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Water clarity variations in Jiaozhou Bay over 39 years based on satellite observations

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Abstract: Water clarity is an important indicator for the water quality of aquatic ecosystems and measured as Secchi disk depth (Z_{SD}). In this study, images from Landsat Thematic Mapper (TM), Enhanced Thematic Mapper Plus (ETM+), and Operational Landsat Imager (OLI) over the period from 1984 to 2022 are used to study the spatiotemporal variation in Jiaozhou Bay, a typical semi-enclosed bay in China, and to gain the insights into the drivers for the variation during the study period. The satellite images are first processed to obtain Z_{SD} , and corrected against the field measurements to ensure the Z_{SD} to be high-quality, and then the spatial and temporal distributions of Z_{SD} are analysed. The results show that the regional monthly average Z_{SD} over the study period are the highest in May and lowest in January. From long-term seasonal observation, it declines most significantly in Summer. In terms of inter-annual variation, the results clearly indicate that 2015 was a turning point, as the regional average Z_{SD} decreased significantly from 1984 to 2014 at a rate of

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approximately 0.022 m/year, but significantly increased from 2015 to 2022 with a rate of about 0.049 m/year. The turning trend of the water clarity in Jiaozhou Bay can be mainly attributed to the increasing sunshine duration during 2015-2022, as well as rapidly reduction emissions of industrial waste from Qingdao city during 2015-2016.

Keywords: Water clarity, Secchi disk depth, Remote sensing reflectance, Landsat, semi-analytical model

1 Introduction

The typical semi-enclosed bays, such as Jiaozhou Bay (JZB) in China, have been the most popular and pleasant areas for people to live. However, due to the increased human activities and rapid economic development, the water quality and ecological equilibrium is under the increased pressure, particularly affected by the global climate change. For example, in JZB, the outbreak of red tide (Dai et al., 2007), green tide (Liu et al., 2011) and the increase in the number of jellyfish (Sun et al., 2012) pose a growing threat to the marine eco-environment. To assess the marine eco-environment, water clarity, which can effectively quantify the availability of light in the water column, is one of the important ecological coastal water quality eutrophication indices (Chawla et al., 2020). Light penetration characteristics can be significantly influenced by multiple variables such as water phytoplankton productivity (Al Shehhi et al., 2019; Swan et al., 2007), suspended particles (Lathrop et al., 1991; Wu et al., 2009), and dissolved substances (Testa et al., 2019), and further impact the balance of aquatic vegetation and phytoplankton biomass. Therefore, understanding the long-term spatiotemporal dynamics of water clarity and its driving factors is crucial for water environment assessment and management.

Typically, water clarity is measured in the field by the depth when dropping vertically a white or black-and-white disc of 30 cm diameter (Secchi disc) in the water until the Secchi disc becoming invisible from the human eye, which is also called the Secchi disc depth (Z_{SD}) (Wernand, 2010). The Z_{SD} measurements are usually carried by the ship surveys, but often limited by weather conditions and costs, and it is difficult to achieve repeated observations in the designated study areas. The development of satellite sensors has provided the possibility to obtain long-term continuous observations of water clarity (Dekker and Peters, 1993). Since the 1990s, satellite ocean colour

sensors with coarse spatial resolution have been used to monitor water clarity (e.g., Moderate Resolution Imaging Spectroradiometer (MODIS) (Doron et al., 2011; Shi et al., 2011), Medium Resolution Imaging Spectrometer (MERIS) (Koponen et al., 2002; Zhang et al., 2003)) has developed towards high spatial resolution (e.g., Sentinel-2 (Soria-Perpinya et al., 2020; Soria-Perpinya et al., 2021), GF-5(Liu et al., 2020)), and its application targets are mainly concentrated in bays (Al Kaabi et al., 2016; Chen et al., 2007), lakes (Li et al., 2019; Liu et al., 2019) and estuaries (Lehmann et al., 2019) to capture dynamic water body changes (Luis et al., 2019). Landsat series sensors, including Landsat-5 Thematic Mapper (TM), Landsat-7 Enhanced Thematic Mapper Plus (ETM+), Landsat-8 Operational Land Imager (OLI), and Landsat-9 OLI, combined with long time series observations, can provide global remote sensing images of nearly 40 years. It has a spatial resolution of 30m, which widely improving the ability of remote sensing to monitor water quality in small regions (Chen and Zhu, 2020).

The development of satellite sensors in recent years has considerably advanced the analysis algorithms for calculating water clarity from remote sensing data, such as the empirical algorithms developed for specific time and/or specific regions (Chen et al., 2007) and analytical or semi-analytical models based on radiative transfer models (Doron et al., 2011; Liu et al., 2020). In particular, the model proposed by Lee et al.(2015) (hereinafter referred to as Lee_2015 model) uses the optical theory to better represent Secchi disk seen by a human eye and has been widely applied to sensors such as MODIS, Landsat (Zhang et al., 2021b), GOCI (Mao et al., 2018; Zeng et al., 2020) and Sentinel-2 (Qing et al., 2021). The model has shown a good performance in the Bohai Sea (Shang et al., 2016), Taihu Lake (Bai et al., 2020), Yangtze River plain lakes (Feng et al., 2019), Tibetan lakes (Liu et al., 2021) as examples in China.

To fully understand the fact that the changes in water quality in JZB is found to have significantly improved in the last decade (Yin et al., 2021a; Zhou et al., 2022), this paper aim was to study the spatial and temporal patterns of Z_{SD} in JZB from 1984 to 2022 to gain the insights into the driving factors for the change of the water quality over this period. The $R_{rs}(443)$ data from TM and ETM are first supplemented, and then the R_{rs} data in Landsat images are evaluated using MODIS Terra (MODIST) images to verify their consistency. Having calibrated remote sensing data with the in-situ observations, the Lee_2015 model was used to determine the Z_{SD} from Landsat sensor data

to obtain the Z_{SD} spatiotemporal distributions within JZB. With the long-term data obtained from the China Meteorological Data Service Center and Qingdao City Statistical Yearbook as auxiliary data, the water quality changes in the bay were correlated with the main climatic factors and human activities to explore the drive factors.

2 Study area and data

2.1 Study area

Jiaozhou Bay is located on the west coast of the Yellow Sea ($120^{\circ}05'\sim 120^{\circ}22'E$, $35^{\circ}57'\sim 36^{\circ}15'N$) (Fig. 1). The maximum length of the bay is about 33.3 km in the north-south direction, and the maximum width is about 27.8 km in the east-west direction (Zhang et al., 2021a). The surface area spans approximately 370 km². The tidal shoal makes up about 29.5% of this area, whereas the water area of 0-5m depth occupies 52.7%. The average water depth is 7.0 m, and the maximum water depth is more than 50 m. The tide type is a regular half-day tide and has a mean range of about 2.71 m. Along the coast, there are more than 10 regional seasonal rivers, such as the Dagu River, flowing in, and the flood season is concentrated in July to September. The rich nutrients brought by these rivers takes an amount of phytoplankton increases that make JZB an excellent sea area for the growth and reproduction of fish, shrimp, and shellfish. Also, the rivers carry many pollutants from industrial and agricultural areas into JZB, which leads to eutrophication and poor self-purification ability of aquatic ecosystem.

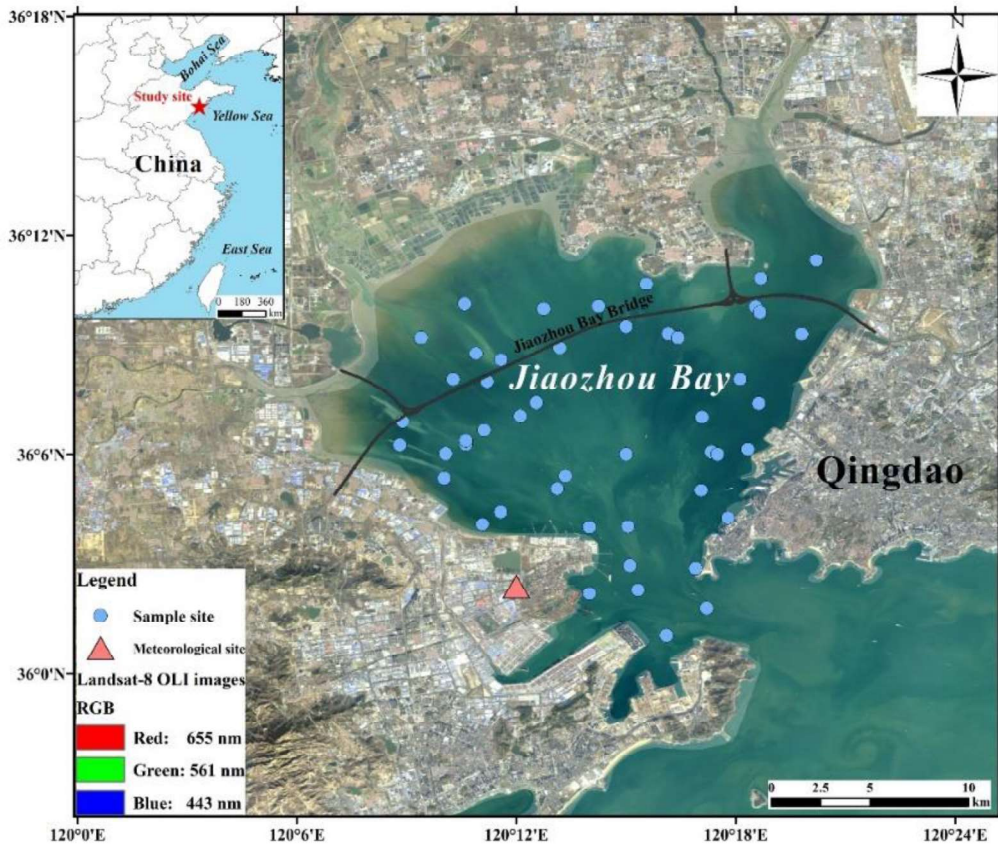


Fig. 1. Geographical location of JZB, meteorological station (red rectangle), and in-suit sampling sites (blue circles) over the period of 1984-2022

