

Article

Changes in Sea Level along the South China Sea Coast Based on the Homogenized Tide Gauge Data

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Abstract: To estimate the changes in the annual mean sea level (MSL) and extreme sea levels (ESLs), the largest collection of tide gauge records from 10 tidal stations along the northern coast of the South China Sea (SCS) were analyzed in this study. Here, all the tide gauge records had been homogenized by a two-step process involving the detection of inhomogeneities, that is, breakpoints caused by non-climatic changes and the application of the adjustment. The study's conclusions, based on the homogenized tide gauge records, can be summarized as follows: The instrument change and station relocation are the main causes for the identified inhomogeneities. From 1989 to 2018, the sea level along the SCS was at an average rate of 4.0 mm per year, as measured by the homogenized tide gauges. The ESLs from the nine tidal stations rose notably with interannual fluctuations, except for the XSA station. Additionally, the ESLs exhibited substantial decadal variations. The ESLs rose along the northern coast of the SCS and were accelerated at most stations throughout the whole study period, especially after the 1980s. There were significant positive correlations between the ESL and the annual MSL at most tide gauges. The MSL's changes, especially long-term changes, play an important role in the change in ESLs.



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Keywords: homogenization; tide gauge data; sea level rise; extreme sea level

1. Introduction

Global warming could lead to a significant rise in sea level. Sea level can be measured as “relative sea level”, which refers to the sea level relative to the coastal area of interest, or as “absolute sea level”, which refers to the sea level as measured from the center of the earth. The global mean sea level (GMSL), which represents the average height of the Earth's oceans based on a reference ellipsoid that roughly matches the Earth's surface, is believed to have increased at a faster pace over the past century, according to the IPCC report in 2019. In 2022, the GMSL was 101.2 mm higher than the level recorded in 1993, making it the highest yearly average throughout the altimetry period (1993–2022) [1]. Ocean thermal expansion, ice sheet and glacier melting, and freshwater input from land all contribute to GMSL increases over the long term. Local mean sea level (MSL) is defined as the average water level observed hourly over a specific period (i.e., 19-year cycle) at a local tide station. This concept accounts for the fluctuating tidal highs and lows resulting from the gravitational forces of the moon and sun. Extreme sea level events (ESLs) are brief coastal floodings lasting from hours to days that can cause severe damage to coastal infrastructure, freshwater resources, and agricultural fields. Tide gauge data have been utilized to study the occurrences of these phenomena. Researchers showed that a higher GMSL, combined

with rising MSL and storm surges, has the potential to worsen extreme sea level events (ESLs) and generate devastating ESLs regionally [2–4]. ESLs have significantly increased the vulnerability of coastal regions, especially some huge coastal cities, to storm surges, coastal erosion, coastal flooding, salinization, and other devastating consequences. The rising of the sea level has emerged as a serious worldwide environmental issue, exerting a substantial effect on regional society, economics, and even national security, in addition to the coastal environment. Thus, coastal cities with high population densities and developed economies are deeply concerned about the sea level rise.

Bordering the Southeast Asian mainland is an arm of the Western Pacific Ocean known as the South China Sea (SCS). Numerous coastal communities along the northern SCS coastline are situated in low-lying areas. These areas are vulnerable to ESL disasters, which are primarily triggered by typhoons, tropical storms, and winter storms. Moreover, several huge coastal cities are situated along the coast of the northern SCS, including Shenzhen, Guangzhou, Zhuhai, Haikou, etc. These cities possess high population densities, large property values, and invaluable historical buildings. The rising occurrence and intensity of coastal floods and storm surges could significantly damage the community and economy in coastal cities [5,6]. In September 2018, Typhoon Mangkhut struck Guangdong Province, causing storm surges exceeding three meters at certain locations and resulting in RMB 5.2 billion in economic losses. Additionally, it caused five fatalities and affected more than three million individuals [7]. Hallegatte et al. (2013) [8] categorized the northern coast of the SCS as one of the most vulnerable areas under global warming. Gao et al. (2019) [9] estimated the demographic and economic vulnerability in coastal regions of China under a sea level rise. The study indicated that the cities of Guangzhou and Shenzhen had the highest levels of exposure, while other locations with high exposure were mainly concentrated in the Yangtze River Delta and northern Jiangsu coastal plains. Protecting coastlines, protecting marine and coastal environments, and preserving coastal ecosystems all depend on better knowledge of the local MSL and ESL changes along the northern SCS coast.

Tide gauge data are more appropriate than satellite altimeter data for monitoring the sea level changes in coastal regions and capturing a variety of various coastal processes and hazard events, such as coast flooding, extreme sea levels, high tides, storm surges, swells, etc. [10]. Numerous studies have been carried out to examine the variations in regional sea levels by tide gauge data. However, the datasets used in these studies were of insufficient temporal and/or spatial coverage (e.g., Feng et al., 2019 [7], utilized observations from only four tide gauges along the SCS coastline) or even inhomogeneities [11]. In fact, studies have found that as one of the conventional observations, long-term tide gauge observations are also liable to be influenced by many sources of inhomogeneity. These sources include the geographical location, instrument change, daily times of measurement, and datum shift (also known as the shift of tide gauge zero), etc. [12–15]. Data inhomogeneity that arises from these non-climatic factors can conceal real changes in the climate and mislead the true climate variation [16,17]. When the fluctuations in long-term records are only associated with changes in the weather and climate, they are considered to be homogeneous or free of inhomogeneities [18,19]. Nevertheless, complete implementation of homogenization techniques in the tide gauge data of China has yet to occur [12]. Long-term sea level records, therefore, need to have a homogenization procedure undertaken so that climate change monitoring and coastal planning can be conducted with confidence. In the absence of these homogeneity assessments, significant caution is required when using any tide gauge data to study and analyze extreme events, such as coastal floodings caused by ESLs.

This study made use of tide gauge records from 10 tidal stations situated throughout the SCS coast (Figure 1). The records of the 10 stations spanned from 30 to 49 years, with a mean time span of 40 years. Initially, the homogenization process of these sea level records was displayed, involving identifying the potential causes of inhomogeneity and how they would affect the data, detection of inhomogeneities, and adjustment. Based

on the homogenized tide gauge data, we made precise estimations of the rates of annual MSL rises (annual MSL means the average height of the sea level over a year) and ESL rises. The correlations between the ESL changes and the possible impact of the annual MSL were investigated. This study also examined whether there has been an acceleration in an increase in ESLs.

