



Estimating total suspended matter using the particle backscattering coefficient: results from the Itumbiara hydroelectric reservoir (Goiás State, Brazil)

Enner Alcântara, Marcelo Curtarelli & José Stech

To cite this article: Enner Alcântara, Marcelo Curtarelli & José Stech (2016) Estimating total suspended matter using the particle backscattering coefficient: results from the Itumbiara hydroelectric reservoir (Goiás State, Brazil), Remote Sensing Letters, 7:4, 397-406, DOI: [10.1080/2150704X.2015.1137646](https://doi.org/10.1080/2150704X.2015.1137646)

To link to this article: <https://doi.org/10.1080/2150704X.2015.1137646>



Published online: 12 Feb 2016.



Submit your article to this journal [↗](#)



Article views: 121



View Crossmark data [↗](#)



Citing articles: 2 View citing articles [↗](#)

Estimating total suspended matter using the particle backscattering coefficient: results from the Itumbiara hydroelectric reservoir (Goiás State, Brazil)

Enner Alcântara ^a, Marcelo Curtarelli^b and José Stech^b

^aDepartment of Cartography, São Paulo State University – Unesp, Presidente Prudente, Brazil; ^bRemote Sensing Division, National Institute for Space Research - INPE, São José dos Campos, Brazil

ABSTRACT

In this study, a quasi-analytical algorithm (QAA)-based model was parameterized using remote-sensing reflectance (R_{rs} , units in sr^{-1}), total absorption coefficient (a_t) and total suspended matter (TSM) concentration. The model was based on the particle backscattering at 561 nm ($b_{bp}(561)$) and was derived from the QAA and TSM concentration. The aim of this work was to parameterize a QAA-based model to estimate the TSM concentration using the Landsat-8 Operational Land Imager (OLI) sensor in the Itumbiara hydroelectric reservoir, Brazil. The results demonstrated that the calibrated model, $\text{TSM} = 0.907 + 5.479 \times b_{bp}(561) + \xi$, had a coefficient of determination of $R^2 = 0.70$ and that the validation had an $R^2 = 0.82$, RMSE = 41.39% and a mean bias of 0.074 mg l^{-1} . The primary observation using the TSM and $b_{bp}(561)$ maps is that waters with lower $b_{bp}(561)$ values have lower TSM concentrations; there is a direct correlation between $b_{bp}(561)$ and TSM concentration.

ARTICLE HISTORY

Received 25 August 2015
Accepted 19 December 2015

1. Introduction

The suspension, transport and deposition of sediment rank among the most important geomorphic processes in shaping the physical landscape and regulating the ecological system. The total suspended matter (TSM) concentration and its distribution are essential for studying the interrelationships among physical, chemical, biological and environmental processes in aquatic systems.

The optical properties of the TSM can be detected using satellite data and quantified using algorithms that are based on the characteristics of the measured light spectra. Substantial efforts have been made to retrieve inherent optical properties (IOPs) from spectral measurements of water colour. Some of these efforts include empirical algorithms (Odermatt et al. 2012), linear matrix inversion (Yang et al. 2011) and quasi-analytical algorithm (QAA) (Lee, Carder, and Arnone 2002).

Among these approaches, the QAA, which is quite effective and simple to implement and apply, is based on the inversion relationship between the remote-sensing reflectance (R_{rs} , units in sr^{-1}) and the IOPs. The two fundamental IOPs are absorption (a , units

in m^{-1}) and volume scattering function (β , units in $\text{sr}^{-1} \text{m}^{-1}$). Other IOPs commonly derived from these include the total scattering coefficient (b , units in m^{-1}), the back-scattering coefficient (b_b , units in m^{-1}) and the attenuation coefficient (c , m^{-1}).

The objective of this work is to evaluate the feasibility of the QAA algorithm developed by Lee, Carder, and Arnone (2002) to estimate the concentration of TSM in a tropical reservoir.

2. Methodological approach

2.1. Study site

The study was conducted in the Itumbiara hydroelectric reservoir (IHR) ($18^{\circ}25' \text{ S}$, $49^{\circ}06' \text{ W}$), a tropical reservoir located in Brazilian West-Central between the States of Minas Gerais and Goiás (Figure 1) (Alcântara et al. 2010).

2.2. Limnological data collection

The samples were collected in 22 different locations (see Figure 1) during the field campaign performed from 9 to 11 September 2009. The collected water samples from the subsurface – approximately 10 cm from the surface – were kept at a cool temperature until the delivery of the samples to the laboratory for the analysis with duplicates. The TSM concentrations were obtained from analytical process in the laboratory. The TSM concentrations were measured by filtering the water samples (taken from 0.5 m below the water surface) on Whatman Grade GF/F filters, which were then dried and weighed on an electronic balance (Wetzel and Likens 2000). The Secchi depth, pH and water temperature were measured using a Secchi disk and an YSI 6600 v2 multiparameter sonde.

