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NEURAL NETWORK MODELING OF LAKE SURFACE CHLOROPHYLL AND SEDIMENT CONTENT FROM LANDSAT TM IMAGERY

Pranab J. BARUAH
Doctoral Program in Engineering, University of Tsukuba, 305 8573, Tel: +81-298-502589
Fax: +81-298-502920, E-mail: p.j.baruah@nies.go.jp, JAPAN

Masayuki TAMURA
Deputy Director, Social and Environmental Systems Division
National Institute for Environmental Studies, 16-2 Onogawa, 305 0053
Tel : +81-298-502479, Fax: +81-298-502572, E-mail: m-tamura@nies.go.jp, JAPAN

Kazuo OKI
Associate Professor, Graduate School of Agriculture and Life Science, The University of Tokyo
Yayoi 1-1-1, Bunkyo-ku, Tokyo 113 8657 Japan, Tel: +81-3-5841-8101
E-mail: agrioki@mail.ecc.u-tokyo.ac.jp, JAPAN

Hitoshi NISHIMURA
Professor, Institute of Engineering Mechanics and Systems, University of Tsukuba, 3058573 Japan,
Tel/Fax:+81-298-535254, E-mail: nishimura@surface.kz.tsukuba.ac.jp, JAPAN

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ABSTRACT: Concentrations of chlorophyll and suspended sediment are two important optically active parameters of inland water quality. In the open ocean, these two parameters can be effectively quantified by empirical algorithms relating remote sensor radiances to surface concentrations. In inland waters, however, the task becomes difficult due to the presence of suspended sediment and dissolved organic matters in high concentrations, often varying independently of each other and overwhelming the signature of chlorophyll. Thus, the transfer function becomes non-linear in nature. Moreover, broad band sensors have to be used in inland waters as the present aquatic satellite sensors lack adequate spatial resolution for monitoring in these waters. In the process, conventional algorithms fail to estimate the water quality parameters effectively. Neural networks has been regarded as a relatively simpler tool to implement with proven success in modeling various nonlinear geophysical transfer functions. In this study, back-propagation neural network is used to model the transfer function between chlorophyll concentration and suspended solid, and sensor-received radiances at the first four bands of LandsatTM. Study area is lake Kasumigaura of Japan, a shallow eutrophic lake with heavy sedimentation. Neural network with only one hidden layer could model both the water quality parameters better than conventional regression techniques from LandsatTM imagery. Root Mean Square Errors(RMSE) in estimating chlorophyll-a were 1.53µg/l(R^2: 0.93) and 4.39µg/l(R^2: 0.31) for neural networks and regression respectively. In estimating suspended sediments, RMSE for regression was 1.47mg/l(R^2:0.92) while for neural network the same was 2.14mg/l(R^2:0.85). Neural network-derived map of chlorophyll-a shows that, the lake is eutrophic even in the low productivity season.

1. INTRODUCTION

Remote sensing of inland water quality has involved mainly estimation of surface chlorophyll and suspended sediment concentrations from sensor-derived radiances. This is because of the fact that, these two parameters are optically active and can adequately represent the inland water quality scenario. Chlorophyll-a(Chl.a) is used as the primary pigment-index for various phytoplanktons in water and is needed for estimating primary productivity, biomass etc. Suspended Sediments(SS) are the most common type of pollutants both in terms of weight and volume in the surface of inland water systems are helpful in determining water dynamics and spread of pollutants(Ritchie et al., 1990). In the open ocean, these parameters have been effectively and easily monitored from remote sensors by constructing simple empirical or ratio algorithms at different remote-sensor bands(Gordon et al., 1983). However, in optically complex inland water the task is often much more difficult due to the presence of suspended minerals and dissolved organic matter, that vary independently of phytoplankton and can overwhelm the spectral signature of chlorophyll. There is also considerable scattering (even in near-IR) from inland waters with high sediment. Thus, the transfer function becomes a nonlinear problem and estimation of water quality parameters, especially Chl.a becomes difficult with regression analysis (Lathrop, 1992) or with model based approaches