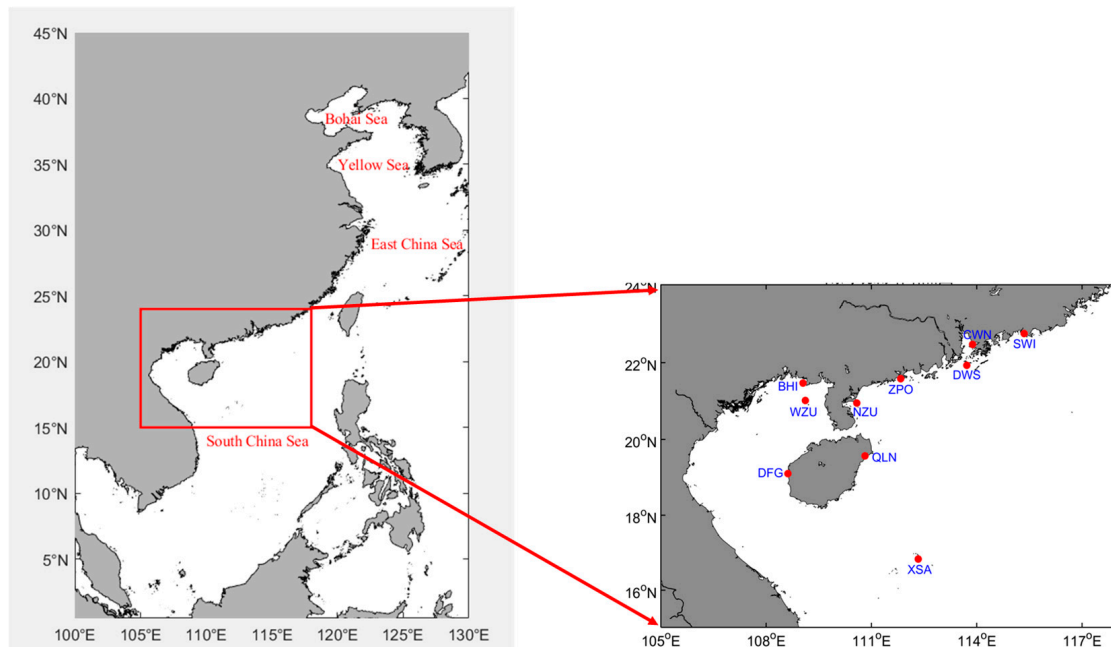


Figure 1. Map of the Northwest Pacific region. The study area is indicated by a red rectangle (**left**). Geographical location of the 10 tidal stations along the SCS coast (red dots) (**right**). Full names and time spans of the 10 tidal stations used in our study are shown in Table 1.

Table 1. Details of the 10 tidal stations.

Station Name	Site ID	Begin Year	End Year	Length (Year)
Beihai	BHI	1970	2018	49
Chiwan	CWN	1986	2018	33
Dongfang	DFG	1970	2018	49
Dawanshan	DWS	1985	2018	34
Naozou	NZU	1989	2018	30
Qinglan	QLN	1989	2018	30
Shanwei	SWI	1970	2018	49
Weizhou	WZU	1970	2018	49
Xisha	XSA	1988	2018	31
Zhapo	ZPO	1970	2018	49

2. Data and Methods

2.1. Tide Gauge Records

Our work was confined to analyzing tide gauge records along the SCS coastline after 1970 since, prior to this, the data contained numerous gaps. Tide gauge hourly sea level records have a span exceeding three decades, a critical factor in long-term trend analysis [20]. In order to eliminate short-term fluctuation, such as diurnal and semidiurnal oscillations, the daily and monthly mean sea levels were calculated using hourly tidal records. Here, we selected the daily mean sea level from 10 tidal stations with long-term records and missing data rates lower than 0.1%. Figure 1 shows the geographical locations of these stations, with further information provided in Table 1. All of these sea level records and metadata information are provided by the South China Sea Bureau

of the Ministry of Natural Resources of China. According to the regulations from “The Specification for Offshore Observations” [21], these observational records have undergone basic quality control for common errors, including a spike test, spurious values test, and spatial-temporal inconsistency test, etc. In routine work, records containing spurious jumps, datum shifts, and time shifts have been eliminated. Three main factors that contribute to the relative sea level (RSL) change at any given location, generally speaking, according to Nicholls et al. (2011) [22], are as follows: (a) GMSL rise; (b) departures from the global average caused by the spatially varying response of atmospheric and oceanic forces and non-uniform distributions of temperature change; and (c) local vertical land movement. It should be noted that tide gauges measure signals from both sea level fluctuations and vertical land motion, and they assess the sea level relative to a fixed benchmark on land; that is, tide gauges measure the RSL. The data were not corrected for vertical land motion and, therefore, represent the sea level relative to the land. Standardized files, called “Hydrological Station History Data File,” contain metadata information pertaining to coastal tide gauges. These metadata included the geographical location, elevations, hydrodynamic environments, datum shifts, measurement precision, station relocation, changes to equipment, etc. These were utilized to confirm the statistically identified breakpoints in our study.

2.2. Methods

2.2.1. Homogenization Method

Non-climatic reasons, such as station relocation and equipment changes, can have long-lasting effects on observation data, leading to the occurrence of inhomogeneity breakpoints in climatic series. These breakpoints can be effectively identified through the utilization of inhomogeneity detection on monthly mean series and metadata verification [23]. Therefore, we performed homogeneity detection on the monthly mean sea level series to obtain the breakpoints. Then, combined with metadata, we identified breakpoints after comprehensive judgment. The quantile-matching (QM) method was used to calibrate the hourly and daily data with verified breakpoints [24,25]. The homogenized monthly mean sea level series was calculated from the homogenized daily mean sea level. Below is the flow chart of the homogenization process (Figure 2).

