Application of Remote Sensing to Generate Historical Water Quality Data to Support Lake Management in Indonesia

Luki Subehi and Fajar Setiawan

1. Introduction

Indonesia has a vast area of inland waters, consisting mainly of lakes, reservoirs, rivers and swamps. Since a great number of natural lakes are distributed in Indonesia, many lakes have not yet been inventoried and completely investigated. In general, tropical lakes in Indonesia are one of the unique ecosystems which provide both ecological and economic services (Subehi et al., 2018). Lakes are very important habitats for human as they provide water for domestic, industrial and agricultural use as well as providing food (Brönmark et al., 2002). Despite their fundamental importance to humans, freshwater systems including lakes have been affected by anthropogenic disturbances. The disturbances have caused several environmental problems such as eutrophication, acidification and contamination by toxic substances. These problems are predicted to continue to increase, especially in developing countries where the development is prioritized over than environmental conservations (Brönmark et al., 2002). Routinely monitoring the water environment is necessary to ensure that the management practices achieve sustainability (Blake at al., 2013). In addition, long-term water quality information on a broad regional and spatial scale is also essential for effective lake management (Olmanson et al., 2008).

Indonesia is listed among the 12 megadiversity countries, ranked the second in the world (the first in Asia) in the number of freshwater fish species. Recently, there is an increasing need to conserve and maintain the ecological balance of inland water system which are subjected to massive pressure. However, the available water quality data for supporting lake management in Indonesia are very limited due to the financial constraints.

Upon the endorsement of a national conference (Konferensi Nasional Danau Indonesia II, KNDI II) conducted from 13th – 14th October 2011 in Semarang, the Ministry of Environment designated 15 lakes as national priority lakes needing urgent attention in order to resolve environmental crisis of the lakes in Indonesia (Kementerian Lingkungan Hidup, 2011). This decision was a follow up of the "Bali Agreement on Sustainable Management of Lakes" approved in the previous KNDI I in Bali in 2009 and unanimously signed up by nine ministers. It is imperative to develop appropriate management plans based on comprehensive scientific studies, including mitigation of disasters and involvement of the community to maintain the sustainability of Indonesian lakes.

The 15 national priority lakes needing the most urgent attention were selected by the Ministry of Environment based on the following criteria:

1) Lake damage: level of sedimentation, pollution, eutrophication, highly reduced quality and quantity of water.
2) Lake utilization: hydropower generation, agriculture, fisheries (aquaculture/floating cage), usable water, religious and culture values, tourism (including lake uniqueness, accessibility, amenity-infrastructure and society condition).

3) Local government's and society's commitment to wisely manage lakes (presence of master plan, local regulation (perda), management committee).
4) Strategic lake: lakes having strategic functions of national interest.
5) Biodiversity: including endemic fish species, aves and vegetation.
6) Carbon urgency: the challenge against global climate change.

Based on the above criteria, the selected 15 priority lakes are: Lake Toba (North Sumatera), Lake Maninjau and Lake Singkarak (West Sumatera), Lake Kerinci (Jambi), Lake Rawa Danau (Banten), Lake Rawapening (Central Java), Lake Batur (Bali), Lake Tempe and Lake Matano (South Sulawesi), Lake Poso (Central Sulawesi), Lake Tondano (North Sulawesi), Lake Limboto (Gorontalo), Lake Sentarum (West Kalimantan), Cascade Mahakam Lake – Lake Semayang, Lake Melintang, Lake Jempang (East Kalimantan), and Lake Sentani (Papua). Figure 1 shows the distribution of the lakes. Lake Maninjau, the case study lake in presented in this paper, is one of the 15 priority lakes. Lake Maninjau, the case study lake in presented in this paper, is one of the 15 priority lakes.