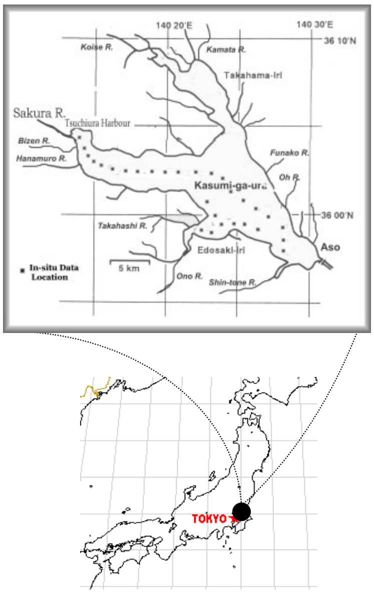

Figure 1. Location of lake Kasumigaura in Japan.

such as Principal Component Analysis(IOCCG, 2000). Non-linear optimization techniques seem to solve the problem. However, the technique is weak to local correlation between the parameters, which is often present, and to wide-range of concentrations. Chebychev polynomial may be another choice though it is quite complex to implement. Neural Network is one of the simplest and fastest to implement choice while modeling in nonlinear environment and has the ability to combine detailed physical description of the remote sensing process in the form of a forward model. It is a proven tool for successful modeling in various nonlinear geophysical transfer function(Thiria et al., 1993), and most of all it does not depend on mutual relationship between the parameters under investigation. Recent years have seen several publications on the use of neural networks for estimation of coastal and oceanic Chl.a (and SS) from simulated bands of ocean-color sensors, such as, SeaWiFS(Gross et al., 1999), MERIS(Sciller et al., 1999) and OCTS(Tanaka et al., 2000). Keiner et al.(1998) estimated Chl.a and SS from LandsatTM visible bands using in-situ data. Use of in-situ data in modeling is preferred as the model can account for the realistic situation involving various noises present in the data(Gross et al., 1999).

This study is a similar effort to the above studies, however with the fact that, the site under consideration is a shallow inland water body eutrophic round-the-year, and with wide range of concentration for both Chl.a and SS(especially, in the blooming season). Here, neural network is employed to demonstrate a robust methodology for estimating surface Chl-a and SS concentration at the lake Kasumigaura, Japan from LandsatTM imagery. Past studies with conventional algorithms failed with poor results in estimating water quality of the lake (Oki, 1997). Another purpose of this study is to know the trophic state of the lake in low-productivity season by mapping the distribution of chlorophyll. In this study, we are using single day data, however, the method can be applied for temporal modeling with the collection of data at different times of the year concurrent with remote-sensor overpass.

1.1 Landsat Thematic Mapper as water color monitor

LandsatTM is not primarily designed for aquatic applications unlike some of the recent sensors dedicated to water color remote sensing, e.g. SeaWiFS, MERIS, IRS-OCM, MODIS with their suitable and narrow bandwidths. However, it has been the best available source of data for monitoring inland water quality due to its higher spatial resolution(30m) compared to the above sensors(0.3~1.1km). Several studies have explored the possibility of using it for estimating water quality parameters(especially, suspended sediment) in coastal and inland waters(Ritchie et al., 1990; Lathrop, 1992; Brivio et al., 2001)

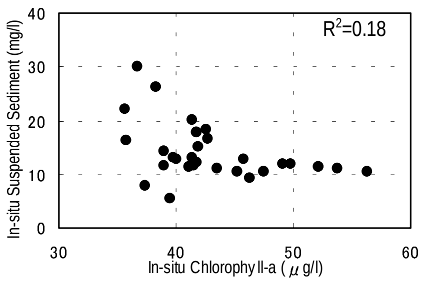

Figure 2. In-situ Chl.a .vs. SS at lake Kasumigaura on 19th Jan,2001

2. STUDY SITE

Study site is the lake Kasumigaura, the second largest lake of Japan with an area of 220km^2 and an average depth of 4m (Fig.1). Several important cities are located around it which are affecting (and are being affected) by the lake water quality. The lake experienced severe bloom of blue green algae in `70s. Since then, several drastic measures have been undertaken to control the eutrophication. Present lake water quality is better than in `70s, but still below standards set for a healthy lake. Around 22 rivers flowing to the lake caries huge amount of sediments(around 1 Mm^3/year) and local government spends heavily each year on dredging the sediments out. Degradation of lake water quality is affecting environment, agriculture, fish-culture, recreation, drinking water quality etc. and effective monitoring techniques are need of the hour for efficient management of the same(Hashimoto, 1995).

