Trends and interannual variability of the South China Sea surface winds, surface height, and surface temperature in the recent decade

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[1] Trends and interannual variability of the surface winds (SW), sea surface height (SSH), and sea surface temperature (SST) of the South China Sea (SCS) in 1993–2003 are analyzed using monthly products from satellite observations. Time series are smoothed with a 12-month running mean filter. The east and north components of the SW, SSH, and SST have linear trends of 0.53 ± 0.35 ms−1 decade−1, −0.04 ± 0.17 ms−1 decade−1, 6.7 ± 2.7 cm decade−1, and 0.50 ± 0.26 K decade−1, respectively. The sea level rising rate and sea surface warming rate are significantly higher than the corresponding global rates. An Empirical Orthogonal Function (EOF) analysis is performed to evaluate the interannual variability. Results show that the first EOF of the SW is characterized by a basin-wide anticyclonic pattern. The corresponding time coefficient function (TCF) correlates with the Nino3.4 index at the 99% confidence level, with a lag of 3 months. The first EOF of the SSH is characterized by a low sea level along the eastern boundary. The corresponding TCF correlates with the Nino3.4 at the 99% level, with a lag of 2 months. The first EOF of the SST is characterized by a basin-wide warming with the highest anomalies in the north deep basin. The corresponding TCF correlates with the Nino3.4 index at the 95% level, with a lag of 8 months. Based on the EOF analysis, the ENSO-associated correlation patterns of the SW, SSH, and SST are presented.


1. Introduction

[2] The South China Sea (SCS) is one of the largest marginal seas of the World Ocean. It extends from the Karimata Strait (~3°S) to the middle of the Taiwan Strait (~23.5°N), and is bordered on the west by the Asian mainland, Indo-China Peninsula, Malay Peninsula and Sumatra, and on the east by Taiwan, the Luzon Strait and the islands of Luzon, Palawan and Kalimantan (Figure 1). It occupies an area of about 3.5 × 106 km2. The present study covers the area from 2°S to 24°N. The deep basin lies in the northern central part of the SCS, with a maximum depth of about 5000 m. On the northwest of the deep basin a shelf extends about 250 km from the mainland coast. For convenience, we will hereafter call it the South China Shelf, and call the associated continental slope the South China Slope. The SCS part of the Sunda Shelf has an even greater area than the South China Shelf, and lies to the southwest of the deep basin.

[3] As an Asian marginal sea, the SCS reveals pronounced seasonal variability under the influence of the East Asian monsoon. On the other hand, as a tropical Pacific marginal sea, the SCS exhibits remarkable interannual variability. Thorough investigations on the seasonal variability have been made previously [e.g., Chu et al., 1997; Ho et al., 2000a; Liang et al., 2000], the present study will concentrate on the interannual variability through analyzing the satellite-observed surface wind (SW) over ocean, sea surface height (SSH) and sea surface temperature (SST) in the ocean in the recent decade (1993–2003).

ERS-1/2 were used by Hwang and Chen [2000] to study the seasonal to interannual variabilities over the SCS.

Seasonal variability of the SCS surface height has been reported in a number of investigations using satellite altimeter data [e.g., Ho et al., 2000a; Hwang and Chen, 2000]. The analysis of Ho et al. [2000b] further revealed a response of the SCS SSH to El Niño. Li et al. [2002] found that the sea level in the SCS was raised with a mean rate of 1 cm yr\(^{-1}\) during the period of 1993–1999.

Chu et al. [1997] used the NCEP monthly SST data set from 1982 to 1994 to study the temporal and spatial variabilities. The seasonal distribution of the SST was well documented and strong warm and cool anomalies in the northern SCS were identified. Klein et al. [1999] found that the SST change in the SCS lagged the ENSO index by 5 months. Wang et al. [2002] reported a strong SCS warm event in 1997–1998, which was closely related with the El Niño event. Liu et al. [2004] found that the variability of winter cold tongue in the SCS was closely correlated with the Niño3 SST.

The abovementioned studies revealed close relationship between the SW, SSH, and SST of the SCS and the ENSO, but mostly focused on an individual parameter or event using data of short temporal coverage. In addition, the trends of these parameters have not been reported except for the SSH. With the availability of more than 10 years of satellite-observed SST, it is now worthwhile to make an integrated analysis of these satellite-observed sea surface fields to provide more systematic views for the trends and interannual variability in the SCS. As an East Asian marginal sea, seasonality dominates the variability. To simplify the analysis, we will only study the interannual variability of the annual mean fields. That is, the interannual variability in seasonality is not considered in the present study.

