



Article Monitoring Total Suspended Sediment Concentration in Spatiotemporal Domain over Teluk Lipat Utilizing Landsat 8 (OLI)

Fathinul Najib Ahmad Sa'ad ^{1,*}, Mohd Subri Tahir ², Nor Haniza Bakhtiar Jemily ³, Asmala Ahmad ⁴ and Abd Rahman Mat Amin ¹

- ¹ Faculty of Applied Sciences, Universiti Teknologi Mara (UiTM), Cawangan Terengganu, Kampus Bukit Besi 23200, Malaysia; abdra401@uitm.edu.my
- ² Department of Business Management, Universiti Teknologi MARA (UiTM), Cawangan Pulau Pinang, Kampus Permatang Pauh 13500, Malaysia; mohdsubri@uitm.edu.my
- ³ Mechanical Section, Universiti Kuala Lumpur Malaysian Spanish Institute, Kulim Hi-Tech Park, Kulim 09000, Malaysia; norhaniza@unikl.edu.my
- ⁴ Faculty of Information and Communication Technology, Universiti Teknikal Malaysia Melaka (UTeM), Durian Tunggal Melaka 76100, Malaysia; asmala@utem.edu.my
- * Correspondence: najib4496@yahoo.com

Abstract: Total suspended sediment (TSS) is a water quality parameter that is used to understand sediment transport, aquatic ecosystem health, and engineering problems. The majority of TSS in water bodies is due to natural and human factors such as brought by river runoff, coastal erosion, dredging activities, and waves. It is an important parameter that should be monitored periodically, particularly over the dynamic coastal region. This study aims to monitor spatiotemporal TSS concentration over Teluk Lipat, Malaysia. To date, there are two commonly used methods to monitor TSS concentration over wide water regions. Firstly, field sampling is known very expensive and time-consuming method. Secondly, the remote sensing technology that can monitor spatiotemporal TSS concentration freely. Although remote sensing technology could overcome these problems, universal empirical or semiempirical algorithms are still not available. Most of the developed algorithms are on a regional basis. To measure TSS concentration over the different regions, a new regional algorithm needs to develop. To do so, two field trip was conducted in the study area concurrent with the passing of Landsat 8. A total of 30 field samples were collected from 30 sampling points during the first field trip and 30 samples from 30 samplings from the second field trip. The samples were then analyzed using an established method to develop the TSS algorithm. The data obtained from the first field trip were then used to develop a regional TSS algorithm using the regression analysis technique. The developed algorithm was then validated by using data obtained from the second field trip. The results demonstrated that TSS in the study area is highly correlated with three Landsat 8 bands, namely green, near-infrared (NIR), and short-wavelength (SWIR) bands, with $R^2 = 0.79$. The TSS map is constructed using the algorithm. Analyses of the image suggest that the highest TSSs are mainly observed along the coastal line and over the river mouth. It suggested that the main contributing factors over the study area are river runoff and wave splash.

Keywords: total suspended sediment; Landsat 8; algorithms; Teluk Lipat

1. Introduction

Total suspended sediment (TSS) is a water quality parameter that can be used to understand sediment transport, aquatic ecosystem health and engineering problems [1]. The changes in suspended sediment concentrations in the time and space domains are generally related to human and natural factors. Human factors consist of, for example, sand dredging activities, sea reclamation, shipping activities, construction, mining, and



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Copyright: © 2021 by the authors. Licensee MDPI, Basel, Switzerland. This article is an open access article distributed under the terms and conditions of the Creative Commons Attribution (CC BY) license (https:// creativecommons.org/licenses/by/ 4.0/). other human activities. Meanwhile, natural factors include rainfall rates, rising temperatures, winds, high waves, and all activities related to climate change. An excessively high total suspended sediments concentration will inhibit the penetration of light into water and disrupt photosynthesis [2], reduce the underwater vertical transmittance and phytoplankton productivity [2], affect the water columns and benthic processes [3], affect the nutrient dynamics [4] and pollutant movement [5,6]. Furthermore, an update of the total suspended sediments data is necessary to evaluate operational policies and provide technical guidance to the public, government, and private sectors in the utilization of coastal regions regarding environmental changes. Then, thorough studies should be done in any location directly exposed to the natural and human-induced suspended sediment.