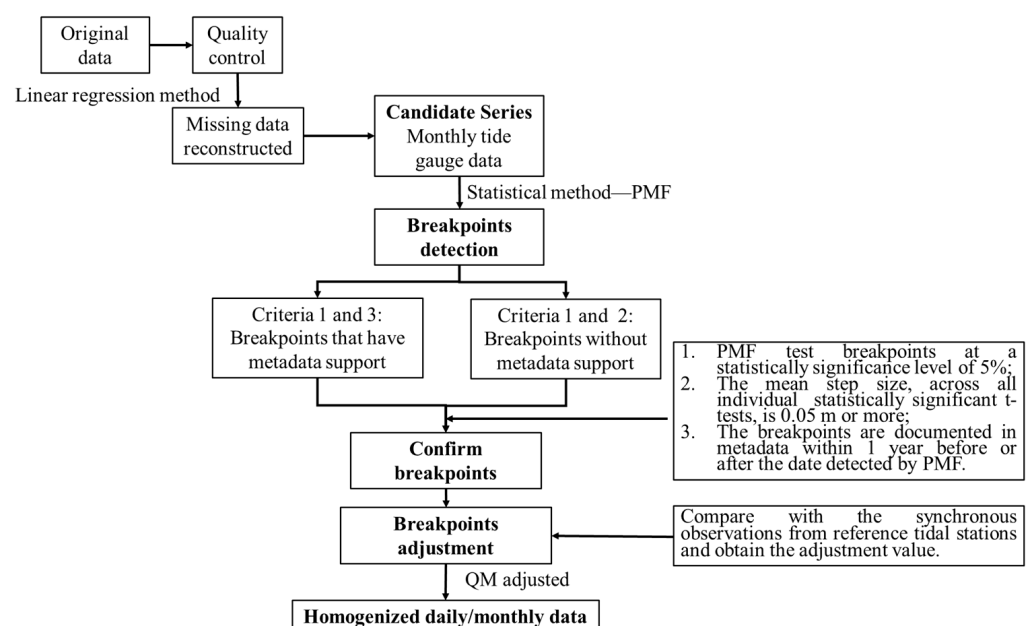


Figure 2. Flow chart of the homogenization process.

The RHtestsV5 software package was employed as the primary approach to detect and adjust breakpoints in the data series. Although its test and adjustment principles are consistent with others, RHtestsV5 is better at analyzing the homogeneity of the element series with a short time scale compared to previous versions [25–27] (freely accessible at <http://etccdi.pacificclimate.org/software.shtml>, accessed on 1 September 2022). The package contains two algorithms: the PMTred algorithm, which utilizes the penalized maximal *t*-test (PMT), and the PMFred algorithm, which utilizes the penalized maximal F-test (PMF) [26]. Both algorithms take the autocorrelated noise effect into consideration and use a recursive testing strategy to handle multiple breakpoints [26]. Due to the sparseness of the observational stations along the SCS coast, we had to use PMFred algorithms in the present study, which do not require a reference series. The technique of quantile-matching adjustment, as described by [24], was employed to adjust the breakpoints.

The PMF test detects each possible breakpoint with a 5% level of statistical significance. The statistical breakpoints derived from the PMF test were subsequently validated by detailed metadata and historical information. Typically, there is only one type of breakpoint that needs to be adjusted, which is identified as a documented breakpoint. This documented breakpoint is determined only when the metadata show a change-occurring date within one year before or after the breakpoint date estimated by the PMF. Instead of using the PMT-estimated date for the adjustment, the documented breakpoint date is utilized in this scenario. These statistical breakpoints, which were undocumented, were preserved without any adjustment.

2.2.2. Percentile Analysis Method

The observed ESL arises from combinations of the MSL, the astronomic tide, and non-tidal residuals [28]. ESLs refer to the highest water level over a specific time period, usually a year. Changes in ESLs have been assessed using a percentile analysis method, which has been widely adopted in previous research [7,29]. In our study, following Woodworth and Blackman (2004) [30], the hourly tide gauge sea levels were arranged in terms of height. Then, these data were used to obtain different percentile levels. In order to ascertain the interannual and long-term trend of ESLs, the percentile analysis method was used to extract three percentiles (99.9%, 99%, and 90%) of the tide gauge sea level in each year during the past decades.

2.2.3. Statistical Methods

Linear trends in the annual MSLs from 1970 to 2018 were calculated using the least-squares linear fitting method for both the raw and homogenized data. Additionally, the significance of each trend was identified and quantified using the Mann–Kendall test and Sen’s slope estimates [31]. The magnitudes of trends and slopes are evaluated at a significance level of 5%.

In 1998, Huang et al. proposed empirical mode decomposition (EMD), a signal processing technique that can decompose any given time series $X(t)$ into its fundamental oscillatory components—referred to as intrinsic mode functions (IMFs)—and a residual component. This allows us to express the original data time series $X(t)$ as:

$$X(t) = \sum_{j=1}^n c_j(t) + r_n(t)$$

where the $c_j(t)$ ($j = 1, 2, \dots, n$) denote the set of IMFs as introduced by Huang et al. (1998) [32], and $r_n(t)$ is the trend within the data (also referred to as the residue).

The IMFs generated symbolize diverse scales of oscillation scales present in the signal. The initial IMF captures the oscillations with the highest frequency, whereas the final IMF captures the oscillations of the lowest frequency. The residual signal that remains after extracting all the IMFs indicates the trend of the original signal. This method relies on data analysis and does not need prior knowledge about the signal’s frequency content

or the characteristics of the underlying oscillations. Because natural signals are normally nonlinear and non-stationary, this method is very valuable for analyzing natural signals. An illustration of this is the estimation of the sea level rising trend. It can be estimated by analyzing its oscillatory behavior by extracting periodic components from original records successively until no periodic component remains [7,33]. Ensemble EMD (EEMD) is an enhanced data analysis technique that incorporates noise to improve upon the EMD method. Its primary objective is to generate IMFs that are more distinctive and have a clearer physical meaning [34]. EEMD involves “sifting” through an ensemble of signals with extra white noise. Unlike the intermittence test for the original EMD algorithm, EEMD can naturally distinguish scales without any a priori subjective criterion selection. The EEMD method was employed in this study to find out if there was acceleration and to determine the long-term trend of the sea level.