2. Data and Data Processing

The data used in the present study contain the monthly mean SW, SSH and SST, covering the period from January 1993 to December 2003. The SW data used in the present work are monthly mean wind fields produced by CERSAT at the French Research Institute for Exploitation of the Sea (IFREMER). The product is derived from the measurements with scatterometers AMI-Wind onboard the European Space Agency satellites ERS-1 (1991–1996) and ERS-2 (1996–2001), NASA scatterometer NSCAT onboard the ADEOS-1 (1996–1997), and SeaWind onboard the QuikScat (1999–present). The CERSAT product also contains wind stresses (WS), which are derived from the SW using the bulk formula of Smith [1988]. The product has a resolution of 1° × 1°. The SSH data set used in the present work are 1/3° × 1/3° anomalies produced by Aviso, France.

Figure 1. Map of the South China Sea. Isobaths are in meters.
The temporal resolution is per 7 days. The data set is prepared by merging the TOPEX/Poseidon (TP), Jason-1 and ERS-1/2 altimeter observations. This weekly data set is averaged to produce monthly mean data set in the present work. The SST data set used in the present study is the monthly NCEP Optimum Interpolation (OI) Sea Surface Temperature Analysis product, which has a resolution of 1° × 1°. The analysis merged the satellite and in situ SST

Figure 2. Climatological mean fields of the surface winds during 1993–2003 for (a) January, (b) July, and (c) annual, and those of the wind stress curl for (d) January, (e) July, and (f) annual. Note: the scales may be different for different panels.
observations by employing the OI method [Reynolds and Smith, 1994]. Since the Aviso SSH data product begins from September 1992, the present study only uses the SW, SSH and SST products from January 1993 to December 2003, though the NCEP OI SST data has a longer time span, from 1982 to present.

[9] For each grid point we first filter out the seasonal variability using an operator of 12-month running mean. We then calculate the mean value and trend through a linear regression analysis. In term of the Fourier spectrum, the 12-month running mean is one of the shortest filters to remove frequencies higher than 1 cycle per year [Emery and Thomson, 2001]. Thus the amplitude modulation of the annual variation, or the interannual variability in seasonality, is also filtered out. The detrended time series are finally used to make the empirical orthogonal function (EOF) analysis and to derive the ENSO-associated correlation patterns.

[10] In addition, we also calculate the climatological (11 year averaged) monthly fields and the annual (ensemble) mean fields for the SW, WS, SSH, and SST. As background fields for the trends and interannual variability, the January,
July and annual climatological mean fields are given in Figures 2, 3, and 4 for the SW, SSH, and SST, respectively. Complete climatological monthly mean fields for 12 months can be found from, for example, Liang et al. [2000] for SW, Ho et al. [2000a] for SSH, and Chu et al. [1997] for SST. Figure 2 illustrates the climatological mean wind and wind stress curl fields for January, July and annual mean. From Figure 2a we can see that in winter the SCS is controlled by intense northeasterly winds. The winds are strongest roughly along the northeast-southwest diagonal from the Luzon Strait to the southwest coast of Vietnam. This wind field yields an anticyclonic wind stress curl over the northwest SCS and a cyclonic wind stress curl over the southeast SCS, with the latter stronger than the former (Figure 2d). In summer the SCS is controlled by the southwesterly winds. The winds are stronger in the south and weaker in the north, and are strongest off the southeast Vietnam coast, resulting in an anticyclonic wind stress curl in the southeast, and a cyclonic curl in the northwest (Figure 2e). This wind stress field can generate the Southeast Vietnam Offshore Current and an anticyclonic gyre in the southern SCS [Fang et al., 1998, 2002]. The annual mean SW field is dominated by northeasterly winds, indicating that the northeast monsoon is stronger than the southwest monsoon for the most part of the SCS (Figure 2c). However, in a small part of the southern SCS the annual mean winds are northward, indicating that the southwest monsoon is stronger than the northeast monsoon in this area. The annual mean wind stress curl field is characterized by a large cyclone over the most SCS in the south and a small anticyclone in the north over the South China Shelf (Figure 2f). Unlike the SW and SST, the absolute mean SSH field cannot be directly observed by altimeters. Thus we can only present the SSH anomalies in Figure 3. Figure 3a shows that the mean January SSH anomalies are low in the deep basin, and high on the Sunda Shelf and the South China Shelf, indicating a basin-wide cyclonic gyre in the SCS. This gyre is separated by an SSH ridge roughly at 12°N into two sub-basin scale gyres. The circulation pattern shown in SSH distribution agrees with the schematic presentation of Fang et al. [1998, Figure 10a], and clearly results from the wind stress curl field (Figure 2d). Figure 3b shows that the mean July SSH anomalies are low on the Sunda and South China Shelves, and high in the deep basin. A small SSH dome can be observed at about 10°N latitude southeast of Vietnam coast. This dome further develops in August and September (figures not shown), indicating an anticyclonic gyre in the southern SCS and an offshore current north of the gyre, which are also consistent with the diagram of Fang et al. [1998, Figure 10b] and observations of Fang et al. [2002]. The July SSH anomaly pattern agrees well with the July wind stress curl pattern (Figure 2e). The mean January SST field is characterized by low temperature in the northwest basin and high temperature in the southeast basin (Figure 4a). The low temperature in the northwest is caused by the winter northeast winds, which play double roles in cooling the seawater in the northern SCS: first, the winds themselves bring cold and dry air to the SCS, and thus cool the seawater through air-sea heat exchange; second, the winds generate southwestward coastal current, which in turn brings cold coastal water from the East China Sea and Taiwan Strait into the SCS. The SST in summer is much more uniform than in winter (Figure 4b). A distinguished feature is that a cold water tongue can be observed immediately east of the Vietnam coast around 12°N latitude. This cold water tongue is an indication of the upwelling reported by Wyrski [1961] and Kuo et al. [2000]. This upwelling should be located on the north side of the Southeast Vietnam Offshore Current [Fang et al., 2002; Xie et al., 2003]. The spatial pattern of the annual mean SST is similar to that of the winter SST, but with a reduced contrast between the southeast and northwest areas.