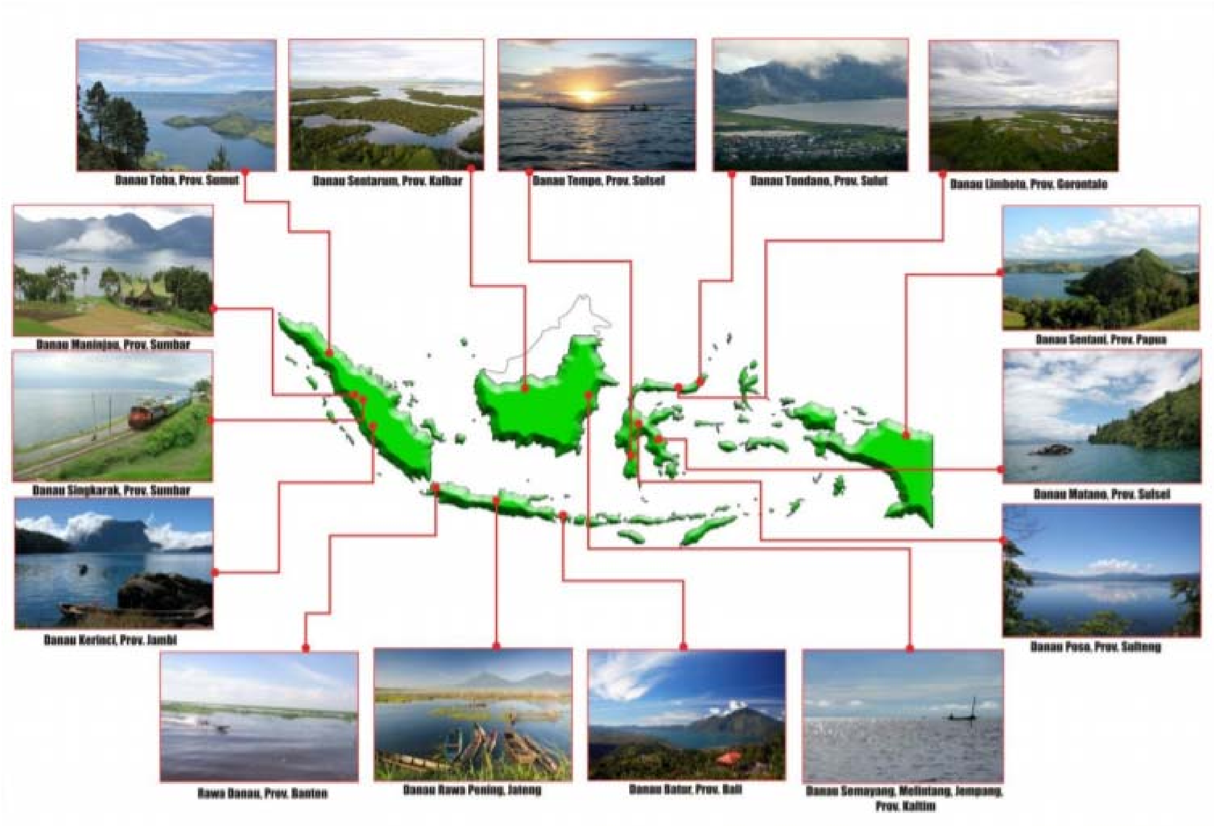

Figure 1. Distribution map of 15 National Priority Lakes in Indonesia
(Kementerian Lingkungan Hidup, 2011)

One of the important water quality parameters is Secchi depth (SD). SD is the simplest and the most often used parameter for limnological measurements because its values are easily understood (Carlson, 1977). Since the change in SD can affect both ecosystems and water amenities, observing SD is one of the key issues in water environmental monitoring and management (Fukushima et al., 2017).

Since conventional water-monitoring methods (e.g., field survey by a boat) are very time-, labor-, and cost-consuming, the maintenance of steady monitoring remains challenging for local and national governments with meager financial resources, especially in developing countries (Matsushita et al., 2016). As a result, the number of available in-situ water quality data is very limited. On the other hand, satellite remote sensing can be considered as a powerful supportive tool for collecting spatial and temporal water quality parameters such as SD (Gholizadeh et al., 2016; Kloiber et al., 2002; Olmanson et al., 2008). Combination of field survey and remote-sensing techniques can provide comprehensive data solutions to address sustainability issues because satellite sensors have a potential to provide better spatial and temporal coverage compared with traditional field survey.

Landsat series is one of the most successful remote sensing satellite missions to observe the earth. Landsat images have been collected and archived regularly since the early 1970s, enabling extraction of some historical water quality information on lakes (Olmanson et al., 2008). The relatively fine spatial resolution (30 m) and long-term data availability of the Landsat system make the Landsat data particularly useful for studying inland Lakes (Kloiber et al., 2002).

Generally, an empirical approach is used to build a model for estimating SD from Landsat TM/ETM+ images due to its simplicity. Band ratio or a combination of single band and band ratio was widely used as the SD predictor. The biggest challenge for using the empirical approach is that in-situ measured SD data are always required to recalibrate the SD estimation model. This requirement will limit applications to lakes without enough in-situ SD data, especially in developing countries such as Indonesia. In addition, different band and band ratio combinations were suggested by previous researches due to the differences in image quality or limnological condition of the water body Zhao at al., 2011. However, Kloiber et al. (2002) mentioned that one set of coefficients of the SD estimation model can be applied for different images across time and space if the atmospheric effects can be removed in advance.

This module introduces the work of Setiawan et al. (2019) on development of an empirical model and its application to capture the long-term change of SD in Lake Maninjau from 1987 to 2018 from Landsat TM and ETM+ data. The objectives of the study were to: (1) Develop a robust SD estimation model by using a wide range of in situ-measured SD values (0.5–18.6 m) collected from nine Indonesian lakes/reservoirs and the corresponding atmospherically-corrected and filtered Landsat TM and ETM+ images; (2) evaluate the performance of the developed SD estimation model using another in situ-measured SD dataset collected from Lake Maninjau, Indonesia; (3) generate a long-term SD database for Lake Maninjau from historical Landsat TM and ETM+ images (1987–2018) using the developed SD estimation model; and (4) determine the water quality changes of Lake Maninjau during the study period by using the generated SD database, in order to further confirm the robustness of the developed SD estimation model.

2. Materials and Methods

2.1 Study Area

Lake Maninjau is located in Agam Regency, West Sumatra Province, Indonesia (between 100° 08' 54"–100° 14' 02" E and 0° 14' 52"–0° 24' 12" S) at 462 m above sea level (Figure 1). The lake's origin was a tectono-volcanic process, and it has a water surface area of 97.37 km^2, maximum length of 16.46 km, and maximum width of 7.5 km [32]. Lake Maninjau is also a deep lake with an average depth of 105 m and a maximum depth of 168 m. The ratio of the lake's watershed area to the water surface area is only 1.44.