3. Results

3.1. Data Homogenization Process

This section provides an illustration of the homogenization process by using the PMF test on the sea level series of the CWN tidal station (referred to as CWN station). The CWN station is located at the geographic coordinates $113^{\circ}53'$ E and $22^{\circ}28'$ N (Figure 1). The time series presented in Figure 3 demonstrates a noticeable and sudden shift occurring after the year 2012. The rising rate of the annual MSL of the CWN station from 1986 to 2018 was 11.5 mm per year. This result was drastically different from the measurements recorded at the two neighboring stations, namely the DWS station (4.9 mm per year) and SW station (2.5 mm per year), that were taken at the same time. The findings indicate that the pace of the sea level increase at CWN station is unplausible, which may be attributable to data inhomogeneity.

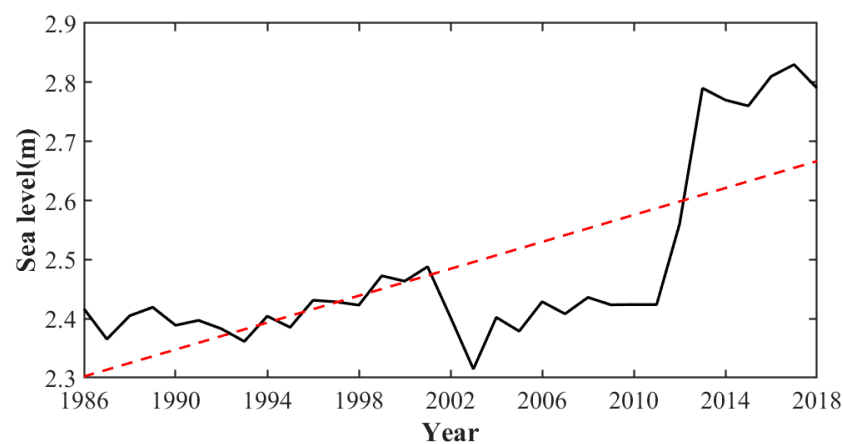


Figure 3. The annual mean sea level of CWN station (solid black line). The red dashed line represents a linear trend.

In this study, the FindUD function of the PMFred algorithm method was used to detect all type-1 changepoints. These breakpoints were statistically significant, even in the absence of metadata support. Next, we incorporated all possible type-0 breakpoints, which refer to the changes documented in the special metadata if they had not already been identified by statistically significant type-1 changepoints. This was performed in order to determine their statistical significance. The statistical test was performed at a significance threshold of 5%. The accuracy of statistically identified breakpoints was validated using metadata and historical information. Only the breakpoints determined by metadata can be called documented, and were retained for adjustment. January 2012 and October 2012 were identified as highly significant breakpoints, exceeding the upper bound of the corresponding 95th percentile of PTmax. This can be clearly visible in Figure 4. According to the metadata and historical information, a new instrument was installed

in August 2012. During the same period, station relocation of the CWN station probably caused changes in the elevation data and benchmarks. It can be inferred that the abrupt shift after the year 2012 was due to anthropogenic factors (i.e., instrument change and station relocation) rather than natural fluctuations in regional climate (Table 2). Thus, October 2012 was identified as the documented breakpoint. To obtain reliable calibration, the sea level series with documented breakpoints was adjusted by using the QM adjustment (the confidence level was $\alpha = 0.99$) based on the reference series. In our study, we chose Guangzhou station and Shenzhen station as the reference stations, both of which are located within 100 km of CWN station. Both Guangzhou and Shenzhen station were recently established around 2009, and both of the two stations' sea level records exhibited a high degree of homogeneity. In contrast to the raw sea level series of the CWN tidal gauge station, the adjusted sea level series displayed greater continuity and stability (Figure 5).

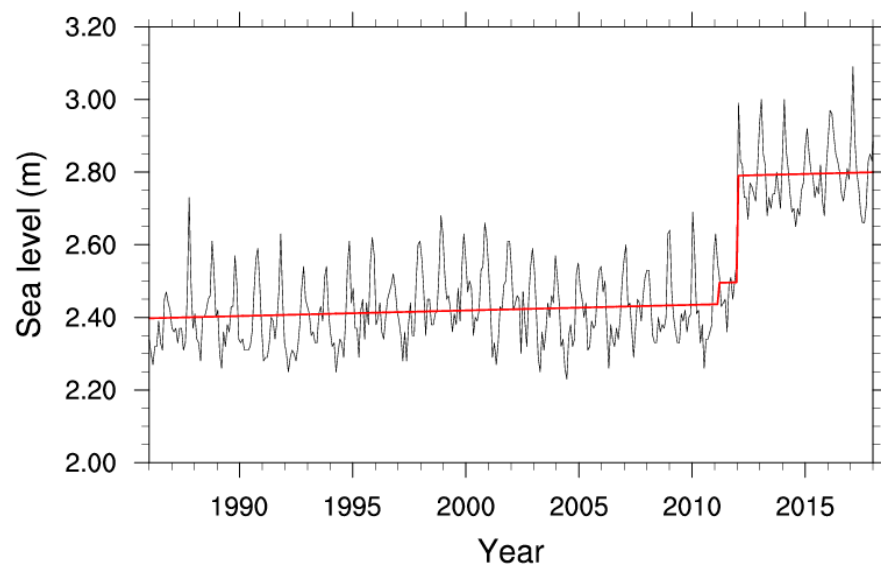


Figure 4. The raw base monthly mean sea level series of CWN station (black solid line) and the estimated mean shifts and linear trend (red solid line).

Table 2. The number of shifts and the causes leading to inhomogenization. NA = not applicable.