3. Linear Trends

[11] The linear trend of a variable $y$ is calculated from its observed values $y_i$ at the times $t_i$, $i = 1, 2, \ldots, N$, by fitting $(t_i, y_i)$ to a linear relation

$$y_i = b_0 + b_1 t_i + \varepsilon_i$$

through least squares method. Here the slope $b_1$ represents the trend, and its uncertainty can be estimated from the residuals $\varepsilon_i$ based on a method described by Emery and Thomson [2001]; see Appendix A of the present paper.

[12] The time series of the area-mean values of the South China Sea SW, SSH and SST are displayed in Figure 5, in which the linear trends from linear regression analysis are shown with straight lines. The rates of trends and their standard deviations are listed in Table 1. Since the calculation is based on the 12-month means, the seasonal variation is not present in the time series curves.

[13] Figure 5a and Table 1 show that the north component of the SW does not have obvious trend during the 1993–2003 period, while the east component has a trend of 0.53 ± 0.35 m s$^{-1}$ decade$^{-1}$. The spatial distribution of the trends of the SW over the SCS is given in Figure 6a. The greater trends during 1999–2003 (Figure 6b) are present over the southern SCS. The westerly trend is consistent with a higher warming rate in the northern SCS than that in the southern SCS (Figure 6c). A convergence of the SW trend can also be found over the northern deep basin. This is also consistent with the greater SST increase in this area.

[14] The mean SSH rising rate for the SCS is 6.7 ± 2.7 cm decade$^{-1}$, which is about 2.4 times the global mean SSH rising rate (2.8 ± 0.4 cm decade$^{-1}$) observed by the TP altimeter over basically the same period [Cazenave and Nerem, 2004], and is about 3.7 times the global mean SSH rising rate (1.8 ± 0.3 cm decade$^{-1}$) during 1950–2000 [Church et al., 2004]. However, the SSH rising rate from the present study is lower than that calculated by Li et al. [2002], who presented an estimate of 1.0 cm yr$^{-1}$ for the SCS for a shorter period (1993–1999). This difference is mainly due to the fact that the SSH in the SCS experienced a decrease during 1999–2003 (Figure 5b). Figure 6b displays the spatial distribution of the SSH rising rates. Most of the SCS has SSH rising rates in the range of 5 to 10 cm decade$^{-1}$, with higher rates in the north and lower in the south. The greatest rate appears in the deep basin west of Luzon and Palawan. From Figure 6b we can see that the sea level rising rates in the southern Luzon Strait are higher than that in the northern Strait. This might indicate that the upper layer westward transport in the Luzon Strait becomes
The area-mean trend of the SCS SST is 0.50 ± 0.26 K decade⁻¹. Since the NCEP OI SST data are available from 1982, we have also calculated the linear trend in the period 1982–2004, yielding a warming rate of 0.26 K decade⁻¹ for the SCS. This shows that the warming rate of the SCS is very small during 1982–1992 and is considerably accelerated in the recent decade. On the other hand, the warming rate of the SCS in the last 22 years is about 2 times the global ocean mean rate (0.14 ± 0.04 K decade⁻¹) between 1960 and 1990 [Casey and Cornillon, 2001]. The higher warming rates are in the northern deep basin and lower rates appear in the southern SCS (including the Sunda Shelf area) and over the South China Shelf (Figure 6c). The highest rate exceeding 0.8 K decade⁻¹ is located west of the Luzon Strait.

