Determination of Secchi Disc depths in Lake Eymir using remotely sensed data

Article *in* Procedia - Social and Behavioral Sciences · December 2011

DOI: 10.1016/j.sbspro.2011.05.173

Available online at www.sciencedirect.com
ScienceDirect
Procedia Social and Behavioral Sciences 19 (2011) 586–592
Procedia
Social and Behavioral Sciences

The 2nd International Geography Symposium GEOMED2010

Determination of Secchi Disc depths in Lake Eymir using remotely sensed data

Onur Yüzügüllü & Aysegül Aksoy*

Department of Environmental Engineering, Middle East Technical University, Ankara 06531, Turkey

Abstract

In this study Secchi disk depths (SDD) are determined in an eutrophic Eymir Lake in Ankara using the multi-spectral image obtained from the Quickbird satellite. For this purpose, empirical models given in literature and artificial neural networks (ANN) are used. SDDs at 17 sampling points in Eymir Lake are measured via field studies. In the satellite image, pixel values at the sampling points are determined using ERDAS Imagine. Results indicate very low correlations between the SDD values calculated using the empirical models and the ones measured in-situ. Correlation of determination values (R2) up to 0.92 are achieved when ANN modeling is applied. In ANN models developed, Levenberg-Marquardt (LM) and gradient decent algorithm (GDA) are the training algorithms that provided the best results. This study indicates that ANN is an important tool in obtaining information from the remotely sensed data.

Keywords: Eymir Lake; Secchi disc depth; Remote sensing; Artificial neural networks

1. Introduction

Remote sensing has become a popular technology for water quality monitoring and management in the recent years. Most of the previous studies revealed that in water systems of large scale, remote sensing can become a viable approach for monitoring of the water quality, providing that there is sufficient number of ground truth data for calibration and verification of the remotely sensed data. One of the advantages of remote sensing is that it provides the spatial variation of water quality parameters over the whole area of concern. Therefore, with ease, it is possible to pinpoint the problematic areas [12]. Providing that water quality regulations are getting stringent, there is need for frequent sampling and water quality assessment. This would, on the other hand, increase the costs of monitoring. With the increase in monitoring costs, remote sensing technology is expected to be more popular in water quality management.

Secchi disc depth (SDD) is one of the water quality parameters that can be derived from the remotely

* Corresponding author. Tel.: +90-312-210-5874; Fax: +90-312-210-2646.
E-mail address: aaksoy@metu.edu.tr

doi:10.1016/j.sbspro.2011.05.173

sensed data. SDD is one of the parameters that can indicate the turbidity level in the water body. It can also be used in assessing the eutrophic characteristics of a water body together with other parameters. In literature, regression analysis and empirical models have been employed in determination of SDD values using remotely sensed data. Other techniques such as neural networks have been used as well. Models were developed in order to predict SDD values in the Gulf of Finland and the Archipelago Sea using regression analysis and neural network modeling [17;18]. Remotely sensed data were obtained from the Landsat TM satellite. In both studies, better results were obtained from neural network models compared to regression analysis. In regression models, calculated coefficient of determination (R2) values were in the range of 0.74 – 0.77. For neural network models, the range was 0.91 – 0.95.

In the study that was conducted in the New York Harbor, the relationship between SDD and spectral bands were studied [8]. It was found that blue and green bands had lower correlation with SDD compared to red band. They pointed out that wavelengths within the red band are less affected from atmospheric conditions. Another result of this study was that inverse correlation existed between SDD and total suspended solids (TSS) quantity. Suspended solids absorb more light in the longer wavelengths of the spectrum. Low TSS concentration provides higher SDD value with higher light penetration [4].

SDD values in Ömerli Dam in Istanbul were studied by use of Landsat TM image [1]. In the field measurements, typical SDD values were measured as 3-6 m. However, in some locations, SDD became lower than 0.7 m. In the correlation analysis performed to predict the relationship between SDD and spectral reflectance values, R2 was calculated as 0.996. Another study in Turkey was conducted in Haliç [5]. In this study SDD values were determined by using average pixel values obtained from different numbers of pixels. Several pixel groups were chosen as 3x3, 5x5, 7x7 and 10x10 for the analysis. As a result, R2 values between field SDD and spectral reflectance values in different bands were calculated in the range of 0.122 – 0.989. In addition to this, an inverse correlation was reported between SDD and chlorophyll-a, as well as between SDD and TSS.

In this study, the relationship between SDD and spectral reflectance values in Lake Eymir is studied using the remotely sensed data. Considering the size of the lake, the image obtained from the Quickbird satellite is used. This satellite provides high spatial resolution images in four spectral bands (red, green, blue, and near infrared). In order to convert the spectral reflectance values to SDD values, empirical equations reported in literature and ANN modeling is used.