2.2 Field data

The field data used in this study includes 772 measurements of Secchi disk depth (Z_{SD}) in JZB conducted at the National Field Scientific Observation and Research Station of JZB Marine Ecosystem of Shandong Province over the period of 2001-2015, and from 5 sea surveys on May 16, 2017, August 9, 2021, October 28, 2021, October 23, 2022, and November 1, 2022. The data sets were quality controlled and the statistic values of maximum, minimum, average, standard deviation, and coefficient of variation for the in-situ Z_{SD} measurements were 4.7 m, 0.4 m, 1.8 m, 0.79 m, and 41%, respectively.

2.3 Satellite data

In this study, 741 satellite images in total are selected, including 351 images of Landsat-5 TM (1984-2011), 240 images of Landsat-7 ETM+ (1999-2021), 129 images of Landsat-8 OLI (2013-

2022), and 21 images of most recent Landsat-9 OLI (2021-2022), as shown in Fig. 2. All satellite images were downloaded from U.S. Geological Survey (USGS) EarthExplorer gateway (<https://earthexplorer.usgs.gov/>). The revisit time of each satellite is 16 days. The spatial resolution of those images is 30 m in the visible domain, and the wavelengths setting of TM and ETM+ images are centred approximately at 480 nm, 561 nm and 660 nm. An additional 443 nm band is contained in Landsat-8/9 OLI images. Due to the Scan Line Corrector failure since May 31, 2003(Chen et al., 2011), the stripe shape data of 196 images on the Landsat-7 ETM+ was missing, so the images were fixed by the Landsat Gapfill model embedded in Environment for Visualizing Images software. All Landsat radiance data from the top of the atmosphere are atmospherically corrected using the Management Unit of the North Sea Mathematical Models (MUMM) embedded in the SeaWiFS Data Analysis System (SeaDAS) software version 9.0.1 to produce the remote sensing reflectance (R_{rs}) product for water pixels. Aerosol mode is Multi-scattering with MUMM correction and MUMM NIR calculation. From the values of Rayleigh-corrected reflectance (dimensionless) centred approximately at 865 nm, the cloud and glint threshold are 0.05 and 0.005 respectively which are used to generate quality control flags (l2_flags). If a pixel is labelled by the flags above, it should remove from the R_{rs} product(Dai et al., 2023).

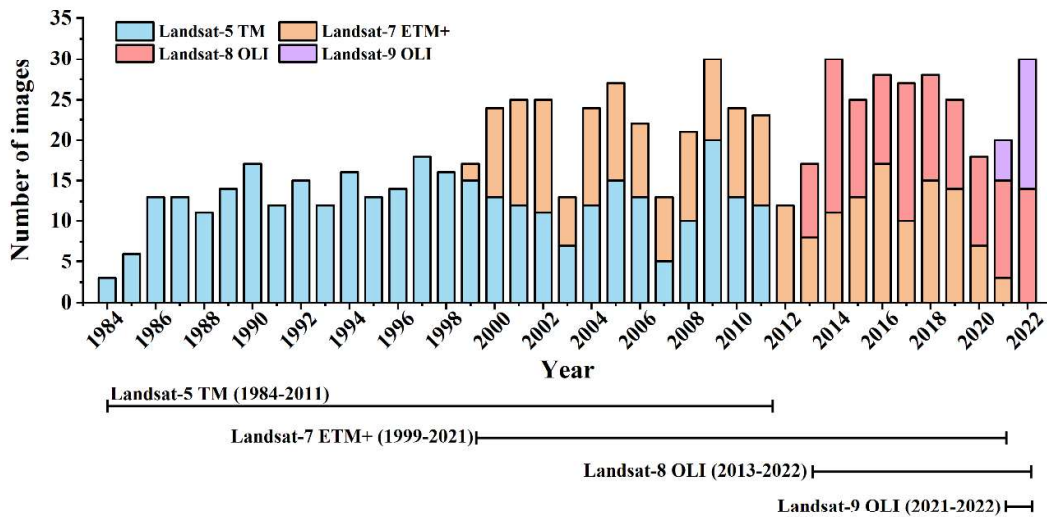


Fig. 2. Landsat images covering JZB from 1984 to 2022 used in this study.

Given that the Landsat series sensors (TM, ETM+, and OLI) do not have synchronized transit time in JZB area, the MODIST sensor, which has been functioning reliably since 1999, offers a

valuable opportunity for cross-validation. MODIST has a pass time that typically occurring between 10:00 to 10:55 AM, as opposed to the Landsat sensors' approximate pass time of 10:30 AM. It allows for the synchronized cross-validation of the consistency of satellite imagery across different R_{rs} bands between the Landsat sensor series and MODIST. The MODIS radiance data from the top of the atmosphere is then processed to generate R_{rs} datasets also using the MUMM module in the SeaDAS software. It contained with four visible bands (centred approximately at 443 nm, 480 nm, 560 nm, 650 nm) with a spatial resolution of 1 km and a geographic projection mode of latitude/longitude cylindrical.

Due to the difference in spatial resolution, the following criteria are adopted for data matching between Landsat and MODIST images: (1) the pixels with solar zenith angle (SOLZ) $> 60^\circ$ in MODIST are excluded in the matching; (2) the minimum distance method is used to obtain the location of Landsat image units matched with MODIST pixel coordinates, and the median and standard R_{rs} values of all pixels in this image units cell (33×33 pixels window) are calculated; (3) the coefficient of variation (CV) is calculated in the imaging unit. If $CV \leq 0.15$, the imaging unit meets the condition of spatial homogeneity; and (4) the total number of valid pixels that meet the above conditions in the imaging unit are counted. If it exceeds 50% of the total number of images, extract the median of the valid values of R_{rs} in the imaging unit. If the median value of R_{rs} in the image cell exceeds 50% of the total number of images, the data matchup is generated with the MODIST data at the corresponding position.

To match the Z_{SD} derived from Landsat retrieval with the in-situ data, a time constraint of ± 2 hours in the same date and spatial window of 3×3 pixels of the Landsat data are applied, so that the in-situ data can be quasi-synchronous with the satellite observations for developing a reliable Z_{SD} model. After the test, we obtained a total of 84 matchups in-situ data used for Z_{SD} modelling, including 31 matchups synchronized with TM, 26 matchups synchronized with ETM+, and 27 matchups synchronized with OLI. The locations of the matchup sample sites between in-situ measured and satellite images are shown in Fig. 1.

2.4 Other data

In addition, the meteorological data in Qingdao meteorological Station (see Figure 1) during 1984-2022 including: the near-surface air temperature (AT), wind speed (WS), sunshine duration (SSD), air pressure (AP), and precipitation (PR), obtained from the China Meteorological Data Service Center (<http://data.cma.cn/>) is used. Based on the daily data obtained, monthly and annual meteorological statistical data, such as mean wind speed, cumulative rainfall, can be further calculated. The data of human activities factors of the gross domestic production (GDP) from 1990 to 2022, local population (PO) from 2005 to 2022, and industrial wastewater discharged (IWD) from 2009 to 2021, obtained from Qingdao statistical yearbook, is also used in this study.

3 Methods

3.1 Overall framework

The flowchart to estimate Z_{SD} and analyse its variation from the Landsat series data is shown in Fig. 3. Firstly, Landsat series image data is pre-processed, including radiometric calibration, atmosphere correction, water pixels extraction, and consistency analysis of Landsat series data refer to MODIST observation. The R_{rs} dataset is constructed after $R_{rs}(443)$ of TM and ETM+ data is estimated subsequently using the blue-band estimation algorithm (Section 3.2). Secondly, the Z_{SD} retrieval model (Lee_2015 model) is used to examine the linear correction against the field data (Section 3.3). Then, long-term Z_{SD} maps of JZB are created and used to study spatiotemporal variation character and possible causes (Section 3.4).

