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Lockdown effects on total suspended solids concentrations in the Lower Min River (China) during COVID-19 using time-series remote sensing images

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ABSTRACT

The COVID-19 pandemic in China in the winter-spring of 2019-2020 has decreased and even stopped many human activities. This study investigates whether there were any changes in the water quality of the Lower Min River (China) during the lockdown period. The time-series remote sensing images from November 2019 to April 2020 was used to examine the dynamics of the river’s total suspended solids (TSS) concentrations in the period. A new remote sensing-based prototype was developed to recalibrate an existing algorithm for retrieving TSS concentrations in the river. The Nechad and the Novoa algorithms were used to validate the recalibrated algorithm. The results show that the recalibrated algorithm is highly consistent with the two algorithms. All of the three algorithms indicate significant fluctuation in TSS concentrations in the Lower Min River during the study period. February (COVID-19 lockdown period) has witnessed a 48% fall in TSS concentration. The TSS in March–April showed a progressive and recovery back to normal levels of pre-COVID-19. The spatiotemporal change of TSS has worked as a good indicator of human activities, which revealed that the decline of TSS in the lockdown period was due largely to the substantially-reduced discharges from industrial estates, densely-populated city center, and river’s shipping. Remote sensing monitoring of the spatiotemporal changes of TSS helps understand important contributors to the water-quality changes in the river and the impacts of anthropogenic activities on river systems.

1. Introduction

Rivers are important natural water resources that are responsible for supplying water to irrigation, industrial needs, and human beings (Rosero-Montalvo et al., 2020). Nevertheless, the quality of river waters is under threat by increasing human activities such as urban development, industrial production, deforestation, and inappropriate use of pesticides and fertilizers, which have adverse impacts on the water quality of rivers. As a result, rivers usually carry significant amounts of total suspended solids (TSS) that modify the quality of river waters (Novoa et al., 2017). Therefore, monitoring the spatiotemporal distribution of TSS in river waters is of significance to the evaluation of the impacts of human activities as well as to the protection of river water quality.

The COVID-19 pandemic in China in the winter-spring of 2019-2020 has decreased and even stopped many human activities due to nationwide lockdown, which in turn would have reduced water pollution in river systems as expected. Therefore, by examining the dynamics of TSS concentrations, this study aims to investigate whether there were any changes in water quality during this period taking the Lower Min River (China) as a case. This should allow us to understand the impacts of anthropogenic activities on river waters.

The traditional in-situ monitoring methods for measuring TSS have disadvantages because of their spatial and temporal limitations (Saberoon et al., 2020). Remote sensing-based observation shows promise as it measures TSS concentrations in natural waters with high spatial and temporal resolutions that can cover all the scales of variability and identify the spatiotemporal extent of TSS (Ondrůsek et al., 2012; Vogelmann et al., 2012). Remote sensing imagery has been frequently employed to detect the spectral signatures of various
suspended solids for estimating TSS concentration in turbid inland waters (Flores et al., 2020; Liu et al., 2020; Mouyen et al., 2018; Olmanson et al., 2016; Wang et al., 2012). Remote sensing-based models that transfer multi-band reflectance to TSS concentrations have usually been developed either empirically or theoretically (Balasubramanian et al., 2020; Doxaran et al., 2002; Thanh et al., 2017). Many of the models were developed based on the relationship between in-situ measured water-quality data and remote sensing data (Feng et al., 2014; Ondrusk et al., 2012; Reddy, 1993). Remote sensing-based TSS measurement has worked as an easily measurable proxy for TSS concentration in a verity of waters (Dogliotti et al., 2015; Saberioon et al., 2020).