With a total of 186 Secchi disk depth (SD) measurements taken during the years 2001–2018, Lake Maninjau has the greatest amount of available water quality data in Indonesia. Other than this dataset, only fragmentary water quality data exist for a few Indonesian lakes and reservoirs as stated by Lehmusluoto and Machbub, 1997. Therefore Lake Maninjau was selected as the case study for this research and the existing SD data for the lake was used to validate the model developed in this research.

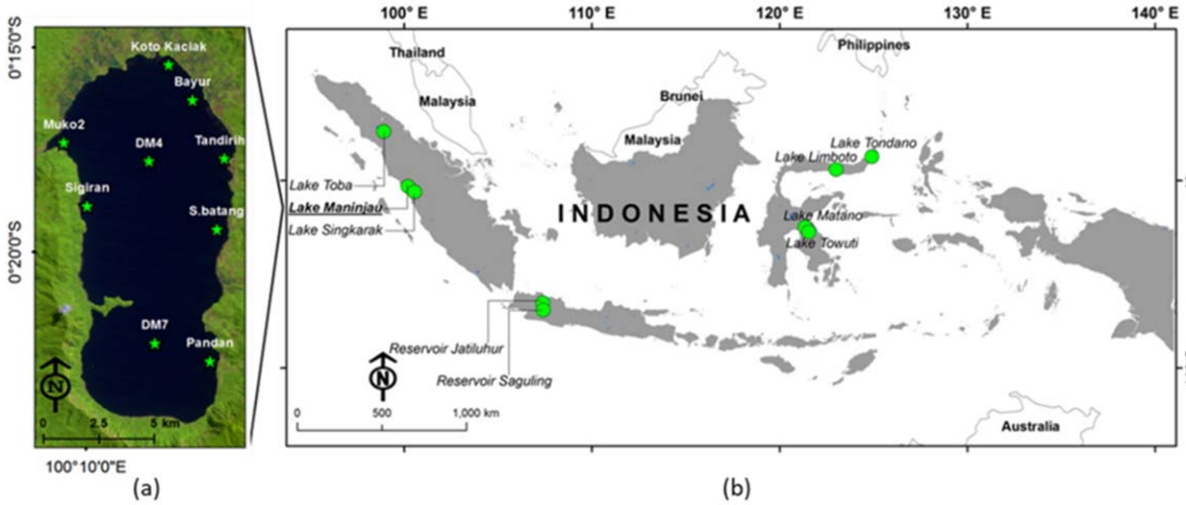

Figure 2. (a) Landsat image of Lake Maninjau in Sumatera Island, Indonesia (acquired on 6 July 2011; R:G:B = 4:5:1; green stars = the measurement sites). (b) Locations of the nine Indonesian lakes investigated in 2011–2014 and used for calibrating the Secchi disk depth (SD) estimation model (green circles).

2.2 Data Collection

2.2.1 In Situ SD Data Collection

Seven field surveys to collect in situ SD data were conducted during the years 2011–2014. A standard 20-cm-diameter Secchi disk painted in white and black quarters was used to measure the SD values. The locations (longitude, latitude) of the SD measurements were recorded using a GPS receiver. In total, 31 in situ SD values from nine Indonesian lakes (Figure 1b, green circles) were collected. Those nine Indonesian lakes are: Maninjau, Singkarak, Saguling, Tondano, Limboto, Toba, Matano and Towuti. The SD values ranged from 0.5 m to 18.6 m. This dataset was used for calibrating the SD estimation models. To validate the SD estimation models, a total of 186 Secchi disk depth (SD) measurements taken during the years 2001–2018 on Lake Maninjau ware used.

2.2.2. Satellite Data Collection

Landsat TM and ETM+ data were used in this study due to their high spatial resolution (30 m) and long-term data availability (since 1984). A total of 309 Landsat TM/ETM+ images were downloaded from the USGS website. These satellite images include:

(1) Seven images corresponding with In-situ data from 9 Indonesian lakes for model calibration.
(2) 21 images corresponding with In-situ SD data of lake Maninjau, during the years from 2001 to 2018 for model validation.
(3) Remaining images covering Lake Maninjau during the years from 1987 to 2018 to show long-term SD of Lake Maninjau.

2.3. Preprocessing of the Landsat TM and ETM+ Images

2.3.1. Removal of Non-Water Pixels

- Extract water pixels inside the lake polygon by allowing for a 90 m buffer from the lake shoreline to avoid the land adjacency effect and shallow water effect.
- Exclude pixels with low quality by flagging them with Band Quality Assessment (BQA) ≠ 672.
- Remove the water pixels contaminated by clouds or cloud shadows by using the combination of the Normalized Different Water Index [NDWI, McFeeters (1996)] and the Modified Normalized Different Water Index [MNDWI, Xu (2006)].

$$\mathbf{NDWI = (dgreen - dNIR)/(dgreen + dNIR),} \quad (1)$$
$$\mathbf{MNDWI = (dgreen - dSWIR)/(dgreen + dSWIR),} \quad (2)$$

where dgreen, dNIR and dSWIR are the DN values at the green band, near-infrared band, and shortwave infrared band, respectively. The contaminated water pixels were the pixels with both NDWI and MNDWI <= 0.