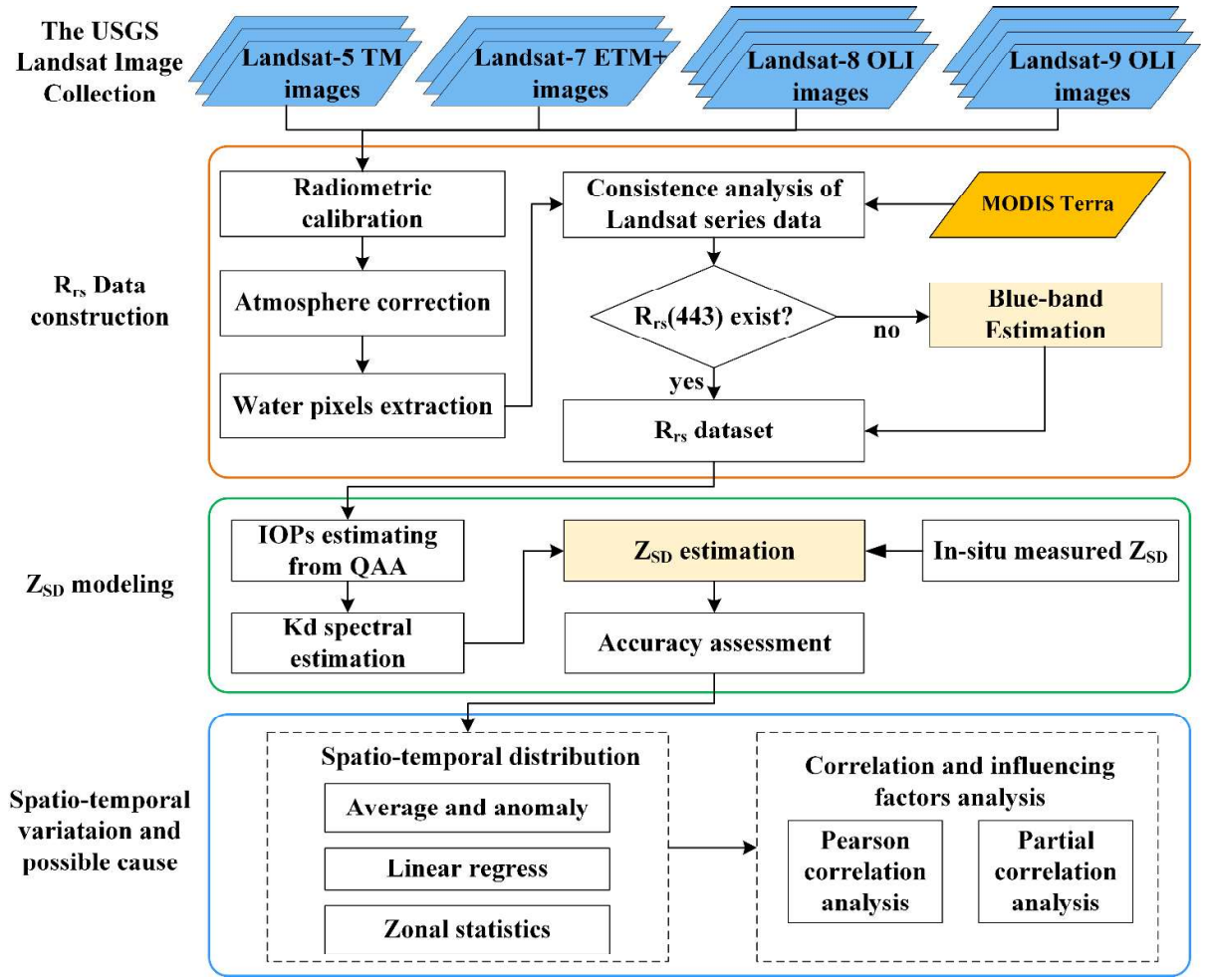


Fig. 3. Flowchart for long-term Z_{SD} estimation based on long-term Landsat series sensors.

3.2 R_{rs} estimation

To derive Z_{SD} from the Landsat satellite images, R_{rs} spectra data at bands 443, 482, 561, and 655 nm is required, as shown in Fig. 3. However, the R_{rs} spectra data at 443 nm band may not be obtained from Landsat TM and ETM+ image due to lacking of reflectance synchronously measurements at satellite transit time in JZB, therefore, in this study, the blue-band estimation (BBE) algorithm suggested by Wei et al. (2020) is used to obtain the reflectance at 412 and 443 nm bands following 3 steps described below:

Step 1 is first to integrate the spectral datasets from those in-situ global measured and simulated by the radiative transfer model. Then, the $R_{rs}(\lambda)$ spectra is discrete sampled at five bands of 412, 443, 482, 561, and 655 nm, and a look-up table (LUT) for all the shape of the R_{rs} spectrum is built. R_{rs} spectrum are normalized with the roots of the respective sum of squares (RSS) as follows:

$$nR_{rs}(\lambda_i) = \frac{R_{rs}(\lambda_i)}{\left[\sum_{j=1}^5 R_{rs}(\lambda_j)^2 \right]^{1/2}}, i = 1, 2, 3, 4, \text{ and } 5 \quad (1)$$

where $nR_{rs}(\lambda_i)$ is the normalized R_{rs} spectrum with subscripts 1-5 corresponding to the five bands from 412 nm to 655 nm, where $\sum_{i=1}^5 nR_{rs}(\lambda_i) = 1$.

Step 2 is to calculate the cosine distance (d) using the spectral angle mapper (SAM) method from the LUT as:

$$d = 1 - \frac{\sum_{i=3}^5 [nR_{rs}^{lut}(\lambda_i) \times R_{rs}(\lambda_i)]}{\sqrt{\sum_{i=3}^5 [nR_{rs}^{lut}(\lambda_i)]^2 \times \sum_{i=3}^5 [R_{rs}(\lambda_i)]^2}} \quad (2)$$

Then, the spectral closest to the given Landsat $R_{rs}(\lambda_{3-5})$ can be identified from $nR_{rs}(\lambda_i)$ by searching $nR_{rs}^{lut}(\lambda)$ spectrum corresponding to the minimum cosine distance.

Step 3 is to replace $nR_{rs}(41x)$ and $nR_{rs}(443)$ in the two expanding expression of $R_{rs}(412)$ and $R_{rs}(443)$ from Eq. (1) with $nR_{rs}^{lut}(412)$ and $nR_{rs}^{lut}(443)$ after the spectral shape closest to $R_{rs}(\lambda_{3-5})$ is determined. So that the two expanding equations are left with only two unknown quantities of $R_{rs}(443)$ and $R_{rs}(412)$. Following that, the estimated value of $R_{rs}(443)$ from satellite observations can be derived as:

$$R_{rs}(443) = \frac{\sqrt{(R_{rs}(482)^2 + R_{rs}(561)^2 + R_{rs}(655)^2)}}{\sqrt{(1 - nR_{rs}^{lut}(412))^2 - nR_{rs}^{lut}(443))^2}} \times nR_{rs}^{lut}(443) \quad (3)$$

The implementation of the BBE algorithm significantly increases the available $R_{rs}(443)$ values with small uncertainty (Yin et al., 2021b). The R_{rs} data used to build the LUT cover water bodies with chlorophyll a from ~ 0.03 to 80 mg/m^3 , suspended sediments from ~ 0.1 to $\sim 100 \text{ g/m}^3$; water depths from ~ 1 m to 1000 m, and seafloor substrates of seagrass, sand, and coral reefs. Although this LUT cannot characterize all spectral shapes in natural water bodies, it covers most water body types in coastal and clear waters. Finally, we used MODIST to assess the data consistency of the $R_{rs}(443)$ estimates.

3.3 Z_{SD} modelling

The novel underwater visibility theory in the Lee_2015 model, establishes the relation of deduced Z_{SD} value and the diffuse attenuation coefficient (K_d) as:

$$Z_{SD, Lee} = \frac{1}{2.5 \text{Min}(K_d^{tr})} \ln\left(\frac{0.14 - R_{rs}^{tr}}{0.013}\right) \quad (4)$$

where, K_d^{tr} is the diffuse attenuation coefficient of downwelling irradiance under the sea surface. $\text{Min}(K_d^{tr})$ represents the minimum K_d spectrum in the visible band (around 443, 488, 560, 650 nm) of the Landsat sensor. R_{rs}^{tr} is the R_{rs} value at the corresponding wavelength associated with $\text{Min}(K_d^{tr})$. K_d at a wavelength of λ is derived through a function of the total absorption (a) and total backscattering (b_b) coefficients (Lee et al., 2013) as:

$$K_d(\lambda) = (1 + m_0 \times \theta_s) \times a(\lambda) + m_1 \times (1 - \gamma \times \frac{b_{bw}(\lambda)}{b_b(\lambda)}) \times (1 - m_2 \times e^{-m_3 \times a(\lambda)}) \times b_b(\lambda) \quad (5)$$

where θ_s is the solar zenith angle above the sea surface (degree). The model parameters m_{0-3} and γ are 0.005, 4.26, 0.52, 10.8, and 0.265, respectively. a and b_b can be obtained from R_{rs} spectral by analytic inversion using the quasi-analytic algorithm (QAA) version 6.0 in this study (Lee, 2014).