Many remote sensing-based algorithms used to measure TSS from water reflectance have method/site-specific limitations (Tavora et al., 2020). Dogliotti et al. (2015) indicated that the existing algorithms faced a challenge, i.e., whether these algorithms could be applied to waters in other regions without calibration. Therefore, the work for developing generic and robust algorithms has also been carried out. Miller and McKee (2004) utilized the MODIS red band to investigate TSS in the Gulf of Mexico based on a relationship between the band and in-situ samples. They suggested that the approach could be applied to other coastal/inland regions because of the robustness of the relationship. Nechad et al. (2010) developed a generic algorithm to measure TSS using in-situ TSS and reflectance spectra collected from the North Sea. The consistency of the results in different sensors suggested that the algorithm be suitable for multi-sensors. Novoa et al. (2017) developed a switching algorithm that automatically selects the most sensitive relationship between TSS and water reflectance signal to avoid saturation effects. They demonstrated that the algorithm could work well with different sensor data. Balasubramanian et al. (2020) presented an inherent optical property-based multi-conditional inversion procedure (SOLID) to retrieve TSS in a variety of waters with in-situ and multi-sensor data. They suggested that SOLID had a potential for estimating TSS in global coastal and inland waters. Tavora et al. (2020) indicated that the use of a single image band might lead to switching the band to another one for different ranges of turbidity because of the saturation of reflectance as TSS concentration varies. Therefore, they proposed a multi-band approach with red and NIR bands and applied it to different estuaries and coastal environments. The method could be general except for the waters dominated by phytoplankton and colored dissolved organic matter (CDOM).

Due to the unavailability of in-situ measurements of TSS data during COVID-19, this study developed a new prototype to recalibrate and extend an existing remote sensing algorithm for retrieving TSS concentrations of the Lower Min River from November 2019 to April 2020. The water-quality scenarios represented by the retrieved time-series TSS images would allow revealing spatiotemporal changes of TSS concentrations and patterns that emerged during the COVID-19 period due to substantially reducing transport and industrial-economic activities. The results would help understand important contributors to the water-quality changes and recognize the impact of anthropogenic activities on river systems.

2. Material and methods

2.1. Study area and data

2.1.1. Study area

The Min River is one of the most important rivers in southeastern China. It has a total length of 562 km. The lower reaches of the river traverse the Fuzhou city area, with a length of about 99 km and a water surface area of 76 km² (Fig. 1). The river is divided into two tributaries by an island. The north tributary flows through the Fuzhou urban area and is about 30 km long. The south tributary surrounds the city and is about 32 km in length.

According to the records of the Zhuqi hydrological monitoring station, the nearest station to the study area, the annual average amount of water flows of the Min River for 2017–2019 is $40.128 \times 10^9$ m³. The monthly precipitation and water-flow amount in the study area during the study period are provided in Table 1.

Table 1

| Month   | Precipitation (mm) | Water flow amount (m³) |
|---------|--------------------|------------------------|
| November 2019 | 0                  | $1.209 \times 10^9$    |
| December 2019  | 38.1               | $1.192 \times 10^9$    |
| January 2020   | 28.2               | $1.336 \times 10^9$    |
| February 2020  | 65.8               | $2.409 \times 10^9$    |
| March 2020     | 262.8              | $4.476 \times 10^9$    |
| April 2020     | 63.9               | $4.542 \times 10^9$    |

Sources: Precipitation: Fuzhou meteorological station (#58847) (http://data.cma.cn); Water flow: Zhuqi station (http://slt.fujian.gov.cn/xsgk/tjxx/swxb).

Fig. 1. Map showing the Fuzhou city area and the Lower Min River flowing through the city.
China. Fuzhou is an old port city and also a major center for light industry. It is one of the most economically productive cities in the province. In 2019, Fuzhou has achieved a GDP of 939.23 billion (Chinese) yuan. The study area has a population of approximately 3.41 million (http://tjj.fuzhou.gov.cn/zz/zwgk/tjjzl/ndbg).

Fuzhou launched its first-level response to COVID-19 on January 24, 2020. Since then, measures have been issued to prevent the spread of COVID-19, which soon led to the lockdown of the city. The measures include encouraging people to stay home, restricting non-essential travel in and out of the community, avoiding public gatherings, canceling events, reducing economic and industrial activities, closing schools, extending the New Year holiday, etc. The implementation of these measures greatly reduced human activities. The restrictions were steadily lifted since late February as the city’s local confirmed case was reported on February 26, 2020. Accordingly, we divided the study period (November 2019–April 2020) into three scenarios: pre-COVID-19 (before February), COVID-19 (February), and post-COVID-19 (after February).