2.3.2. Reduction of Noise Effects on the Remaining Water Pixels

- Apply iterative median filter with a 3 x 3 pixel window to the image until no further change in pixel values is observed, to save the time limit the iteration until 1000 times.
- Repeat the first iterative median filter with a 5 x 5 pixel window

2.3.3. Conversion of DN to Radiance

$$\mathbf{L_{\lambda} = G_{rescale} * QCAL + B_{rescale}} \quad (3)$$

Where;

$\mathbf{L_{\lambda}}$ = Spectral radiance at the sensor's aperture [W/(m^2·sr·µm)];

QCAL= Quantized calibrated pixel value [DN];

$\mathbf{B_{rescale}}$ = band-specific rescaling bias factor from Chander et al. (2009) [W/(m^2 sr µm))/DN];

$\mathbf{G_{rescale}}$ = band-specific rescaling gain factor from Chander et al. (2009) [W/(m^2 sr µm)];

2.3.3. Minimizing atmospheric effects using 6S

Carry out a Rayleigh scattering correction using 6S radiative transfer model without considering aerosol effects based on Vermote et al., (1997). A standard tropical atmospheric model was selected for this correction. The Rayleigh corrected reflectance (**R_{rc}**) for each band can be obtained using the following equations:

$$\mathbf{R_{rc} = y / (1. + xc*y),} \qquad (4)$$

$$\mathbf{y = xa * (L_{\lambda}) - xb} \qquad (5)$$

where **xa**, **xb**, **xc** are the coefficients calculated using the 6S code.

2.3.3. Mitigating aerosol scattering effect

$$\mathbf{R_c(\lambda) = R_{rc}(\lambda) - min\ (R_{rc}(4), R_{rc}(5)),} \qquad (1\cancel{6})$$

where **$R_c(\lambda)$** is the atmospherically corrected reflectance at Landsat visible bands, (**$R_{rc}(4)$**) is Rayleigh corrected reflectance at the near infrared and (**$R_{rc}(5)$**) is middle infrared band.

2.4. SD Estimation Model Development and Accuracy Assessment

2.4.1. Development of the Empirical SD Estimation Models

The general equations of the SD estimation models developed from the 31 in situ SD values from nine Indonesian lakes and the preprocessed Landsat data are as follows:

$$\mathbf{\ln (SD) = a + b\ (single\ band),} \qquad (7)$$

$$\mathbf{\ln (SD) = a + b\ (band\ ratio),} \qquad (8)$$

$$\mathbf{\ln (SD) = a + b\ (band\ ratio) + c\ (single\ band),} \qquad (9)$$

$$\mathbf{\ln (SD) = a + b\ (band\ ratio\ 1) + c\ (band\ ratio\ 2),} \qquad (10)$$

where a, b, and c are coefficients and can be obtained by fitting the calibration data.

2.4.2. Accuracy Assessment

The root means square error (**RMSE**), the mean normalized bias (**MNB**), and the normalized mean absolute error (**NMAE**) were the three indices used to assess the accuracy of the developed models. These indices are defined as follows:

$$\mathbf{RMSE} = \sqrt{\frac{\sum_{i=1}^{N}\left(X_{esti,i} - X_{meas,i}\right)^2}{N}}, \qquad (11)$$

$$\mathbf{MNB\ (\%) = mean\ (\varepsilon_i),} \qquad (12)$$

$$\mathbf{NMAE\ (\%) = mean\ (|\varepsilon_i|),} \qquad (13)$$

where $\boldsymbol{X_{esti,i}}$ and $\mathbf{X_{meas,i}}$ are the estimated and measured SD values, respectively, n is the number of samples, and $\boldsymbol{\varepsilon_i} = 100\times(X_{esti,i} - X_{meas,i})/X_{meas,i}$ is the relative difference between the estimated and measured SD values.

3. Results

3.1. Empirical Models for Estimating the SD from Landsat TM/ETM+ Data

The model calibration step produced 42 models. Out of these models with poor performance were excluded from further analyses by using thresholds of R^2 values <0.9 and RMSE values >2.5 m. As the result, 17 SD estimation model remained, as shown in Table 1.

Table 1. The developed SD estimation models and their performances using calibration data

Variable	Name	ln (SD) =	R^2	RMSE (m)	MNB (%)	NMAE (%)
Band ratio	A	–2.45 + 1.81(TM1/TM3)	0.97	1.6	10.1	34.7
	B	–3.29 + 3.93(TM1/TM2)	0.91	2.1	16.6	50.7
Band ratio and single band	A1	–4.36 + 1.87(TM1/TM3) + 49.01(TM1)	0.99	0.8	4.4	25.0
	A2	–4.48 + 2.33TM1/TM3) + 28.22(TM2)	0.98	0.8	5.4	24.3
	A3	–3.85 + 2.24(TM1/TM3) + 25.83(TM3)	0.98	0.9	6.6	27.2
	B1	–4.43 + 3.94(TM1/TM2) + 30.99(TM1)	0.92	1.9	12.5	46.7
	B2	–4.47 + 4.52(TM1/TM2) + 14.93(TM2)	0.92	1.9	13.9	49.4
	B3	–3.71 + 4.18(TM1/TM2) + 7.18(TM3)	0.91	2.0	15.8	50.3
Two band ratios	AB	–2.49 + 1.76(TM1/TM3) + 0.12(TM1/TM2)	0.97	1.6	10.2	34.6
	AC	–1.80 + 1.95(TM1/TM3) – 0.53(TM2/TM3)	0.97	1.4	10.2	34.3
	AD	–4.34 + 2.35(TM1/TM3) + 1.45(TM3/TM1)	0.98	1.0	8.1	26.4
	AE	–4.17 + 2.22(TM1/TM3) + 0.96(TM2/TM1)	0.97	1.3	8.6	30.5
	AF	–3.94 + 2.00(TM1/TM3) + 1.89(TM3/TM2)	0.97	1.3	9.9	33.7
	BC	–4.84 + 3.37(TM1/TM2) + 1.26(TM2/TM3)	0.96	2.0	13.0	42.0
	BD	–3.05 + 3.80(TM1/TM2) – 0.16(TM3/TM1)	0.92	2.2	16.7	51.1
	BE	–6.78 + 5.60(TM1/TM2) + 1.70(TM2/TM1)	0.91	1.9	14.2	48.8
	BF	–1.18 + 3.45(TM1/TM2) – 2.67(TM3/TM2)	0.95	2.1	14.4	45.2