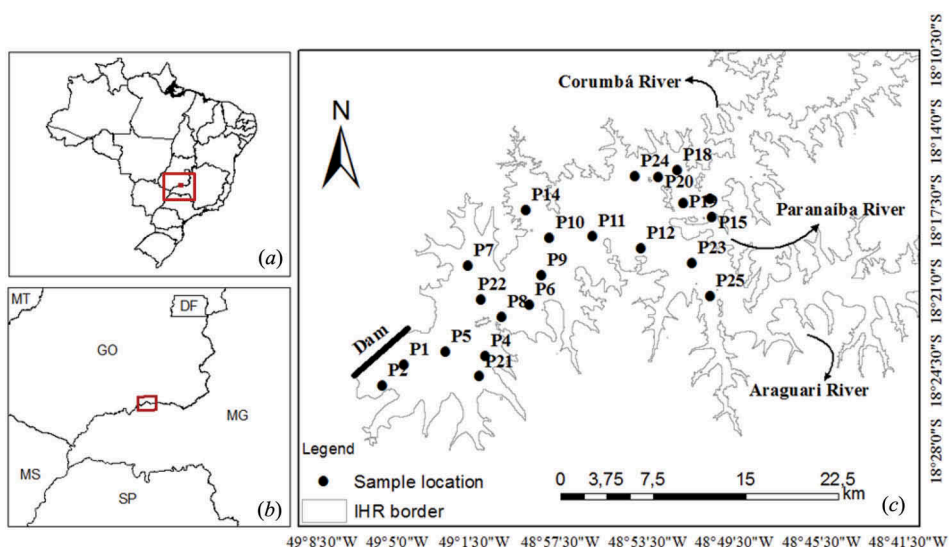


Figure 1. (a) Brazil, (b) location of the IHR between Minas Gerais (MG) and Goiás (GO) State and (c) the IHR boundary and sampling location.

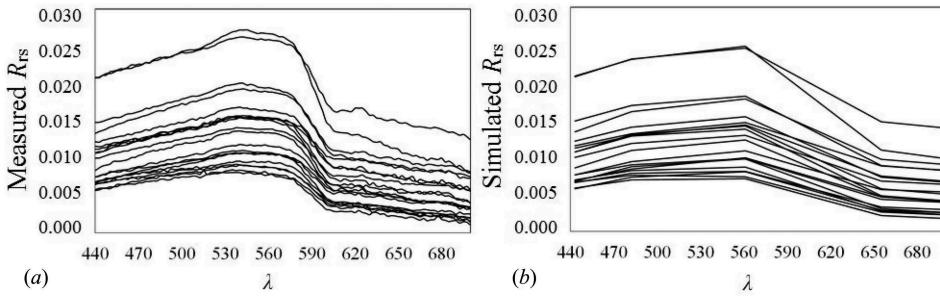


Figure 2. Measured in situ R_{rs} spectra (a) and Landsat-8 simulated R_{rs} (b).

2.3. Total absorption coefficient

The spectral absorption coefficient is one of the IOPs that influence the reflectance of aquatic systems. IOPs consist of absorption and scattering coefficients of several natural constituents, such as coloured dissolved organic matter, phytoplankton and non-algal particles. The total absorption coefficient (a_t , units in m^{-1}) at any point within natural water body can be described in terms of the additive contribution of its components as:

$$a_t(\lambda) = a_w(\lambda) + a_p(\lambda) + a_g(\lambda), \quad (1)$$

where λ is the wavelength, $a_w(\lambda)$, $a_p(\lambda)$ and $a_g(\lambda)$ are the spectral absorption coefficients of water, particles and soluble components, respectively.

2.4. Radiometric data collection

The R_{rs} spectra above the water surface were measured using an ASD FieldSpec spectrometer (Analytical Spectral Devices, Inc., Boulder, CO, USA) in the IHR. All radiometric quantities were measured 10 times each to reduce the noise. R_{rs} was then computed following Mobley (1999):

$$R_{rs} = \frac{L_u}{E_s} = \frac{(L_t - \rho L_s)}{E_s}, \quad (2)$$

where L_s is the incident sky radiance; L_t is the total radiance measured above the surface and is composed of the leaving-water radiance (L_u) and the portion of the L_s that is reflected by water surface (L_r); E_s is the incident sky irradiance and ρ is a reflectance factor related to the direction, wavelength, wind speed, sensor field of view (FOV), and sky radiance distribution. Mobley (1999) suggest the use of $\rho \approx 0.028$ for wind speeds less than 5 (units in m s^{-1}) or in an overcast sky.