2.1.2. Remote sensing data

Time-series remote sensing images used are Landsat-5 Thematic Mapper (TM), Landsat-8 Operational Land Imager (OLI), and China’s Gaofen-1 (GF-1) Wide Field of View (WFV) images (Table 2). The TM/OLI surface reflectance products (LSRP) were downloaded from the United States Geological Survey website (https://earthexplorer.usgs.gov). The downloaded LSRP product has already been atmospherically corrected. The WFV data were downloaded from the China Centre for Resources Satellite Data and Application (http://36.112.130.153:7777/DSSPlatform/productSearch.html). The imagery has four 16 m-resolution visible to NIR bands that have almost the same wavelength ranges as the corresponding bands of TM/OLI. The downloaded GF-1 images were atmospherically corrected with the models of Chander et al. (2009) and Chavez (1996) and then coregistered and resampled to 30 m resolution to match the used Landsat image.

2.2. Algorithms used

Due to no in-situ data available for the study period (no field campaign could be conducted during this hard time, and the river’s hydrological monitoring station does not regularly monitor TSS data), three remote sensing-based algorithms were used in this study. The basic algorithm is the one specially developed for the Lower Min River by Wen and Xu (2008, 2009), which is then recalibrated to extend its use at the present time (for simplicity, we use Wen algorithm to represent both original and recalibrated Wen algorithms hereinafter). The other two are the generic algorithms of Nechad et al. (2010) and Novoa et al. (2017) that are used for validation of the recalibrated Wen algorithm.

2.2.1. Wen algorithm

Wen and Xu (2008, 2009) estimated the TSS concentrations in the Lower Min River. The Landsat TM image acquired on Sep-8-2006, coupled with simultaneous in-situ water and spectral samples, was used to develop an algorithm for the estimation. They tested the relationship between the in-situ data and the satellite data by using the single band, multiple bands, and band ratio methods with different regression methods. They found that the green and red bands were most sensitive to TSS in the river and achieved the following best estimation algorithm:

\[
TSS = 3793.7(\rho_{\text{green}} + \rho_{\text{red}})^2 - 16.5
\]

where \(\rho_{\text{green}}\) and \(\rho_{\text{red}}\) are the surface reflectance of the green and red bands.

Inspection of the reflectance spectra of the present waters in the study river courses can find that the green and red bands are still the most notable bands for identifying TSS. This distinguishing feature on which the Wen algorithm was based is still valid presently. In relatively low TSS waters, the peak of the reflectance is located in the spectral region of the green band (Fig. 2a). An increase of TSS results in the peak of the reflectance of the green band to shift towards the red band region (Fig. 2b).

2.2.2. Recalibration of the Wen algorithm

To avoid the time-specific limitation of an algorithm that was developed for a special period, recalibration is usually required to adjust its coefficients for a defined period (James, 2016). Therefore, we recalibrated the Wen algorithm to extend the original period (2006) to the present one (2019–2020). Due to the unavailability of in-situ measured TSS data at this special time, a prototype was developed for the recalibration solely using remote sensing techniques. A 5-step recalibration procedure is outlined below (Fig. 3):

1. Atmospheric and geometric corrections: Conduct the corrections for all of the used images to remove the atmospheric effects and allow accurate overlay between the images.
2. Producing Water-only image: Use the modified normalized difference water index (MNDWI) of Xu (2006) to mask out the non-water information from the image to form a water-only image:

\[
\text{MNDWI} = (\rho_{\text{green}} - \rho_{\text{NIR}})/(\rho_{\text{green}} + \rho_{\text{NIR}})
\]

where \(\rho_{\text{NIR}}\) is the reflectance of a middle infrared band, such as the OLI band 6.

If an image has no middle infrared band, like GF-1, use the normalized difference water index (NDWI) of McFeeters (1996) instead:

\[
\text{NDWI} = (\rho_{\text{green}} - \rho_{\text{NIR}})/(\rho_{\text{green}} + \rho_{\text{NIR}})
\]

where \(\rho_{\text{NIR}}\) is the reflectance of a near-infrared band.

3. Identification of pseudo-invariant feature (PIF) pixels: PIF identification aims to perform relative radiometric normalization. PIF pixels were used to match one image to another based on regression analysis as the PIFs are the pixels that can reasonably be expected to have constant reflectance over time in a pair of images (Schott et al., 1988; Xu, 2008; Young et al., 2017).