3.2. Validation of the 17 Selected SD Estimation Models in Lake Maninjau

Seventy four (74) in situ data collected from Lake Maninjau during 2001-2018 were compared with the match-up estimated SD from 17 selected models. Since the BF model showed the highest R^2 value (0.60; Table 2), the closest distance to the observed point (Figure 3), the highest WIA value (0.83; Table 2), a smaller RMSE value (1.01 m; Table 2), and a higher NSME value (0.43; Table 2), we chose this model for further analysis.

Table 2. Performance of 17 Selected SD Estimation Models in Lake Maninjau (n=74)

Model	ln (SD) =	R^2	WIA*	NSME **	RMSE (m)	MNB (%)	NMAE (%)
A	–2.45 + 1.81(TM1/TM3)	0.42	0.68	–0.88	1.83	83.46	89.83
A1	–4.36 + 1.87(TM1/TM3) + 49.01(TM1)	0.34	0.65	–1.29	2.02	45.98	63.67
A2	–4.48 + 2.33TM1/TM3) + 28.22(TM2)	0.39	0.66	–1.35	2.05	61.35	73.23
A3	–3.85 + 2.24(TM1/TM3) + 25.83(TM3)	0.44	0.72	–0.61	1.70	57.25	69.72
AB	–2.49 + 1.76(TM1/TM3) + 0.12(TM1/TM2)	0.32	0.62	–1.24	2.00	98.44	106.40
AC	–1.80 + 1.95(TM1/TM3) – 0.53(TM2/TM3)	0.36	0.69	–0.52	1.65	81.22	93.08
AD	–4.34 + 2.35(TM1/TM3) + 1.45(TM3/TM1)	0.32	0.63	–1.37	2.06	88.98	99.28
AE	–4.17 + 2.22(TM1/TM3) + 0.96(TM2/TM1)	0.25	0.54	–2.63	2.55	115.41	122.65
AF	–3.94 + 2.00(TM1/TM3) + 1.89(TM3/TM2)	0.36	0.69	–0.51	1.64	76.59	90.17
B	–3.29 + 3.93(TM1/TM2)	0.54	0.83	0.53	0.92	30.67	54.19
B1	–4.43 + 3.94(TM1/TM2) + 30.99(TM1)	0.35	0.76	0.16	1.23	13.44	48.66
B2	–4.47 + 4.52(TM1/TM2) + 14.93(TM2)	0.48	0.82	0.46	0.98	14.80	45.81
B3	–3.71 + 4.18(TM1/TM2) + 7.18(TM3)	0.52	0.83	0.52	0.93	22.72	50.20
BC	–4.84 + 3.37(TM1/TM2) + 1.26(TM2/TM3)	0.40	0.71	–0.29	1.52	84.90	92.43
BD	–3.05 + 3.80(TM1/TM2) – 0.16(TM3/TM1)	0.54	0.83	0.53	0.92	33.19	55.38
BE	–6.78 + 5.60(TM1/TM2) + 1.70(TM2/TM1)	0.38	0.76	0.37	1.07	26.62	55.97
BF	–1.18 + 3.45(TM1/TM2) – 2.67(TM3/TM2)	0.60	0.83	0.43	1.01	56.47	67.43

Note: * Willmott Index of Agreement; ** Nash–Sutcliffe model efficiency.

