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Original research article

An Alternative Model to Estimate Total Suspended Solids Concentrations using Landsat 8 Imagery in Indonesia

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ABSTRACT

A regular monitoring program of water quality is generally performed using a direct measurement method, which requires substantial efforts and resources. These issues can be minimised using several options, one of which is Landsat 8 (L8). This imagery has been broadly used to measure several water quality parameters, especially Total Suspended Solids (TSS) concentrations, even in Indonesia. This paper will compare several models from previous studies and a modified model generated using data from various sites. The comparison is based on their competencies to estimate TSS concentrations. The competencies are determined by the coefficient of correlation (r), correlation of determination (R2), and residual standard error (RSE) parameters as these three parameters are strongly correlated, generally applied, and provide distinctive determinations. The best model should have the highest r and R2 values, while the RSE value should be the lowest. The results imply that TSS model 4 generated in this study provides comparable results with TSS model 1, which has been generally used in Indonesia and provided favourable results. Thus, it can be an alternative model to estimate TSS concentrations in Indonesia.

1. Introduction

Water is a foundation element for living beings, for humans in particular. There are numerous problems in water resources, water quality in particular. In Indonesia, fifteen major lakes have extreme eutrophication conditions. Moreover, only four out of 44 large rivers are in favourable conditions [1]. These conditions imply the water quality conditions are severe in Indonesia. Thus, a periodic water quality monitoring program should be implemented to control water quality conditions in a particular area.

However, this program involves great effort, mainly if the direct measurement method is applied. Although this method can achieve real-time data, it is inefficient and ineffective. It has limitations, such as 1) abundant resources (cost, time, and labour) are needed, 2) temporal and spatial variations are impossible to be monitored, 3) it must be a challenge to monitor inaccessible areas, and 4) errors in accuracy may occur in field samplings and laboratory examinations [2]–[4]. A remote sensing system can be the alternative for this issue. This system has been broadly applied for monitoring water quality for more than four decades [2]–[4]. There are several advantages proposed by it, such as 1) the possibility to perform spatial and temporal monitoring in an entire waterbody, 2) fully-synchronised water quality data of abundant waterbodies, 3) the availability of entirely historical records and trends of water quality data, and 4) possibility to determine the best time to do field surveys and the best location to take samples. These points show that the system has several advantages. Thus, it can be an alternative to performing a water quality monitoring program.

Water quality has several parameters. Water clarity affects the photosynthesis process in a waterbody as the sunlight is affected by water clarity to penetrate water. A clear waterbody implies an excellent water quality status. Suspended materials affect water clarity level; the higher suspended material concentrations in a waterbody, the murkier it becomes. Thus, sunlight is hard to penetrate water to engage in photosynthesis. The materials are usually stated as total suspended solids (TSS), measuring their concentration [2]. Therefore, determining this parameter in a particular waterbody is vital to ensure its water quality.

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There are numerous sensor types in remote sensing. One of which is Landsat 8 (L8). Several reasons why this sensor is chosen are presented as follows. Firstly, a strong correlation is present between TSS and L8 because TSS is optically active (can absorb and scatter light) [2]. Secondly, TSS determination with L8 has been proved by several studies providing promising results [2], [5]–[16]. Thirdly, this sensor has also been proven to have better capabilities to determine TSS concentration than different sensors, such as Worldview-2, Sentinel-2, Planetscope, and the older version of L8 or Landsat 7 [17]–[21]. Lastly, this sensor presents favourable results in determining TSS concentration with an accuracy of more than 90% [2], [9]–[16]. Thus, these facts imply that TSS concentration can be effectively determined using L8.

This paper will generate a new modified model using data from several previous studies to determine TSS concentration. Additionally, a comparison between the capability of the new modified model and previous models from previous studies (which only use data from a specific location) will be performed using data from various locations. The comparison will decide the best model to estimate TSS concentration in Indonesia. Moreover, the result will present a consideration of each model's capability to be applied in several locations in Indonesia.

