Multi-Dimensional Analysis on the Temporal and Spatial Variability of Sea Surface Salinity in South China Sea

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Abstract. Sea surface salinity (SSS) is an important parameter of the physical marine environment and its variation has significant effects on the hydrodynamic environment in the South China Sea. With the developing of sea surface salinity retrieval technology based on SMOS data, intuitive SSS could be obtained. Study on the SSS could help better understand the role of salinity in ocean circulation and the global water cycle. In this paper, multi-dimensional analysis methods will be applied to study on the temporal and spatial variability pattern of sea surface salinity from 2014 to 2019 in South China Sea. In this paper, to reveal the temporal and spatial variability of SSS in South China Sea, time series analysis, geostatistical method and EOF decomposition algorithms were adopted. The purpose is studying on the temporal and spatial variability pattern of sea surface salinity from 2014 to 2019 in South China Sea.

1. Introduction
Sea surface salinity (SSS) is an important parameter of the physical marine environment and its variation has significant effects on the hydrodynamic environment in the South China Sea. Sea surface salinity is being measured globally by the Soil Moisture and Ocean Salinity (SMOS) satellite mission [1]. The SMOS data for the period of January 2014 to the end of 2019 were used here. The Aquarius product used is the Version 4.0, Level-3, daily average SSS that combined the data from ascending and descending orbits [2][3]. The data are on a 15’ grid. Salinity is derived through the relation between brightness temperature (BT), sea surface temperature (SST) and sea roughness [1]. With the developing of sea surface salinity retrieval technology based on SMOS data, intuitive SSS could be obtained [4]. Study on the SSS could help better understand the role of salinity in ocean circulation and the global water cycle [5]. In this paper, multi-dimensional analysis methods will be applied to study on the temporal and spatial variability pattern of sea surface salinity from 2014 to 2019 in South China Sea. At first, to research the overall trend of SSS in the South China Sea, monthly 15’ resolution data from 2014 to 2019 has been calculated. Time series plots showed the periodic and seasonal fluctuation of SSS. Trend lines which be calculated by least square method show annual changes. Secondly, focus on the spatial distribution, geostatistical method has been used to produce the spatial distribution plots of SSS in the South China Sea. Overall trend of spatial variability could be found easily from the plots. Apparent difference also was showed when comparing the SSS in near land and centre area of the South China Sea. Some high (or low) SSS value areas were distinguished from spatial distribution plots. They also varied monthly and seasonally. At last, aim to understand the month to month variations of SSS anomalies from 2014 to 2019, EOF (Empirical Orthogonal Functions) analysis on monthly SSS data was performed. Before performing the EOF decomposition, Gaussian filter was employed to remove long-term trends and decadal variations of SSS and circulation anomalies. First 3 modes accounted for 45% of the total monthly variance of SSS in the South China Sea. It could be confirmed that the first 3 modes represented the overall trend of SSS anomalies. So in this paper, first 3 modes were explained...
individually to reveal the temporal and spatial variability of SSS anomalies in each mode, and some plots showed the detail intuitively. To reveal the temporal and spatial variability of SSS in South China Sea, time series analysis, geostatistical method and EOF decomposition algorithms were adopted in this paper. Some results showed, the overall trend of SSS in South China Sea is decline slowly from 2014 to 2019 and perform fluctuation seasonally. Spatially, obvious difference of SSS was also existed from north to south (or east to west). From the distribution plots, several high level areas could be easily found. Through the ranges of these areas changed by month to mouth, but was not distinguished. By performing the EOF decomposition, SSS anomalies fluctuated temporally and spatially by different ways. Studying on the temporal and spatial changing patterns of the SSS, will helped to understand interaction of the oceanic-atmospheric in South China Sea.

2. Data and method

2.1. Data

ESA’s Soil Moisture Ocean Salinity (SMOS) Earth Explorer mission is a radio telescope in orbit, but pointing back to Earth not space [6]. Its microwave imaging radiometer using aperture synthesis (MIRAS) radiometer picks up faint microwave emissions from earth’s surface to map levels of soil moisture, sea surface salinity, sea ice thickness and others geophysical variable such as wind speed over ocean and freeze/thaw soil state [7]. SMOS level2 ocean salinity (OS) product comprises sea surface salinity measurement geo-located in an equal-area grid system ISEA 4H9 [8]. The product contains one single swath-based sea surface salinity retrieved with and without land-sea contamination correction, SSS anomaly based on WOA-2009 referred to Land-Sea corrected sea surface salinity, brightness temperature at the top of the atmosphere and at the sea surface with their corresponding uncertainties [9]. The pixels are consolidated in a pole-to-pole product file (50 minutes of sensing time), with a maximum size of about 10MB (25MB uncompressed data) per half orbit (29 half orbits per day) [10]. Spatial resolution is in the range of 30-50km.