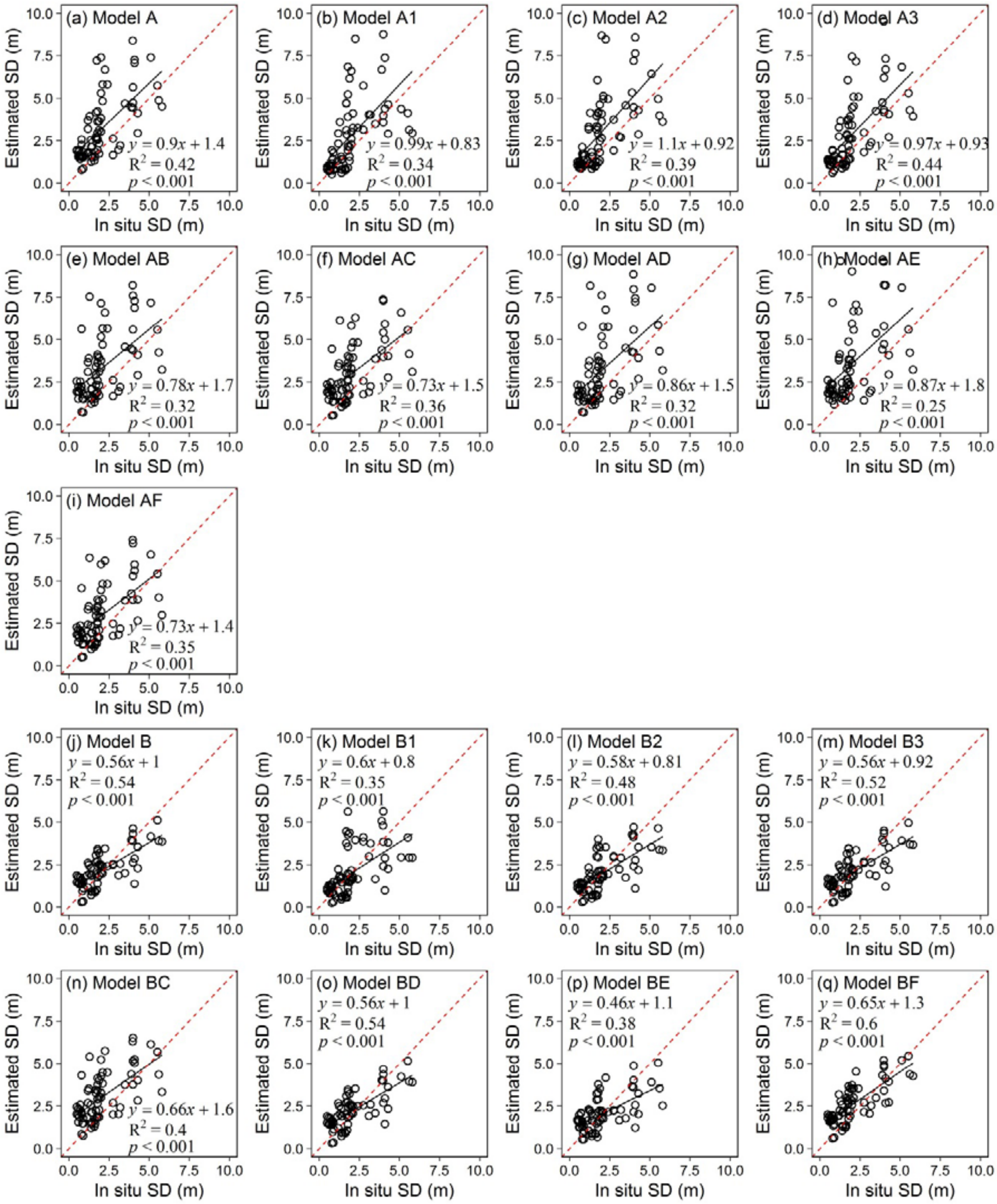

Figure 3. Comparisons of the in situ-measured SD values of Lake Maninjau and the corresponding estimated SD using the 17 selected SD estimation models (n = 74).

3.3. Long-Term SD Changes in Lake Maninjau from the Landsat TM/ETM+ Time Series

The final model selected was the model BF, with the following SD equation is:

$$\mathbf{SD = exp\ \{ -1.18 + 3.45(TM1/TM2) - 2.67(TM3/TM2)\}} \quad (14)$$

Where TM1, TM2 and TM3 is the atmospherically corrected reflectance of Landsat band 1 (Blue), band 2 (Green) and band 3 (Red) resulted from section 2.3 respectively. Using this model, satellite images of studied lakes can be used to generate SD values and profiles of long-term change of water quality can be predicted.

With a total of 186 Secchi disk depth (SD) measurements from 41 field surveys taken during the years 2001–2018, Lake Maninjau has the greatest amount of available water quality data in Indonesia. Other than this dataset, only fragmentary water quality data exist for a few Indonesian lakes and reservoirs (Lehmusluoto and Machbub, 1997). Therefore, Lake Maninjau was used for long-term SD change simulation. Images with lake water pixels less than 50% were excluded to maintain the representativeness of the averaged SD value.

Time-series data analyses using LOESS (**L**ocally w**E**ighted **S**catterplot **S**moothing) work in R language was implemented to compare the pattern of temporal change of estimated SD and In situ data (Figure 4). The water transparency in the lake showed a continuous decrease until 2011, a smaller tendency to increase in 2011–2015, and a decreasing trend again in 2015–2018. These water transparency variations observed from the Landsat-based SD estimations can be validated by the in-Situ SD after 2001 (Figure 4, blue points and trend line), which showed a similar fluctuation pattern of SD values.