The reference wavelengths used in the QAA_v6 calculations include 55x and 670 nm. Due to the contamination of chlorophyll fluorescence in the coastal waters, the $R_{rs}(670)$ measured at the sea surface is prone to exceed 0.0015 sr^{-1} , at which time the reference wavelength should be set to 670 nm. Comparing the band settings of the Landsat series sensors, the red band of OLI is 655 nm, which has a large wavelength deviation from 670 nm. Here, the polynomial equation obtained by Wei et al. (2019) from fitting a large amount of measured data is used to convert the satellite observation of $R_{rs}(655)$ to $R_{rs}(670)$ as follows:

$$R_{rs}(670) = 10^{P_1 X^3 + P_2 X^2 + P_3 X + P_4}, X = \log_{10} R_{rs}(655) \quad (6)$$

where the model coefficients P_{1-4} are 0.0775, 0.6585, 2.7692, and 1.433, respectively.

The optical properties of the nearshore waters are very complex, and the semi-analytical model can not get the best performance in all areas. Therefore, the empirical relationship is introduced into

the model of Equation (4), to better match with the field-measured data in JZB. The linear correction equation is expressed as:

$$Z_{SD,corr} = a_0 \times Z_{SD,Lee} + a_1 \quad (7)$$

Here, a_0 and a_1 are model constants from fitting $Z_{SD,Lee}$ from field-measured data.

3.4 Analytical methods

The means and anomalies of various variables are calculated to reveal the temporal characteristics of geophysical parameters. The means are arithmetic average results of adding a set of data and dividing it by the number of data points. Time series anomalies are calculated by subtracting the mean from each valid data point, a method employed to determine the extent to which a data point deviates significantly from the mean. The zonal statistics is used to analyse the spatial distribution quantitatively. Correlation analysis describes the degree of correlation in two or more variables. Specifically, simple correlation analysis displays the relationship between two variables, while partial correlation analysis shows the degree of correlation between two variables after excluding certain factors (Peng et al., 2023).

3.5 Accuracy assessment

The coefficient of determination (R^2), root mean square error (RMSE), and mean absolute percentage error (MAPE), were calculated to assess the accuracy of validation, and goodness-of-fit as follows:

$$R^2 = \frac{\left[\sum_{i=1}^N (x_i - \bar{x})(y_i - \bar{y}) \right]}{\sum_{i=1}^N (x_i - \bar{x})^2 \sum_{i=1}^N (y_i - \bar{y})^2} \quad (8)$$

$$RMSE = \sqrt{\sum_{i=1}^N (x_i - y_i)^2 / N} \quad (9)$$

$$MAPE = \frac{1}{N} \sum_{i=1}^N \left(\frac{|x_i - y_i|}{x_i} \right) \times 100\% \quad (10)$$

where, the subscript i represents an individual data point, and n is the number of samples. When used for R_{rs} consistency assessment, x and y are the reference truth value and the band value to be evaluated, respectively. When used to evaluate the accuracy of the Z_{SD} model, x and y are the measured and estimated values of Z_{SD} respectively.

4 Results

4.1 Cross-validation of R_{rs} data

Fig. 4 shows the comparisons of R_{rs} derived from the Landsat images and MODIST at each band. The distribution of scatters indicate highly consistence of R_{rs} for each band in general, but most of the Landsat data overestimate the $R_{rs}(443)$ from TM and ETM+ in comparison with the MODIST data. From the comparison of linear regression results, OLI agrees better with MODIST than TM and ETM+, with the best performance of Landsat-9 OLI. Due to the similar revisit time, the differences in data bias shown for each band are small, despite the different number of matched pairs of data acquired by each sensor. Comparing the degree of matches with each MODIST band, the Landsat sensors showed the highest linear correlation at the 650 nm band ($R^2 > 0.66$, $RMSE \leq 0.005 \text{ sr}^{-1}$).

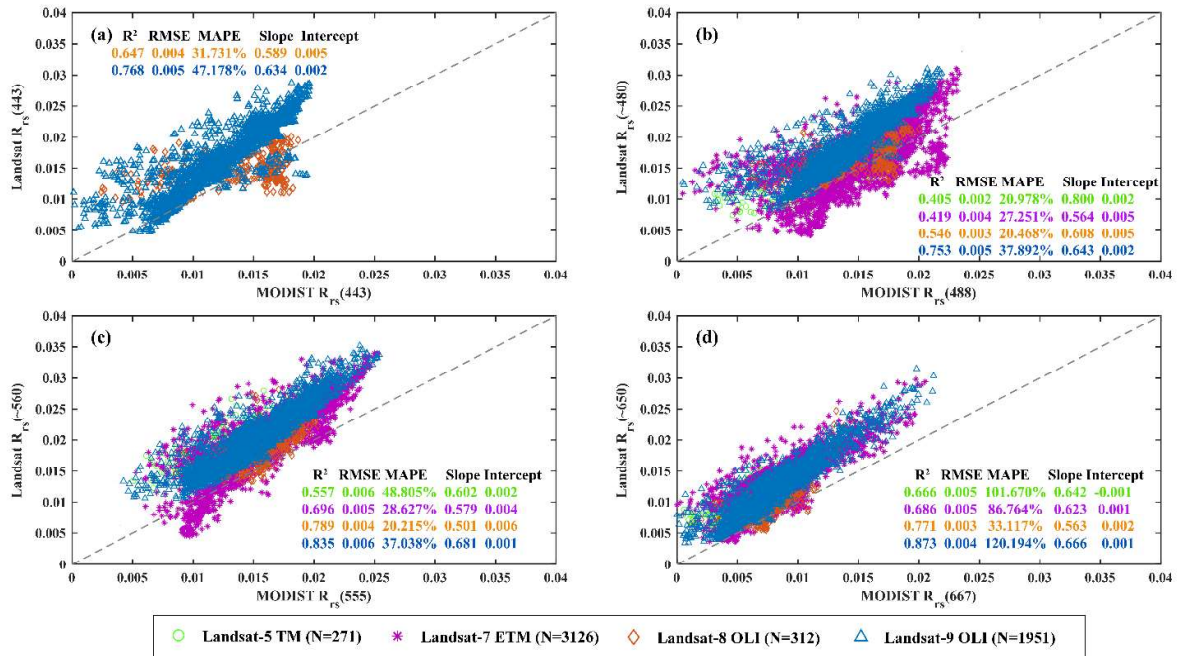


Fig. 4. Comparisons of R_{rs} centred approximately at 443 nm (a), 480 nm (b), 560 nm (c), and 650 nm (d) derived from Landsat series sensors and with those obtained from MODIS Terra (MODIST) between 1984 and 2022 in JZB.

Focusing on $R_{rs}(443)$, Fig 5 shows the estimation by the virtual band estimator algorithm on TM and ETM+ which compared with MODIST images on the same date in JZB. Most of the scatter points are distributed around 1:1 line, and maintain a certain moderate correlation with MODIST images. To reduce the data discrepancy between Landsat sensors, the R_{rs} of each band were linearly corrected by the regression coefficients in Table 1 and then used in the subsequent inversion process. The similar central wavelengths and the small R_{rs} differences provide good preconditions for the joint Landsat series sensors for water transparency estimation in JZB.

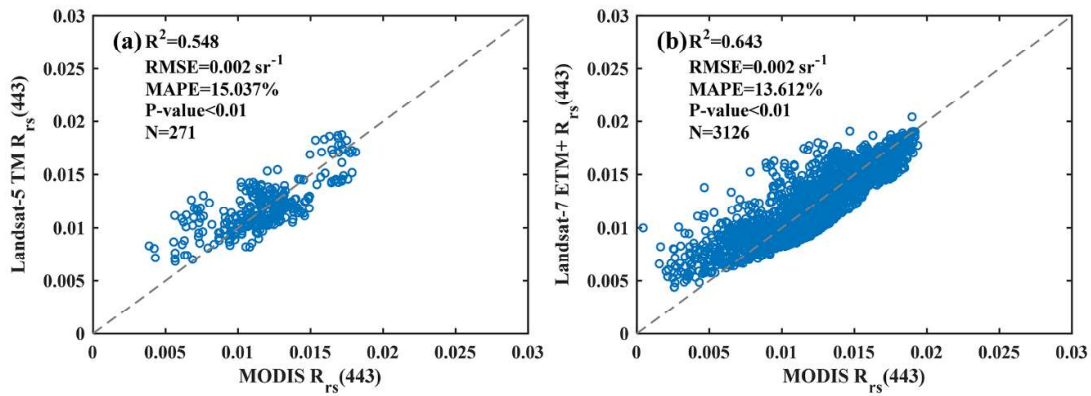


Fig. 5. Comparisons of $R_{rs}(443)$ estimated by the virtual band estimator algorithm on Landsat-5 TM (a) and Landsat-7 ETM+ (b) with those from concurrent MODIS images in JZB.