3. IN-SITU AND SATELLITE DATA PROCESSING

Surface water samples were collected for Chl.a(HPLC) and SS concentrations for a total of 29 locations spread over the lake (shown in Fig.1) on 19th January, 2001 concurrent with LandsatTM overpass. In-situ Chl.a concentrat-ion is found to vary from 36.5 to 56.2μg/l and SS concentrations varying from 5.5 to 30.1mg/l. January and February is the coldest month in the region with lowest chlorophyll level in a year. All the samples were collected between 08:30 to 11:30JST to coincide with the LandsatTM overpass at around 09:55JST. Fig.2 shows the plot of Chl.a versus SS concentrations for the 29 locations. It should be noted that, ~50% of Chl.a concentrations fall in the range 39-42μg/l.

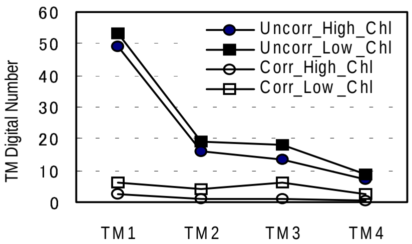

Figure 3. DN of TM bands before and after atmospheric correction

The Landsat TM imagery for 19th January, 2001 is acquired from NASDA. The day was clear with no cloud over the lake area.For atmospheric correction, dark pixel subtraction method is used (Brivio et al., 2001). Usual methods used in the mid-oceanic waters using near-IR bands are not suitable for sediment-laden inland waters as the assumption of zero water-leaving radiance in near-IR breaks down(IOCCG, 2000). This is a first order techniques where the lowest DN value in a certain band is subtracted from that band over the entire image. The effect from atmosphere is assumed constant over the entire lake. For single scene imagery, however, this type of atmospheric correction is not much of significance as it accomplices just the magnitude-reduction of DN values. Fig.3 shows the plot of DN values at TM bands1-4 before and after the atmospheric correction. While dealing with multi-temporal data, however, a more accurate method should be used (Keiner et al.,1998).

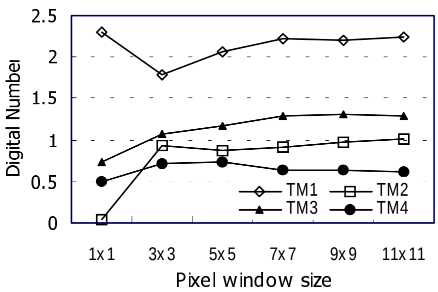

Figure 4. Optimum pixel-window for noise-reduction

The portion containing the lake Kasumigaura is extracted from the TM imagery and geo-referenced to a standard 1:50,000 map. Average DN is found to approach a fairly constant value for a 7 by 7 pixel array size and hence it is selected as the minimum appropriate to reduce sensor noise. The whole image is re-sampled to a pixel size of 7 by 7 and DN values for all the 29 in-situ locations are extracted out (Figure 4). A land-mask is applied using NDWI (Mcfeeters, 1996).

3.1 Selection of bands

Table 1. First four Bands of LandsatTM

Spectral band	Bandwidth (μ m)
TM1 (blue)	0.45-0.520
TM2 (green)	0.52-0.60
TM3 (red)	0.63-0.69
TM4 (near-IR)	0.76-0.90

The three visible bands are generally sufficient for estimating Chl.a and SS in surface water(Bukata et al., 1995). However, several studies have indicated that, near-IR wavelength-range could be useful(Ritchie et al., 1990; Lathrop et al., 1992; Han et al., 1997), especially, when the spectral behavior of the of the water body is dominated by SS present in surface water. With the increasing concentration of suspended sediments, the reflected radiance tends to saturate to give a curvilinear relationship between the two(Curran and Novo, 1988). The point of saturation is wavelength dependent and with SS concentrations between 0 to 50 mg/l, it can influence any of the wavelengths, thus effecting the estimation of Chl.a. From the in-situ data, it is found that SS has very strong correlation with band 1 to 4, especially with band 3 and 4 (R^2>0.74). Individual correlation (R^2) of these first four bands of TM with Chl.a concentrations are 0.25, 0.32, 0.30 and 0.23. Bands 5 & 7 gave correlation <0.01. Our initial test-runs with neural network using the first four TM bands also gave better result than with only the three visible bands. Hence, the first four bands(Table 1) of LandsatTM are selected for modeling.