4. Interannual Variability

4.1. Empirical Orthogonal Function Decomposition

To study the interannual variability, the mean values and linear trends are first removed from the smoothed values through the 12-month running averaging, the EOF

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**Figure 5.** Time series of South China Sea regional means of (a) the east and north components of surface winds, (b) the sea surface height anomalies, overlaid with the normalized inverse Nino3.4 Index, and (c) the sea surface temperature. The time series are filtered through 12-month running mean. Straight lines indicate linear trends.
analysis is then performed to extract the dominant patterns and their associated time coefficient functions (TCF). If the parameter anomaly at the grid location \( m \) (\( m = 1, 2, \ldots, M \)) and at the time \( t \) (\( t = 1, 2, \ldots, N \)) is \( x(m, t) \), then these anomalies can be expanded into a series of modes [cf. Storch and Zwiers, 1999]:

\[
x(m, t) = \sum_{i=1}^{K} \alpha_i(t) F_i(m),
\]

where \( F_i(m) \) is the \( i \)-th EOF, representing the spatial pattern of the \( i \)-th mode; \( \alpha_i(t) \) is the TCF of the \( i \)-th mode; \( K = \min(M, N) \). These modes are arranged in order of magnitudes of their corresponding variance \( \lambda_i \), which is equal to the \( i \)-th eigenvalue of the covariance matrix of \( x(m, t) \). \( \lambda_i \) represents the variance explained by the \( i \)-th mode. For convenience the TCFs are normalized in the present study to satisfy

\[
\sum_{i=1}^{N} \alpha_i^2(t) = 1.
\]

As a result, the variance is contained in the EOFs, that is,

\[
\frac{1}{M} \sum_{m=1}^{M} F_i^2(m) = \lambda_i.
\]

The value of \( \lambda_i^{1/2} \) represents the standard deviation of the \( i \)-th EOF.

To extract the EOFs of both east and north components of the surface winds with common TCFs, we use the real-vector method proposed by Kaihatu et al. [1998]. This method is a special case of the multivariate EOF analysis employed by Picaud et al. [2002].

The variances (eigenvalues) of the three leading modes for the SW, WS, SSH and SST are listed in Table 2. It can be seen that the first modes of all these four parameters can explain at least 50% of their corresponding total variances. The eigenvalues of the second and third modes of the SSH are of similar magnitude. According to the North’s selection rule [cf. Storch and Zwiers, 1999] these two modes are mixed. The third modes of the SW and WS, and the second and third modes of the SST are even smaller. Therefore, in the following we will only present the components with contribution exceeding 15%.

4.2. SW Variability

The first EOFs and the associated TCFs of the SW and WS are shown in Figure 7, which explain 55% and 68%, respectively, of their total variance. The first EOFs clearly demonstrate an anticyclonic pattern. The first TCFs exhibit fluctuations closely correlated with the Niño3.4 index, which is the mean SST anomaly averaged over a central-eastern equatorial Pacific region (5°S–5°N, 170°W–120°W) [Trenberth, 1997]. A lagged linear regression analysis indicates that the first TCF of the SW is best correlated with the Niño3.4 SST, with correlation coefficient equal to 0.90, when the first TCF lags the Niño3.4 SST by 3 months. The correlation is statistically significant above the 99% confidence level (see Appendix A for estimation of significance levels). Three major peaks correspond well to the 1994–1995, 1997–1998 and 2002–2003 El Niño events, when the SW over the SCS exhibits anticyclonic anomaly. Two major troughs in the first TCF correspond well to the 1995–1996 and 1998–2000 La Niña events, when the SW over the SCS exhibits cyclonic anomaly. Wang et al. [2000] found that an anomalous anticyclone (cyclone) was present in the western North Pacific during warm (cold) event. The EOF 1 pattern shown in Figure 7 agrees with the finding of Wang et al. [2000] and appears as the southwesternmost portion of the western North Pacific anticyclone (cyclone). From this mode we can see that the northeast monsoon (Figure 2a) weakens (intensifies) during El Niño warm (cold) phase over the northern SCS, including the Taiwan and Luzon Straits, but not over the southern SCS. The first EOF pattern of the WS is very similar to that of the SW (Figure 7c). The first TCF of the WS is also best correlated with Niño3.4 at the 99% confidence level, with a lag of 2 months (Figure 8d).

The second modes of the SW and WS, which are displayed in Figure 8, account for 21% and 16%, respectively, of their corresponding total variances. The second EOF of the SW is even simpler than the first EOF, showing a southwesterly pattern. It is worthy to note that, unlike the first EOF, which has a rotary feature, the second EOF pattern of the SW is characterized by the spatial uniformity. The TCF of the second mode does not have a significant correlation (coefficient equals to 0.24) with the Niño3.4 index. Instead, it has a certain correlation with the Indian Ocean Dipole (IOD) mode index, which is defined by Saji et al. [1999] as the SST difference between the tropical western Indian Ocean (50°E–70°E, 10°S–10°N) and the tropical southeastern Indian Ocean southwest of Sumatra (90°E–110°E, 10°S–Equator). The maximum coefficient is 0.58 when the second TCF leads the IOD index by 4 months (Figure 8b). The correlation is significant at the 95% confidence level. In particular, the highest peaks in 1994 and 1997 correspond fairly well to those of the IOD index. The correlation between the SCS SW and the IOD found in the present study is consistent with the analysis of Saji et al. [1999]. The composite diagrams of Saji et al. [1999, Figure 2] indicate that the southwesterly wind anomaly prevails over the SCS several months before the negative SST anomaly peak appearing to the southwest of Sumatra. It seems that the spatially uniform southwesterly wind anomaly over the SCS may be used as an indication of occurrence of the IOD mode. The second EOF pattern of the
4.3. SSH Variability