4.2 Correction of Z_{SD} retrieval

Fig. 6 shows the comparison between the Z_{SD} estimated with the Lee_2015 model and the field measurements. Z_{SD} values were highly correlated with the measured data (P -value<0.01), with $R^2=0.857$ ($N=31$) for TM, $R^2=0.792$ ($N=26$) for ETM+, and $R^2=0.884$ ($N=27$) for OLI. The inversion results obtained for TM, ETM+, and OLI are linearly corrected by Equation (6) with a_0 of 1.293, 1.314, and 1.186, and a_1 of -0.499, -0.407, and -0.262, respectively.

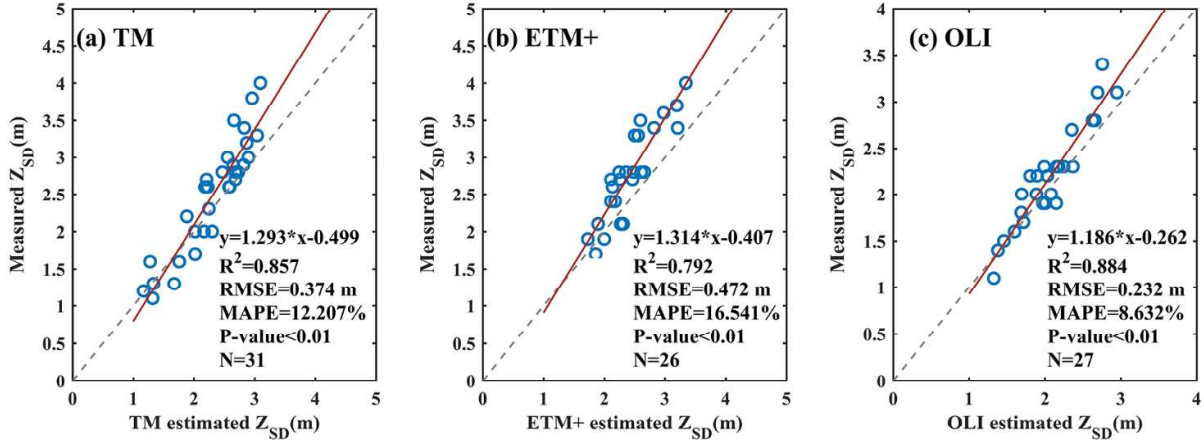


Fig. 6. Comparison of estimated Z_{SD} from Landsat sensors of TM (a), ETM+ (b), and OLI (c) by the Lee_2015 model, and measured data.

4.3 Spatio-temporal patterns of Z_{SD}

4.3.1 Monthly and Seasonal variations

Fig. 7 shows the monthly spatial distributions of Z_{SD} and the area averages. It is clearly that Z_{SD} gradually increases from the north-western nearshore waters of JZB towards the bay entrance with an obvious strip distribution. From temporal variation, the monthly mean Z_{SD} of entire region ranges from 1.45-2.17 m, with the highest in May and the lowest in January. From the statistical result of sub-region S_1 - S_4 which located at the north-west, north-east, central and mouth of the Jiaozhou Bay, the Z_{SD} values in the central area (S_3) and the bay mouth (S_4) reach their peak in May, aligning with the entire regional monthly mean trend and exhibiting a more significant pattern. However, the northern bay areas (S_1 and S_2) display a distinct characteristic, with relatively lower Z_{SD} values during the period from March to August. Limited to the 16-day revisit time of Landsat sensors, there is a lack of available monthly data, so these do not represent meaningful statistical averages.

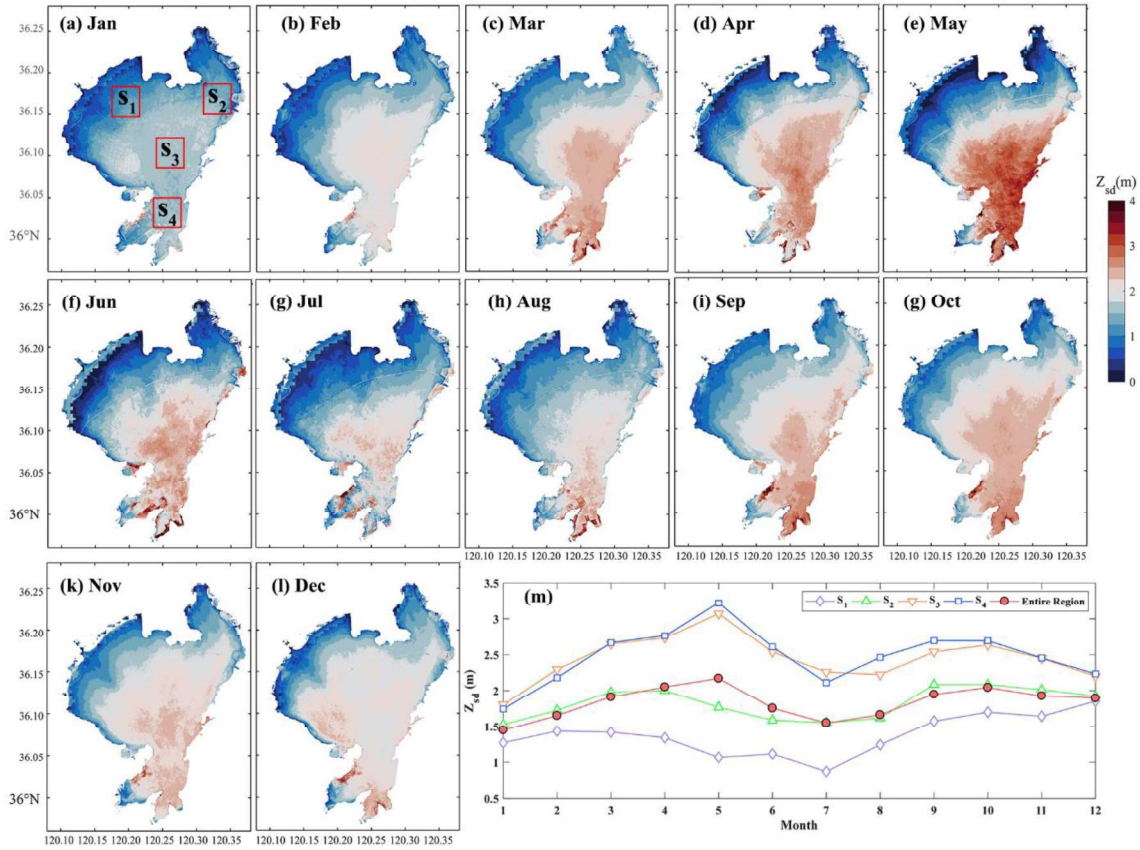


Fig. 7. Monthly spatial patterns of derived Z_{SD} in JZB during 1984–2022 (a-l) and comparison of monthly averages Z_{SD} variations in sub-region S_1 - S_4 and entire JZB area (m). S_1 , S_2 , S_3 , and S_4 are located at the north-west, north-east, central and mouth of the Jiaozhou Bay respectively.

To more specifically explore seasonal variations, the seasonal average Z_{SD} anomaly variation for the entire JZB from 1984 to 2022 is shown in Fig. 8. On the Z_{SD} anomaly time series, all seasons show downward trend, and show the most significant in summer, but there is some special variation changes. It is shown that the Z_{SD} is lower than the average level in spring from 2015 to 2022, which means that the water quality deteriorated significantly. However, the difference between Z_{SD} below average value in summer from 2016 to 2021 gradually decreases, and the Z_{SD} in autumn and winter from 2018 to 2022 is very close to the average value from 2019 to 2022, indicating that the declining trend of water quality has been mitigated to some extent.