Site ID	Number of Breakpoints	Causes
BHI	0	NA
CWN	2	Datum (i.e., tide gauge zero) shift
DFG	1	Datum (i.e., tide gauge zero) shift
DWS	2	Datum (i.e., tide gauge zero) shift
NZU	2	land subsidence
QLN	2	Datum (i.e., tide gauge zero) shift
SWI	1	Station relocation
WZU	0	NA
XSA	0	NA
ZPO	0	NA

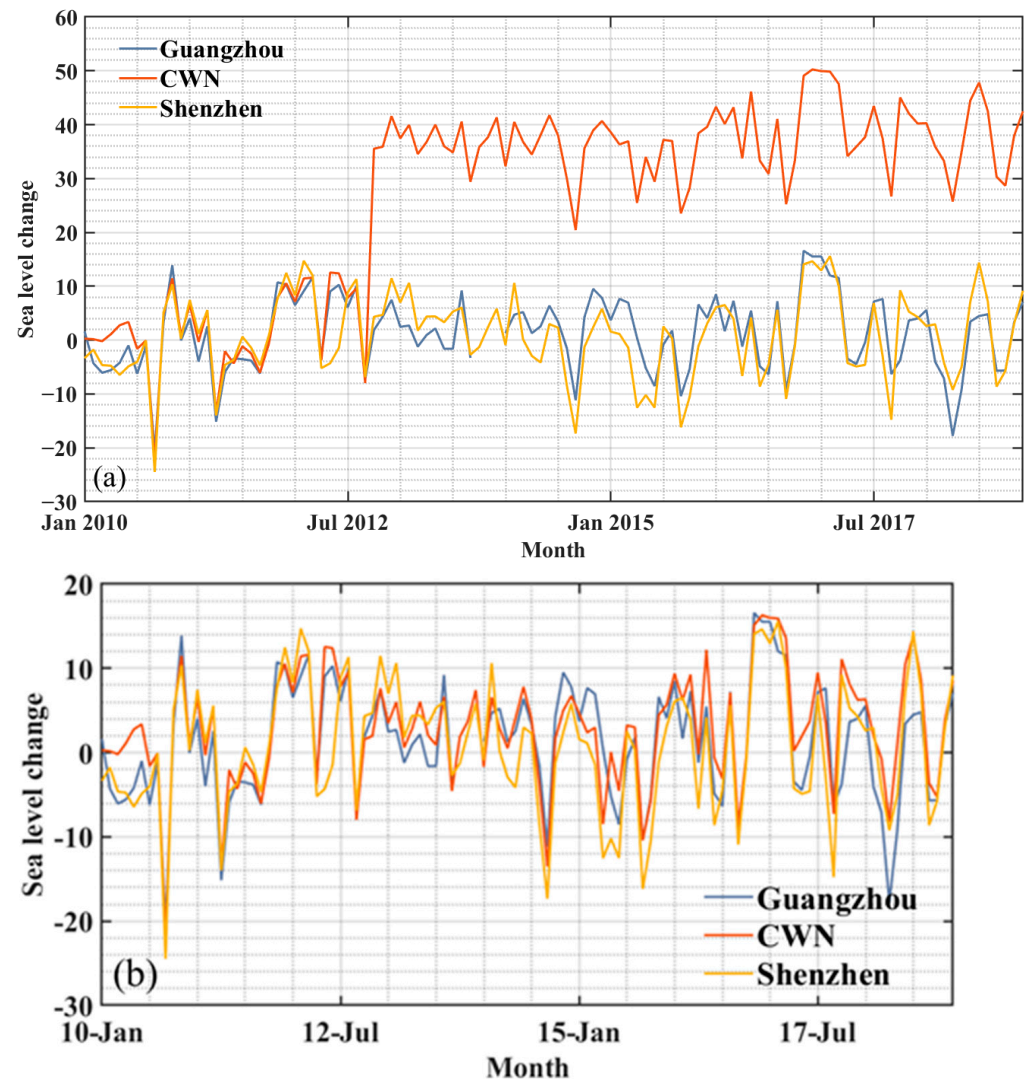


Figure 5. Comparing the base series of the CWN tidal station with the reference series of the Guangzhou tidal station and Shenzhen tidal station before (a) and after (b) adjustments to correct inhomogeneities resulting from tide gauge zero shifts in October 2012 to December 2018.

3.2. Changes in MSL and ESLs

To study coastal sea level changes along the SCS, we employed the homogenized tide gauge sea level from the 10 representative tidal stations. The annual mean sea level series of the SCS from 1989 to 2018 is shown in Figure 6a. This time series was the simple arithmetic mean of the sea level at the 10 stations. From 1989 to 2018, the coastal sea level experienced a substantial increase, with a rate of 4.0 mm per year. Researchers in China used satellite altimetry data to assess the sea level changes in the country's coastal areas during 1993–2018 [35]. The results displayed that the rising rates of the annual mean sea levels of the four major sea areas of China were the East China Sea (3.8 mm per year), Yellow Sea (3.7 mm per year), Bohai Sea (3.6 mm per year), and SCS (3.3 mm per year). Our result, based on tide gauge data, is close to their conclusion. Our result is also an approach to the result of the *South China Sea Marine Disaster Bulletin 2019*¹, which estimates the rising rate of 3.5 mm per year around the coastal SCS from 1980 to 2018 by tide gauge data. The sea level in our study rose up to 58 mm during 2012–2018. In 2012, the annual mean sea level reached its highest value in the past 30 years, about 89 mm higher than normal (i.e., the 1993–2011 average) (Figure 6a). Figure 6b shows the distribution of sea level rising rates of the 10 tide gauge stations. Overall, these sea level series of the 10 stations show significant rising trends (Table 3). However, the rates are highly nonuniformly distributed

in space. We can see that the rates of the DWS (4.8 mm per year), QLN (5.1 mm per year), and NZU (5.6 mm per year) tide gauges are much faster than the rates of other tide gauges (Table 3, Figure 7). The coastal sea level rise rates of BHI, SWI, and ZPO were much slower, with rates of 1.8 mm per year, 1.7 mm per year, and 2.4 mm per year, respectively. Moreover, we used satellite altimeter data to calculate the rate of the sea level rise in the SCS from the same period, 1989–2018. The result from tide gauges is similar to the rate distribution of the sea level based on satellite altimeter data from the same period, 1989 to 2018 (figure omitted).