[21] Figure 9 displays the first EOF mode of the SSH, which accounts for 50% of the total variance. The associated TCF has a very high correlation with the Niño3.4 index. The coefficient is equal to 0.94 with Niño3.4 leading SSH by 2 months. The correlation is well above the 99% confidence level. The spatial pattern is characterized by low sea level along the SCS eastern boundary and relatively high sea level in the central western area. It is consistent with the sea level variability in the tropical Pacific, which has low sea level in the west during El Niño events [e.g., McPhaden et al., 1998]. The relatively high sea level in the central western SCS indicates that the winter cyclonic circulation (Figure 3b) is reduced during the El Niño period, which is a result of the anticyclonic anomaly of the wind stress [Wang et al., 2006]. The area-mean SSH anomalies during the El Niño (La Niña) events are negative (positive) as shown in Figure 9. This feature can also be seen from the comparison between the SSH curve and the inverse Niño3.4 curve in Figure 5b. The SSH curve is characterized by the troughs (relative to the straight line) during the 1994–1995, 1997–1998 and 2002–2003 El Niño events and the peaks during the 1994–1995 and 1998–2000 La Niña events, with a few months of delay.

4.4. SST Variability

[22] The first EOF mode of the SST variability contributes 79% to the total variance. The spatial pattern and time coefficients are presented in Figure 10. It can be seen that the first TCF closely correlates with the Niño3.4 index. A lagged linear regression calculation reveals that the maximum correlation appears when the first TCF of the SCS lags the Niño3.4 SST by 8 months. The correlation coefficient is 0.62, which is above the 95% confidence level. The maximum lagged correlation coefficient between the first mode of the SCS SST variability and the IOD index is 0.48, also with an 8-month lag. The correlation is significant above the 90% confidence level, but below the 95% confidence level.

[23] The spatial pattern of the first EOF exhibits basin-wide warming, indicating that the entire SCS is warmed up following the El Niño events, with a delay of 8 months. The lagged response of the SST to ENSO is common in most

Table 2. Variances of the First Three EOFs of the Surface Wind (SW), Wind Stress (WS), Sea Surface Height (SSH), and Sea Surface Temperature (SST) of the South China Sea

<table>
<thead>
<tr>
<th>Parameter</th>
<th>EOF</th>
<th>Variance</th>
<th>Ratio</th>
<th>S.D.</th>
</tr>
</thead>
<tbody>
<tr>
<td>SW</td>
<td>1</td>
<td>0.099 m²s⁻²</td>
<td>0.55</td>
<td>0.31 ms⁻¹</td>
</tr>
<tr>
<td></td>
<td>2</td>
<td>0.038 m²s⁻²</td>
<td>0.21</td>
<td>0.19 ms⁻¹</td>
</tr>
<tr>
<td></td>
<td>3</td>
<td>0.018 m²s⁻²</td>
<td>0.10</td>
<td>0.13 ms⁻¹</td>
</tr>
<tr>
<td>WS</td>
<td>1</td>
<td>16.9 × 10⁻⁵ N²m⁻⁴</td>
<td>0.68</td>
<td>4.11 × 10⁻³ Nm⁻²</td>
</tr>
<tr>
<td></td>
<td>2</td>
<td>4.1 × 10⁻⁵ N²m⁻⁴</td>
<td>0.16</td>
<td>2.01 × 10⁻³ Nm⁻²</td>
</tr>
<tr>
<td></td>
<td>3</td>
<td>1.6 × 10⁻⁵ N²m⁻⁴</td>
<td>0.06</td>
<td>1.27 × 10⁻³ Nm⁻²</td>
</tr>
<tr>
<td>SSH</td>
<td>1</td>
<td>2.390 cm²²</td>
<td>0.50</td>
<td>0.55 cm</td>
</tr>
<tr>
<td></td>
<td>2</td>
<td>0.541 cm²²</td>
<td>0.11</td>
<td>0.74 cm</td>
</tr>
<tr>
<td></td>
<td>3</td>
<td>0.455 cm²²</td>
<td>0.10</td>
<td>0.67 cm</td>
</tr>
<tr>
<td>SST</td>
<td>1</td>
<td>0.0635 K²</td>
<td>0.79</td>
<td>0.25 K</td>
</tr>
<tr>
<td></td>
<td>2</td>
<td>0.0074 K²</td>
<td>0.09</td>
<td>0.09 K</td>
</tr>
<tr>
<td></td>
<td>3</td>
<td>0.0045 K²</td>
<td>0.06</td>
<td>0.07 K</td>
</tr>
</tbody>
</table>