2. Method

The steps required to reach the aims stated in the introduction (**Figure 1**) are:

2.1. *Data Collection*

Data collection is the first step of this study. Two data types are used in this study: data of TSS field measurement and L8 image. Firstly, a model is generated using TSS field measurement data from several previous studies on the northern sea of Java island, Indonesia (**Figure 2**). Meanwhile, the performance ability of the TSS models is evaluated and compared using data from various places and times (**Figure 3**). Although the data come from multiple sites and times, this variousness has been proven not to affect the analysis and still provides favourable accuracy results (> 90%) and minimal errors (< 14%) [2], [4], [12], [22]. These points indicate applying L8 using data from various places and time is not a major issue. This study uses nine locations with 159 sampling points (134 points to generate models and 25 points to evaluate the models). The data are mostly surrounding Surabaya city, East Java Province and Semarang city, Central Java Province [8], [12]–[14], [23]–[27]. Furthermore, the consistency in estimating TSS concentration using L8 of the most excellent model generated in this study and previous models (models coming from several previous studies [12]–[14] and presented in Equations 3-4) will be compared, and their accuracy will be evaluated. Data from four locations with 57 sampling points are used for these analyses [28]–[31]. The second dataset (L8 data) are free-downloaded and collected from the USGS website [32]. The L8 images and their metadata (Calibration Parameter Files or CPFs), used for the correction processes, are included in the downloaded datasets. These data have already been geometrically and radiometrically calibrated [33]–[35]. Thus, they are typically ready to use. However, as

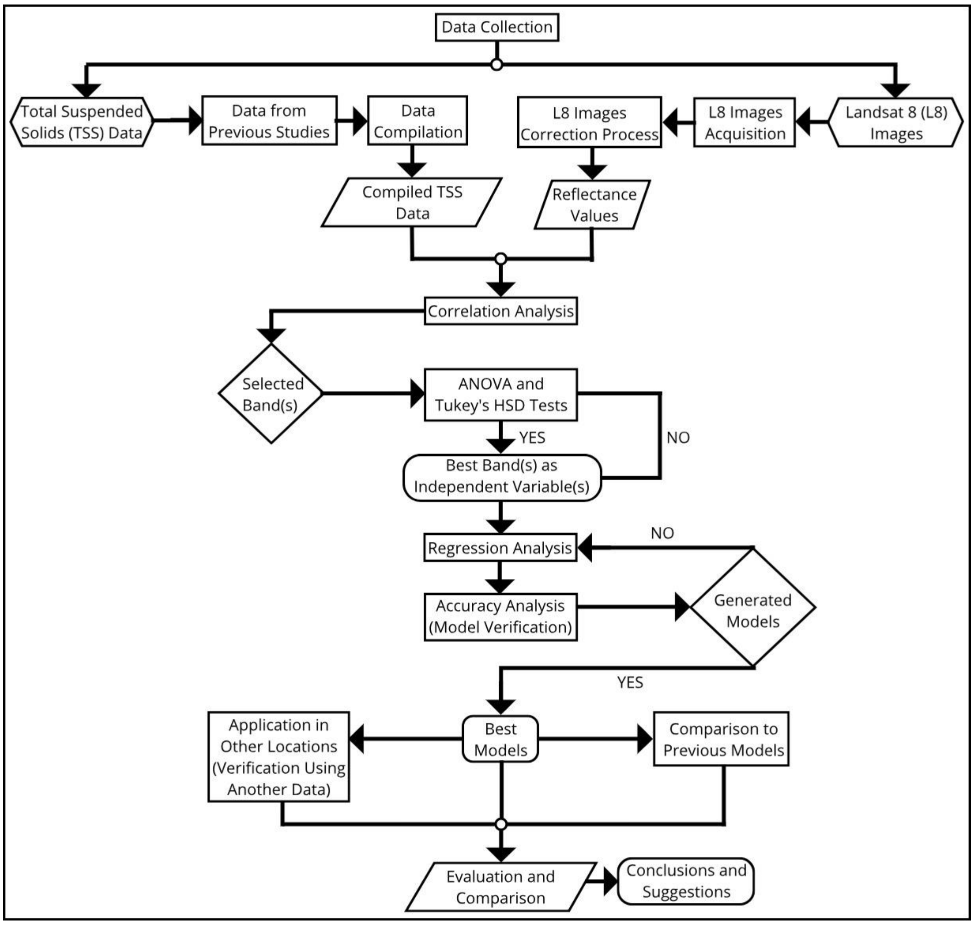

Figure 1. Research procedures

the images are in Digital Number (DN) units, they need to be converted to the Top of Atmosphere (TOA) reflectance for correction and interpretation processes [35]. The operations are performed using the QGIS application with two equations involved. Rescalling the DN to TOA is performed using the Eq (1).

$$\rho_\lambda{}' = M_\rho \cdot Q_{cal} + A_\rho \tag{1}$$

where: $\varrho\lambda'$ is the TOA Planetary Spectral Reflectance, without solar angle correction (Unitless), $M\varrho$ is the scaling factor of radiance multiplicative for the band (REFLECTANCEW_MULT_BAND_n from the metadata), $A\varrho$ is the scaling factor of radiance additive for the band (REFLECTANCEW _ADD_BAND_n from the metadata), while Qcal is the pixel value of Level 1 in DN.