To reduce the sun glint effect and boat shadow on the water, the field method measurements proposed by Mobley (1999) were used.

2.5. Satellite imagery

The Landsat program has provided the longest record of Earth observations from space. The Operational Land Imager (OLI) aboard Landsat-8 was launched in February 2013 to continue Landsat's mission of monitoring Earth systems. The OLI is a push-broom sensor, with long arrays of detectors forming the image as the satellite moves across the Earth,

Table 1. Summary of the eight Landsat-8/OLI images used for this study (dates, solar zenith and azimuth angle).

Image date	Solar zenith angle (°)	Solar azimuth angle (°)
5 January 2014	28.96	103.08
6 February 2014	31.62	89.44
27 April 2014	43.43	43.44
29 May 2014	49.39	36.61
14 June 2014	51.07	36.00
16 July 2014	50.34	38.88
1 August 2014	47.81	41.83
4 October 2014	29.81	64.84

covering a 15° FOV with a swath of 185 km (Knight and Kvaran 2014). Eight cloud-free level-1T images (path/raw 221/73) were downloaded from the USGS Global Visualization Viewer – GloVis website (<http://glovis.usgs.gov/>) (see Table 1 for dates).

The raw Digital Number was converted to the Top-of-Atmosphere planetary reflectance using the rescaling coefficients available in the image's metadata file. The images were atmospherically corrected using Fast Line-of-sight Atmospheric Analysis of Spectral Hypercubes (FLAASH). FLAASH (Adler-Golden et al. 1999) is based on the radiative transfer code MODerate spectral resolution atmospheric TRANsmittance – MODTRAN 4 (Berk et al. 2000). The surface reflectance images were converted to R_{rs} through division by π (Moses et al. 2012).

To simulate the $R_{rs}(\lambda_i)$ signals that would be recorded by satellite sensor channels centred at wavelength λ_i , weighted averages of each R_{rs} spectrum were calculated by using as weights the spectral band responses of OLI (Barsi et al. 2014), as given below

$$R_{rs_s}(\lambda) = \frac{\sum_{\lambda} R_{rs}(\lambda) \times S(\lambda)}{\sum_{\lambda} S(\lambda)}, \quad (3)$$

where $S(\lambda)$ is the OLI spectral response function and $R_{rs_s}(\lambda)$ is the simulated R_{rs} .

According to Barsi et al. (2014), the spectral response characteristics of the OLI instrument, similar to any remote-sensing instrument, are key to understanding and utilizing the data. The spectral simulated data were then used to estimate the particle backscattering coefficient using the QAA algorithm.

2.6. Quasi-analytical algorithm

Combined with downwelling light from the sun and sky, absorption and backscattering determine the appearance of the water colour, which is normally measured by the water-leaving radiance or R_{rs} . Methods to retrieve the optical properties remotely have been under investigation for several decades. One of these methods is the QAA, which was originally developed by Lee, Carder, and Arnone (2002). From the original QAA version 5, only six steps (Table 2) were used to estimate the particle backscattering (b_{bp}).

2.7. TSM model based on QAA

To run the QAA model, the reference wavelength was fixed at 561 nm to be compatible with the Landsat-8 spectral band. A correlation analysis was run between the b_{bp} coefficient and the TSM concentration measured in situ to select the best wavelength



Table 2. Steps to derive the particle backscattering $b_{bp}(\lambda)$ from Landsat-8/OLI images. $r_{rs}(\lambda)$ denotes the underwater surface remote-sensing reflectance; $u(\lambda)$ denotes the ratio between the backscattering coefficient and the sum of the absorption and backscattering coefficients. Where g_0 ($= 0.0895$) and g_1 ($= 0.1247$) are coefficients, and their values vary with sun-sensor angular geometry, although they are considered wavelength and water property independent; λ_0 is a reference wavelength, and b_{bw} is the backscattering of pure water. Source: (Lee et al. 2009).