*Quotient of the variance of each mode and the total variance.
Standard deviation.
tropical oceans, and was attributed to the effect of atmospheric bridge and the thermal inertia of the ocean mixed layer by Klein et al. [1999], Alexander et al. [2002], and Wang et al. [2004]. For the SCS, in particular, the post-ENSO warming can be partially attributed to the weakening of the northeast monsoon during the El Niño periods in the northern SCS, including the Taiwan and Luzon Straits, as shown in the first EOF pattern of the SW (Figure 7a). The weakened northeast monsoon brings less cold water into and less cold and dry air over the SCS, and hence results in a higher SST anomaly in the months following the El Niño events. The greatest warming appears in the northern deep basin, located northwest of the Luzon Island. It may be a result of the anticyclonic wind stress anomaly (Figure 7c). The second greatest warming is located southeast of the Indo-China Peninsula, in consistence with the finding of Xie et al. [2003].

[24] The 1997–1998 strong warm event of the SCS SST was probably first reported by Wang et al. [2002]. This warm anomaly started in spring 1997 and terminated in spring 1999, with the highest annual mean anomaly of about 0.7°C (see also Figure 5c). This abnormal warming is consistent with the global warming event in 1998 [Folland et al., 2001]. China also experienced the warmest year of the century in 1998 [Gong and Wang, 1999].

[25] To examine the robustness of the first EOF obtained from the analysis for the period of 1993–2003, we have also performed the same analysis for 1982–2004, using the NCEP OI SST data set. The obtained EOF pattern is very similar to the 1993–2003 result, and the first TCF is best correlated with the Nino3.4 SST at a 6-month lag, with a correlation coefficient equal to 0.55.

4.5. ENSO-Associated Correlation Patterns

[26] In the preceding subsections we have presented the EOF patterns of the SW, SSH, and SST. The EOF analysis shows close correlations of these parameters with the Nino3.4 index. The analysis also provides time lags for maximum correlations. Though the leading EOFs account for most part of the total variance, it is still worth showing the ENSO-associated correlation patterns through a direct linear regression analysis. In the calculation, the Nino3.4 index is still used to represent the ENSO fluctuations.
In the associated pattern analysis the anomalous variable \( y \) at the grid location \( m \) and the time \( t \) is expressed by [cf. Storch and Zwiers, 1999]

\[
y(m, t) = b(m) x(t - \tau) + \text{noise},
\]

where \( x \) is the normalized Nino3.4 index; \( y \) is the variable, representing the SW, SSH, or SST; \( \tau \) is the time lag; \( b \) is the regression coefficient. In the present analysis \( \tau \) is taken equal to the time lag of the first mode of each parameter with respect to the Nino3.4 index. That is, \( \tau = 3 \) months for the SW, 2 months for the SSH, and 8 months for the SST. The regression coefficient \( b \) carries the same unit as \( y \). When \( x = 1 \) the value of \( y \) associated with \( x \) is equal to \( b \). The spatial distribution of \( b \) is referred to as the associated correlation (or regression) pattern.

The ENSO-associated correlation pattern of the SCS SW is shown in Figure 11. The spatial pattern is very similar to the first EOF pattern (Figure 7). From Figure 11 we can observe that the correlation of the SW with the Nino3.4 index is statistically significant at the 95% confidence level for the most part of the SCS. Only in a small area southwest of Luzon the correlation is below the 90% confidence level. Since the normalized Nino3.4 index reaches a peak value of about 2.5 (see thin line on Figure 7b) in the 1997/1998 winter El Niño, the annual mean northeasterly winds in the northern SCS is reduced by about 2 m s\(^{-1}\) around early 1998.

The ENSO-associated correlation pattern of the SCS SSH (Figure 12) is also similar to its first EOF pattern (Figure 9). The correlation of the SSH with the Nino3.4 SST is statistically significant at the 95% confidence level in the most SCS. The correlation is statistically insignificant (below the 90% confidence level) in the central western SCS. During the 1997/1998 El Niño event the annual mean sea level in the eastern SCS is lowered by about 5 cm.

The ENSO-associated correlation pattern of the SCS SST (Figure 13) shows that the high correlation appears in the southern SCS, mostly exceeding the 95% confidence level. The highest regression coefficient is over 0.22, indicating that the annual mean SST is higher than normal by 0.55°C after the 1997–1998 El Niño. The relatively high correlation appears in the northern deep basin, with a correlation also at the 95% confidence level. In the area near the Luzon Strait and Luzon Island, and over the South China Shelf the correlation is below the 95%, or even below the 90% confidence level. The ENSO-associated pattern of the SST has a certain similarity to the first EOF pattern.
but the differences are also obvious. This is due to the fact that the correlation coefficient of the first TCF with the Nino3.4 index is 0.62, indicating that the ENSO-associated part can only account for 38% of the variance in the first mode.