Next, the rescaled results are used to calculate the true TOA reflectance values the Eq (2).

$$\rho_\lambda = \frac{\rho_\lambda{}'}{cos(\theta_{SZ})} = \frac{\rho_\lambda{}'}{sin(\theta_{SE})} \tag{2}$$

where: ϱ_λ is the TOA Planetary Reflectance, θ_{SE} is the local sun elevation angle (SUN_ELEVATION from the metadata), while θ_{SZ} is the local solar zenith angle (90° - θ_{SE}).

2.2. *Independent Variable Determination*

The independent variables (the best band or band ratio) for model generation are determined in the second step. The first four bands of L8 (Band 1 – Band 4 or B1 – B4) will be used, although there are 11 L8 bands. This decision is made as these bands are sensitive to TSS [2], [9]. Furthermore, several combinations between B3 and B4 are used as these bands are highly correlated to TSS based on correlation analysis. Moreover, the B2/(B2+B3+B4) ratio and its combinations are also used [12]. This process uses a parametric statistical test as the available data are more than 30 samples and are ratio data type [36]–[38]. Moreover, this method has been used by several studies to correlate water quality parameters using L8 images by applying the Pearson method [9], [39]–[41]. The correlation coefficient (r) is used for this process by selecting the highest values, while the classification is detailed in **Table 1**. The one-way analysis of variance (one-way ANOVA) and Tukey's HSD (Honest Significant Difference) test are used to evaluate the selected independent variables by determining their significance [37], [42], [43]. The variables with the highest significance are used to generate models. Performing the tests is aided by an application called RStudio. This application has several benefits: 1) numerous studies in various fields have been used this application, 2) supports are available and easy to access, 3) it is an open-source application, and 4) the developer and user base is huge and expanding [44]. Therefore, it is used to help perform the tests.

2.3. *Independent Variable Determination*

The regression analysis for model generation is used in the third step. The ordinary least square (OLS) and generalised least square regression (GLS) methods are used because they have been broadly adopted to generate TSS models with L8 images. The GLS method generally donates more sophisticated estimation results than the results using the OLS method, which can only give an accuracy of less than 80% [12]–[14], [46]–[50]. Therefore, this study uses the GLS method to generate TSS models. **Figure 2** shows the data used for this analysis. The coefficient of correlation (r), correlation of determination (R2), and residual standard error (RSE) parameters are used to evaluate the models' capability to estimate TSS using the accuracy analysis. **Figure 2** show the TSS sampling points to evaluate all models. **Table 1** presents the classification for r, while **Table 2** shows the classification for R2. The tables indicate that the best model should be the highest in r and R2, and the lowest in RSE, where this parameter indicates the model's error value [51]. This step also uses RStudio to help with the analyses. Therefore, the most sophisticated TSS model is present.