Teluk Lipat, Malaysia, is located on the east coast of the Malaysian peninsular. This area is directly exposed to at least four suspended sediment-induced agents, such as river runoff, dredging activities and reclamation work. During the northeast monsoon season, it is also directly prone to high waves that commonly cause coastal erosion. Since Teluk Lipat is a human settlement with recreational and fishing locations for coastal anglers, it is very important to periodically monitor the spatiotemporal sediment concentration over this area. However, to date, there are no TSS data because there have been no relevant studies conducted in this location. It is well known that remote sensing sensors are widely used to monitor TSS concentrations all over the globe. The advantage of remote sensing technology is its ability to provide a historical dataset that can be used to track past events over a selected location. The remote sensing technique utilized an algorithm that was developed to measure TSS concentration over a selected region. To date, many TSS algorithms have been developed using numerous remote sensing methods, but the universal empirical or semiempirical algorithms are still unavailable [7–13]. In order to monitor the TSS concentration in space and time domain over this study area, an algorithm needs to be developed.

Recently, two methods have been used to monitor TSS concentration over a wide water region. The first is field sampling, which is known to be a very expensive and timeconsuming method. In this procedure, water samples are collected and, after that, sifted to extricate total suspended sediment. The sifted material is, at that point, dried, weighed, and isolated by sample value to get the total suspended sediment. This strategy gives exact and point-based estimation; in any case, spatial varieties are occasionally captured, and temporal resolution is frequently limited [3–5]. The second uses remote sensing technology that can monitor spatiotemporal TSS concentration for free. In this technique, researchers use a few wavelengths and then relate them to the field measured TSS to develop a TSS algorithm. The utilization of remote sensing technology can diminish costs and increase spare time [6]. To date, many algorithms have been developed using various remote sensing sensors, such as MODIS, SeaWiFS, MERIS and Landsat [14]. In this study, because Landsat 8 (OLI) with a medium spatial resolution (30 m), 185 km swath, 16-day revisit time and can be obtained for free, it was considered suitable for this study area [15].

Generally, there are two distinct approaches that could be utilized to obtained water quality parameters such as TSS and Chll-a utilizing remote sensing techniques. These two approaches are empirical or semiempirical and analytical or semi-analytical methods [16,17]. Empirical or semi-empirical methods apply simple or multiple regression between measured water quality parameters and remote sensing reflectance of certain wavelengths to obtain estimated water quality parameters. The disadvantage of this method is that it is regional in nature and quite costly, particularly during field sampling procedure implementations. Meanwhile, the simplicity and rapidity of the data processing with sufficient accuracy are their main advantages [13,18]. The second approach is analytical or semi-analytical. This method incorporates spectral optimization approaches and is based on solutions to the radiative transfer equations [18]. The inversion of the radiative transfer equations is mainly based on the neural network approach, utilizing a large database of radiative transfer simulations such as the Case-2 Regional/Coast Colour (C2RCC) algorithm [19], and by using a windows-based program for modeling and analyzing optical in situ measurements

in aquatic environments, such as the Water Color Simulator (WASI) [20,21]. In general, the advantages of this method are that the algorithms can be applied to the different water bodies, and the field sampling data are not required to develop the algorithm. However, the effectiveness of this kind of algorithm relies on the accuracy of the selected spectral models for the absorption coefficients of individual constituents that are present in the water; furthermore, this is a time-consuming process [18]. In general, C2RCC only works well in optically deep water, whereas water constituents such as CDOM and sediment are neglected and WASI requires more experience and supervision in defining the initial values of the parameters [21]. With the intention being to regionally monitor TSS with low cost, simple and rapid data processing, and with a sufficiently accurate empirical method, this method will be utilized in this study.