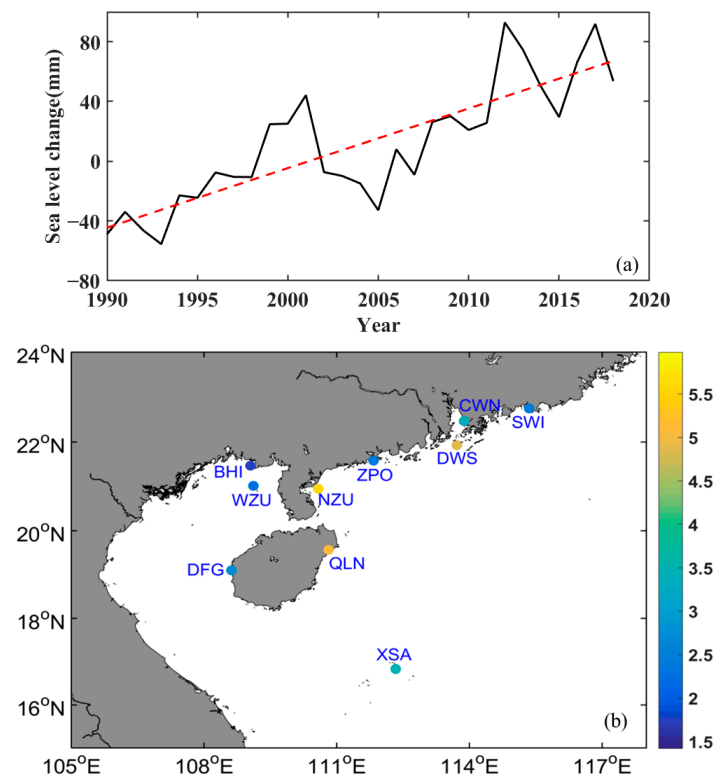


Figure 6. Simple annual mean sea level time series averaged the sea level at 10 representative tidal stations from 1989 to 2018. The red dashed line represents a linear trend. The annual mean sea level in 2012 was 89 mm higher than normal (i.e., the 1993–2011 average), making it the highest since 1989 (due to the different starting times of the 10 tidal gauge stations, we used their overlapping times here, 1989–2018) (a); sea level rising rates of the 10 tidal stations (units: mm per year) (b).

Table 3. Long-time trend of the 99.9%, 99%, and 90% levels and the annual MSL at the 10 tide gauges (units: mm per year).

Tide Gauge	BHI	CWN	DFG	DWS	NZU	QLN	SWI	WZU	XSA	ZPO
99.9% level	3.5	1.5	2.6	3.0	8.3	2.6	1.7	4.0	1.5	2.2
99% level	2.3	2.9	2.9	2.6	4.7	4.7	2.1	2.8	1.9	1.9
90% level	1.8	4.0	2.7	3.4	4.2	4.6	2.1	2.2	2.3	1.9
Annual MSL	1.8	3.4	2.8	4.8	5.6	5.1	1.7	2.3	3.5	2.4

Bold indicates trends that are statistically significant at the 95% confidence level.

Using the homogenized sea level data, the 99.9%, 99%, and 90% percentiles of the sea levels each year at all 10 tidal gauges were calculated and are shown in Figure 7, respectively. The findings indicated that sea levels at the 99% and 90% percentiles of the sea level at nine of the ten tidal stations rose notably with interannual fluctuations, except XSA (Figure 7). In the past 30 years, the 99.9% percentile sea levels of the NZU and WZH stations have risen at a much higher rate of 8.3 mm per year and 4.0 mm per year, respectively. However,

the rising rates of the 99.9% percentile values of the CWN, XSA, and SWI stations are much smaller—less than 2.0 mm per year—and have not passed the 95% confidence level. At XSA, the 99.9%, 99%, and 90% percentiles of the sea levels presented were considered as nearly no significant linear trends at a 95% confidence level. Decadal and interannual variations were present at all tidal stations throughout the three percentile levels. The interannual variations were most significant at the 99.9% and 99% percentiles, especially at the DFG, DWS, and WZU stations, where the amplitude of interannual variations exceeded 0.40 m. These results are extensions of the work of Feng and Jiang in 2019, which were only based on four tide gauge stations. The results are similar to their conclusion.

