L, et al. 2008. Spatial match-mismatch in the Benguela upwelling zone: should we expect chlorophyll and sea-surface temperature to predict marine predator distributions?. *Journal of Applied Ecology*, 45(2): 610–621, doi: [10.1111/j.1365-2664.2007.01447.x](https://doi.org/10.1111/j.1365-2664.2007.01447.x)
- Guo Lin, Xiu Peng, Chai Fei, et al. 2017. Enhanced chlorophyll concentrations induced by Kuroshio intrusion fronts in the northern South China Sea. *Geophysical Research Letters*, 44(22): 11565–11572, doi: [10.1002/2017GL075336](https://doi.org/10.1002/2017GL075336)
- Hersbach H, Bell B, Berrisford P, et al. 2020. The ERA5 global reanalysis. *Quarterly Journal of the Royal Meteorological Society*, 146(730): 1999–2049, doi: [10.1002/qj.3803](https://doi.org/10.1002/qj.3803)
- Huynh H N T, Alvera-Azcárate A, Beckers J M. 2020. Analysis of surface chlorophyll *a* associated with sea surface temperature and surface wind in the South China Sea. *Ocean Dynamics*, 70(1): 139–161, doi: [10.1007/s10236-019-01308-9](https://doi.org/10.1007/s10236-019-01308-9)
- Jang P G, Lee T S, Kang J H, et al. 2013. The influence of thermal-haline fronts on chlorophyll *a* concentrations during spring and summer in the southeastern Yellow Sea. *Acta Oceanologica Sinica*, 32(9): 82–90, doi: [10.1007/s13131-013-0355-8](https://doi.org/10.1007/s13131-013-0355-8)
- Keiner L E, Yan X H. 1998. A neural network model for estimating sea surface chlorophyll and sediments from thematic mapper imagery. *Remote Sensing of Environment*, 66(2): 153–165, doi: [10.1016/S0034-4257\(98\)00054-6](https://doi.org/10.1016/S0034-4257(98)00054-6)
- Koenker R, Hallock K F. 2001. Quantile regression. *Journal of Economic Perspectives*, 15(4): 143–156, doi: [10.1257/jep.15.4.143](https://doi.org/10.1257/jep.15.4.143)
- Kosaka Y, Xie Shangping. 2013. Recent global-warming hiatus tied to equatorial Pacific surface cooling. *Nature*, 501(7467): 403–407, doi: [10.1038/nature12534](https://doi.org/10.1038/nature12534)
- Kouketsu S, Kaneko H, Okunishi T, et al. 2016. Mesoscale eddy effects on temporal variability of surface chlorophyll *a* in the Kuroshio Extension. *Journal of Oceanography*, 72(3): 439–451, doi: [10.1007/s10872-015-0286-4](https://doi.org/10.1007/s10872-015-0286-4)
- Landerer F W, Flechtner F M, Save H, et al. 2020. Extending the global mass change data record: GRACE Follow-On instrument and science data performance. *Geophysical Research Letters*, 47(12): e2020GL088306
- Lee K, Baek H J, Cho C H. 2013. Analysis of changes in extreme temperatures using quantile regression. *Asia-Pacific Journal of Atmospheric Sciences*, 49(3): 313–323, doi: [10.1007/s13143-013-0030-1](https://doi.org/10.1007/s13143-013-0030-1)
- Lévy M, Franks P J S, Smith K S. 2018. The role of submesoscale currents in structuring marine ecosystems. *Nature Communications*, 9(1): 4758, doi: [10.1038/s41467-018-07059-3](https://doi.org/10.1038/s41467-018-07059-3)
- Li Yuanlong, Han Weiqing, Wilkin J L, et al. 2014. Interannual variability of the surface summertime eastward jet in the South China Sea. *Journal of Geophysical Research: Oceans*, 119(10): 7205–7228, doi: [10.1002/2014JC010206](https://doi.org/10.1002/2014JC010206)
- Li Yan, Wang Qingyuan, Li Qingquan, et al. 2021. An asymmetric variation of hot and cold SST extremes in the China Seas during the recent warming hiatus period. *Scientific Reports*, 11(1): 2014, doi: [10.1038/s41598-020-79854-2](https://doi.org/10.1038/s41598-020-79854-2)
- Liao Enhui, Lu Wenfang, Yan Xiaohai, et al. 2015. The coastal ocean response to the global warming acceleration and hiatus. *Scientific Reports*, 5(1): 16630, doi: [10.1038/srep16630](https://doi.org/10.1038/srep16630)
- Liu K K, Chao S Y, Shaw P T, et al. 2002. Monsoon-forced Chlorophyll distribution and primary production in the South China Sea: Observations and a numerical study. *Deep-Sea Research Part I: Oceanographic Research Papers*, 49(8): 1387–1412, doi: [10.1016/S0967-0637\(02\)00035-3](https://doi.org/10.1016/S0967-0637(02)00035-3)