2.2. Method

To reveal the pattern and the variety of the SSS in the South China Sea, in this paper, the changing trends and the spatial distribution pattern of SSS’s ABS would be described. Then the temporal and spatial distribution pattern of the SSS abnormal value would be analysed. The total changing and distribution features of the South China Sea SSS from 2014-2019 would be research in detail below.

2.2.1. The changing pattern with time of SSS. At first, to analysis the change pattern with time of SSS the absolute value, the monthly average value of the South China Sea SSS from 2014 to 2019 has been applied to plot the trend. Linear fitting of monthly mean absolute value of SSS with least square method was used here to obtain the intuitive trends with of SSS. Then based on the overall analysis, deep research to focus on the season and area was applied. The least square method was used here is a mathematical optimization technique for finding the best matching function of data by minimizing the sum of squares of errors. The monthly mean value dataset of SSS \( x(x_1, x_2, x_3, \ldots, x_n) \), the corresponded value \( y(y_1, y_2, y_3, \ldots, y_n) \). Hypothesis fitting line formula \( y = f(x) = a \cdot x + b \), when the square of the deviation between the value of \( y(x_i) \) and the estimated values on the fitting line is the smallest:

\[
\text{bias} = \sum (y(x_i) - f(x_i))^2 = \sum (y(x_i) - (ax_i + b_i))^2
\]  

The fitting formula is the best one. So the parameters in the fitting formula can be obtained:

\[
a = \frac{\sum x_i \cdot \sum y_i - n \cdot \sum x_i \cdot y_i}{\sum x_i^2 - n \cdot \sum x_i^2}
\]
b = \frac{\sum x_i y_i - \sum x_i \sum y_i}{\sum x_i^2 - n \sum x_i^2} \tag{3}

a is the trend slope of the fitting formula.

Using the method, we did the research on the long term changing trend of the South China Sea SSS. And on the basis, the variation trend of each sea area in each season was calculated.

2.2.2. Spatial distribution of the SSS. To study on the spatial distribution of the South China Sea SSS ABS, geostatistical analysis algorithm was applied to generate the monthly and quarterly average SSS spatial distribution map from 2014 to 2019. Through comparison, we could easily found the difference of the SSS in spatial distribution.

2.2.3. Temporal and spatial distribution features of the SSS anomaly. To research the volatility of the South China Sea SSS, empirical orthogonal function decomposition algorithm (EOF algorithm in short) was be used to decompose the SSS anomaly after levelling into multiple modes. Then the spatial distribution maps in first three modes were plotted. EOF algorithm is a method to analyse the structural features of matrix data and extract the main data features. Now EOF algorithm has been widely used in geosciences. When processing geoscience data, the eigenvector of data matrix is spatial samples, which means the eigenvector of spatial distribution. The principal components of the matrix correspond the time variation, which is called time coefficient. So EOF algorithm is always called spatiotemporal decomposition algorithm in geoscience. The specific steps of EOF algorithm are as follows:

- Matrix $X_{m \times n}$ means the SSS anomaly data after levelling processing. Calculating the cross product of $X$ and its transpose matrix $X^T$:

  $$C_{m \times m} = \frac{1}{n} X \times X^T \tag{4}$$

  Here $C$ is covariance matrix.

- Calculate the eigenvalues $\lambda_1, \ldots, \lambda_m$ and the eigenvector $V_{m \times m}$, let them meet the follow formula:

  $$C_{m \times m} \times V_{m \times m} = V_{m \times m} \times \Lambda_{m \times m} \tag{5}$$

  $\Lambda$ is the diagonal matrix sized $m \times m$,

  $$\Lambda = \begin{pmatrix}
  \lambda_1 & \cdots & 0 \\
  \vdots & \ddots & \vdots \\
  0 & \cdots & \lambda_m
  \end{pmatrix} \tag{6}$$

  Mostly eigenvalues are arranged from small to large, $\lambda_1 > \lambda_2 > \cdots > \lambda_m$. Here $\lambda$ should be larger or equal to 0 since $X$ is measured value. Each non-0 eigenvalue corresponds to a column of eigenvectors, called EOF modal. For example, $\lambda_1$ corresponds to the first column of $V$ $EOF_1 = V(:,1)$, which is the first modal; $\lambda_k$ corresponds to the $k$-th column of $V$ $EOF_k = V(:,k)$, which is the first modal.