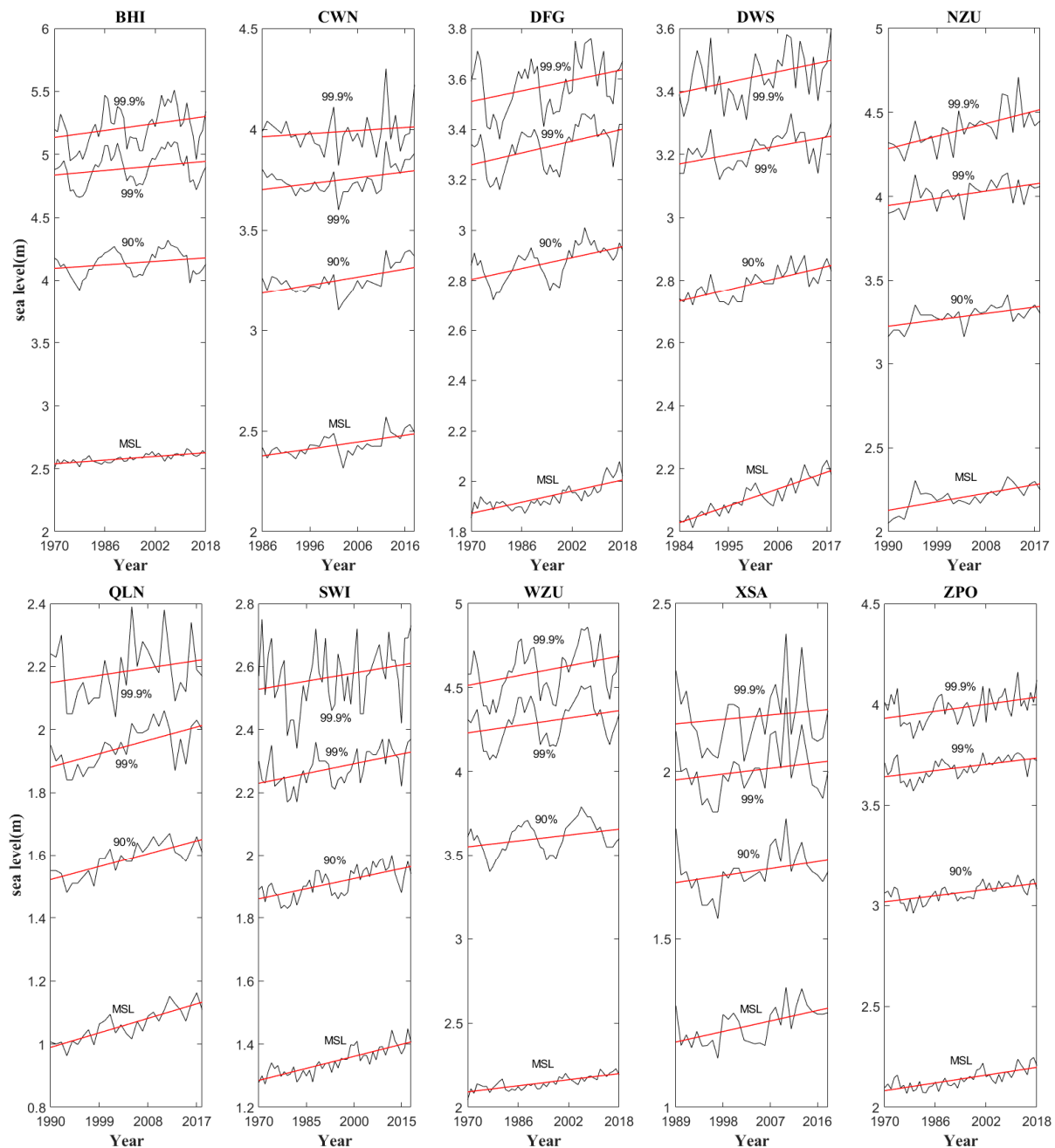


Figure 7. The annual MSL and 99.9%, 99%, and 90% percentile sea levels at the 10 tidal stations (black solid lines). The solid red lines represent the linear trends.

In our study, EEMD was further adopted to analyze the long-term nonlinear trends of ESLs along the SCS. As illustrated in Figure 8, nine of the ten tidal stations exhibit an

overall rising trend during the study period, except for the QLN station. Meanwhile, at different tidal stations, the ESL trends generated from EEMD exhibit variable time-varying characteristics. The rising rates of the DFG, DWS, and NZU stations have accelerated since the beginning years. At BHI and ZPO, the rising patterns exhibited as essentially linear before 2005, and then the increase trends slowed down afterward. Nearly linear increase trends were observed at WZU during the whole period. At the CWN, SWI, and XSA stations, the increase rate decelerated before 2000. After 2000, however, the rising rate accelerated. The increase trends at QLN exhibited a virtually linear pattern from 1995 to 2005, followed by a decline from 2006 to 2018.

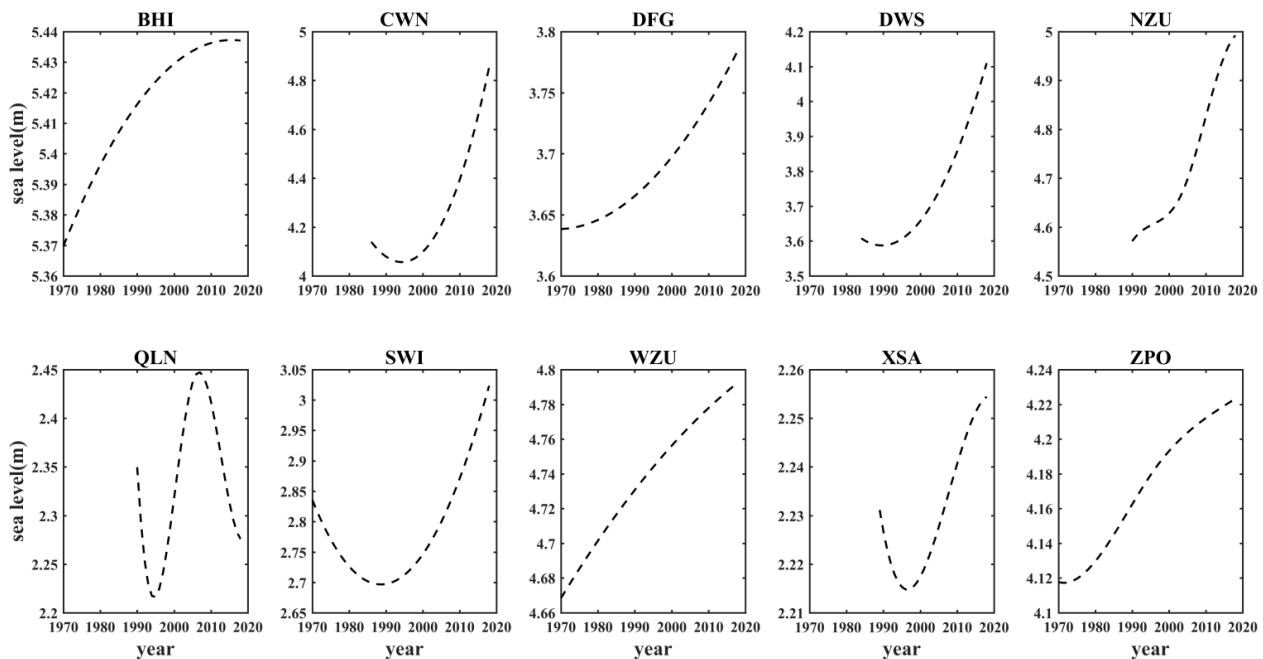


Figure 8. Long-term trends of the ESLs at 10 tidal stations along the SCS coast.