- Liu Jianguo, Chen Muhong, Chen Zhong, et al. 2010. Clay mineral distribution in surface sediments of the South China Sea and its significance for in sediment sources and transport. *Chinese Journal of Oceanology and Limnology*, 28(2): 407–415, doi: [10.1007/s00343-010-9057-7](https://doi.org/10.1007/s00343-010-9057-7)
- Liu Fenfen, Chen Chuqun, Zhan Haigang. 2012. Decadal variability of chlorophyll *a* in the South China Sea: a possible mechanism. *Chinese Journal of Oceanology and Limnology*, 30(6): 1054–1062, doi: [10.1007/s00343-012-1282-9](https://doi.org/10.1007/s00343-012-1282-9)
- Liu Xiao, Levine N M. 2016. Enhancement of phytoplankton chlorophyll by submesoscale frontal dynamics in the North Pacific Subtropical Gyre. *Geophysical Research Letters*, 43(4): 1651–1659, doi: [10.1002/2015GL066996](https://doi.org/10.1002/2015GL066996)
- Liu Fenfen, Tang Shilin. 2022. A Double-peak intraseasonal pattern in the chlorophyll concentration associated with summer upwelling and mesoscale eddies in the western South China Sea. *Journal of Geophysical Research: Oceans*, 127(1): e2021JC017402
- Liu Jianguo, Xiang Rong, Chen Zhong, et al. 2013. Sources, transport and deposition of surface sediments from the South China Sea. *Deep-Sea Research Part I: Oceanographic Research Papers*, 71: 92–102, doi: [10.1016/j.dsr.2012.09.006](https://doi.org/10.1016/j.dsr.2012.09.006)
- Longhurst A, Sathyendranath S, Platt T, et al. 1995. An estimate of global primary production in the ocean from satellite radiometer data. *Journal of Plankton Research*, 17(6): 1245–1271, doi: [10.1093/plankt/17.6.1245](https://doi.org/10.1093/plankt/17.6.1245)
- Lu Wenfang, Luo Yawei, Yan Xiaohai, et al. 2018a. Modeling the contribution of the microbial carbon pump to carbon sequestration in the South China Sea. *Science China: Earth Sciences*, 61(11): 1594–1604, doi: [10.1007/s11430-017-9180-y](https://doi.org/10.1007/s11430-017-9180-y)
- Lu Wenfang, Oey L Y, Liao Enhui, et al. 2018b. Physical modulation to the biological productivity in the summer Vietnam upwelling system. *Ocean Science*, 14(5): 1303–1320, doi: [10.5194/os-14-1303-2018](https://doi.org/10.5194/os-14-1303-2018)
- Lu Wenfang, Su Hua, Yang Xin, et al. 2019. Subsurface temperature estimation from remote sensing data using a clustering-neural network method. *Remote Sensing of Environment*, 229: 213–222, doi: [10.1016/j.rse.2019.04.009](https://doi.org/10.1016/j.rse.2019.04.009)
- Lu Wenfang, Yan Xiaohai, Jiang Yuwu. 2015. Winter bloom and associated upwelling northwest of the Luzon Island: a coupled physical-biological modeling approach. *Journal of Geophysical Research: Oceans*, 120(1): 533–546, doi: [10.1002/2014JC010218](https://doi.org/10.1002/2014JC010218)
- Ma Jinfeng, Liu Hailong, Zhan Haigang, et al. 2012. Effects of chlorophyll on upper ocean temperature and circulation in the upwelling regions of the South China Sea. *Aquatic Ecosystem Health & Management*, 15(2): 127–134
- Martinez E, Gorgues T, Lengaigne M, et al. 2020. Reconstructing global chlorophyll-*a* variations using a non-linear statistical approach. *Frontiers in Marine Science*, 7: 464, doi: [10.3389/fmars.2020.00464](https://doi.org/10.3389/fmars.2020.00464)
- Ni Qinqiao, Zhai Xiaoming, Wilson C, et al. 2021. Submesoscale eddies in the South China Sea. *Geophysical Research Letters*, 48(6): e2020GL091555
- Palacz A P, Xue Huijie, Armbrrecht C, et al. 2011. Seasonal and interannual changes in the surface chlorophyll of the South China Sea. *Journal of Geophysical Research: Oceans*, 116(C9): C09015
- Shen Chunyan, Zhao Hui, Chen Fajin, et al. 2020. The distribution of aerosols and their impacts on chlorophyll-*a* distribution in the South China Sea. *Journal of Geophysical Research: Biogeosciences*, 125(6): e2019JG005490
- Su Hua, Wu Xiangbai, Lu Wenfang, et al. 2017. Inconsistent subsurface and deeper ocean warming signals during recent global warming and hiatus. *Journal of Geophysical Research: Oceans*, 122(10): 8182–8195, doi: [10.1002/2016JC012481](https://doi.org/10.1002/2016JC012481)