Theoretically, a single band could be used to develop the robust and sensitive TSS algorithm; if an appropriate band is chosen [3,22,23], successfully developed robust linear algorithm between TSS and red wavelength (0.62–0.67 μ m) of the MODIS Terra sensor have been demonstrated over the Gulf of Mexico. However, the developed algorithm is easy to saturate when the TSS increases significantly [24]. Due to the complexity of the water body, such as the color and size of the particles, the use of more than one wavelength is more practical [22,23,25] and less sensitive to backscatter variability [26]. Recently, many researchers have developed robust and sensitive TSS algorithms by utilizing several remote sensing bands ranging from blue to the near-infrared spectrum of lights over different regional areas. Since the late 1970s, the marvel of the total suspended sediment incrementally increasing with the brilliant vitality developing from the surface waters within the visible and near-infrared (NIR) districts of the electromagnetic range has been noted [27].

Many researchers are as of now fascinated by estimating the total suspended sediment concentration by utilizing remote sensing technology. To realize this objective, field and remote sensing information must be utilized. In common, researchers calibrate remote sensing information using field information to create an algorithm. Most researchers have proposed a relationship between reflected solar radiance measured by satellite-based rebellious and field-measured total suspended sediments inside a wide range of inland and coastal waters. In previous studies, total suspended sediment remote sensing models were used by previous researchers [28–31]. However, the developed algorithms are highly regionally dependent. It is a drawback that the developed algorithm can only be applied over the study area and cannot be used in other regions. This is due to the differences in water constituents, such as sediment color, size shape and even concentration, that could influence light absorption, scattering and reflectance. That is why regional TSS algorithms must be developed. Table 1 shows examples of a TSS algorithm that was developed by using various remote sensing sensors and bands around the globe. The number of bands used varies from single-band [3,32], two-band [28,30,33,34] and [1,29,35–37] and [38], threeband [39] to four-band algorithms [23]. Recently, it was found that the difference in water constituents and seasonal dependence does not solely depend on geographical regions [23]. **Table 1.** Review of previous TSS algorithms. For TM 4 and TM 5, the wavelength of B1,B2,B3 and B4 are 0.45–0.52, 0.52–0.60, 0.63–0.69, 0.76–0.90 μ m, respectively. For Landsat 8, the wavelength for B2,B3,B4 and B8 are 0.45–0.51, 0.53–0.59, 0.64–0.67, 0.50–0.68 μ m, respectively. For MSI (MultiSpectral Instrument), the wavelength for B5 is 704.5 nm. For OCM-2, the wavelength for B5 and B6 are 546–566 and 610–630 nm, respectively. For MODIS Aqua, the wavelength for B1 is 620–670 μ m. For SPOT, the wavelengths for B2 and B4 are 0.61–0.68, 1.58–1.75 μ m.

Sensor	Bands	TSS Algorithm	Study Area	References
TM 5	1, 2, 3, 4	$\begin{split} TSS &= 361.89 \ Rrs(0.69) - 1018.25 \ ((Rrs0.60)/Rrs(0.69)) - \\ 1919.21((Rrs(0.52)/(Rrs(0.69)) - 26.15(Rrs(0.69)/Rrs(0.90))) - 182.90 \ Rrs(0.52) \\ &+ 28855.76 \end{split}$	Florida USA	[23]
OLI 8	3,4	log10 (TSM) = 1.291 + 63.85 Rrs(0.67) - 50.46 Rrs(0.59)	Zhuhai-Macau Bridge Region, Hong Kong	[38]
TM 5	2, 3	$\ln(SSC) = (4.38 ((Rrs(0.69)/Rrs(0.60))) - 0.75$	Araguaia River–Brazil	[1]
MSI	5	TSM = 0.7198 exp[329.73 Rrs(704.5)]	The Pertusillo Lake Case Study (Italy)	[40]
OLI 8	3, 4	$TSS = 172.19 \ln 2[Rrs(0.59)/Rrs(0.67)] - 190.809 \ln[Rrs(0.59)/Rrs(0.67)] + 61.6$	Inland Reservoir, South China	[37]
OCM-2	5,6	TSS = 5846.1((Rrs(566)/Rrs(630)) - 516.82	West Bengal	[36]
OLI	2, 3	$\log TSS = 1.5212[\log(Rrs(0.51)/\log(Rrs(0.59))] - 0.3698$	Indonesia	[29]
OLI	2, 3, 8	$TSS = -191.02 \operatorname{Rrs}(0.51) + 36.8 \operatorname{Rrs}(0.59) + 172:66 \operatorname{Rrs}(0.68) + 4.57$	Xin'anjiang Reservoir	[31]
TM 4	4	$TSS = 229,457.695 \operatorname{Rrs}(0.90)^2 + 146.462 \operatorname{Rrs}(0.90) + 5.701$	Bohai Gulf	[32]
TM 5	2, 3	$\log \text{TSS} = 6.2244 (\text{Rrs}(0.60) + \text{Rrs}(0.90) / [\text{Rrs}(0.60) * \text{Rrs}(0.69)] + 0.892$	Yangtze estuary	[35]
Modis Aqua	1	TSM = -1.91 (1140.25)Rrs(670)	Northern Gulf of Mexico	[3]
SPOT	2, 4	TSS = 29.022 exp 0.0335((Rrs(1.75)/Rrs(0.68))	Gironde estuaries	[28]
TM 5	1, 2	TSS = 16.826 - 5.2369 ((Rrs(0.52)/Rrs(0.60))	Moroton Bay	[30]
TM5	1, 2	ln TSS = $2.71 ((\text{Rrs}(0.52)/\text{Rrs}(0.60))^2 - 9:21 ((\text{Rrs}(0.52)/\text{Rrs}(0.60)) - 8.45)$	Enid Reservoir in north-central Mississippi	[34]
TM 5	1, 3	TSS = 0.0167 exp[12.3 (Rrs(0.69)/Rrs(0.52)]	Embayment of Lake Michigan	[33]