4. NEURAL NETWORKS

Several types of neural networks are available depending on the type of application. This study uses the popular NN algorithm, namely, the Back-Propagation Neural Network(BPNN) (Fausset, 1994). Following section details the neural network(s) used in this study.

4.1 Algorithm

In our study, Chl.a and SS are modeled separately by two independent network models to enhance performance(Kasilingam et al., 1997). This is necessary as we have fewer data than prescribed for robust modeling (explained later). Fig.5 shows the basic structure of NN used in this study. BPNN is a feed-forward multi-layer network comprised of three distinct layers, namely, input layer, output layer and hidden layer. Hidden layers may be more than one. In this study only one hidden layer is used as it is proven to be sufficient in modeling any complex problem. Nodes (or neurons) in each layer is connected to next layer by weighted interconnection. In our case, inputs are the DN values at first four bands of Landsat TM and output is either Chl.a or SS concentration. The main concept with NN modeling is to find the appropriate weights in the interconnections which can simulate in-situ Chl.a or SS concentration from the given in-situ DN values. This is done as follows:

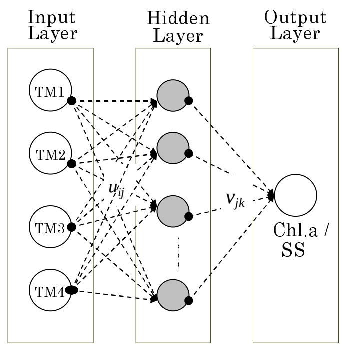

Figure 5. Neural network configuration used in this study (see text for notations; biases are not shown)

The inputs (in-situ DN values) coming from the input layer nodes to any hidden layer node undergoes two functions before becoming the output from the hidden layer. The first function is a summation function which sums up the products of inputs and the corresponding weights of the links. This sum is then added to a `bias` and undergoes the second function, known as the ‘squashing function’, thus producing the output from the node. Same procedure of summation and squashing is performed at the output layer nodes using the outputs from the hidden layer nodes. The result is the network output at the output node as given in Eqn. 1:

$$y_k = f(\beta_k + \sum_{j=1}^{m} v_{jk} . f(\alpha_j + \sum_{i}^{n} u_{ij} . TM_i)) \quad (1)$$

where, y_k:network output(concentrations of Chl.a or SS) at k; j: hidden node (total m); i: input node (total n); TM_i: input to the network; u_{ij}, v_{jk}: weights of the links; α_j,β_k: biases; f: Squashing function. Binary sigmoid is used as the squashing function given in Eqn.2:

$$f(x) = \frac{1}{1 + e^{-gx}} \quad (2)$$

where, 'g' is the slope parameter(Fausset, 1994). The final output (y_k) is compared with corresponding in-situ concentration. The difference is then back-propagated to update the weights and biases in the networks. This process of simulation by minimizing the difference is called `training` of the network. The ability of the trained network to predict from unseen data is then checked with the validation data.

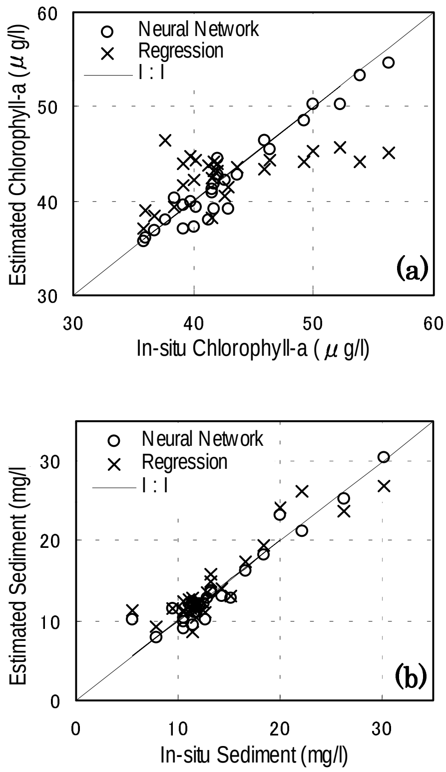

Figure 6. In-situ .vs. estimated (a)Chl.a and (b) SS by neural networks.