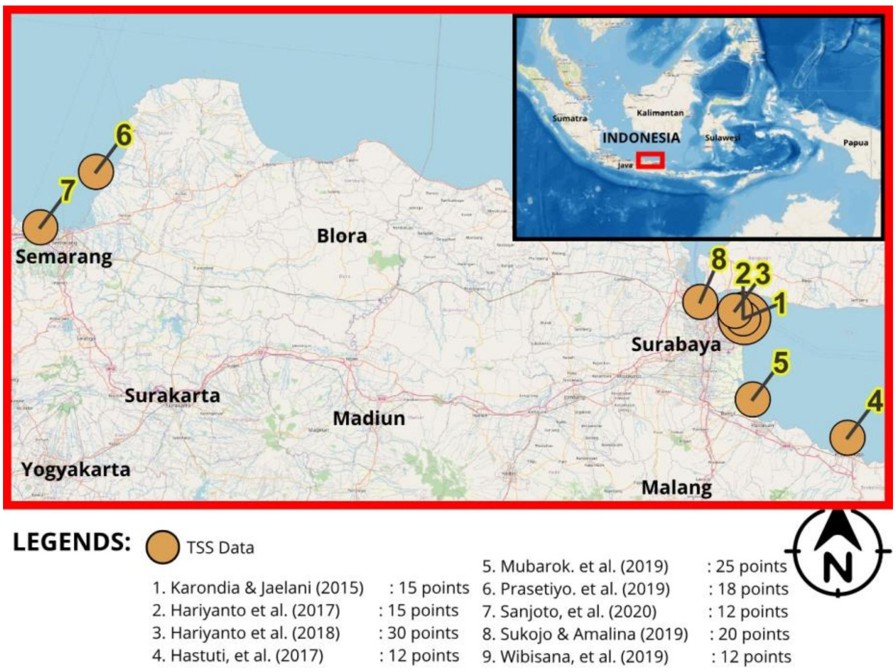

Figure 2. TSS sampling points to generate a TSS model

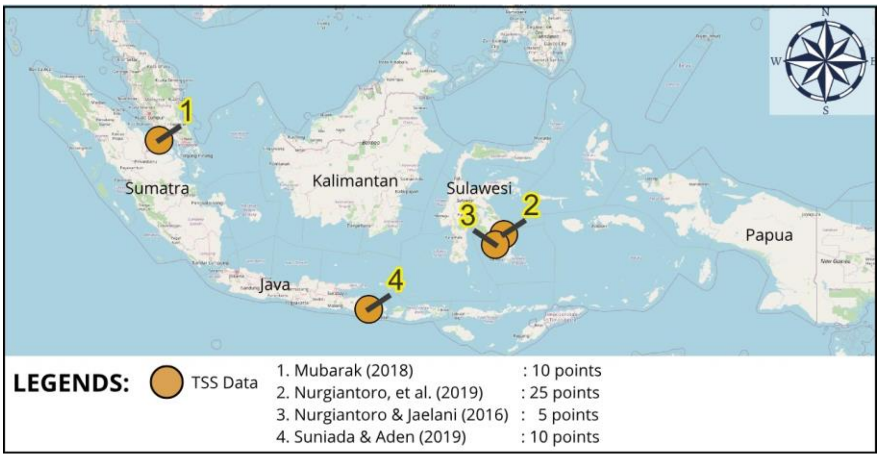

Figure 3. TSS sampling points to evaluate all models

Table 1. A classification of correlation coefficient (r) [45]

Correlation coefficient (r) value	Interpretation
0.00 – 0.09	Negligible correlation
0.10 – 0.39	Weak correlation
0.40 – 0.69	Moderate correlation
0.70 – 0.89	Strong correlation
0.90 – 1.00	Very strong correlation

Table 2. A classification of determination coefficient (R2) [51]

The determination coefficient (R^2) value	Interpretation
≤ 0.50	Not satisfactory
$0.50 < R^2 \leq 0.70$	Satisfactory
$0.70 < R^2 \leq 0.80$	Good
> 0.80	Very good

2.4. *Evaluation and Comparison Between All Models*

The final step is to evaluate and conclude the best model to estimate TSS concentration. This step has the same processes as the previous one. However, it uses other data sets (see Figure 3). Furthermore, three TSS models from previous studies [12]–[14] with more than 90% of accuracies are used for comparison:

- TSS Model 1 [12]:

$$TSS\ (mg/L) = 7.9038 \times e^{(23.942 \times Rrs(\lambda 4))} \tag{3}$$

- TSS Model 2 [14]:

$$TSS\ (mg/L) = 5.1271 \times e^{(27 \times Rrs(\lambda 4))} \tag{4}$$

- TSS Model 3 [13]:

$$TSS\ (mg/L) = 3.3238 \times e^{(34.099 \times Rrs(\lambda 4))} \tag{5}$$

where: Rrs(λ4) is the reflectance value of Band 4 (Red) and mg/L is milligram/litre.

The parameters used for the evaluation are r, R^2, and RSE. The best model is indicated by consistent high r and R^2 values and low RSE values in all locations of the validation data. The tests in this step also use the RStudio application to aid the analyses.

3. Result and Discussion

3.1. *Correlation Analysis*

The independent variables used for model generation are determined using this analysis. The details of L8 bands as independent variables are already detailed in the previous section. Several parameters are provided by this analysis, such as the t-test statistic value (t), degrees of freedom (df), the significance level of the t-test (p-value), and correlation coefficient (r). The most influential parameter is the p-value, as a favourable variable must possess a p-value less than 0.05 or the result is significant. This parameter with t and r parameters is strongly correlated. If the p-value result is small, the t and r values will be high, and vice versa. The analysis shows that most variables are highly correlated to TSS. However, this study only takes the best ten variables for further analysis. This decision is taken as these variables have the highest r values and are generally moderately correlated to TSS [45]. The correlation analysis results are detailed in Table 3. The highest r is 0.6414 (B4/B2 as the independent variable), while the lowest is -0.5724 (B3/B4 as the independent variable). There are two variables with negative r values, B2/(B2+B3+B4) and B3/B4, while others have positive ones (see Figure 4). The negative r value indicates that the independent and dependent variables correlate negatively (TSS values are high when the reflectance values are low, and vice versa). All the details are depicted in Figure 4. The results indicate that all variables can generate TSS models as the correlations are favourable. Therefore, the next step can be engaged.