Steps	Property	Derivation	Approach
0	r_{rs}	$= R_{rs} / (0.52 + 1.7R_{rs})$	Semi-analytical
1	$u(\lambda) = \frac{b_b(\lambda)}{a(\lambda) + b_b(\lambda)}$	$= \frac{-g_0 + [(g_0)^2 + 4g_1 r_{rs}(\lambda)]^{1/2}}{2g_1}$	Semi-analytical
2	$a(561)$	Laboratory (Nascimento 2010)	Measured
3	$b_{bp}(561)$	$= \frac{u(\lambda_0)a(561)}{1 - u(561)} - b_{bw}(561)$	Analytical
4	Y	$= 2.0 \left(1 - 1.2 \exp \left(-0.9 \frac{r_{rs}(443)}{r_{rs}(561)} \right) \right)$	Empirical
5	$b_{bp}(\lambda)$	$= b_{bp}(561) \left(\frac{561}{\lambda} \right)^Y$	Semi-analytical

to calibrate the model. This correlation analysis showed that the $b_{bp}(561)$ coefficient achieved the highest correlation coefficient ($r = 0.50$); thus, this coefficient was used to fit a regression model. This fitted model was calibrated using 13 TSM sampled data and was validated using 9 TSM sampled data.

3. Results

3.1. Limnological characterization

The TSM concentration in the IHR ranged from 0.25 to 1.81 (units in mg l^{-1}) during the field campaign and can be considered a very clean environment, with a Secchi depth of up to 7 m. The water can be considered neutral, with a mean pH value of 6.99. Table 3 summarizes the limnological data collected in field.

Nascimento (2010) collected data during the dry season in the IHR and found that the TSM concentration varied from 0.60 to 1.54 mg l^{-1} ($\pm 0.25 \text{ mg l}^{-1}$). These data show that this reservoir has a very low TSM concentration along the year.

3.2. Simulated R_{rs} data

The measured R_{rs} is shown in Figure 3(a), and the simulated R_{rs} is shown in Figure 3(b). The sample spots with high reflectance for longer wavelengths have low TSM concentration, and the spectra with lower reflectance have the highest chlorophyll-*a* concentrations.

The primary spectral factors that explain the water reflectance sensitivity to TSM changes are particle size, sediment type and concentration range (Nechad, Ruddick, and Park 2010). Using the simulated R_{rs} and the QAA, the $b_{bp}(561)$ was calculated, and a regression was realized with TSM concentration.

Table 3. Statistical summary of limnological data collected during the field campaign performed from 9 to 11 September 2009. TSM is the total suspended matter (units in mg l^{-1}), SD is the Secchi depth (units in m) and T is the water temperature (units in $^{\circ}\text{C}$).

Parameter	Minimum	Maximum	Mean	Standard deviation
TSM	0.25	1.81	1.12	± 0.40
SD	4.00	7.00	5.50	± 0.82
pH	6.29	7.90	6.99	± 0.47
T	24.8	25.9	25.28	± 0.37

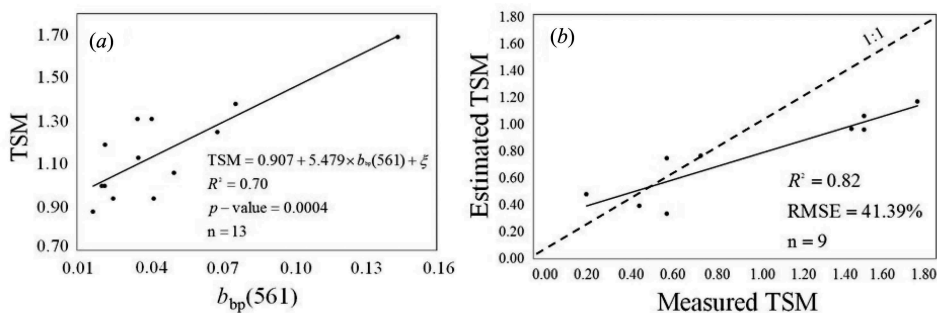


Figure 3. Fitted TSM model using the calibration data set (a) and the model validation (b).

3.3. TSM model based on $b_{bp}(561)$

A model was obtained through calibration (Figure 4(a)) and then the model was validated (Figure 4(b)). The calibrated model obtained an R^2 of 0.70 ($n = 13$) using a linear function, $TSM = 0.907 + 5.479 \times b_{bp}(561) + \xi$. The ξ represents the mean bias ($=0.074 \text{ mg.l}^{-1}$) observed during the validation procedure. The bias was taken into consideration to keep the errors as low as possible. The validation result shows that the fitted model underestimates the TSM concentrations when the concentration is lower than 0.60 mg l^{-1} and overestimates when the concentration ranges from 0.60 to 1.40 mg l^{-1} . The best results are obtained for concentrations above 1.40 mg l^{-1} .