The aim of this study was to monitor the spatial and temporal TSS concentration over Teluk Lipat, Malaysia. The remote sensing technique was used in this study. To fulfil the aim, three objectives were set up. The first objective was to develop and validate the regional TSS algorithm utilizing the Landsat 8 (OLI) dataset. The second objective was to develop the TSS concentration map of the study area. The third objective was to analyze and investigate the TSS concentration in the space and time domains. To achieve the above-mentioned objective, two field trips were conducted in the study area. The water sample was then processed in the lab to obtain the measured TSS. The relation between the measured TSS and the Landsat surface reflectance was determined by using a regression technique. The algorithm was developed empirically by using three Landsat 8 (OLI) bands: band 3 (Green, $\lambda = 0.53-0.59 \mu m$), band 5 (near Infrared, $\lambda = 0.85-0.88 \mu m$) and band 6 (short-wave infrared, $\lambda = 1.57-1.65 \mu m$). A TSS map was then created by applying the developed algorithm. The map was then analyzed to extract the required information. Since the algorithm was only validated with the data that was acquired over the study area, the application of the developed algorithm was limited to Teluk Lipat, Malaysia.

2. Materials and Methods

2.1. Study Region

Teluk Lipat, as shown in Figure 1, is located in Terengganu, Malaysia. In 2011, severe erosion occurred along this beach due to a high tidal surge phenomenon. The tidal wave ravaged the wall road and crumpled the trees along the coastline. This beach extends approximately 13 km to Kuala Dungun from Bukit Bauk, which is in the south. A university, a school and residential housing are located along this coastline. The study region covers the latitude range of $4^{\circ}39'5.12''-4^{\circ}48'21.74''$ north and the longitude range of $103^{\circ}23'28.33''-103^{\circ}30'12.11''$ south.



Figure 1. Study area.