2. Methodology

2.1. Study Area

Lake Eymir is at 20 km south of Ankara. It is located at 39.28 N and 32.30 E, at an altitude of 969 m [14]. It is an important recreational area for the citizens of Ankara with its 13 km of shoreline [15]. It has a basin area of 971 km^2, including the catchment area of the Mogan Lake which is hydraulically connected to Eymir Lake. Of this area, 46 km^2 is the catchment basin of the Eymir Lake. The area of the lake is approximately 1.25 km^2, with approximate dimensions of 3000 m x 500 m x 5.5 m [3]. The average lake volume is 3.88 x 106 m^3 [9]. Since 1958, the lake has been in the land allocated to the Middle East Technical University. It has been used as the water supply of the university campus area until 1990. Between 1970 and 1995, the lake received the wastewater discharges arising from the Golbasi Municipality and residential districts nearby. As a result, the water quality deteriorated and the lake became highly eutrophic [2;6;16]. Due to its rich ecosystem, the lake, the area surrounding the lake, and 245 km^2 of the catchment basin have been declared as a “Special Environmental Protection Area” in 1990 (declaration number 90/1117 in 22.10.1990). The lake is depicted in Figure 1.

2.2. Field Measurements

In order to gather field SDD data a field study is conducted within two weeks after the satellite image is taken. SDD measurements are employed at 17 points in the Lake. These points are depicted in Figure 1. For the measurements of SDDs, a standard black and white Secchi disc of 0.2 m diameter. The coordinates of the measurement points are recorded by Magellan Sportak GPS receiver.

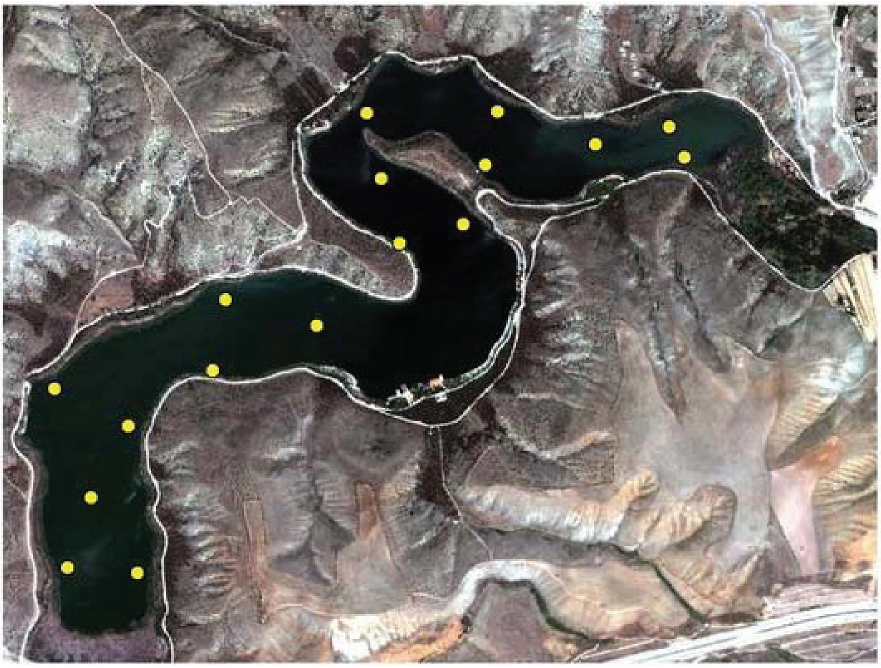


Fig. 1. Lake Eymir and SDD Measurement Points

2.3. Information about Satellite Imagery

The satellite image for the study is obtained from the Quickbird 2 satellite on June 26th of 2005. Band wavelength ranges for the Quickbird 2 satellite is given in Table 1. Panchromatic image in the Quickbird 2 satellite has a ground resolution of 0.61 m. The resolution of the multispectral image is 2.5 m. Radiometric and geometric corrections are employed before pixel values are used for SDD determination.