5. Conclusions and Discussion

The trends and the interannual variability of the SW, SSH and SST over/in the SCS in 1993–2003 are evaluated on the basis of satellite observations. The area-mean of the north component of the SW does not have a detectable trend, while the east component has a linear trend of $0.53 \pm 0.35$ ms$^{-1}$ decade$^{-1}$. In the southern SCS the westerly trends are about $1.0$ ms$^{-1}$ decade$^{-1}$. The SSH has an area-mean linear trend of $6.7 \pm 2.7$ cm decade$^{-1}$, which is about 2.6 times of the global mean rising rate from the TP altimetry. The SSH rising rates are higher in the northern deep basin. As Li et al. [2002] reported, the altimeter data agreed well with the ground station measurements, and the rising rates derived from altimetry were reliable. The area-mean linear trend for the SST is $0.50 \pm 0.26$ K decade$^{-1}$ in 1993–2003, while the trend is $0.26$ K decade$^{-1}$ in 1982–2004, suggesting that the warming is significantly accelerated in the recent decade. Though the linear trends in the SSH and SST are quite high, the time span of the observations is not sufficient for inferring long-term trends. It is most likely that a substantial part of the detected trends is attributed to the inter-decadal variability in the region. Thus further monitoring the trends is necessary.

The SSH rising rate in the deep basin is about 8 cm decade$^{-1}$ (Figure 6b). The SSH rising rate has the following relationship to the heat storage rate [cf. Yan et al., 1995, 2004; Chambers et al., 1997]

$$R_{HS} = \rho C_p \alpha^{-1} R_{SSH},$$

where $R_{HS}$ and $R_{SSH}$ denote the rates of the heat storage and sea surface height, respectively; $\rho$ is the water density; $C_p$ is
the specific heat of seawater; $\alpha$ is the thermal expansion coefficient of seawater. For a rough estimation, we take $\rho = 1025 \text{ kg m}^{-3}$, $C_p = 4000 \text{ J kg}^{-1}\text{K}^{-1}$, and $\alpha = 0.25 \times 10^{-3}$ K$^{-1}$, yielding

$$R_{HS} \approx R_{SSH} \times 16.4 \text{ GJ m}^{-3}. \quad (7)$$

Inserting $R_{SSH} = 8 \text{ cm decade}^{-1}$ gives $R_{HS} = 1.31 \text{ GJ m}^{-2} \text{ decade}^{-1} = 4.2 \text{ Wm}^{-2}$. This suggests that there is a mean net downward heat flux of 4.2 Wm$^{-2}$ passing through the SCS surface over the period of 1993–2003, provided that the heat exchange trends through the open boundaries are insignificant. The heat storage rate is equivalent to a depth-mean temperature rising rate of 0.8 K decade$^{-1}$ if we assume that the temperature change is limited to the upper 400 m, as did in most previous works. This rate happens to roughly agree with the SST warming rate in the SCS deep basin (Figure 6c). This result seems to indicate that the trend of SST is not only a surface phenomenon, but also reflects the warming rate in the upper ocean.

[33] On the interannual timescale, the SW, SSH and SST all show significant correlation with the ENSO variability. The numerical results from our separate study reveal that the circulation in the SCS is also closely correlated with the ENSO variability [Wang et al., 2006].

[34] The first EOF of the SW is characterized by a basinwide anticyclonic pattern, which appears as the southwesternmost portion of the western Pacific anticyclone [Wang et al., 2000]. The corresponding TCF highly correlates with the Nino3.4 index. The correlation coefficient is 0.90 when the first TCF lags the Nino3.4 SST by 3 months. The second EOF of the SW is characterized by a nearly uniform southwesterly. Its TCF has a certain correlation with the IOD index. The coefficient is 0.58 when the second TCF leads the IOD by 4 months, indicating that the second EOF of SW over the SCS could potentially be used as an indication of the IOD mode. The ENSO-associated correlation pattern is similar to the first EOF, and indicates that the northeast monsoon weakens during the El Nin ˜o period over the northern SCS, but not over the southern SCS.

[35] The first EOF of SSH is characterized by the low sea level along the eastern boundary of the SCS. The corresponding TCF is highly correlated with the Nino3.4 index. The correlation coefficient is equal to 0.94 when the TCF lags the Nino3.4 index by 2 months. The ENSO-associated correlation pattern is basically the same as the first EOF.

[36] The first EOF of SST is characterized by a basinwide warming. The corresponding TCF closely correlates with the Nino3.4 index. The correlation coefficient is equal to 0.62 when the first TCF lags the Nino3.4 index by
Figure 12. Same as Figure 11, but for the 2-month lagged sea surface height, contours in centimeters.