4.2 Training and Validation data

Twenty samples out of 29 is selected as training data. Selection of training data is done by first arranging the entire sample set in decreasing order of Chl.a (or SS) concentration and then, starting from the top, picking up every two values and leaving one. Again, out of the remaining nine samples, six are used as validation data and the rest three samples are used during training process as the training-testing data(Fausset, 1994). For effortless robust training, around 150 training data are required for a 4-6-1 network expected to give 80% accuracy (Fausset, 1994). Therefore, the role of training-testing data is significant to develop an effective model (with a small training data-set) which can generalize well from unseen data (validation data). All in-situ concentrations are scaled to [0.1,0.9] to match with the range of binary sigmoid function, [0,1].

4.3 Hidden layer nodes

Using too few hidden layer nodes may not resolve a complex problem, while, by using too many the network looses the capacity to generalize by overfitting(Masters, 1993). Thus, initial training runs on the networks is performed to find the optimum number. Six(6) and 3 hidden layer nodes are found to be sufficient for satisfactory modeling of Chl.a and SS respectively without overfitting. In this study, numbers of input nodes and output nodes are 4 and 1 respectively for both networks estimating Chl.a and SS.

4.4 Training parameters

Batch updating of weights is adopted. Error during the training process is monitored with Mean Squared Error(MSE) (Masters, 1993). Training is started with a training rate of 0.3 and varied as the training progresses. Adaptive slope for the sigmoid function, as described in Fausset(1994) is incorporated. Training is terminated when the RMSE of the training-testing set between two consecutive passes reaches the minimum.

5. RESULTS AND APPLICATION:

5.1 Regression Analysis

To compare the performance of the neural network with standard method of water quality estimation various linear and logarithmic regression models are tried. Table 2 (next page) lists some of comparable regression models for chlorophyll-a estimation and developed using the entire in-situ data. Many in the list are from published literature and were used effectively to estimate inland water quality at respective sites. In a similar way, various models are tried for estimation of SS and the best one is selected. Upon selection of the best combination of bands or band ratios, coefficients of regression model equations are re-calculate using only the training data used in NN modeling. This ensures un-biased comparison with the NN models. Eqn.3 and 4 gives the best regression models :

Table 2. Regression models developed for Chl.a estimation

Dependent	Independent (TM Bands)	R^2
Chl.a	1/2	0.27
Chl.a	3/1, 1	0.34
Chl.a	3/1, 2	0.35
Chl.a	3/1, 3	0.33
Chl.a	3/2, 1	0.25
Chl.a	(3-1)/2	0.29
Chl.a	1, 2, 3, 4	0.35
Chl.a	1, 2, 3^2, 4^2	0.359
ln(Chl.a)	1, 2, 3^2, 4^2	0.368
ln(Chl.a)	ln(1), ln(2)	0.35
ln(Chl.a)	2, $(3/1)^2$	**0.372**
ln(chl.a)	1/ln(3+1)	0.366

Chlorophyll(C, μ g/l):

$$lnC = 48.31 - 1.52\ TM2 - 5.579[TM3/TM1]^2 \quad (3)$$

Suspended Sediment (S, mg/l):

$$S = 6.7571 + 0.298858\ TM1 + 2.922987\ TM3 \quad (4)$$

Significance parameters, namely, coefficient of determination(R^2) and Root Mean Square Error(*RMSE*) are computed for both NN and regression models. Due to narrow range of in-situ concentrations, %-age *RMSE* (with the mean) is not a good measure to compare between the models. Hence, Relative MSE (*Rel. MSE)* (Masters, 1993) is also computed for all the models. Overall performance of all the developed models over the entire data is computed. From the comparison statistics(Table 3) it is evident that, NN outperforms regression analysis in estimating both Chl.a and SS at the study site. However, in estimating SS, regression has comparable performance(R^2:0.85) to NN (R^2:0.92). The main reason for the poor performance of regression analysis is it's inability to model the unknown non-linearity of the transfer function arising from factors such as overwhelming of signature of chlorophyll by other components, such as, Colored Dissolved Organic Material(CDOM), contributing to the lake water color(IOCCG, 2000). Other possible reasons can be errors in sampling, errors in match-ups between satellite imagery and in-situ location etc. Fig.6 shows graphical representations of comparison between neural network and regression analysis. From the fig.6 it is evident that, NN find it difficult to model Chl.a in the range 39~42μg/l, comprising of ~50% of total samples. This is due to the fact that, LandsatTM radiance(DN) value are usually not exactly same for same concentrations due to errors in match-ups or difference of scale between satellite and in-situ data.