2.2. Data Sampling and Analysis

Two field trips were conducted in the study area. The first and second field trips were conducted on 28 March 2018, and 16 April 2019, respectively. During the first campaign, 30 in situ samples were collected from 30 sampling points. Meanwhile, 30 water samples were obtained from the second field trip collected from 30 stations. The distance between each sampling point is 1 km. Both field trips were conducted concurrently with the passing of Landsat 8 over the study area. Sample testing was conducted 2 h before and 2 h after the passing of Landsat 8 to maintain a strategic distance from the impact of TSS changeability related to tides and nearby streams [5,41]. Water samples, approximately 1.5 L, were collected inside a profundity of 1 m, and sample concentrations were measured employing a pondering method [42,43]. The TSS concentration was calculated based on the difference of a filter paper before (without TSS residue) and after (with TSS residue) the filter was dried. A Sartoris MGF glass fiber filter (47 mm diameter) was used. In this study, a well-mixed sample was filtered through a weighed standard glass-fiber filter, and the TSS residue was retained on the filter. Before removing the filter from the filtration apparatus, 3 successive 10 mL volumes of deionized water were used to wash the filter, allowing complete drainage between washings. Then, the filter was removed and dried in an oven at 103–105 °C for 1 h and left it cool in desiccators. The cool filter paper with TSS residue was weighed using a weighing balance. The process of heating, cooling, and weighing was repeated until a constant weight was obtained or until weight change was less than 4% of the previous weighing or 0.5 mg—whichever was less. The TSS concentration in the water sample was calculated using the following formula:

$$TSS (mg/L) = \frac{(A - B)}{Volume of filtered sample (L)}$$
(1)

where,

A = mass of filter + dried residue (mg), P_{i} = mass of filter (term quotiekt) (mg)

B = mass of filter (tare weight) (mg)

2.3. Landsat 8 Dataset

This study utilized Landsat 8 level 1 TP products. Level 1 TP is the most elevated quality of level 1 product that is reasonable for pixel-level time series analysis. The image

acquired on 28 March 2018, was used for model implementation. Meanwhile, the image acquired on 16 April 2019, was elaborated for validation purposes. Images acquired on 23 November 2018, 17 September 2017, 26 June 2016, and 23 July 2020, were used to develop the TSS concentration map over the study area. These images were carefully selected to ensure minimal cloud cover. All images were downloaded from the EarthExplorer website and, after that, processed using ENVI 5.1. Atmospheric correction was executed to eliminate the effect of the atmospheric haze present in the image. A few atmospheric corrections are accessible. The DOS atmospheric method was used in this study due to its effectiveness in eliminating atmospheric hazards. This atmospheric correction method has been widely used by many researchers in order to obtain water quality parameters around the globe [3,44–50]. To realize this objective, radiometric calibration was performed to convert radiance, and the surface brightness was measured directly by the satellite, to the unit with less surface reflectance utilizing metadata which approximated the procurement time and sun elevation when the image was taken [50]. From that point, the DOS calculation was performed. DOS searched each band for the darkest pixel value. Expecting that dark objects do not reflect light, any esteem more prominent than zero must have come about from atmospheric scattering. Such scattering was removed by subtracting this esteem from every pixel within the band. This basic procedure is compelling for haze correction in multispectral information, but ought to not be utilized for hyperspectral information. Clouds that were shown within the image were masked utilizing Landsat 8 cloud mask product. During this process, the classification of pixel QA bands was analyzed. The pixel QA band quality conditions are expressed as a cloud confidence level. In this study, only pixels with a clear condition (no cloud), low cloud confidence (LCC) and low cloud shadow (LCS) were used in the cloud masking method [32,51,52].

2.4. Matchup

In this study, three methods were tested for matchup analysis: 1×1 , 3×3 and 5×5 pixel windows. In the 1×1 pixel method, the station coordinate was directly matched to the associated pixel. To improve the interpretability and quality of the remote sensing images, radiometric correction was performed by comparing the coordinates on Landsat 8 products with the images on Google Maps. The comparison showed that the coordinates exactly matched the Google Map coordinates. The surface reflectance values of the 3×3 and 5×5 -pixel methods were averaged to the pixel grid, surrounding the sampling point to diminish per-pixel noise.

2.5. Accuracy Assessment Method of Models

In order to validate the accuracy of the TSS spectral models, atmospheric correction and mapping of TSS concentrations, the most frequently used methods including the determination coefficient (R^2), the RMSE and mean relative error (MRE), were also used in the study for the convenience of comparison by different readers.

RMSE =
$$\sqrt{\frac{\sum_{i=1}^{i=n} (x_i - x'_i)^2}{n}}$$
 (2)

$$MRE = \frac{\sum_{i=1}^{i=n} \left| \frac{x_i - x_i}{x_i} \right|}{n} \times 100\%$$
(3)

where x_i is the in-situ value, x'_i is the estimated value, *i* is the *i*th element, and *n* is the number of elements. Figure 2 summarized the flowchart of the data processing scheme of this study.