The next step was to apply the QAA model on the R_{rs} derived from Landsat-8 atmospheric corrected images to obtain the $b_{bp}(561)$ coefficient. Once we obtained the b_{bp}

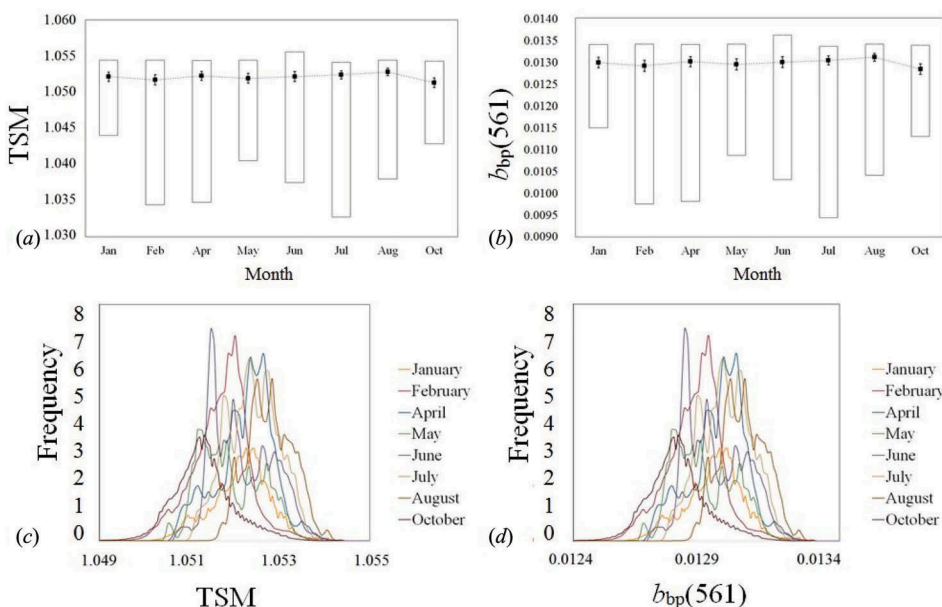


Figure 4. Statistics for the TSM concentration based on OLI images, and $b_{bp}(561)$ estimated using the QAA algorithm. The descriptive statistics, maximum, minimum, mean and standard deviation for the TSM (a) and for the $b_{bp}(561)$ coefficient (b), and the frequency (units in %) of occurrence of different values of the TSM (c) and of the $b_{bp}(561)$ coefficient (d).

(561) coefficient for each pixel, the fitted model, $TSM = 0.907 + 5.479 \times b_{bp}(561) + \xi$, was applied to estimate the spatially distributed TSM concentrations.

3.4. QAA applied to Landsat-8 images

The basic statistics for the TSM concentration based on the OLI images and the $b_{bp}(561)$ coefficient estimated using the QAA model are shown in Figure 5. The maximum, minimum, mean and standard deviation for the TSM concentration (Figure 5(a)) show that the minimum concentrations occurred in July and October and the highest occurred in June and August. The standard deviations were higher for February and May and were lower for August and July. The same patterns were obtained for the $b_{bp}(561)$ coefficient because there is a linear relationship with the TSM, as also observed by Babin et al. (2003). Wu et al. (2011), studying the Poyang Lake, found a non-linear relationship between the b_{bp} coefficient at 700 nm and the TSM concentration. However, both agree that when the b_{bp} coefficient increases, the TSM also increases.

Because the equation used to estimate the TSM concentration using the $b_{bp}(561)$ coefficient was linear, Figure 5 shows the same frequency distribution for both (Figures 5 (c) and (d)). The TSM histogram (Figure 5(c)) and the $b_{bp}(561)$ coefficient (Figure 5(d)) showed the lowest values in October and highest values in August. The maps of the $b_{bp}(561)$ coefficient and the TSM concentrations (for January, June and October) are shown