- Calculating the principle of matrix. By projecting EOF onto the original matrix $X$, the time coefficients corresponding to all space eigenvectors are obtained.

  $$PC_{m \times n} = V_{m \times m}^T \times X_{m \times n} \tag{7}$$

  Here each row of $PC$ is the time coefficient corresponding to each eigenvector. $PC(1,:)$ is the time coefficient of the first EOF modal.

Through the three aspects study above, we could fully understand the spatiotemporal distribution and variation characteristics of the South China Sea SSS.
3. Results

3.1. Changing trend analysis of SSS

Based on the retrieved SSS, monthly mean SSS could be derived by interpolation method. SSS changing trend chart could be plotted by the monthly mean SSS. At the same time, the long term of SSS in the South China Sea was analysed by linear fitting based on the least square method, as shown in the Fig 1.

As can be seen from Fig 1, the overall trend of SSS in the South China Sea in the 6 years from 2014 to 2019 fluctuates periodically and tends to decrease continuously. Over the past 6 years, SSS in the South China Sea has generally remained at a high level in 2014 and 2015, and fluctuated significantly from 2015 to 2018, but decreased significantly in 2019, with SSS remaining between 32.2 to 32.6 psu. As the Fig 1 shows, the minimum SSS of each year basically occurred around May, and then gradually increased, and reached the highest value of the whole year around November and then began to fluctuate and decline. Based on the statistical analysis of monthly mean SSS data, the seasonal trend chart of SSS in the South China Sea is shown in Fig 2. It is obtained by taking March, April and May of each year as spring, June, July and August as summer, September, October and November as autumn, and December, January and February as winter. Combined with Fig 1 and 2, it can be seen that the maximum SSS occurred in spring, the salinity is generally low in summer, and fluctuates at an average level in autumn and winter.

Fig 3 shows the monthly variation trend of SSS in the South China Sea during the last 6 years. The similarities and differences of SSS changes of each year could be found in the chart. Except for 2018, the SSS of the South China Sea increased at the beginning of the year and reached its highest point around March. Although there was a rapid decline, it rose slowly after reaching its lowest point around
May, and then declined after reaching a higher value between October and November. According to the comprehensive analysis of Fig 2 and 3, SSS in the South China Sea fluctuated at a high level in winter, decreased at a low level in spring, climbed at a low level in summer and fluctuated at a low level in autumn.

![Monthly changing trend of SSS in the South China Sea from 2014 to 2019](image)

**Figure 3.** The overall trend of SSS in the South China Sea from 2014 to 2019.

![The spatial distribution of average SSS in the South China Sea from 2014 to 2019](image)

**Figure 4.** The spatial distribution of average SSS in the South China Sea from 2014 to 2019.

3.2. **Spatial and temporal distribution characteristics of SSS**

On the basis of interpolation processing of the monthly average data of SSS in the South China Sea, the average SSS distribution chart from 2014 to 2019 was obtained by using the geostatistical analysis algorithm, which indicated the overall spatial distribution trend, as shown in Fig4. As can be seen from the figure, the SSS in the South China Sea generally showed a trend of decreasing from north to south and from the periphery of the land to the central sea. Especially around Guangdong, south of Taiwan island and north of Luzon island, the sea area has the highest salinity, while the lowest value appeared around Nansha Trough.

As can be seen from the monthly average spatial distribution characteristics of SSS in the South China Sea in the Fig5, SSS tended to decrease from northeast to southwest at all times of the year, and in most
areas was distributed between 31psu and 34psu. The high level area existed in the 15° N north of South China Sea, the southeast of Taiwan island and Luzon Strait area, where the SSS value is higher than 34psu for most of the year. The high salinity tongue began to retreat to the east in May, and invaded to the southwest in October. The salinity distribution in the south-western part of the South China Sea increased significantly from November to next May compared with June to October. The monthly change of SSS around Nansha Trough was not obvious compared with other areas.