To identify PIFs, the red and green bands of all the water-only images including the 2006 mage have to be normalized between 0 and 1. The following is the normalization of the red band (the green band can follow the same procedure):

| Date (MM-DD-YY) | Sensor | Resolution (m) | Usage |
|-----------------|--------|----------------|-------|
| 09-18-2006      | TM     | 30             | Reference image for algorithm recalibration |
| 01-24-2019      | WFV    | 16             | Retrieving TSS for comparison |
| 01-28-2019      | WFV    | 16             | Retrieving TSS for comparison |
| 11-11-2019      | WFV    | 16             | Retrieving TSS in pre-COVID-19 period |
| 12-11-2019      | OLI    | 30             | Retrieving TSS in pre-COVID-19 period |
| 02-01-2020      | WFV    | 16             | Retrieving TSS in COVID-19 period |
| 02-10-2020      | WFV    | 16             | Retrieving TSS in COVID-19 period |
| 02-18-2020      | WFV    | 16             | Retrieving TSS in COVID-19 period |
| 03-16-2020      | OLI    | 30             | Retrieving TSS in post-COVID-19 period |
| 04-09-2020      | WFV    | 16             | Retrieving TSS in post-COVID-19 period |
| 04-16-2020      | WFV    | 16             | Retrieving TSS in post-COVID-19 period |
where $\rho'_{\text{red}}$ is the normalized reflectance of the red band. The minimum ($\rho_{\text{red.min}}$) and maximum ($\rho_{\text{red.max}}$) values used for normalization were derived from the maximum and minimum values of all the red bands of the used images in the study period rather than from those of each image itself:

$$\rho_{\text{red.max}} = \max(\rho_{\text{red1}}, \rho_{\text{red2}}, \ldots, \rho_{\text{redn}})$$  \hspace{1cm} (5)$$

$$\rho_{\text{red.min}} = \min(\rho_{\text{red1}}, \rho_{\text{red2}}, \ldots, \rho_{\text{redn}})$$  \hspace{1cm} (6)$$

where $n$ is the number of the used water-only images.

Each of the normalized red bands was divided into multiple levels at 0.02 intervals to generate a leveled water image (up to 50 levels). Each leveled water image was then respectively overlaid on the 2006 image that is the base image for the development of the Wen algorithm and therefore is served as a reference image for recalibration. A detection of pixel-wise similarity between each overlaid image pair was performed. The pixels with the same level in each image pair were regarded as the pixels that did not change over time, i.e., the PIF pixels.

### 2.2.3. Algorithms for validation

**Nechad algorithm:** The single band algorithm of Nechad et al. (2010) was used to validate our recalibrated algorithms as it is a widely-applied generic algorithm (Dogliotti et al., 2015; Novoa et al., 2017; Pahlevan et al., 2019). The algorithm is expressed as:

$$\text{TSS} = A_\rho(\lambda)\rho(\lambda) + B_\rho(\lambda)$$  \hspace{1cm} (7)$$

where $A_\rho(\lambda)$, $B_\rho(\lambda)$, and $C_\rho(\lambda)$ are dimensionless variables at wavelength $\lambda$, $R_{rs}$ is the remote sensing reflectance at wavelength $\lambda$. According to Nechad et al. (2010), $A_\rho(\lambda)$, $B_\rho(\lambda)$, and $C_\rho(\lambda)$ for the Green band (hereinafter Nechad (G)) are 112.18, 3.34, and 14.49, and for the Red band (hereinafter Nechad (R)) are 362.09, 1.65, and 17.36, respectively.

**Novoa algorithm:** Novoa et al. (2017) developed another generic algorithm (hereinafter Novoa algorithm). It automatically selects the most sensitive relationship between TSS and water reflectance signal to avoid saturation effects while calculating TSS concentrations. The Novoa’s switching bands and criteria used in this study are summarized below:

$$\begin{align*}
\text{TSS} = 130.1\rho(561) & \quad \text{if } \rho(655) < 0.007 \\
\text{TSS} = \alpha_1[130.1\rho(561)] + \beta_1[531.5\rho(655)] & \quad \text{if } 0.007 \leq \rho(655) < 0.016 \\
\text{TSS} = 531.5\rho(655) & \quad \text{if } \rho(655) \geq 0.016
\end{align*}$$  \hspace{1cm} (9)$$
where 561 and 655 nm correspond to the green and red bands, respectively; \( \alpha_1 = \ln [0.016/\rho (655)}/0.8266; \beta_1 = \ln[\rho(655)/0.007]}/0.8266.