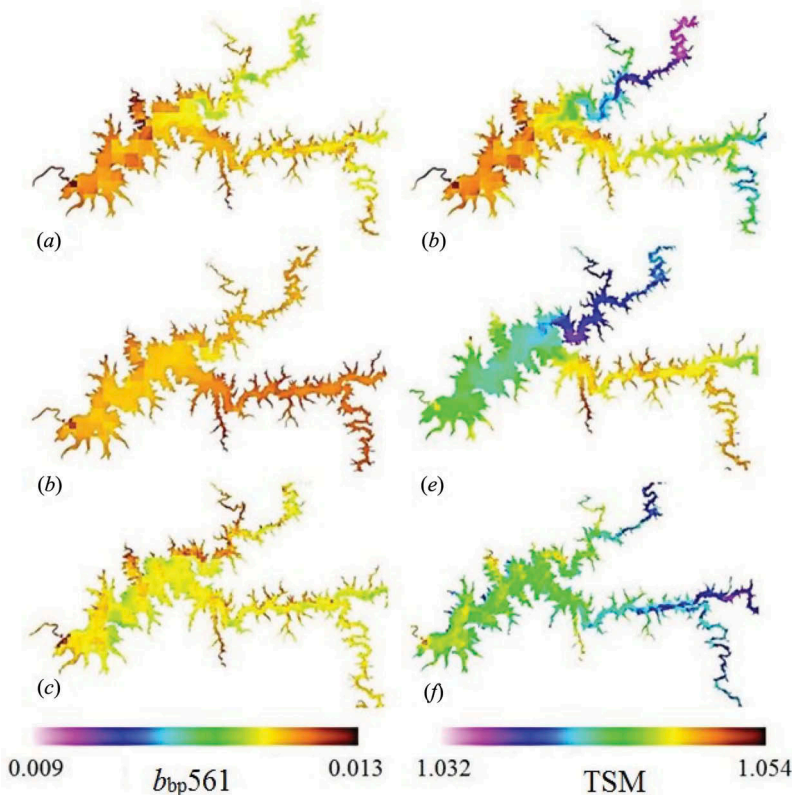


Figure 5. Spatial distribution of the $b_{bp}(561)$ coefficient in the study area for January (a), June (b) and October (c), and the estimated TSM concentration for January (d), June (e) and October (f).

in Figure 6. The primary observation from this figure is that reservoir's water spots with lower $b_{bp}(561)$ coefficient values represent lower TSM concentrations, that is, there is a direct correlation between the $b_{bp}(561)$ coefficient and the TSM concentration.

In general, the IHR shows a higher TSM concentration in the main body and near the dam compared to that in the littoral and transition zones during the entire year. May (map not show) and June months are exceptions, with higher TSM concentration in the Paranaíba transition zone than in the other areas. Figure 6 also shows that there is a very small TSM concentration during the year. Considering the limnological data summary shown in Table 3 and the data collected during the dry season by Nascimento (2010), a very small variability throughout the year was expected. This low variation is also corroborated by the results obtained by Rangel et al. (2012) that measure the turbidity in IHR in three periods, that is, the pre-rainy, post-rainy and dry season (between 2004 and 2005), and found a mean value of 2.6 NTU, which can be considered very clean water. However, we must consider that our model was fitted with a $R^2 = 0.70$ and was validated with an RMSE of 41.39%; thus, errors of estimation are expected. Another limitation of this statistical-based model is the adjustment of a few measurements. Despite this small data set, the results should be viewed as an opportunity for future research, taking in consideration the limitations noted in this and other research.

Among the factors often cited in the literature to explain the TSM surface heterogeneity in lakes and reservoirs, we can highlight the preferential wind direction, the reservoir fetch, the presence of submerged aquatic vegetation, the presence of tributaries, the reservoir topography, and the land use and land cover of drainage basin (Zhang et al. 2014). According to Nascimento et al. (2013), the areas along Corumbá River are primarily occupied by natural and semi-natural vegetation; and the areas along the Araguari River are primarily occupied by cultivated and managed terrestrial areas (see Figure 1 for location). The hydrodynamics and mixing process are other factors that can influence the TSM surface heterogeneity and can explain the fact that in areas near the land, the TSM concentration is slightly higher (Liu et al. 2014).

4. Conclusions

Although the water from the Itumbiara reservoir has high transparency and low TSM, the fitted model has sufficient capability to map the TSM concentration using the results from QAA; however, the model should be improved to reduce the errors. Some authors (e.g., Yang et al. 2013) have suggested that this is because the reference wavelength used (561 nm) should be shifted to longer wavelengths (~720 nm) when applying QAA in inland waters.

There is a direct correlation between the particle backscattering coefficient and the TSM concentrations. In addition, there is a strong influence on the model of the rainy season and wind velocity and direction on the water surface. In January and February, the influence of rain dominates the TSS concentration coming from the watershed. From May to September, the wind is primarily responsible for resuspension of the sediments from the bottom to increase the TSM concentration. From October to December, the rain starts to increase, and then the material from the watershed enters into the reservoir.

More research is needed to determine the appropriate wavelength to be considered as a reference and consequently to minimize the errors in estimating the particle backscattering coefficient using QAA.

Acknowledgements

The authors thank Renata Nascimento for the use of the data set in this work.

Disclosure statement

No potential conflict of interest was reported by the authors.