3.2. *Correlation Analysis*

Each variable should have significant input to the model. Thus, a significance test is required to determine significance

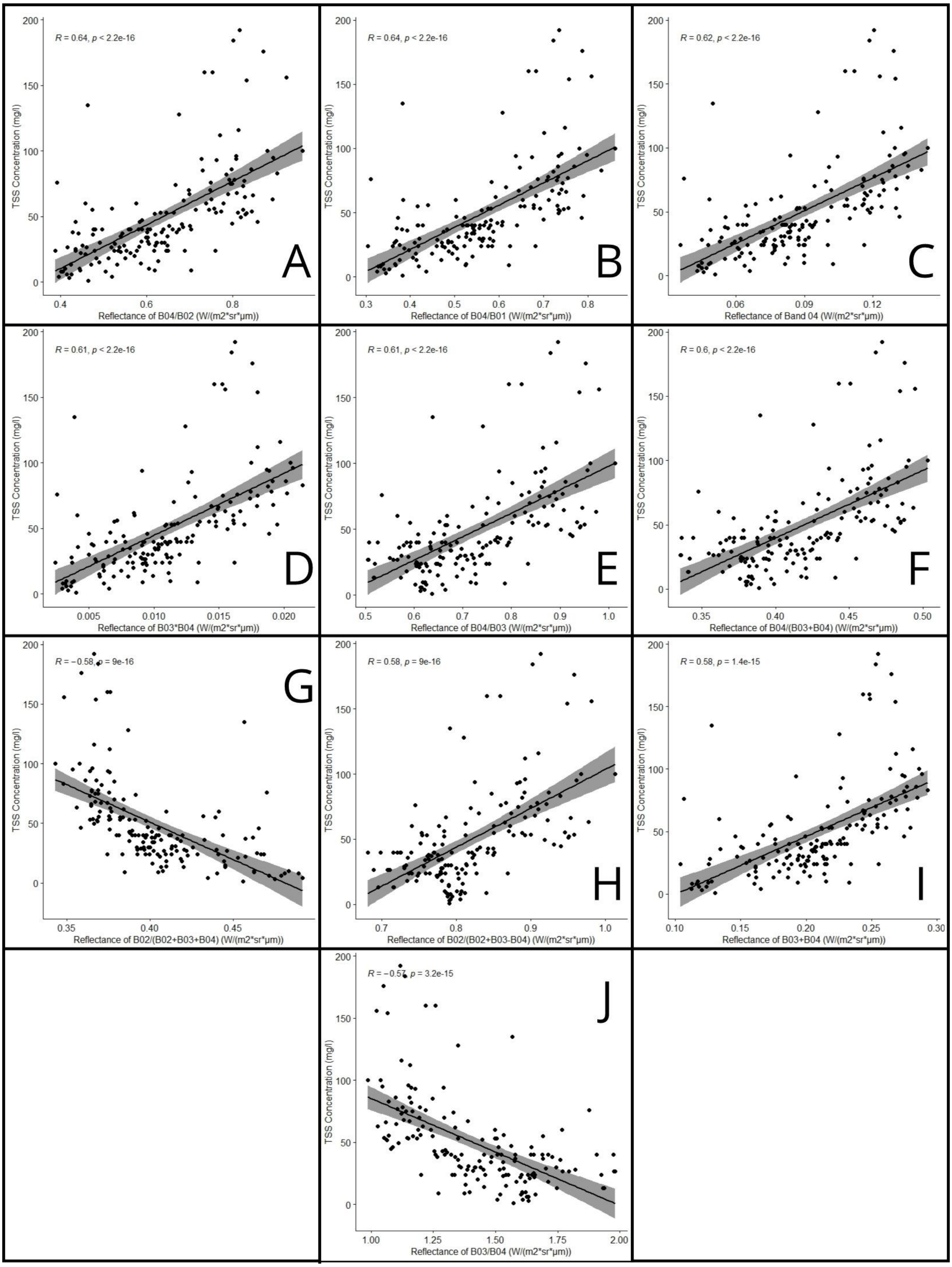

Figure 4. The best ten L8 band combinations based on the correlation analysis

levels between independent variables. All independent variables presented in **Table 3** are tested. ANOVA test is performed first to figure out the significance between the variables. The F value from the test is 2455 (**Table 4**). The F distribution table is required to evaluate this number. The evaluation needs two df numbers, the numerator (dfnum) and the denominator (dfden). The numerator is shown as the df between-groups (dfBG) in the RStudio application, while the denominator is presented as the df within-groups (dfWG). The F values at the 0.05 (F95) and 0.01 (F99) levels can be decided by using these numbers. The F95 and F99 values at 1955 for dfnum at 14 and dfden are 3.00 and 4.61, respectively, as shown in the F distribution table. The results are detailed in Table 4. Yet, they do not indicate the significance of every variable. Therefore, this issue is solved by performing Tukey's HSD test, and the results are presented in Figure 5 in boxplots. Each box shows a number group of each independent variable. The bold middle line is the median, the lower edge of the box is the lower quartile (the number below 25% of the numbers), and the upper one is the upper quartile (the number surpasses 75% of the numbers). Meanwhile, the upper and lower lines sticking out of the box include the values outside it. The results show that an insignificance between several