Figure 13. Same as Figure 11, but for the 8-month lagged sea surface temperature, contours in degrees.
8 months. In particular, the 1997–1998 El Niño mature phase was reached around November 1997, while the warmest anomaly in the SCS appeared around July 1998. The time lag can ease the difficulty in predicting the SCS anomalies. This result might also be useful for predicting the flood in the Changjiang River Valley in China, since it is found that the flood and drought in the Changjiang River Valley is related to the SCS SST [Zhang et al., 2003]. In particular, the SCS warm event and the severe disastrous flood of the Changjiang River Basin took place simultaneously in the summer of 1998. The following factors might collectively contribute to the extreme 1998 warm event in the SCS. First, the 1998 warm air temperature was the warmest of the world [Folland et al., 2001], including the SCS and its surrounding areas, especially over China [Gong and Wang, 1999]. Second, the weakened northeast monsoon brought less cold and dry air to the atmosphere over the SCS, and induced weaker southwestward cold coastal current toward the SCS [Wang et al., 2006]. Third, as suggested by Xie et al. [2003], the change of wind field in the summer of 1998 suppressed the upwelling southeast of Vietnam, and was in favor of the maintenance of the warm event. However, a more detailed quantitative analysis of the atmospheric bridge process is still needed in the future studies. The SSH is depressed during El Niño, thus the heat storage is also reduced; while the SST increases during El Niño. So unlike the situation of linear trends, the interannual variation of SST behaves quite differently from that of the heat storage or the integrated seawater temperature beneath the sea surface.

[37] In the present study, however, the time series are highly autocorrelated. In this case, the effective number of degrees of freedom is smaller than the number of data points. The method for calculating the effective degrees of freedom used in the present study is based on Emery and Thomson [2001], Section 3.15. For any variable \( \zeta \), the autocovariance function \( C_\zeta(\tau_k) \) is calculated from

\[
C_\zeta(\tau_k) = \frac{1}{N - 1 - k} \sum_{i=1}^{N-k} (\zeta_i - \bar{\zeta})(\zeta_{i+k} - \bar{\zeta}_{i+k}),
\]

where \( \tau_k = k\Delta\tau \), with \( \Delta\tau \) standing for the sampling interval. In particular, when \( k = 0 \), we have

\[
C_\zeta(0) = \frac{1}{N - 1} \sum_{i=1}^{N} (\zeta_i - \bar{\zeta})^2 = s_\zeta^2.
\]

Correspondingly, the confidence level of the correlation coefficient \( r \) can be evaluated by comparing the value of \(|r|\) to the critical value of \( r_\alpha \) where \( \alpha \) is the significance level. The critical value can be obtained from a standard table [e.g., Emery and Thomson, 2001, Appendix E].

[46] In the present study, however, the time series are highly autocorrelated. In this case, the effective number of degrees of freedom used in the present study is based on Emery and Thomson [2001], Section 3.15. For any variable \( \zeta \), the autocovariance function \( C_\zeta(\tau_k) \) is calculated from

[41] In the trend estimation, the decorrelation timescale is calculated from

\[
T = \frac{1}{C_\zeta(0)} \sum_{k=0}^{n-1} \frac{\Delta\tau}{2} [C_\zeta(\tau_k + \Delta\tau) + C_\zeta(\tau_k)].
\]
Since the time series in the present study are not sufficiently long, the summation here is made from \( k = 0 \) to the data point immediately preceding the first zero-crossing point as proposed by Emery and Thomson [2001]. The effective degrees of freedom is taken

\[
N^* = N \Delta t / T.
\]  

(A13)

The standard deviation of the trend is then

\[
\Delta \sigma = s_x / \left[ (N^* - 1)^{1/2} s_x \right].
\]  

(A14)

The confidence interval for level \( \alpha \) is given by

\[
\pm (s_{t,n/2,\nu}) / \left[ (N^* - 1)^{1/2} s_x \right],
\]  

(A15)

where \( \nu = N^* - 2 \), \( t_{n/2,\nu} \) is the \( \alpha/2 \) -quantile of the \( t \)-distribution with \( \nu \) degrees of freedom, which can be obtained from, for example, Emery and Thomson [2001, Table D. 3a].

[42] For the regression analysis the decorrelation time-scale \( T \) is found by

\[
T = 1 / C_0 / C_0 \sum_{k=0}^{w-1} \Delta t / 4 \left[ C_k (\tau_k + \Delta \tau) + C_k (\tau_k) \right] \cdot \left[ C_k (\tau_k + \Delta \tau) + C_k (\tau_k) \right].
\]  

(A16)

[43] Note: There are typographic errors in equations (3.15.12a), (3.1512b), (3.15.15a), and (3.15.15b) in the work of Emery and Thomson [2001]. That is, the power 1/2 in these equations should appear after \( (N - 1) \) and \( (N^* - 1) \), respectively (R. E. Thomson, personal communication, 2005). The errors have been corrected in the present Appendix A.

References


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