### 2.3. Evaluation metrics

Three metrics, Pearson’s correlation coefficient \( R^2 \), mean absolute error (MAE), and root mean square error (RMSE), were used to evaluate the performances of Wen, Nechad, and Novoa algorithms. The MAE and RMSE are defined as:

\[
MAE = \frac{1}{n} \sum_{i=1}^{n} |P_i - Q_i| \tag{10}
\]

\[
RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^{n} (P_i - Q_i)^2} \tag{11}
\]

where \( P_i \) represents the pixel value of the estimated/to be validated TSS, \( Q_i \) represents the pixel value of the referenced TSS, and \( n \) is the number of samples.

### 3. Results

#### 3.1. TSS retrievals

The Wen algorithm was recalibrated using the developed recalibration prototype to retrieve TSS in the Lower Min River for the period from November 2019 to April 2020. Fig. 4 is the statistical characteristics of TSS concentrations of the river in the period retrieved using the recalibrated algorithms:

![Fig. 4. Statistical characteristics of the estimation. (a): Plot showing minimum, maximum, median, and the range of mean ±1 standard division (note: the maximum values are picked at the upper limit of the 99.9% of the data range to avoid spikes); (b): Fluctuation of the mean TSS concentrations across the study period.](image)

\[ TSS_{11–11–2019} = 3793.7\left[(0.8831\rho_{g\text{reen}} + 0.0178) + (1.91\rho_{r\text{ed}}^2 + 0.2324\rho_{r\text{ed}} + 0.0536)^2\right] - 16.5 \]

\[ TSS_{12–11–2019} = 3793.7(0.0654^{1.497}\rho_{g\text{reen}} + 0.4568\rho_{r\text{ed}}^2)^2 - 16.5 \]

\[ TSS_{01–01–2020} = 3793.7(0.0681\rho_{g\text{reen}}^2 + (0.7473\rho_{r\text{ed}} + 0.0236)^2 - 16.5 \]

\[ TSS_{10–10–2020} = 3793.7(0.4822\rho_{g\text{reen}}^2 + 0.6418 + (0.6983\rho_{r\text{ed}} + 0.025)^2 - 16.5 \]

\[ TSS_{18–10–2020} = 3793.7(0.6987\rho_{g\text{reen}} + 0.8190^2 + (0.7538\rho_{r\text{ed}} + 0.0198)^2 - 16.5 \]

\[ TSS_{16–2020} = 3793.7\left[(0.667\rho_{g\text{reen}} + 0.0017) + (0.7545\rho_{r\text{ed}} + 0.0061)^2\right] - 16.5 \]

\[ TSS_{16–2020} = 3793.7\left[0.957\rho_{g\text{reen}} + 0.0035 + (0.6821\rho_{r\text{ed}} + 0.0291)^2\right] - 16.5 \]

\[ TSS_{16–2020} = 3793.7(0.3214\rho_{g\text{reen}} + 0.4411 + (0.5652\rho_{r\text{ed}} + 0.0396)^2\right] - 16.5 \]

#### 3.2. Validation

Due to the unavailability of in-situ measurements, the performances of the recalibrated algorithms were validated with the two generic algorithms, Nechad and Novoa algorithms, respectively.

The TSS concentrations retrieved from the Sep-18-2006 image via the three algorithms were firstly compared since the image is the base image for developing the Wen algorithm. A total of 6716 pixels sampled in a 4 × 4 grid across the entire image were collected for the validation. The systematic sampling throughout the image with a great number of samples would allow sufficient and objective comparison of the three algorithms with a wide range of values (Jensen, 2005; Xu, 2010).

The comparison between Wen and Novoa algorithms indicates that the results of the two algorithms are well comparable \( R^2 = 0.95 (p < 0.001), \) MAE = 6.48, and RMSE = 8.63) (Fig. 5a). However, the Nechad (R) algorithm shows underestimation when compared against the Wen algorithm, with relatively high MAE (10.23) and RMSE (13.39) (Fig. 5b). The Nechad (G) algorithm has more serious underestimation than Nechad (R). Nevertheless, a combination of Nechad (R) and Nechad (G), i.e., Nechad (R) + Nechad (G), can greatly improve the estimation, which reduces MAE and RMSE to 8.96 and 10.08, respectively (Fig. 5c).