variables exists from the test, shown by the adjusted probability values between two variables which are more than 0.05. The list of insignificant variables is B1, B2, B3, and B4 (see Figure 5 as these variables have similar scores). The chosen variable is B4, which has the highest r values at 0.6234. Meanwhile, the r values of B1 – B3 are 0.4107, 0.43, and 0.48, respectively. Other variables are significant to each other (see Figure 5 as these variables have various scores). Thus, these ten variables are used for the following analyses. The selected independent variables are shown in Table 5.

Table 3. Correlation analysis results of L8 band combinations for TSS model generation

No	Band or Band Combinations	t-test Statistic Value (t)	Degrees of Freedom (df)	Significance Level of t-test (p-value)	Correlation Coefficient (r)
1	B4/B2	10.47	157	8.42E-20	0.6414
2	B4/B1	10.46	157	9.28E-20	0.6408
3	B4	9.99	157	1.70E-18	0.6234
4	B3*B4	9.69	157	1.08E-17	0.6117
5	B4/B3	9.68	157	1.13E-17	0.6114
6	B4/(B3+B4)	9.36	157	8.21E-17	0.5983
7	B2/(B2+B3+B4)	-8.96	157	8.97E-16	-0.5817
8	B2/(B2+B3-B4)	8.96	157	9.02E-16	0.5816
9	B3+B4	8.89	157	1.36E-15	0.5787
10	B3/B4	-8.75	157	3.22E-15	-0.5724

Table 4. ANOVA test results

Source of Variation	Degree of Freedom (df)	Sum Square (SS)	Mean Square (MS)	F Value	p-value	F_{95}	F_{99}
Between-groups	14	287.46	20.533				
Within-groups	1955	16.69	0.008	2455	<2E-16	3.00	4.61
Total	1969	304.15					

Table 5. List of independent variables to generate TSS models

No	Band or Band Combinations	No	Band or Band Combinations
1	B4/B2	6	B4(B3+B4)
2	B4/B1	7	B2/(B2+B3+B4)
3	B4	8	B2/(B2+B3-B4)
4	B3*B4	9	B3+B4
5	B4/B3	10	B3/B4