Funding

This work was supported by INCT for Climate Change (under grants CNPq 5737797/2008 and FAPESP 08/57719-9) and by the São Paulo Research Foundation (FAPESP) (under grant 2007/08103-2). Marcelo Curtarelli is grateful to the Brazilian Council of Technological and Scientific Development (CNPq) for the doctorate-level scholarship (under grant 161233/2013-9). Enner Alcântara thanks CNPq for the Research Productivity Scholarship (under grant 300301/2012-0).

ORCID

Enner Alcântara  <http://orcid.org/0000-0002-7777-2119>

References

- Adler-Golden, S. M., M. W. Matthew, L. S. Bernstein, R. Y. Levine, A. Berk, S. C. Richtsmeier, P. K. Acharya, et al. 1999. "Atmospheric Correction for Shortwave Spectral Imagery Based on MODTRAN4." In: *SPIE Proceedings, Imaging Spectrometry* 3753: 61–69. doi:10.1117/12.366315.
- Alcântara, E. H., J. L. Stech, J. A. Lorenzetti, M.-P. Bonnet, X. Casamitjana, A. A. Trevenzoli, and E. M. L. M. Novo. 2010. "Remote Sensing of Water Surface Temperature and Heat Flux over a Tropical Hydroelectric Reservoir." *Remote Sensing of Environment* 114: 1–15. doi:10.1016/j.rse.2010.06.002.
- Babin, M., A. Morel, V. Fournier-Sicre, F. Fell, and D. Stramski. 2003. "Light Scattering Properties of Marine Particles in Coastal and Open Ocean Waters as Related to the Particle Mass Concentration." *Limnol. Oceanogr.* 48: 843–859. doi:10.4319/lo.2003.48.2.0843.
- Barsi, J. A., K. Lee, G. Kvaran, B. L. Markham, and J. A. Pedelty. 2014. "The Spectral Response of the Landsat-8 Operational Land Imager." *Remote Sensing* 6: 10232–10251. doi:10.3390/rs61010232.
- Berk, A., G. P. Anderson, P. K. Acharya, J. H. Chetwynd, L. S. Bernstein, E. P. Shettle, M. W. Matthew, and S. M. Adler-Golden. 2000. "MODTRAN4 User's Manual." Hanscom AFB: Air Force Research Laboratory, Space Vehicles Directorate, Air Force Material Command, MA 01731-3010. Bedford, MA: Air Force Material Command.
- Chen, S., and T. Zhang. 2015. "Evaluation of a QAA-Based Algorithm Using MODIS Land Bands Data for Retrieval of IOPS in the Eastern China Seas." *Optics Express* 23: 13953–13971. doi:10.1364/OE.23.013953.
- Knight, E., and G. Kvaran. 2014. "Landsat-8 Operational Land Imager Design, Characterization and Performance." *Remote Sensing* 6: 10286–10305. doi:10.3390/rs61110286.
- Le, C., C. Hu, J. Cannizzaro, D. English, F. Muller-Karger, and Z. Lee. 2013. "Evaluation of Chlorophyll-*a* Remote Sensing Algorithms for an Optically Complex Estuary." *Remote Sensing of Environment* 129: 75–89. doi:10.1016/j.rse.2012.11.001.
- Lee, Z., K. Carder, and R. A. Arnone. 2002. "Deriving Inherent Optical Properties from Water Color: A Multiband Quasi-Analytical Algorithm for Optically Deep Waters." *Applied Optics* 41: 5755–5772. doi:10.1364/AO.41.005755.
- Lee, Z., B. Lubac, J. Werdell, and R. Arnone. 2009. "An Update of the Quasi-Analytical Algorithm (QAA V5)." Accessed February 12, 2014. http://www.ioccg.org/groups/Software/OCA/QAA_v5.pdf
- Li, L., L. Li, and K. Song. 2015. "Remote Sensing of Freshwater Cyanobacteria: An Extended IOP Inversion Model of Inland Waters (IIMIWI) for Partitioning Absorption Coefficient and Estimating Phycocyanin." *Remote Sensing of Environment* 157: 9–23. doi:10.1016/j.rse.2014.06.009.