Table 3. Comparison statistics between neural networks and regression analysis (models applied to entire data)

	Chlorophyll-a			*Suspended Sediment*		
	R^2	*RMSE(μ g/)*	*Rel. MSE(%)*	R^2	*RMSE(μ g/l)*	*Rel. MSE(%)*
Neural Network	0.93	1.53	8.10	0.92	1.47	8.00
Regression	0.31	4.39	53.29	0.85	2.14	16.78

RMSE: Root Mean Square Error; *Rel. MSE*: Relative Mean Square Error

5.2 Application

Finally, spatial distribution diagrams of Chl.a and SS at the lake is generated by passing the LandsatTM imagery through the respective NN model. Fig.7 shows the NN derived Chl.a and SS at the lake. Banding effects present in the diagrams are inherited from the original TM imagery and no de-striping procedure is performed. From the diagrams, it is seen that, SS variations are not consistent with Chl.a variations throughout the lake which is also evident from the in-situ data. Low-Chl.a with high SS(Tsuchiura side, refer fig.1), high Chl.a with low SS(middle and towards Tsuchiura) and low Chl.a with low SS(middle left) combinations can be seen. High Chl.a with high SS pattern is hardly present. For a Chl.a concentration of 30μg/l (lowest range in the index, Fig.7a), Trophic State Index(TSI) by Carlson(1976) is 64. Therefore, >90% of the lake is euthropic (TSI>50) even in this low-productivity season.

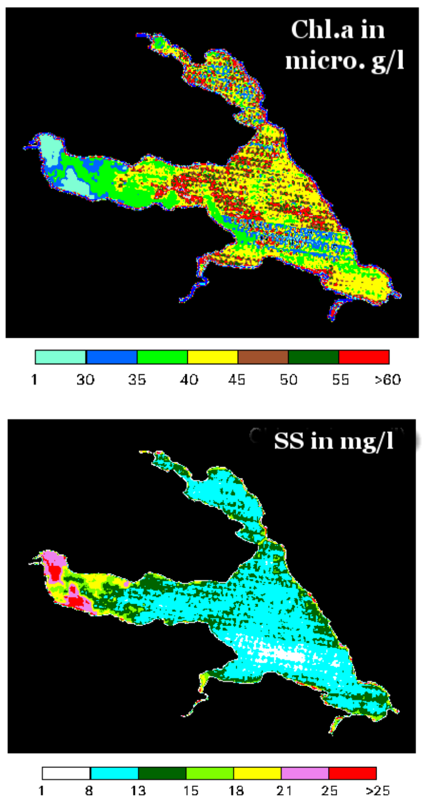

Figure 7. Maps of Chl.a(μg/l) and SS (mg/l) at the lake Kasumigaura on 19th Jan, 2001 by neural networks

5.3 Future direction

The developed model dealt with single scene imagery. It could satisfactorily model the Chl.a and SS in a low productivity season at the site. However, in the future, more samples at different times of the year representing different spectral characteristic of the lake water is necessary for a robust temporal model. Moreover, the method can be extended to model other optically active parameters such as DOC, CDOM or secchi disk depth at the site using recently launched ASTER(doesn`t have blue band) along with LandsatTM. Development of a similar model for estimating water quality parameters in coastal areas from MODIS imagery incorporating the atmospheric correction scheme in the model itself (using relevant MODIS bands) can provide for reliable estimates of coastal water quality and aquatic bio-mass.

6. CONCLUSION: Neural network model with only one hidden layer is shown to be useful in satisfactorily estimating lake water quality from a LandsatTM imagery in a low-productivity season. Spatial distribution maps of chlorophyll and suspended sediment are produced by the developed model. Neural network was able to model the nonlinear transfer function better than the traditional regression analysis. However, the NN model found it difficult to model in large number of samples in a very narrow concentration range. It is found that, suspended sediments can be effectively estimated by simple regression in a low productivity season in the lake, though a network model provides for the best result. In the future, for a robust model to effectively represent the lake water quality, sampling at different times of the year is proposed to account for varying optical characteristics. As shown in this study, LandsatTM with neural networks can be quite useful getting synoptic views of small to medium size optically complex water bodies like lake Kasumigaura where modern sensors like MODIS or SeaWiFS become redundant due to their low spatial resolution, and where traditional algorithms fails. In the future, the methodology can be extended to monitor other parameters such as DOC, CDOM etc. using recent sensors such as ASTER along with LandsatTM.

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