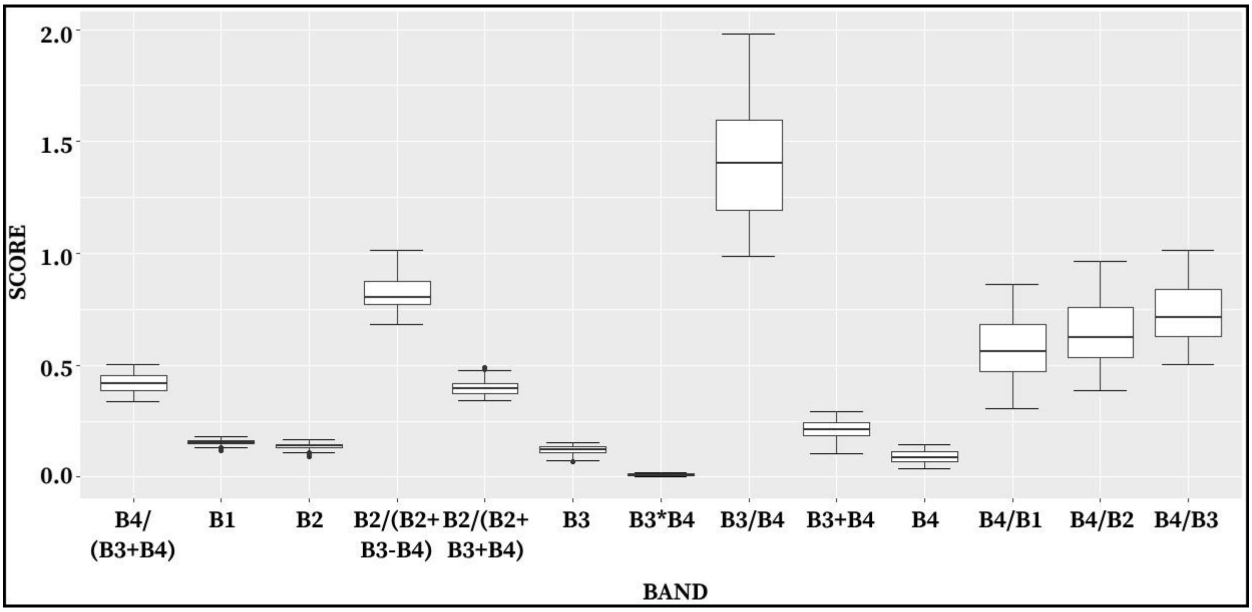

Figure 5. Boxplot of Tukey's HSD test results

3.3. *Regression Analysis*

The regression analysis generates several models. However, the most sophisticated five generated models are presented in Table 6. In general, all models can fit the scatter plots well, as the p-values of the models are less than 0.05. Moreover, all models are classified as "satisfactory" (see Table 2) as the R^2 values are more than 0.5. It means that the models can be applied because they fulfil the minimum requirement to be satisfying models [51]. The most sophisticated model is the one with the highest R^2 value at 0.517. Furthermore, it has the least RSE at 0.5727. These points indicate that it performs the best in estimating TSS concentration than others. The model has five independent variables: B4/B1, B4/B3, B4/(B3+B4), B3+B4, and B3/B4 with an Eq (6).

Based on Eq (6) $Rrs(\lambda 1)$ is the reflectance value of Band 1 (Coastal/Aerosol), $Rrs(\lambda 3)$ is the reflectance value of Band 3 (Green), while $Rrs(\lambda 4)$ is the reflectance value of Band 4 (Red). However, it is important to evaluate the model's performance to estimate TSS concentration using various data sets by an accuracy test. The next sub-section discusses this issue in detail.

3.4. *Evaluation and Comparison Between All Models*

The performance ability of the four models is compared to evaluate each model. The models are presented in Eq (3) to Eq (6) [12]–[14], which are addressed as TSS Model 1 – 4, respectively. The three main parameters (r, R2, and RSE values) are used to evaluate the models by an accuracy test. The TSS values from the estimation results of each model are compared to the values from the validation data coming from this study and other points. This comparison becomes points to be evaluated. Although the validation from a location shows that the models cannot provide favourable estimations, generally, all models have similar capabilities to estimate TSS concentration as the three-parameter values are comparable. The unfavourable results come up because only five data are available in this location [30]. The minimum required data for validation are eight samples, but the suggested numbers are 25 points [52]. Thus, the parameter values in this location cannot be used to evaluate the model. However, the models' capabilities are favourable based on the validation results in other locations [28], [29], [31], as follows. Firstly, the models are capable of providing p-values less than 0.05, implying the estimations from the model correlate to the validation data. Secondly, most r values are categorised as moderate to strong [45] because the values are ranged between 0.68 – 0.86. The values indicate that the estimations from the models are moderate to strongly correlated to the validation data. Lastly, most R2 values indicate that the models are capable of providing satisfying results as they are more than 0.5 [51]. The details are presented in Table 6. However, deciding on the best model is crucial, so it can be broadly applied to estimate TSS concentrations, especially in Indonesia.

The best model is decided by determining which model provides the highest r and R^2 values and the lowest RSE value. There are two best models compared to the other ones: TSS model 1 and TSS model 4. These models provide comparable high r and R^2 values, and low RSE value (see Table 6). TSS model 4 donates better parameter values in several areas [28], [29], [31], while TSS model 1 provides better results by using validation data in this study. However, the values are comparable. For example, the R^2 values of each model are 0.5140 and 0.5056 by using validation data in this study, while they are 0.4707 and 0.4735 by using validation data in other locations [28], [31] for TSS models 1 and 4, respectively (see 'This Study' and 'Other Validation Data' column for TSS model 1 and 4 in Table 6). However, overall, TSS model 4 provides better estimations than TSS model 1 as the validation

$$TSS\ (mg/L) = e^{8.326\left(\frac{B4}{B1}\right) - 42.883\left(\frac{(B4}{B3}\right) + 223.773\left(\frac{B4}{B3+B4}\right) - 5.858(B3+B4) + 17.935\left(\frac{B3}{B4}\right) - 87.593} \quad (6)$$