- Liu, X., Y. Zhang, M. Wang, and Y. Zhou. 2014. "High-Frequency Optical Measurements in Shallow Lake Taihu, China: Determining the Relationships between Hydrodynamic Processes and Inherent Optical Properties." *Hydrobiologia* 724: 187–201. doi:10.1007/s10750-013-1733-0.
- Lobo, F., M. Costa, S. Phillips, E. Young, and C. McGregor. 2014. "Light Backscattering in Turbid Freshwater: A Laboratory Investigation." *Journal of Applied Remote Sensing* 8: 083611. doi:10.1117/1.JRS.8.083611.
- Mobley, C. D. 1999. "Estimation of the Remote Sensing Reflectance from Above-Surface Measurements." *Applied Optics* 38: 7442–7455. doi:10.1364/AO.38.007442.
- Moses, W. J., A. Gitelson, R. L. Perk, D. Gurlin, D. C. Rundquist, B. C. Leavitt, T. M. Barrow, and P. Brakhage. 2012. "Estimation of Chlorophyll-a Concentration in Turbid Productive Waters Using Airborne Hyperspectral Data." *Water Research* 46: 993–1004. doi:10.1016/j.watres.2011.11.068.
- Mueller, J. L., G. S. Fargion, and C. R. McClain. 2002. "Oceans Optics Protocols for Satellite Ocean Color Sensor Validation". Revision 4, volume IV: Inherent optical properties. 76. Greenbelt: NASA.
- Nascimento, R. F. F. 2010. *Utilização de dados MERIS e in situ para a caracterização bio-óptica do reservatório de Itumbiara, GO*. São José dos Campos: Dissertação (Mestrado em Sensoriamento Remoto) – Instituto Nacional de Pesquisas Espaciais. <http://urlib.net/sid.inpe.br/mtc-m19@80/2010/03.15.18.39>.
- Nascimento, R. F. F., E. Alcântara, M. Kampel, and J. Stech. 2013. "An Assessment of the Support Vector Machine for A CBERS-2 CCD Image Classification: A Case Study of a Tropical Reservoir in Brazil." *Revista Brasileira De Cartografia* 65: 431–439.
- Nechad, B., K. G. Ruddick, and Y. Park. 2010. "Calibration and Validation of a Generic Multisensor Algorithm for Mapping of Total Suspended Matter in Turbid Waters." *Remote Sensing of Environment* 114: 854–866. doi:10.1016/j.rse.2009.11.022.
- Odermatt, D., A. Gitelson, V. E. Brando, and M. Schaepman. 2012. "Review of Constituent Retrieval in Optically Deep and Complex Waters from Satellite Imagery." *Remote Sensing of Environment* 118: 116–126. doi:10.1016/j.rse.2011.11.013.
- Pope, R. M., and E. S. Fry. 1997. "Absorption Spectrum (380–700 nm) of Pure Water. II. Integrating Cavity Measurements." *Applied Optics* 36: 8710–8723. doi:10.1364/AO.36.008710.
- Rangel, L. M., L. H. S. Silva, P. Rosa, F. Roland, and V. L. M. Huszar. 2012. "Phytoplankton Biomass Is Mainly Controlled by Hydrology and Phosphorus Concentrations in Tropical Hydroelectric Reservoirs." *Hydrobiologia* 693: 13–28. doi:10.1007/s10750-012-1083-3.
- Wetzel, R. G., and G. Likens. 2000. *Limnological Analyses*. New York: Springer-Verlag. doi:10.1007/978-1-4757-3250-4.
- Wu, G., L. Cui, H. Duan, T. Fei, and Y. Liu. 2011. "Absorption and Backscattering Coefficients and Their Relations to Water Constituents of Poyang Lake, China." *Applied Optics* 50: 6358–6368. doi:10.1364/AO.50.006358.
- Wu, G., L. Liu, F. Chen, and T. Fei. 2014. "Developing MODIS-Based Retrieval Models of Suspended Particulate Matter Concentration in Dongting Lake, China." *International Journal of Applied Earth Observation and Geoinformation* 32: 46–53. doi:10.1016/j.jag.2014.03.025.
- Yang, W., B. Matsushita, J. Chen, and T. Fukushima. 2011. "A Relaxed Matrix Inversion Method for Retrieving Water Constituent Concentrations in case II Waters: The Case of Lake Kasumigaura, Japan." *IEEE Transactions on Geoscience and Remote Sensing* 49: 3381–3392. doi:10.1109/TGRS.2011.2126048.
- Yang, W., B. Matsushita, J. Chen, K. Yoshimura, and T. Fukushima. 2013. "Retrieval of Inherent Optical Properties for Turbid Inland Waters from Remote Sensing Reflectance." *IEEE Transactions on Geoscience and Remote Sensing* 51: 3761–3773. doi:10.1109/TGRS.2012.2220147.
- Zhang, Y., K. Shi, X. Liu, Y. Zhou, and B. Qin. 2014. "Lake Topography and Wind Waves Determining Seasonal-Spatial Dynamics of Total Suspended Matter in Turbid Lake Taihu, China: Assessment Using Long-Term High-Resolution MERIS Data." *PloS One* 9: e98055. doi:10.1371/journal.pone.0098055.