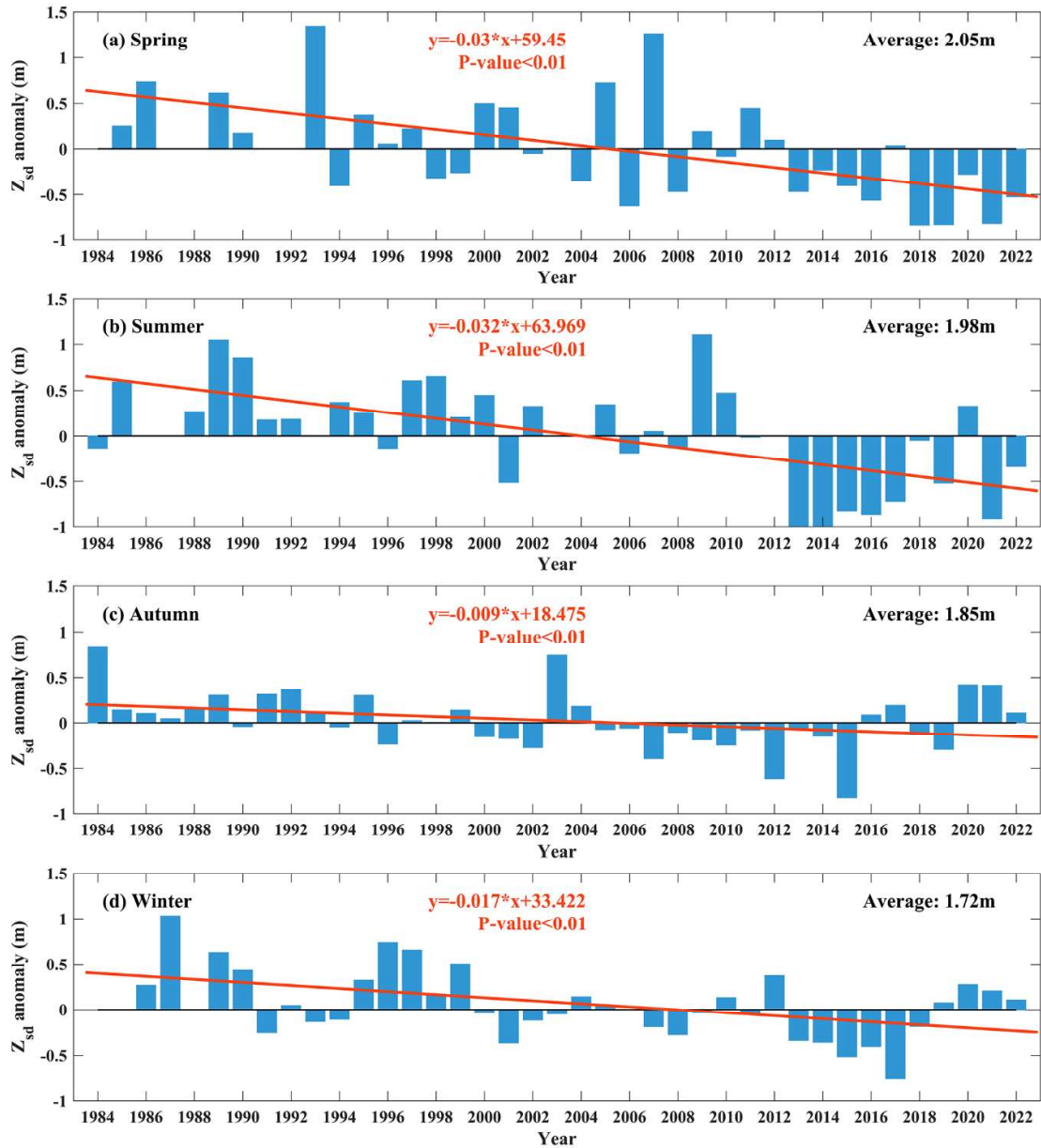


Fig. 8. Temporal anomalies variation of Z_{SD} for the entire JZB in spring (a), summer (b), autumn (c), and winter (d), respectively during 1984–2022. (Spring: March–May; Summer: June–August; Autumn: September–November; and Winter: December–February.)

4.3.2. Inter-annual variation

Fig. 9 shows yearly average over the entire JZB and four sub-regions of Z_{SD} for the period from 1984 to 2022. In Fig 9(a), the regression lines clearly indicated two distinguish trends of the variation of Z_{SD} for entire region. By dividing the whole time series into two segments year after year for linear fitting, calculating the sum of squared residuals and the significance test, it finally determined 2015

as the turning point year. Then, from the statistical analysis during 1984-2014, the Z_{SD} decreases at a rate of 0.022 m/year with $R^2=0.516$ ($P\text{-value}<0.01$), but from 2015 to 2022, the Z_{SD} increases at a rate of 0.049 m/year with $R^2=0.543$ ($P\text{-value}<0.05$). There is a clear indication that the water quality started to improve since 2015.

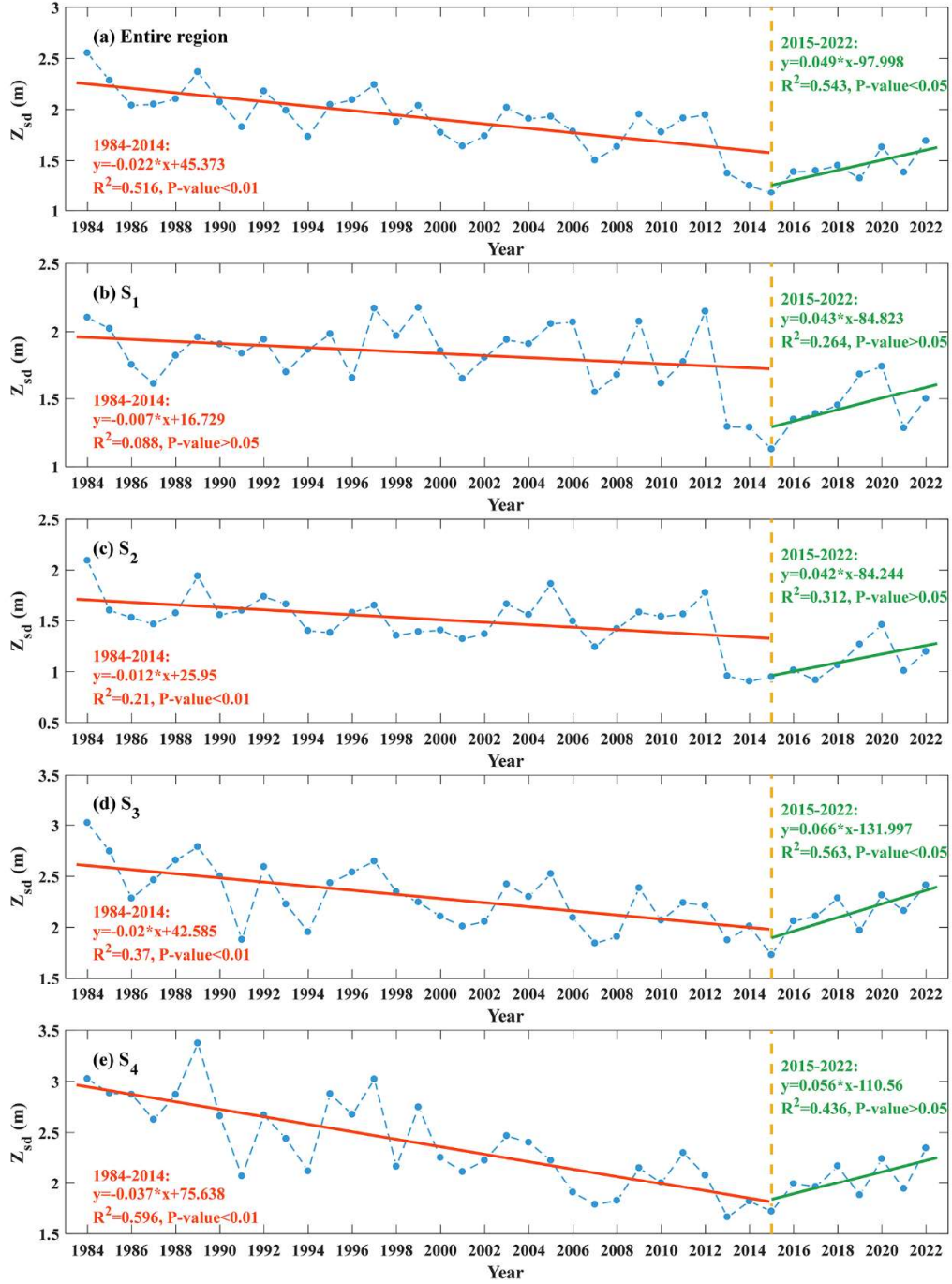


Fig. 9. Inter-annual variations of Z_{SD} over the entire region(a) and four sub-regions(b-e) in JZB during 1984-2022.

Fig 9(b-e) gives a clearer understanding of the Z_{SD} interannual variations before and after 2015 in four sub-regions of the JZB. During 1984-2014, the changes of Z_{SD} in north-east (S_2), central (S_3) and mouth (S_4) of Jiaozhou Bay were significant ($P<0.01$), while the changes of Z_{SD} in northwest (S_1) fluctuated year by year but did not decrease significantly. From 2015 to 2022, due to the few of statistical data, Z_{SD} in all four sub-regions showed an increasing trend, and only the central Bay (S_3) was more significant ($R^2=0.563$, $P\text{-value}<0.05$).