Table 6. Results of the accuracy test of all TSS models

Parameter	TSS Model 1 [12] Performances				TSS Model 2 [14] Performances			
	Data Sources for Evaluation				Data Sources for Evaluation			
	This Study	Nurgiantoro et al. [29]	Nurgiantoro & Jaelani [30]	Other Validation Data [28], [31]	This Study	Nurgiantoro et al. [29]	Nurgiantoro & Jaelani [30]	Other Validation Data [28], [31]
t	4.93	6.52	-0.74	3.65	4.83	6.42	-0.74	3.62
df	23	23	3	15	23	23	3	15
p-value	5.53E-05	1.19E-06	5.15E-01	2.36E-03	7.04E-05	1.49E-06	5.15E-01	2.52E-03
r	0.7169	0.8055	-0.3912	0.6861	0.7099	0.8013	-0.3912	0.6829
RSE	20.36	37.91	120.60	4.44	20.57	38.27	120.60	4.46
R^2	0.5140	0.6488	0.1530	0.4707	0.5040	0.6421	0.1531	0.4664
F-statistic	24.32	42.88	0.54	13.34	23.37	41.26	0.54	13.11

Parameter	TSS Model 3 [13] Performances				TSS Model 4 (This Study) Performances			
	Data Sources for Evaluation				Data Sources for Evaluation			
	This Study	Nurgiantoro et al. [29]	Nurgiantoro & Jaelani [30]	Other Validation Data [28], [31]	This Study	Nurgiantoro et al. [29]	Nurgiantoro & Jaelani [30]	Other Validation Data [28], [31]
t	4.60	6.19	-0.74	3.54	4.85	8.08	-0.25	3.67
df	23	23	3	15	23	23	3	15
p-value	1.28E-04	2.61E-06	5.15E-01	2.96E-03	6.77E-05	3.63E-08	8.21E-01	2.26E-03
r	0.6918	0.7903	-0.3910	0.6749	0.7111	0.8599	-0.1407	0.6881
RSE	21.09	39.19	120.60	4.51	20.53	32.65	129.80	4.43
R^2	0.4786	0.6245	0.1529	0.4555	0.5056	0.7394	0.0198	0.4735
F-statistic	0.46	38.26	0.54	34.57	23.52	65.25	0.06	13.49

results from two of three validation data sets are more favourable (the r and R^2 values are higher, while the RSE values are lower). The r values of TSS model 4 are 0.8599 and 0.6881, while they are 0.8055 and 0.6861 in TSS model. Next, the R^2 values of TSS model 4 are 0.7394 and 0.4735, while they are 0.6488 and 0.4707 in TSS model 1. Meanwhile, the RSE values of the TSS model are 32.65 and 4.43, while they are 37.91 and 4.44 in TSS model 1 1 (see 'Nurgiantoro et al.' and 'Other Validation Data' column for TSS model 1 and 4 in Table 6). These values indicate that TSS model 4 is the best model to estimate TSS concentration in Indonesia. However, TSS model 1 has been broadly used in Indonesia by several studies [12], [13], [15], [16], [23], [26]–[28], [53], [54]. Moreover, it also provides favourable results in estimating TSS concentration. Therefore, it is suggested that an accuracy test is required to decide which model performs better in a specific location.

4. Conclusions

This study generates a modified model using data from various sites and times to determine TSS concentration using L8 images. The model (TSS model 4) provides a favourable result as the p-value is less than 0.05, the r value is 0.711 (good correlation), and the R2 value is 0.5056 (satisfactory). Moreover, the accuracy test results indicate that this model performs the best as it promotes consistently high r and R2 values and low RSE values in two out of three validation locations compared to the other three models. It may imply that this model is the best model to estimate TSS concentration in Indonesia. However, TSS model 1 has been broadly used in several studies and donates favourable results too. Thus, these two models can be alternatives to perform such analysis. An accuracy test is required to select the best model to be applied for a specific location. However, the TSS model 4 may be suitable for coastal areas are the validation data used for the analyses coming from the same settings.

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Author Declaration

Authors' contributions and responsibilities

The authors made substantial contributions to the conception and design of the study. The authors took responsibility for data analysis, interpretation and discussion of results. The authors read and approved the final manuscript.

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The authors declare no competing interest.

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