![Figure 5. The monthly spatial distribution of average SSS in the South China Sea from 2014 to 2019.](image)

![Figure 6. The seasonal spatial distribution of average SSS in the South China Sea from 2014 to 2019.](image)

As can be seen from Fig6, the SSS of South China Sea showed obvious seasonal changes, with a low salinity value in winter and spring while a high value in summer and autumn, which is closely related to rainfall. The salinity around the south of Taiwan island and Luzon strait is in high level all over the year, and generally higher than south. Preliminary assessment is related to the Kuroshio.

### 3.3 Temporal and spatial distribution features of the SSS anomaly

EOF analysis of SSS data is to process correlated salinity data into no-correlated bands, remove noise components and reduce data dimensions. Because there is a high correlation between SSS data of each band, EOF transform to find a new coordinate system origin in the average data, through the axis of rotation to achieve maximum variance data, so the output data of each band between unrelated \([11]\). After transform data generated band is a linear combination of the original salinity data band. Due to the
difference dimensions, sizes and evaluation indexes of each factor in EOF analysis, in order to make
them comparable, it is necessary to normalize these original data. In this paper, 6 years’ SSS data were
anomaly. Then the total 72 monthly average data from 2014 to 2019 were transformed by EOF. The
characteristic roots of the covariance matrix and characteristic equation are obtained from the anomaly
data, and the spatial modes are determined according to the cumulative variance percentage. As can be
seen from Table 1, the contribution rate of the cumulative variance of the first 7 modes of SSS anomalies
in the South China Sea accounts for 59.87% of the total variance. Among them, there is a significant
difference between the first mode and the second mode, and then the difference between the modes is
obviously reduced. In order to explore the spatial and temporal distribution characteristics of SSS
anomalies in the South China Sea, the first three modes are selected for analysis.

Table 1. Variance of first 7 modes.

| Mode   | Variance contribution rate/% | Total variance contribution rate/% |
|--------|------------------------------|----------------------------------|
| 1st    | 29.20                        | 29.20                            |
| 2nd    | 9.42                         | 38.62                            |
| 3rd    | 6.70                         | 45.32                            |
| 4th    | 5.18                         | 50.50                            |
| 5th    | 4.39                         | 54.89                            |
| 6th    | 2.97                         | 57.86                            |
| 7th    | 2.01                         | 59.87                            |

According to EOF decomposition, the variance contribution rate of the first mode explains 29.2% of the
total variance, and reflects the overall trend and distribution of SSS in the South China Sea in the past 6
years. As can be seen from Fig 7(b), the anomalous values of SSS in the first mode are negatively
correlated in most areas, indicating that the changes in the spatial distribution of SSS are in good causation. The areas with significant change of SSS anomalies are the north coast of Guangdong Province, the south of Taiwan island, the north of Luzon islands and the southwest of Nansha islands. Obviously, the change of SSS is more significant as it is closer to the land, which is affected by the relationship between rainfall and evaporation. Fig 7(a) shows the time coefficient corresponding to the spatial distribution in the first mode. The time coefficient corresponding to the spatial distribution represents the temporal variation characteristics of the spatial distribution of salinity anomalies. Combined with Fig 7(a) and (b), it can be found that the time coefficient of SSS in the South China Sea shows obvious periodic changes, and the amplitude of change continues to decrease during the 6 years. When the time coefficient is positive, the SSS of the whole research area increases, and when the time coefficient is negative, the SSS decreases. In the past 6 years, the time coefficient of SSS in the South China Sea has significantly increased in the positive value of periodic changes and significantly decreased in the negative value. With the passage of time, SSS in the South China Sea increased more than decreased. As can be seen from Fig 7(a), the time coefficient reached its maximum peak between October and November of each year. It can be seen that the SSS raise fastest during this period every year. The time coefficient reached the minimum value between March and May of each year, indicating that the SSS declines the fastest during this period of each year.
4. Conclusion

Through the above analysis, it can be seen that the SSS changes more significantly as it gets closer to the land and more gently as it gets closer to the centre of the sea area. It can be inferred that human activities and surface runoff injection have a great influence on the change of SSS. It can be seen from the analysis of time series that the SSS changes periodically with the seasons, indicating that the influence of temperature, evapotranspiration and rainfall also seriously affects the changes of SSS value.
SSS, therefore, is not a single ocean environment element, especially in the local environment just like the South China Sea, analysis of SSS time-space distribution and change rule could be seen as an important role in the analysis of sea-air system, and also helps further understanding of ocean circulation to monitor and predict the el nino phenomenon has important scientific significance.

5. References

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