Figure 2. Data processing flowchart.

3. Results and Discussion

3.1. Pixel Dimension

Regression was conducted by utilizing the three windows $(1 \times 1, 3 \times 3 \text{ or } 5 \times 5)$ to determine which one was the best for this study. The results confirmed that the 3 × 3 window achieved the best R² value compared with those of the two other windows. Table 2 shows the result of the application of different windows. It can be clearly seen that the lowest and highest R² values were obtained by the 1 × 1 and 3 × 3 windows, respectively. The R² value for each window is given by 0.62, 0.79 and 0.77, respectively. This result indicated that the regression coefficient decreased when the window was larger than 3 × 3. Furthermore, 3 × 3 windows instead of 1 × 1 and 5 × 5 windows have been widely used and discussed by previous researchers [34,53–56].

Table 2. Regression analysis for different windows.

Window	Algorithm	R ²
1 × 1	y = 659.26x - 468.15	0.62
3 imes 3	y = 564.68x - 881.98	0.79
5×5	y = 557.53x - 358.4	0.77

3.2. TSS Concentration Algorithm

The TSS concentration retrieval algorithm was created utilizing the regression algorithm between the in situ TSS concentration and the in situ-measured remote sensing reflectance, Rrs (λ), based on single-band, two-band, and three-band proportion reflectance combinations. The in situ TSS concentration and in situ Rrs (λ) were utilized as the dependent and independent variables, respectively. Among the few combinations, the most elevated relationship between the two variables was shown by the most elevated coefficient of determination (R²), which was chosen as the retrieval algorithm. The regression algorithm for TSS concentrations is displayed in Table 3.

Table 3. Regression results of TSS against several Landsat 8 bands. B_1 - B_7 represent the designated band of Landsat OLI. The wavelength for seven spectral Landsat bands (B_1 - B_7) used in this study are 0.43–0.45, 0.45–0.51, 0.53–0.59, 0.64–0.67, 0.85–0.88, 1.57–1.65 and 2.11–2.29 μ m, respectively.

Band	Best Fit Equation	R ²
Single		
B ₁	$TSS = -114.26 \operatorname{Rrs}(B_1) + 14.859$	0.0607
B ₂	$TSS = -91.935 Rrs(B_2) + 15.012$	0.0505
B ₃	$TSS = -50.83 \text{ Rrs}(B_3) + 13.746$	0.0414
B_4	$TSS = -88.187 \operatorname{Rrs}(B_4) + 13.782$	0.0767
B5	$TSS = -74.862 Rrs(B_5) + 13.626$	0.0815
B ₆	$TSS = -124.15 Rrs(B_6) + 14.25$	0.1061
B ₇	$TSS = -156.87 \text{ Rrs}(B_7) + 14.122$	0.1092
Two band		
B_6/B_7	$TSS = 15.55 Rrs(B_6/B_7) - 9.1884$	0.0605
B_6/B_5	$TSS = 0.2873 \text{ Rrs}(B_6/B_5) + 11.304$	0.0001
B_3/B_4	$TSS = 4.131 \ Rrs(B_3/B_4) + 4.3269$	0.1131
Three band		
TSS/B ₁ vs. B_2/B_3	TSS= Rrs $(B_1)[-2502.5 \text{ Rrs}(B_2/B_3) + 2330]$	0.2819
TSS/B ₆ vs. B_4/B_5	$TSS = Rrs(B_4)[1426(B_5/B_6) - 745.37]$	0.3707
TSS/B ₆ vs. B ₃ /B ₅	$TSS = Rrs (B_6)[564.68 Rrs(B_3/B_5) - 381.98]$	0.7900
TSS/ B_7 vs. B_3/B_4	$TSS = Rrs (B_{7})[566.47 Rrs(B_3/B_4)2 - 635.62 Rrs(B_3/B_4) + 116.79]$	0.7619
TSS/ B_6 vs. B_3/B_4	$TSS = Rrs (B_6)[399.41 Rrs(B_3/B_4)2 - 439.7 Rrs(B_3/B_4) + 97.191]$	0.7570