The TSS results retrieved from the images listed in Table 2 using the recalibrated Wen algorithms were then validated with Novoa and Nechad algorithms. Fig. 6a shows that the TSS concentrations retrieved by the three algorithms all experienced a drop in February, indicating a real TSS decline in the month despite different algorithms used. The validation shows that the recalibrated Wen algorithms have a high degree of agreement with the Novoa algorithms \( R^2 = 0.935 (p < 0.001), \) MAE = 3.93, and RMSE = 4.23). The regression line is very close to the 1:1 line in the scatter plot (Fig. 6b). The results of Nechad (R) and Nechad (G) show notable underestimation when compared with others. The regression line of Nechad (R) vs. Wen deviates greatly from the 1:1 line (Fig. 6c). Nevertheless, three February results of Nechad (R) are comparable with those of Wen and Novoa and even identical with the Wen’s measurement on February 1 (both achieve 38.01). Accordingly, Nechad (R) is suitable for estimating the TSS for the three February images, whereas a combination of Nechad (G) and Nechad (R) is more suitable for the rest of the used images. Such reconfigured Nechad results (hereinafter Nechad (reConf)) has the strongest correlation with that of the recalibrated Wen algorithm, with the highest \( R^2 \) and the lowest MAE and RMSE errors (Fig. 6d).
3.3. Spatiotemporal changes of TSS

3.3.1. Temporal changes

Fig. 4b is the characterization of mean water TSS concentrations that allow for the investigation of TSS variation during the study period. TSS was high in winter (November–December), low in early spring (February), and moderate to high in spring (March–April). A sharp decline in TSS concentrations with narrow distribution ranges can be examined across all three February images. The mean TSS declined from 73.75 mg/L (Dec-11-2019) to 38.01 mg/L (Feb-1-2020). This great decline magnitude (~48%) was associated with the city’s lockdown duration (January 24 to February 26), suggesting that lockdown-induced reduction of human activities had a significant impact on the water quality of the river. Fig. 7 is the retrieved TSS images. The three February TSS images are dominated by dark blue to light green colors, suggesting a low TSS level observed, whereas two November–December
images and three March–April images have yellow to red tones appearing in eastern, southern, and northeastern river courses that flow through the city’s industrial estate areas (see Fig. 9 for details), indicating higher TSS levels measured. The yellow to red tones appearing in the March–April images suggest a progressive recovery back to normal TSS levels in the river.

To examine whether the observed drop of TSS in February is a common phenomenon in the study river, TSS images in the early spring of 2019 that occurred in absence of COVID-19 were served as a baseline for comparison with the TSS images of February 2020. Due to the lack of simultaneous images, two images of almost the same period in 2019 (Jan-24-2019 and Jan-28-2019) were used for the comparison. Estimation shows that the mean TSS concentrations of these two images were 68.12 and 72.79 mg/L, respectively. This suggests that the mean TSS concentrations in this period should be around 70 mg/L rather than around 37 mg/L observed in February 2020. A decline of 47% year-on-year is really an abnormal phenomenon. Fig. 8 illustrates a prominent color difference between the two spring TSS images.

To detect spatiotemporal patterns of TSS, the images belonging to each of three scenarios (Table 2) were averaged to form a composite image (Fig. 9). The use of several images during the same scenario can avoid occasional change in a single image used to represent a scenario and therefore, enables to quantify TSS dynamics more objectively. Inspection of the three composite images shows that the river courses with high TSS concentrations in both pre- and post-COVID-19 images occur mostly in the eastern, southern, and northeastern city areas where main industrial estates of the city are located, some of which are labeled with A, B, C, and D in Fig. 9.

Based on the spatial pattern of TSS in the pre-COVID-19 scenario, we divided the study river courses into four portions, which are western portion, city portion, eastern and southern (E-S) portion, and north-eastern portion (Fig. 9). Fig. 10 shows that all of the four river portions had a notable TSS decline in the COVID-19 scenario. However, the magnitudes of the decline were different. The city and the E-S portions (main human-activity areas) dropped faster than the other two portions.