- Tang Shilin, Liu Fenfen. 2020. Remote sensing of phytoplankton decline during the late 1980s and early 1990s in the South China Sea. *International Journal of Remote Sensing*, 41(15): 6010–6021, doi: [10.1080/01431161.2020.1718241](https://doi.org/10.1080/01431161.2020.1718241)
- Wahr J, Molenaar M, Bryan F. 1998. Time variability of the Earth's gravity field: hydrological and oceanic effects and their possible detection using GRACE. *Journal of Geophysical Research: Solid Earth*, 103(B12): 30205–30229, doi: [10.1029/98JB02844](https://doi.org/10.1029/98JB02844)
- Wang Guizhi, Shen S S P, Chen Yao, et al. 2021a. Feasibility of reconstructing the summer basin-scale sea surface partial pressure of carbon dioxide from sparse *in situ* observations over the South China Sea. *Earth System Science Data*, 13(3): 1403–1417, doi: [10.5194/essd-13-1403-2021](https://doi.org/10.5194/essd-13-1403-2021)
- Wang Tianhao, Yu Peng, Wu Zelun, et al. 2021b. Revisiting the intraseasonal variability of chlorophyll-*a* in the adjacent Luzon Strait with a new gap-filled remote sensing data set. *IEEE Transactions on Geoscience and Remote Sensing*, 60: 4201311
- Watkins M M, Wiese D N, Yuan Dah-Ning, et al. 2015. Improved methods for observing Earth's time variable mass distribution with GRACE using spherical cap mascons. *Journal of Geophysical Research: Solid Earth*, 120(4): 2648–2671, doi: [10.1002/2014JB011547](https://doi.org/10.1002/2014JB011547)
- Wiese D N, Landerer F W, Watkins M M. 2016. Quantifying and reducing leakage errors in the JPL RL05M GRACE mascon solution. *Water Resources Research*, 52(9): 7490–7502, doi: [10.1002/2016WR019344](https://doi.org/10.1002/2016WR019344)
- Wiese D N, Yuan D N, Boening C, et al. 2018. JPL GRACE Mascon Ocean, Ice, and Hydrology Equivalent Water Height Release 06 Coastal Resolution Improvement (CRI) Filtered Version 1.0. Pasadena: DAAC
- Wilson C, Adamec D. 2001. Correlations between surface chlorophyll and sea surface height in the tropical Pacific during the 1997–1999 El Niño–Southern Oscillation event. *Journal of Geophysical Research: Oceans*, 106(C12): 31175–31188, doi: [10.1029/2000JC000724](https://doi.org/10.1029/2000JC000724)
- Xiao Wupeng, Wang Lei, Laws E, et al. 2018. Realized niches explain spatial gradients in seasonal abundance of phytoplankton groups in the South China Sea. *Progress in Oceanography*, 162: 223–239, doi: [10.1016/j.pocean.2018.03.008](https://doi.org/10.1016/j.pocean.2018.03.008)
- Xie Shangping, Xie Qiang, Wang Dongxiao, et al. 2003. Summer upwelling in the South China Sea and its role in regional climate variations. *Journal of Geophysical Research: Oceans*, 108(C8): 3261, doi: [10.1029/2003JC001867](https://doi.org/10.1029/2003JC001867)
- Yan Xiaohai, Boyer T, Trenberth K, et al. 2016. The global warming hiatus: slowdown or redistribution?. *Earth's Future*, 4(11): 472–482, doi: [10.1002/2016EF000417](https://doi.org/10.1002/2016EF000417)
- Yang Yuanjian, Xian Tao, Sun Liang, et al. 2012. Summer monsoon impacts on chlorophyll-*a* concentration in the middle of the South China Sea: climatological mean and annual variability. *Atmospheric and Oceanic Science Letters*, 5(1): 15–19, doi: [10.1080/16742834.2012.11446961](https://doi.org/10.1080/16742834.2012.11446961)
- Ye Haijun, Kalhor M A, Morozov E, et al. 2018. Increased chlorophyll-*a* concentration in the South China Sea caused by occasional sea surface temperature fronts at peripheries of eddies. *International Journal of Remote Sensing*, 39(13): 4360–4375, doi: [10.1080/01431161.2017.1399479](https://doi.org/10.1080/01431161.2017.1399479)
- Yu Yi, Wang Yuntao, Cao Lu, et al. 2020. The ocean-atmosphere interaction over a summer upwelling system in the South China Sea. *Journal of Marine Systems*, 208: 103360, doi: [10.1016/j.jmarsys.2020.103360](https://doi.org/10.1016/j.jmarsys.2020.103360)
- Yu Yi, Zhang Haoran, Jin Jiangbo, et al. 2019. Trends of sea surface temperature and sea surface temperature fronts in the South China Sea during 2003–2017. *Acta Oceanologica Sinica*, 38(4): 106–115, doi: [10.1007/s13131-019-1416-4](https://doi.org/10.1007/s13131-019-1416-4)
- Zhao Hui, Tang Danling. 2007. Effect of 1998 El Niño on the distribution of phytoplankton in the South China Sea. *Journal of Geophysical Research: Oceans*, 112(C2): C02017
- Zhao Kaiguang, Wulder M A, Hu Tongxi, et al. 2019. Detecting change-point, trend, and seasonality in satellite time series data to track abrupt changes and nonlinear dynamics: a Bayesian ensemble algorithm. *Remote Sensing of Environment*, 232: 111181, doi: [10.1016/j.rse.2019.04.034](https://doi.org/10.1016/j.rse.2019.04.034)
- Zheng Quanan, Xie Lingling, Xiong Xuejun, et al. 2020. Progress in research of submesoscale processes in the South China Sea. *Acta Oceanologica Sinica*, 39(1): 1–13, doi: [10.1007/s13131-019-1521-4](https://doi.org/10.1007/s13131-019-1521-4)