As shown by Table 3, the highest R^2 value for single-band regression obtained by SWIR (short-wave infrared) wavelength with the value is 0.1092. Meanwhile, the lowest was obtained by the blue band, with $R^2 = 0.0505$. Meanwhile, the result of two band shows that the lowest R^2 obtained by the ratio of SWIR/NIR bands with the value is 0.0001 and the highest value obtained by ratio green to red bands with the R^2 value is 0.1131. The above result shows that the regression between TSS/Rrs(B₆) in Teluk Lipat waters was strongly associated with Rrs(B₃)/Rrs(B₅), with the highest coefficients of determination $R^2 = 0.7900$ with the standard error of estimate (SEE) being 119.804.

Figure 3 shows the plot of TSS over band 6 against $\text{Rrs}(B_3)/\text{Rrs}(B_5)$. The R² and adjR^2 for this plot are given by 0.79 and 0.77, respectively. As compared to the algorithm developed by [32], this result fully utilized the different sensitivities of the green, NIR and SWIR bands to TSS concentrations, as proven by many previous studies [25,57]. Furthermore, the effectiveness of NIR wavelengths to assess TSSs is well documented [58]. Thus, these band combinations were selected for estimating TSS in Teluk Lipat. The equation is given by

$$\Gamma SS = x_1 \left[a \left(\frac{x_2}{x_3} \right) - b \right] \tag{4}$$

where,



Figure 3. Regression model for TSS Concentration Over Study Region.

 $x_1 = \text{Rrs}(B_6)$ $x_2 = \text{Rrs}(B_3)$ $x_3 = \text{Rrs}(B_5)$ a = 564.68, b = 381.98

3.3. Validation of the TSS Concentration Model

To predict the TSS concentration using the Landsat 8 OLI data, the atmospherically corrected band ratio of the validation points coordinates obtained from the second field trip on 16 April 2019 were used. Only seven points from the second campaign were used for validation. This is because 27 sampling points were covered by clouds and failed the cloud masking process. From the previous researcher, the number of points for validation is considered acceptable if it is comparable to the test point data [59-61]. The reflectance ratios of the validation points were given as the input to the prediction model Equation (4) and the model output was considered as the predicted TSS concentration values of the validation points (satellite-derived). The regression model statistics between laboratoryderived in situ TSS concentration value and model-fitted TSS concentration value of the validation points revealed a strong correlation $R^2 = 0.8406$ with an RMSE of 1.50 mg/L and MRE = 9.14%. The testing of the accuracy level of TSS concentrations from satellite data within situ data is presented in Figure 3. The root means square error (RMSE) has been used as a standard statistical metric to measure model performance in meteorology, air quality, and climate research studies [62–64]. The mean relative error (MRE) is another useful measure widely used in model evaluations. While they have both been used to assess model performance for many years, there is no consensus on the most appropriate metric for model errors. In the field of remote sensing, many present the RMSE as a standard metric for model errors [62-64], while a few others choose to avoid the RMSE and present only the MRE, citing the ambiguity of the RMSE claimed by [65–69]. While the MRE gives the same weight to all errors, the RMSE penalizes variance as it gives errors with larger absolute values more weight than errors with smaller absolute values. The calculation results of the accuracy test between the measurement of in situ data with the prediction of the distribution of TSS are distinguished by RMSE and MRE. Based on Figure 3, the root mean square error in the statistical test was 1.50 mg/L. The size of the error is shown based on the difference between the value of the estimated data and in situ data. The greater the value of RMSE means that the results of the estimation model produced were increasingly inappropriate when compared to in situ. In this study, the RMSE value was smaller than the MRE value shown in Figure 4, which indicated that this model was accurate. There is no size or limit for determining how big the RMSE value is, but the condition is that the RMSE value should not be greater than the MRE value. The mean relative error (MRE)

value of 9.14% indicated the error rate expressed in percent (%). Error values (MRE) below 30% could be used as proof of the validity of the model [70].



Figure 4. Validation graph of the TSS Concentration.