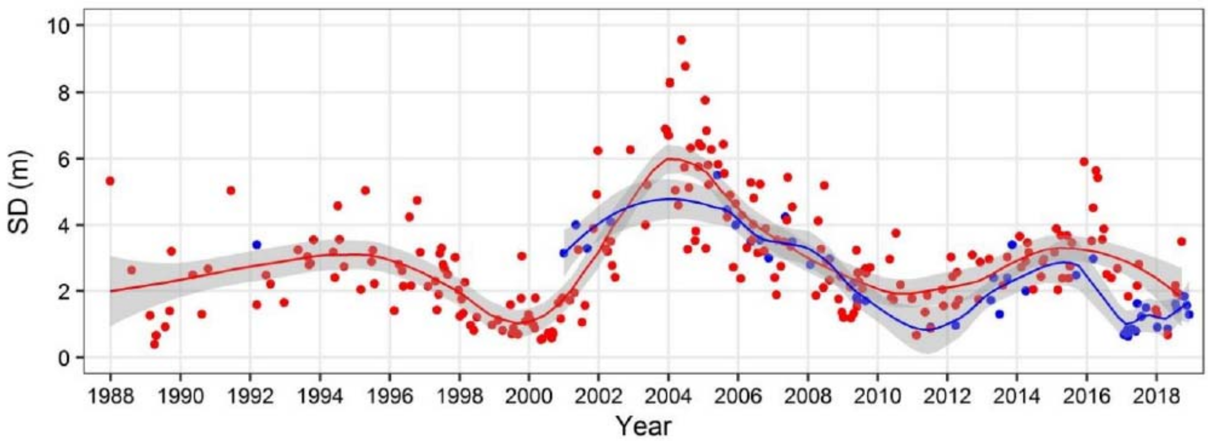

Figure 4. Long-term changes in the water transparency in Lake Maninjau from 1987 to 2018. Red points: The averaged SD values estimated from the preprocessed Landsat using the BF model. Blue points: The averaged in situ SD values for 41 field surveys. Red line: Obtained from the red points via a trend analysis in R language. Blue line: Obtained from the blue points via a trend analysis in R language. Gray areas: 95% confidence intervals of the trend analysis

4. Discussion

4.1. Applicability of the Developed SD Estimation Model

The developed model is an empirical model to estimate SD values from Landsat TM/ETM+ data. Although the number of data pairs is small, the pairs were collected from nine Indonesian lakes with a wide dynamic range of SD values (0.5–18.6 m). A series of preprocessing steps was conducted, including the removal of contaminated water pixels, the filtering of the images, and the mitigation of the atmospheric effects, before the Landsat data were used. These efforts enable the developed SD estimation model to be applied to different Landsat images cross time and space [6,28,29].

In contrast, because of the fewer available bands and the broad bandwidths of Landsat TM and ETM+ sensors, the changed IOPs in different waterbodies are probably not the main cause to affect the robustness and universality of the developed SD estimation model. Nevertheless, the developed SD estimation model still needs to be further validated by using more comprehensive data pairs collected from various waters or simulation experiments.

4.2. Reliability of the Estimated SD Values from Landsat Data

Low SD estimated using the developed model is supposed to have high correlation with the blooming algae as shown in Figure 5. A green color appearing on the water surface of true color Landsat image is suspected as a heavy algae bloom.

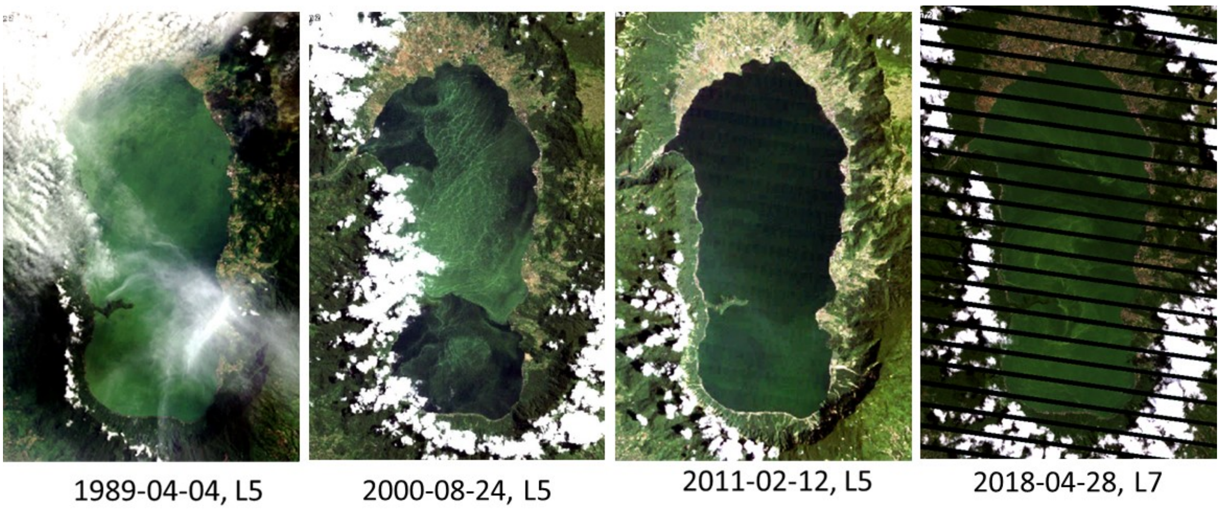

Figure 5. Low SD value was estimated using the developed model for images acquires at April 4th 1989, August 24th 2000, February 12th 2011 and April 28th 2018. SD was estimated as 0.3 m, 0.58 m, 0.66 m and 0.67, respectively. Low SD values highly related with the blooming algae.

The continuous decrease in the SD values revealed during period from 2004 to 2012 by both the in situ-measured and Landsat-based SD values can be explained by the dramatically increased number of fish cages in Lake Maninjau. In 2005, the number of fish cages in the lake was 4,920 units, and this number increased to 8,955 units in 2006 and 13,129 units in 2010 (Figure 1d). We observed a strong correlation between the number of fish cages and the Landsat-based SD values during the period 2004–2012 ($R^2 = 0.88$; Figure 6). This result indicates that the number of fish cages in Lake Maninjau is probably a major driving factor of water transparency in the lake.