Changes in ESLs can be separated into changes in their components (the MSL and its dynamical factors; that is, tides and storm surge parts) [20,29]. To assess the possible impacts of mean sea level variability on the ESL changes, we first calculated the correlations between the 90% percentile ESL and the annual MSL of the 10 tidal stations. The overall correlation for all 10 tidal stations is 0.43 (above the 99% confidence level). The findings shown in Table 4 (the third column) indicate a statistically significant relationship between the ESLs and annual MSL at the following seven tidal stations: CWN, DFG, DWS, NZU, SWI, XSA, and ZPO. The correlation coefficients of the seven tidal stations were in the range of 0.38 to 0.63 and exceeded the 99% confidence level. However, the correlation coefficients of the three tidal stations, QLN, BHI, and WZH, do not pass the 95% confidence level (Table 4). This finding aligns with prior research conducted in different regions by Woodworth and Blackman (2004) and Marcos et al. (2012) [30,36], etc. When the long-term trends were removed, the correlation coefficients between the ESLs and annual MSLs decreased notably and became statistically insignificant at a 95% confidence level for most tidal stations (Table 4, the fourth column). This result indicated that the MSL changes play an important role in the changes in ESLs, especially for the long-term trends. However, it is worth mentioning that there were three tide gauges, BHI, WZH, and XSA, where the correlations became larger and exceeded the 99% confidence level. Thus, for the BHI and WZH tidal stations, the mean sea level is a key factor in the changes of interannual-to-decadal ESL variability rather than the secular ESL trend. For the XSA tide gauge, the mean sea level modulates both the secular ESL trend and the interannual-to-decadal ESL variability in the study period.

Table 4. For the 10 tidal stations, correlation coefficients between the MSL and ESL were initially calculated (referred to as C1). The correlation coefficients between the MSL and ESL after removing long-term trends were referred to as C2. P1/P2 represents the p -value from the t -test, where $p < 0.05$ indicates a significant correlation at a 95% confidence level.

	C1	P1	C2	P2
BHI	0.18	0.21	−0.47	<0.01
CWN	0.46	<0.01	0.2	0.26
DFG	0.38	<0.01	−0.19	0.19
DWS	0.58	<0.01	−0.17	0.32
NZH	0.63	<0.01	0.20	0.30
QLN	0.20	0.29	−0.19	0.31
SWI	0.51	<0.01	0.31	0.08
WZH	0.25	0.20	−0.54	<0.01
XSA	0.58	<0.01	0.76	<0.01
ZPO	0.52	<0.01	0.28	0.13

4. Discussion and Conclusions

We obtained all long-term tide gauge records from the South China Sea Bureau of the Ministry of Natural Resources of China. Then, we utilized the largest collection of 10 available tide gauge records along the northern coast of the SCS, in contrast to only the 2~4 stations utilized in the majority of previous studies. First, we have extended the current homogenization methods to identify and adjust inhomogeneity in the data resulting from non-climate factors, such as station relocation and instrument change. Then, we analyzed the changes in annual MSLs and ESLs along the northern coast of the SCS using the homogenized data. Finally, we also calculated the precise extreme sea level rise rates by the EEMD method in order to assess whether the ESLs were accelerating or decelerating. The conclusions based on the homogenized tide gauge records can be summarized as follows:

- (1) The instrument change and station relocation are the main causes of the identified inhomogeneities. Based on the homogenized tide gauges, from 1989 to 2018, the coastal sea level experienced a substantial increase, with a rate of 4.0 mm per year.
- (2) The spatial patterns of the rates of annual MSLs and ESLs along the SCS coast were investigated. Annual MSL rise rates of DWS, NZU, and QLN were the fastest three stations, while the annual MSL rise rates of BHI, SWI, and ZPO were the slowest stations. The results showed that the ESLs from nine tide gauge stations rose notably with interannual fluctuations, except XSA. Additionally, the ESLs exhibited substantial decadal variations.
- (3) The ESL rises along the northern coast of the SCS were accelerated at most stations throughout the whole study period, especially after the 1980s, while the acceleration patterns varied by station location.
- (4) There were significant positive correlations between the ESL and the annual MSL at most tide gauges. However, the correlation coefficients between the ESL and MSL after removing the long-term trends notably reduced and became statistically insignificant at a 95% confidence level at most tidal stations. It confirmed that for most tidal stations, the long-term trends of ESLs along the SCS coasts were significantly related to the changes in the annual MSL.

This study describes homogenous long-term tide gauge observations along the SCS, which were well suited to assess the changes in annual MSLs and ESLs in this region. Our work provides an improved understanding of the changes in mean and extreme sea levels along the SCS coast. On the other hand, the underlying physical processes and driving mechanisms that affect the regional sea level and ESL changes have been inadequately explained. Future studies will focus on an analysis of the dynamic linkage between ESL changes in the SCS coast and ocean/atmosphere dynamics, such as Arctic Oscillation (AO), Atlantic Multidecadal Oscillation (AMO), El Niño–Southern Oscillation (ENSO) and Pacific Decadal Oscillation (PDO).

It is certain that there are still many uncertainties in the research on the characteristics and trends of sea level and extreme water level changes. Thus, strengthening the multi-element collaborative observation of land–sea interaction systems, improving the accuracy of sea level observations, and developing advanced mathematical statistics and modeling methods, are the focus of future work. The focuses include a benchmark tidal level determination, simulations of changes in local ESLs under a GMSL rise, and using statistical or dynamic models to analyze the nonlinear effects of the wind, waves, tides, and other factors on ESLs, etc. Coastal zones are the core areas of population and economic distribution in a country or region worldwide. How to adapt to and mitigate the negative impact of sea level rises is a highly challenging problem for decision-makers and managers. Therefore, governments and coastal communities should be guided by advanced concepts such as land–sea coordination, a resilient coastal city, and coastal zone ecological restoration [37–39]. Several effective measures are as follows:

- (1) Establish a three-dimensional monitoring network for coastal cities, implement intelligent monitoring and early intelligent warning systems in key areas, and strengthen basic data-sharing mechanisms among multiple disciplines.
- (2) Assess the sea level rise risks under multiple climate scenarios and climate tipping points; assess the exposure risk of critical infrastructure in coastal hotspots; and implement risk investigation and hidden danger investigation in key coastal areas.
- (3) Strengthen the resilience of coastal protection and the protection of coastal habitats, such as mangroves and other wetlands, coastal barrier islands, and lagoons, and make the most of the natural protective role of mangroves, salt marshes, and seagrass meadows.
- (4) Coordinate the development of land–sea spaces; enhance the tide-proof and drainage capabilities of coastal cities; enhance the resilience of coastal cities, e.g., raise the elevation of buildings, roads, and infrastructure above anticipated flood levels; and install flood barriers, waterproof buildings, and construct or renovate coastal protection projects, etc.

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Note

- ¹ <https://scs.mnr.gov.cn/>, accessed on 1 September 2023.

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