3.4. TSS Concentration Mapping

The above-developed algorithm was tested over the study for the number of Landsat datasets. The images were carefully selected and processed to produce the TSS map. Figure 5a–d show the Landsat true color images (Red: Band 4, Green: Band 3, Blue: Band 2) acquired. Meanwhile, Figure 5e–f shows the TSS concentration map derived from Landsat dataset utilizing the above-mentioned algorithm.



Figure 5. Cont.



Figure 5. (**a**–**d**) Colored RGB image acquired from Landsat 8 dataset for the date of 23 November 2018, 17 September 2017, 26 June 2016, and 23 July 2020. (**e**–**h**) Corresponding TSS map for given date.

Figure 5a,e show a Landsat true color image and TSS map constructed over the study area for 23 November 2018. Points A, B, and C represent river estuary, coastal, and open water areas. It can be clearly seen that the highest TSS is observed along the coastal line, with the highest value being 15.99 mg/L, covers an area of 9.43 km². The lowest TSS concentration is observed at point C, as represented by purple. The moderate TSS concentration, the yellowish color in Figure 5e, covers an area of about 23.11 km².

Figure 5b shows true color images over the study area for the date of 17 September 2017. It can clearly be seen that the sediment plume at the river mouth appears to be moving north. Meanwhile, Figure 5f shows the TSS concentration produced from the developed algorithm for the abovementioned date. The range of TSS concentrations for this date is 0 to 10.09 mg/L. The sediment plume shown in the true color image was successfully mapped. The concentration of this plume is between 8.06 and 10.09 mg/L, as shown in the legend, and covers an area of 7.00 km². The same sediment concentration was observed along the coastal line. The highest TSS concentration is at point A, located at the river mouth. The low TSS observed at points B and C are represented by the bluish and purple color.

Figure 5c,g are the images obtained over the study area on 26 June 2016. In Figure 5g, the variation of TSS concentration along the coastal line can be clearly seen. The highest TSS concentration is observed at point B and along the coastal line. At this point, the highest TSS concentration is about 15.90 mg/L. At point A, a moderate TSS concentration can be seen, as represented by the yellow and greenish color. Far from the coastal line as at point B, the TSS concentration decreased gradually. For this date, the TSS concentration varies from 2.07 to 15.90 mg/L.

Figure 5d shows the RGB image for the date of 23 July 2020. The highest TSS concentration is 14.07 and covers an area along the coastal line, particularly over the river estuary, point A. A moderate TSS concentration was observed at points B and C. The TSS value at points C and B is 9.00 and 11.00 mg/L, respectively, as shown in Figure 5h. Visual observation shows that the sediment appeal drifted to the south.

4. Conclusions

The main intention of this study monitors spatiotemporal TSS concentration over Teluk Lipat Malaysia utilizing Landsat 8 datasets. The three earlier stated objectives were successfully achieved. In this study, the regional TSS algorithm with regression coefficient, $R^2 = 0.79$ utilizing three Landsat 8 channels (Green, NIR, and SWIR), was successfully developed and validated. The regression statistics model between laboratory-derived in situ value and model-fitted TSS concentration value of the validation points revealed a strong correlation with $R^2 = 0.8406$, RMSE of 1.50 mg/L, and MRE = 9.14%. The TSS map is constructed using the developed algorithm. Analyses of the map suggested that most of the suspended sediment was distributed along the coastal line and over the river mouth. It is suggested that the TSS in this area are mostly transported by the river and induced by the wave. Others identified that the suspended, induced factors are sand dredging activities and embarkment projects. This study successfully and clearly determined the direction of sediment transport. Thus, these variables ought to be considered in future studies to make strides in the adaptiveness of the demonstrated assistance. TSS in coastal waters continuously and significantly shifts in the daytime due to water runoff, diurnal tidal periodicity, human exercises, and coming within the deficient, worldly determination of these sensors. This issue postures one of the restrictions in giving a high-accuracy strategy for checking TSS concentration in coastal ranges. Therefore, the researchers suggest that a similar study needs to be conducted in a different location for comparison. This study suggests that a similar study in Penang, Malaysia, would be useful as it is currently active in the reclamation activities and has higher effects on coastline changes, socio-economic and development issues. The basic comparison may provide a better understanding of the aptness of the assessment method of models.

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