4.4 Correlation and influencing factors analysis

Considering the potential influencing factors of the long-term changes of Z_{SD} in the entire JZB, the interannual variation status of the five meteorological elements and three human activity elements were separately recorded. Fig. 10 (a-h) shows annual average of: air temperature (AT), wind speed (WS), sunshine duration (SSD), air pressure (AP), precipitation (PR), gross domestic production (GDP), local population (PO) and industrial wastewater discharge (IWD) during 1984-2022. The observation records of weather stations in the past 39 years show that the average surface temperature has increased from 12.17 °C in the previous five years (1984-1988) to 13.94 °C in the recent five years (2018-2022), and the annual increase rate is about 0.039 °C/year. At the same time, the wind speed has decreased from 5.43 m/s in the previous five years to 3.28 m/s in the recent five years. The annual rate of decline is about 0.067 m/(s·y). Besides, the precipitation in Jiaozhou Bay gradually increased, the air pressure gradually decreased, and the sunshine duration first decreased and then increased. On socio-economical elements, both GDP and PO have been in a state of growth, but IWD has sharply decreased from 1,0556,600 tons in 2015 to 561,300 tons in 2017. Fig. 10(i-k) shows the relationships of Z_{SD} with meteorological factors in the periods of 1984-2022, 1984-2014 and 2015-2022 respectively, while Fig. 10(l) shows the correlation of Z_{SD} with human activity factors for the period of 2009-2021. In Fig 10 (i-l), both Pearson and Partial correlations are presented and the asterisk corresponds cases when $P\text{-value}<0.05$ (indicating a significant correlation). Z_{SD} had significant Pearson correlation with AT, WS, SSD, and AP both in 1984-2014 and 2015-2022, but the partial correlation with SSD was the strongest in 2015-2022. It indicates that SSD is the main meteorological factor affecting the interannual variation of Z_{SD} in the past 39 years.

In terms of human activity factors, the correlation between Z_{SD} and GDP, PO and IWD were not significant. However, IWD dropped sharply from 2015 to 2016 and then remained at a low level, while Z_{SD} increased significantly after 2015. The rapid reduction of industrial waste emissions in Qingdao city played a very important role in improving the water clarity. So that, the turning trend of the water clarity in JZB can be mainly attributed to the rapidly reduction of industrial waste emissions from Qingdao city during 2015-2016, as well as the increase in sunshine duration during 2015-2022.

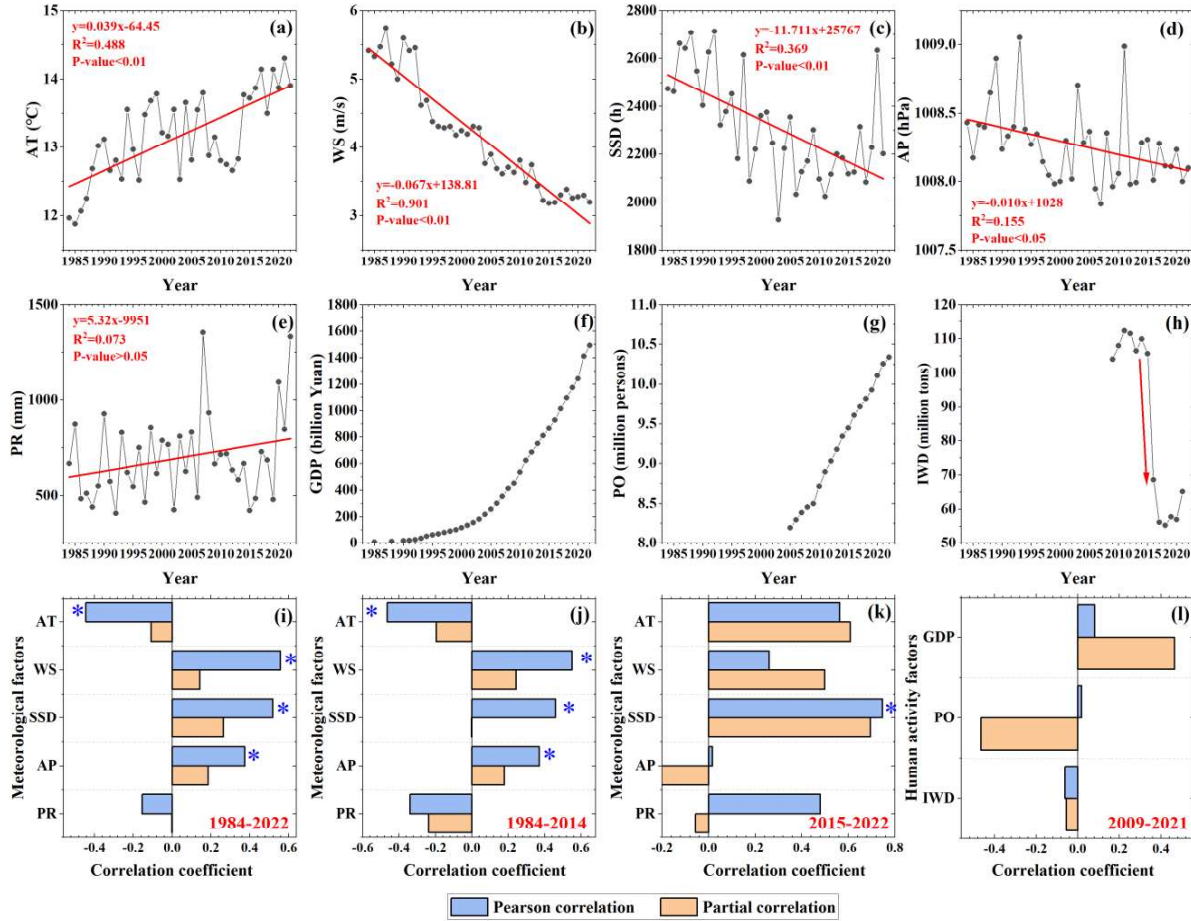


Fig. 10. Variations of meteorological elements (a-e) and human activity factors (f-h) during 1984-2022, and relationships of Z_{SD} with meteorological factors in the period of 1984-2022 (i), 1984-2014 (j), and 2015-2022 (k), and with human activity factors during 2019-2021 (l). AT denotes air temperature, WS denotes wind speed, SSD denotes sunshine duration, AP denotes air pressure, PR denotes precipitation, GDP denotes gross domestic production, PO denotes local population, and IWD denotes industrial wastewater discharged. The asterisk corresponds to $P\text{-value} < 0.05$.

5 Discussion

5.1 Consistency assessment of R_{rs} products

Landsat TM, ETM+, and OLI have the same spatial resolution and similar spectral bands, and each sensor L1T product is geolocated and topographically corrected. Since the individual sensors operate on different orbits and do not have images of same-day transit in the regions, the radiometric properties of the Landsat images were usually compared between sensors in past studies by matching them with sensors having similar spectral settings, spatial resolution, and the same transit area using a strict spatiotemporal matching criterion (Barnes et al., 2014; Chander et al., 2009).

When using MODIST to evaluate the consistency of Landsat sensor R_{rs} , a transit time difference of ± 1 h is considered. Utilizing a similar time window can effectively reduce discrepancies in atmospheric and water properties. However, several technical problems persist. Firstly, although the spectral bands are similar, the width and center positions of the spectral bands are not the same. In general, the spectral band of MODIST is narrower than that of TM and ETM+ and is similar to that of OLI. How to correctly transmit optical properties from a band location to the center of a specified band is an urgent problem to be solved through a large number of field measurements of ocean colour remote sensing. Secondly, the accuracy of R_{rs} data products will also be affected by the difference in radiation measurement accuracy of ocean colour sensors (Hu et al., 2012). The radiometric accuracy of MODIST is 12 bits. The image performance observed by Landsat-8 OLI with 12-bit quantization and Landsat-9 OLI with 14-bit quantization is similar with MODIST. Under typical radiation, the signal-to-noise ratio (SNR) of transmitting Landsat-9 OLI data is improved by 25% compared to Landsat-8 OLI data transmission. However, Landsat-5 TM and Landsat-7 ETM+ operate at 8-bit quantization levels, which is significantly lower than the MODIST. When two bands are used to estimate aerosol scattering from TM and ETM+ images during the atmospheric correction, considerable noise may accumulate and be transmitted from the near-infrared band to the visible band (Xu et al., 2020), and the noise of the obtained R_{rs} products will also increase. For the data collected by satellite sensors, the SNR is higher with the increase of quantization. However, the growth trend is not linear, but shows a gradual slowdown. When the quantization exceeds 10 bits, the increase in the SNR is almost negligible (Wang and Huang, 2005). Thirdly, the spatial scale difference is obvious, and the pixel window obtained by Landsat matching is large, so the uniformity

of the target is difficult to guarantee(Lee et al., 2012). For pixels with 1km interval in MODIST R_{rs} products, the mean value matching of 33×33 pixel windows in Landsat images is required. In practice, more observation areas are spatially heterogeneous, and the products with low spatial resolution do not necessarily match the simple arithmetic or geometric mean of the pixel windows in the products with high spatial resolution.

As evaluated by MODIST as shown in Fig. 4, the R_{rs} product of TM, ETM+, and OLI is in a good agreement, with linear regression slopes less than 1 and $R^2 > 0.40$, which greatly reduces the uncertainty generated in the process of sensor radiometric calibration and atmospheric correction.