Supplementary information:

Fig. S1. Trends of sea surface temperature in the whole year for linear trend of classic least squares model (a), 75th quantile (b), 50th quantile (c), and 25th quantile (d). e–h are for winter and i–l are for summer.

Fig. S2. Trends of wind speed in the whole year for linear trend of classic least squares model (a), 75th quantile (b), 50th quantile (c), and 25th quantile (d). e–h are for winter and i–l are for summer.

Fig. S3. Trends of mixed layer depth in the whole year for linear trend of classic least squares model (a), 75th quantile (b), 50th quantile (c), and 25th quantile (d). e–h are for winter and i–l are for summer.

Fig. S4. Trends of gridded absolute dynamic height in the whole year for linear trend of classic least squares model (a), 75th quantile (b), 50th quantile (c), and 25th quantile (d). e–h are for winter and i–l are for summer.

Fig. S5. Trends of steric height in the whole year for linear trend of classic least squares model (a), 75th quantile (b), 50th quantile (c), and 25th quantile (d). e–h are for winter and i–l are for summer.

Fig. S6. Trends of sea surface temperature front in the whole year for linear trend of classic least squares model (a), 75th quantile (b), 50th quantile (c), and 25th quantile (d). e–h are for winter and i–l are for summer.

Fig. S7. The mean of chlorophyll *a* concentration, sea surface temperature, wind speed, mixed layer depth, steric height, sea surface temperature front in the last five years (2015–2019) minus the mean of the first five years (2005–2009).

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