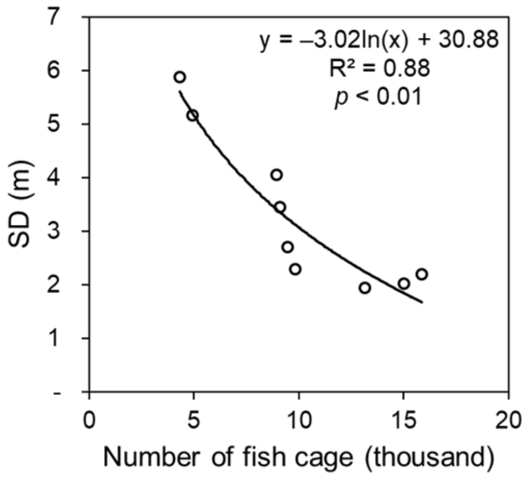

Figure 6. Relationship between the number of fish cages and the Landsat-based SD values during the period 2004–2012 in Lake Maninjau (*n* = 9).

REFERENCES

Blake, A., Schaeffer., Kelly G., Schaeffer., Darryl K., Ross, S., Lunetta., Robyn C., & Richard W: Barriers to adopting satellite remote sensing for water quality management. IJRS, Vol. 34:21, pp. 7534-7544, 2013.

Bonansea, M.; Rodríguez, C.; Pinotti, L.; Ferrero, S. Using multi-temporal Landsat imagery and Linear mixed models for assessing water quality parameters in Rio Tercero reservoir (Argentina). *Remote Sens. Environ.* 2015, *158*, 28–41, doi:10.1016/j.rse.2014.10.032.

Brönmark, C., & Hansson, L: Environmental issues in lakes and ponds: current state and perspectives. Environmental Conservation, Vol 29(3), pp. 290-307, 2002.

Carlson, R.E: A trophic state index for lakes. Limnology and Oceanography, Vol.22, pp. 361-369, 1977.

Chander, G.; Markham, B.; Dennis, D.L. Summary of current radiometric calibration coeffcients for Landsat MSS, TM, ETM+, and EO-1 ALI sensors. Remote Sens. Environ. 2009, 113, 893–903.

Fukushima,T., Matsushita, B., Yang, W., Jaelani, L.M: Semi-analytical prediction of Secchi depth transparency in Lake Kasumigaura using MERIS data. Limnology, The Japanese Society of Limnology, Vol.19(1). pp.89-100, 2017.

Gholizadeh, H. M., Melesse, M.A., Reddi, L: A Comprehensive Review on Water Quality Estimation Using Remote Sensing Techniques. Sensors Vol. 16,1298, pp.1-43, 2016.

Kementerian Lingkungan Hidup. Profil 15 Danau Prioritas Nasional (2010 – 2014) Technical Report, 2011.

Kloiber, SM., Brezonik, PL., Bauer, ME: Application of Landsat imagery to regional-scale assessment of lake clarity, Water Research Vol. 26, pp. 4330-4340, 2002.

Lehmusluoto, P. and Machbub, B.: National inventory of the major lakes and reservoirs in Indonesia. Expedition Indodanau Technical Report, 1997.

Matsushita, B., Yang, W., Jaelani, L., Setiawan, F. Fukushima, T: Monitoring water quality with remote sensing image data, Remote Sensing for Sustainability, Editors: Qihao Weng, CRC Press. pp. 163-189, 2016.

McFeeters, S. K: The use of normalized difference water index (NDWI) in the delineation of open water features. IJRS, Vol.17, pp.1425–1432, 1996.

Olmanson, L. G., Bauer, M. E., & Brezonik, P. L: A 20-year Landsat water clarity census of Minnesota's 10,000 Lakes. Remote Sensing of Environment, Vol. 112, pp. 4086–4097, 2008.

Setiawan, F., Matsushita, B., Hamzah, R., Jiang, D., Fukushima, T: Long-Term Change of the Secchi Disk Depth in Lake Maninjau, Indonesia Shown by Landsat TM and ETM+ Data. Remote Sens. 2019, 11, 2875; doi:10.3390/rs11232875.

Sriwongsitanon, N.; Surakit, K.; Thianpopirug, S. Influence of atmospheric correction and number of sampling points on the accuracy of water clarity assessment using remote sensing application. *J. Hydrol.* 2011, *401*, 203–220, doi:10.1016/j.jhydrol.2011.02.023.

Subehi, L, Ridwansyah, I., & Fukushima, T.: Dissolved oxygen profiles and its problems at Lake Maninjau, West Sumatera – Indonesia. Proceeding of the 17th World Lake Conferences (WLC); Harmonious Coexistence of Humans and Lakes; Toward Sustainable Ecosystem Services, pp.322, 2018.

Vermote, E.F.; Tanré, D.; Deuzé, J.L.; Herman, M.; Morcrette, J.L. Second Simulation of the Satellite Signal in the Solar Spectrum, 6S: An Overview. IEEE Trans. Geosci. Remote Sens. 1997, 35, 675–686.

Wickham, H. Ggplot2: Elegant Graphics for Data Analysis; Springer: New York, NY, USA, 2016.

Xu, H: Modification of normalized difference water index (NDWI) to enhance open water features in remotely sensed imagery. IJRS, Vol. 27, pp. 3025–3033, 2006.

Zhao, D., Cai, Y., Jiang, H., Xu, D., Zhang, W., An, S: Estimation of water clarity in Taihu Lake and surrounding rivers using Landsat imagery. Adv. Water Resour. Vol.34 (2), pp. 165–173, 2011.