5.2 Uncertainties of Z_{SD} retrieval in coastal waters

From the Lee_2015 model, the Z_{SD} is determined by the minimum value of the K_d spectrum in the visible range (443-655 nm), which is obtained by ocean colour remote sensing, indicating a good correlation between ocean colour and water clarity (Wang et al., 2020). The changes in the water constituents such as chlorophyll-a, suspended matter and chromophoric dissolved organic matter were captured in the remotely sensed reflectance spectra by radiometric measurements from satellite remote sensing. Due to the nature of semi-closed bays, when using satellite remote sensing to monitor the water clarity changes in coastal waters, the results can be affected it requires appropriate atmospheric correction model, the applicability of the inversion algorithm, and the influence of tidal height on coastal water environment at different times.

Due to the adjacency effects, the R_{rs} products of coastal waters are very vulnerable to the influence of complex multiple scattering in the atmosphere-land system(Vanhellemont and Ruddick, 2018), and the accuracy of the atmospheric correction is highly dependent on the accurate understanding of the surface types and aerosol patterns in the study area(Wei et al., 2018). Since the assumption of black pixels to the water-leaving radiance in the near-infrared band in open ocean waters is invalid in coastal waters, the development of atmospheric correction models in turbid waters focuses on designing effective schemes to estimate the water-leaving radiance in the near-infrared band, such as layered removal(Mao et al., 2021), multi-layer neural networks(Fan et al., 2017), etc., to expect an accurate atmospheric correction in turbid waters. It should be noted that even if the best atmospheric correction scheme is used for the Landsat series sensors, considerable

uncertainties may exist. And also remarkable residual errors existed in most TM/ETM+ bands in aquatic applications with uncertainty of $> 50\%$ when given any atmospheric correction approach or spectral band(Xu et al., 2020).

In previous studies, MODIS has been widely used in remote sensing monitoring of water clarity (Shang et al., 2016; Wu et al., 2008). We linearly fit all the R_{rs} obtained from Landsat images after atmospheric correction to the MODIST band, then all the Landsat R_{rs} products provide a robust result when performing Z_{SD} inversion. Therefore, the accuracy of the Z_{SD} inversion results in coastal waters is greatly attributed to the applicability of the inversion algorithm. When applying the Lee_2015 model, it is first necessary to obtain the intrinsic optical characteristics of the water body by QAA algorithm from R_{rs} information, and then obtain the K_d spectrum. According to the QAA modelling process, the algorithm has the best effect in extracting the total water absorption in optical deep water, but the optical characteristics of coastal water are relatively complex, and the high variability of R_{rs} with the change of water quality makes the performance of QAA decline significantly(Zhu and Yu, 2013). Although the agreement between the Lee_2015 model and the measured data is very good in some ocean, coastal and lake regions of the world, it does not mean that the Lee_2015 model can be perfectly applied to all coastal waters. Based on the data of the field measured, it is very necessary to evaluate and correct the data of every link in the application process of the Lee_2015 model(Rodrigues et al., 2017).

Ocean tide is one of the most significant periodic phenomena in marine activities, and it is the main driving factor for the diurnal variation of suspended particulate matter concentration in coastal areas(He et al., 2013). As a typical regular semi-diurnal tidal area, JZB only takes about 6 hours to change from high water to low water in a tidal cycle, and the tidal range can reach about 3.5 m. As the average water depth of JZB is only 7 meters, the re-suspension of sediments and nutrients driven by tidal fluctuations leads to the large changes of water components at different times of the day, which has a great impact on the monitoring of water clarity.

In addition, a single Landsat sensor captures imagery of the same area only once every 16 days. Compared with MODIS, Sentinel-2, and other sensors, the observation frequency and accuracy of Landsat were greatly reduced, and the image was highly susceptible to weather conditions such as

cloudy, sea fog, and rainfall. In addition, the observation of the JZB Bay area by Landsat lasted 39 years. With limited field-measured data, it is difficult to ensure the accuracy of the inversion algorithm correction.

Although the available images observed by Landsat in the waters of JZB are not evenly distributed in each season, the variation trend of Z_{SD} shown in Fig. 9 is in good agreement with the previous research results obtained by using the GOCI sensor. For example, Z_{SD} has increased significantly from 2015 to 2021 (Zhou et al., 2022). It indicates that the overall change of Z_{SD} in JZB over the past 39 years based on the Landsat acquisition is reasonable. In the future, frequent field surveys and Landsat-8/9 observations in JZB will provide more useful information for water quality monitoring.

5.3 Drivers of Z_{SD} variation in JZB

As an important parameter to describe the water optical properties, water transparency is directly related to phytoplankton, suspended matter and chromophoric dissolved organic matter. The proportion of these three water optical components determines the degree of penetration and attenuation on underwater light (Gattuso et al., 2006). The coastal sea area is most strongly affected by human activities. Meteorological and human activities combined lead to changes in the concentration of water optical components, and further affect the water transparency status indirectly (Capuzzo et al., 2015).

With the change of meteorological conditions, such as wind speed and air pressure decreased, the precipitation increased, and the sunshine duration first decreased and then increased, the water transparency of Jiaozhou Bay shows a trend of decreasing first and then increasing, as shown in Fig. 9. One hand, after the temperature rises, heat is transferred at the atmosphere-water interface, through processes such as conduction, convection, and radiation, results in increases in air pressure and water temperature as air temperature rises, thus promoting the reproduction of phytoplankton biomass (Hu et al., 2022). With the decrease of wind speed, the wind-driven sediment resuspension is weakened, the phytoplankton aggregation is more stable. These changes significantly reduced the water clarity, which was consistent with the trend of Z_{SD} variations from 1984 to 2014 in this study. On the other hand, the temperature and wind speed of the meteorological factors could make an

important impact on the water environment, but the change is not limited to these elements. In China, the change in wind speed is attributed to global warming and air pollution, and is also highly correlated with the incident solar radiation on the sea surface(Xu et al., 2006). The increase of sunshine duration usually means that the atmospheric conditions are better, which is conducive to the growth of aquatic plants, accelerates the consumption of nutrients, promotes the sedimentation and decomposition of phytoplankton, and the photodegradation of water pollutants (Wild, 2009). It may be the reason for the higher Z_{SD} caused by the increase of SDD from 2015 to 2022.

Meteorological conditions also feed back into human activity in the Jiaozhou Bay. Since the reform and opening in the 1980s, changes in land surface roughness caused by urban land utilization and building height has affected regional climate to a certain extent (Zhang et al., 2018). At the same time, the discharge of nutrients and pollutants caused by land development and industrial development poses a great threat to aquatic ecosystems. As industrialization and economic development in Qingdao city, the increased GDP and PO and decreased IWD jointly affect the change of water environment in JZB. In Fig. 10, the reduction of industrial wastewater discharge in Qingdao after 2015 and then remained low level are important factors for the significant improvement of water quality in JZB. Therefore, in the rapid economic development, it is particularly necessary to conduct real-time evaluation and synchronous management of Marine water quality.

6 Conclusions

Using Landsat TM/ETM+/OLI images from 1984-2022, the spatiotemporal variation and drivers of Z_{SD} in JZB are explored in this study. With the BBE algorithm to determine $R_{rs}(443)$ for TM and ETM+ images and the evaluation with MODIST, the data match-up between Landsat and MODIST shows considerable consistency (linear regression slope was less than 1, $R^2>0.40$), although OLI images are found to be better than those from TM and ETM+, with the best being Landsat-9 OLI images. This approach greatly reduces the uncertainty of sensor radiation calibration and atmospheric correction process. The Z_{SD} estimated from Lee_2015 model with the linearly corrected R_{rs} data as input shows a significant correlation with the in-suit measurements ($R^2>0.79$, MAPE<17%). The spatial and temporal distribution of Z_{SD} in JZB for 39 years indicate that the

regional monthly average Z_{SD} is highest in May and lowest in January. Z_{SD} in the central of JZB is in a relatively stable state for all seasons, and the decline of seasonal water clarity is found most significant in the coastal region and bay mouth. The inter-annual variation after 2015 is identified as the turning point that the regional average Z_{SD} from 1984 to 2014 exhibits a notable decrease with an average rate of approximately 0.022 m/year, which is strong correlated by wind speed, and there is a significant increase from 2015 to 2022 with an average rate of about 0.049 m/year. This can be primarily attributed to the increase of SSD during 2015-2022, but also benefited from the sharp reduction of industrial waste discharge in 2015-2016.

This is a clear demonstration that the water quality in JZB can be significantly affected by human activities, as well as changes of natural environment. It is vital to have a balanced strategic policy for industrialization and sustained marine environment for the areas such as JZB.

CRediT authorship contribution statement

Yan Zhou: Conceptualization, Investigation, Formal analysis, Visualization, Writing – original draft, Writing – review & editing. **Dingfeng Yu:** Conceptualization, Writing – review & editing. **Lei Yang:** Visualization. **Yingying Gai:** Resources, Formal analysis, Writing – review & editing. **Ze Zheng Yi:** Resources. **Qing Yuan:** Resources. **Zhen Han:** Resources. **Shunqi Pan:** Writing – review & editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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