The TSS has increased in the post-COVID-19 scenario but also has
different magnitudes. The mean TSS in the west portion increased by two times and was even near one time higher than that in pre-COVID-19, whereas the mean TSS in the city and E-S portions were still lower than those in pre-COVID-19 despite the increase. However, the city portion’s TSS has raised close to that in pre-COVID-19, whereas the E-S portion’s TSS is still 26 mg/L lower than that in pre-COVID-19.

### 3.3.2. Spatial changes

To investigate the spatial changes of TSS over the three scenarios, each composite TSS image was further divided into six levels at intervals of 30 mg/L. The image-differencing change detection technique was applied to the 6-leveled images (Fig. 11). The positive values in the resultant differencing images identify the positions where TSS increased, whereas the negatives values indicate the locations where TSS declined. A value of 0 suggests no change between the adjacent two scenarios.

Statistics of the differencing images illustrate a substantial decline of high TSS level areas due to lockdown. The TSS-declined area makes up 76% of the entire study river area, while the TSS-increased area accounts only for 0.04% (Table 3). Consequently, there is almost no pinkish color shown in the differencing image (Fig. 11a). Moreover, the magnitude of the decline is great as the total area of Levels -2 and -3 makes up near 45% of the study river area. The greatest decrease (Level -3, dark blue color) occurs in the river courses running through eastern and southern industrial estates (marked A and D in the figure). The TSS in the river passing through city center also dropped by one to two levels (green to blue tone). River portions with no TSS change (yellow color) only occur.

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**Fig. 9.** Three composite images representing three scenarios. Labeled areas are A: factories, B: port and factories, C: factories, D: factories and villages.

**Fig. 10.** Temporal changes of mean TSS in each river portion over three scenarios.
in the marginal areas of the city.

In the post-COVID-19 scenario, the city has begun to return to its normal state. Table 3 shows that the TSS concentrations increased in almost the entire study river courses since no TSS-decrease river course was detected and the TSS unchanged area only accounts for 0.49%. However, the magnitude of the TSS rise is mainly by one level (76.55%). The different spatial patterns emerged in the change detection images show an opposite trend to the TSS level changes in industrial estate areas, which had a two-level decrease in the COVID-19 period but a one-level increase later in post-COVID-19 (Fig. 11a, b). This indicates that industrial production has not yet been fully restored.

4. Discussion

The lockdown measures have resulted in a substantially reduction of human activities which in turn had significant effects on TSS concentrations in the Lower Min River. Official statistics data of Fuzhou shows that the lockdown has caused a significant fall in industrial production from a year-on-year perspective (http://tjj.fuzhou.gov.cn/zz/zxgz/tjyw/pmsl/). The value-added of large industrial enterprises of the study area decreased by ~16.3% from January to February (lockdown period), and then by ~10.4% (January–March) and ~5.9% (January–April). Despite a decline, the magnitude of the decline was gradually narrowed from February to April. This trend is highly consistent with TSS changes as shown in Fig. 4, both dropped rapidly in the February lockdown period and then had a slow recovery in March-April with gradual liftings of the restrictive measures, indicating a close relationship between industrial production and TSS concentrations.

Total Retail Sales (TRS) that are closely related to human social and economic activities also have a similar change. TRS decreased by ~27.2% (January–February), ~24.5% (January–March), and ~20.5% (January–April), when compared with the same periods of 2019 (http://tjj.fuzhou.gov.cn/zz/zxgz/tjyw/pmsl/), suggesting a great reduction of human social and economic activities in February and then a gradual restoration in March-April. This also resulted in a similar TSS change trend.

Although the Min River is no longer a main waterway for shipping, its northeastern portion, where Fuzhou’s largest port is located, still works for shipping. Monthly container shipping data (http://www.mot.gov.cn/tongjishuju/gangkouhuowulvkettl) shows a moderate correlation with the monthly average TSS ($R^2 = 0.532$) (Table S1). This suggests the shipping may have a moderate influence on TSS changes of the river as boat traffic can induce turbulence. Fig. 12 illustrates the moving boats or boat wakes in the northeastern portion of the river in the pre-lockdown, lockdown, and post-lockdown periods. Boat traffic almost stopped during lockdown and only a few boat wakes are visible. The number of boats increased after lockdown and some pinkish-red color appearing in the northeastern course in Fig. 11b suggests a relatively quick recovery in the river’s shipping in the post-lockdown period.

It could be argued that the changes of TSS could result from water flow changes rather than lockdown measures. However, according to the data of Zhuqi station, the water flow in lockdown period (February) was rising instead of falling, which was nearly one time higher than January (Table 1). Data shows that precipitation in February was also much higher than in pre-COVID-19 scenario (Table 1). Therefore, the sharp TSS decline in February could not be caused by rainfall and associated water flow changes. Correlation analysis between tidal fluctuation and TSS concentrations yields very low $R^2$ values of 0.072–0.117 (Table S2, Fig. S1). This also suggests that tidal fluctuation may have almost no impact on the TSS change.

Spatiotemporally, the impact of human activities is in line with spatial variations of TSS. The three composite scenario images and the four divided river portions (Figs. 9 and 10) all show a general eastward increase trend of TSS, where city center and industrial estates are located, mirroring increasing water pollution eastward synchronously with increasing human activities. This suggests that the TSS sources were mainly locally originated rather than the discharge from upstream areas as the west portion of the river is dominated with blue color

Despite no in-situ data, the measurements of the recalibrated Wen algorithms show a high agreement with those of the generic algorithms of Novoa and Nechad (reConf). This suggests that the developed recalibration method has the potential for extending the use of an existing algorithm solely based on the remote-sensing method, which may have practical advantages for the recalibration when in-situ measurements are not available.

The strong fit between the Novoa and the Wen algorithms suggests that the switch of band and criteria of the Novoa algorithm allows the algorithm to be more flexible to different TSS levels since the algorithm...
integrates different bands and was tested with a wide TSS dataset (2.6–1579 mg/L). Balasubramanian et al. (2020) and Tavora et al. (2020) compared several TSS-estimate algorithms and both achieved good results for the Novoa algorithm.

The underestimation of Nechad (R) and Nechad (G) probably results from the relatively narrow TSS range of the in-situ data used for testing the algorithm (1.24–110.27 mg/L), which may have caused the saturation as TSS concentration rise. Tavora et al. (2020) indicated that the reflectance in the visible spectral region could suffer from saturation in high TSS water conditions. In this Min River case, the Nechad (R) algorithm performed quite well in relatively low TSS concentration waters but not so well in high TSS waters. A similar result was also found in the comparison made by Balasubramanian et al. (2020), in which the Nechad algorithm worked well in the clean Type II green water but relatively poorly in the Type III brown water (see Fig. 3 of Balasubramanian et al. 2020 for the water-category classification). Novoa et al. (2017) also recommended the use of Nechad (R) for the water with a low to moderate TSS range (9.2–28.1 mg/L). Nevertheless, this study found that for relatively high TSS waters, an addition of Nechad (G) to Nechad (R) would solve this underestimate problem.

5. Conclusions

This paper examined the TSS dynamics in the Lower Min River during COVID-19 via recalibrated Wen algorithms and time-series satellite images. The good match-ups between the TSS measurements of the recalibrated Wen algorithms and those of Novoa and Nechad (reConf) algorithms suggest that the developed new prototype can extend the use of an existing algorithm.

This work finds a significant temporal variability of TSS concentrations in the study river courses during the study period. The lockdown measures of Fuzhou have resulted in a 48% fall in TSS concentrations in February 2020. The changes in the spatiotemporal patterns and magnitudes of TSS concentrations during the study period suggest that the industrial production, social and economic activities, and river’s shipping appear to be the main factors contributing to the river’s TSS decline in the lockdown period.

These findings are valuable for determining the role of human influences on the river-water quality as well as for locating the position of the main TSS sources. This high temporal resolution, remote sensing-based approach for TSS estimation can potentially support efforts to monitor and manage the water quality of river systems.

CRediT authorship contribution statement

Hanqiu Xu: Conceptualization, Methodology, Data curation, Validation, Visualization, Funding acquisition, Writing - original draft, Writing - review & editing. Guangzhi Xu: Data curation, Visualization. Xiaole Wen: Methodology. Xiujuan Hu: Data curation. Yifan Wang: Data curation.

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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Appendix A. Supplementary material

Supplementary data to this article can be found online at https://doi.org/10.1016/j.jag.2021.102301.

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