Table 1. Quickbird 2 Satellite Wavelengths

Bands	Wavelength (μm)
Band 1 (Blue)	0.45-0.52
Band 2 (Green)	0.52-0.60
Band 3 (Red)	0.63-0.69
Band 4 (Near Infrared)	0.76-0.90

2.4. Regression Analysis

Based on the literature survey, following equations are compiled for the determination of SDD values [1;4;5;7;8;13;17;18;19]. The performance of these equations in determination of the Secchi depths in Lake Eymir are tested based on the R^2 values. For this purpose, Microsoft EXCEL is used. For the determination of reflectance values in the pixels covering the lake area, ERDAS Imagine software is used. Tested equations are stated below. In the given equations, the band numbers refer to the ones given in Table 1.

$$SDD = \frac{\text{Band 1 - Band 4}}{\text{Band 2 - Band 4}} \qquad (1)$$

$$SDD = \frac{\text{Band 1 - Band 4}}{\text{Band 3 - Band 4}} \qquad (2)$$

$$SDD = 1.378 + 0.043 \text{ Band 1} + 0.002 \text{ Band 2} - 0.142 \text{ Band 3} - 0.256 \text{ Band 4} \qquad (3)$$

$$SDD = 1199.93 - 55.9 \text{ Band 3} \qquad (4)$$

$$\ln(SDD) = 37.36 - 11.15 \ln(\text{Band 3}) \qquad (5)$$

$$SDD = 10.41 - 46.54 \ln(\text{Band 2}) \qquad (6)$$

$$SDD = 208\ e^{-9.82\frac{\text{Band 3}}{\text{Band 1}}} \qquad (7)$$

$$SDD = 0.74 - 0.05 \text{ Band 3} + 1.8 \frac{\text{Band 1}}{\text{Band 3}} \qquad (8)$$

2.5. Artificial Neural Network (ANN) Model

Besides empirical models given above, ANN modeling is used in the determination of SDD using remotely sensed data. ANN is widely used in the modeling of non-linear and complex relationships [10]. It provides a non-linear adaptive processing of the data in a mathematical structure. This structure is called the ANN architecture. Basically ANN is composed of an input layer, an output layer and hidden layers connecting the input layer to the output layer. As seen in Figure 2, the structure is mainly composed of two building units; processing units (neurons or nodes) and weighted connections (links). Each processing unit has several output connections that lead to other processing units or the desired values. Weights are referred to as the connection parameters. In this study, feed forward ANN is used. The input data is divided into three parts for the training, validation and testing stages of the ANN model. The aim of the training is to minimize the output error by use of different training algorithms. The connection values are adjusted during the training phase for better results. Data in the input units pass through hidden layers containing the weighted connections and finally reaches to output units. The error, the difference between the predicted and goal (measured) values, are then propagated backwards for the adjustment of the weights. Validation stage is used to prevent over training of the ANN model. Testing is used to check whether trained ANN can be used for prediction. The ANN model can be used for real time forecasts if successful results are obtained in all three stages.

In this study, an automated ANN architecture generation code [11] is utilized. This software creates ANN architectures that can contain one or two hidden layers and up to 90 neurons in each layer. In addition, different training algorithms are tested. As a result, the best ANN structure is obtained by combining different activation functions and the SDD can be modeled with the least deviation between the observed and simulated SDD values. With ANN modeling, the pixel values given in the red, blue, green, and near infrared bands are used to derive the SDD values.

Since the resolution of the Quickbird image is high, the risk of having spatial error in the location of sampling points can impact the results. For this purpose, the neighbouring pixels are considered for averaging purposes as well. For this purpose, the average pixel values belonging to pixel sets 1x1, 3x3, 5x5 pixels are used in the analysis. Therefore, testing of the empirical equations and ANN modelling is applied for the average pixel values belonging to these pixel sets.

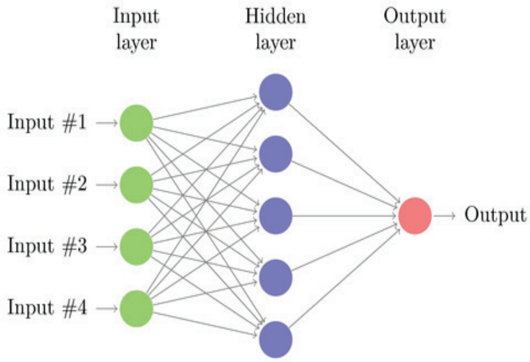


Fig. 2. An ANN architecture with one hidden layer

3. Results and Discussion

The distribution of the SDD values in Lake Eymir is depicted in Figure 3. As seen in the figure, SDD values are low at the inlet (bottom left portion in Figure 4) of the lake. The SDD increases as travelled from the inlet to the middle section of the lake. Approximately 1/3 of the lake closer to the outlet area has very low SDD values. This distribution is in line with the algae distribution in the lake [6]. Moreover, areas closer to the outlet of the lake has lower depth and higher turbidity. In return, the SDD values are expected to be low in this portion of the lake. At locations where the water is deeper, higher SDD values are recorded.

The linear relationships between measured SDD values in-situ and pixel values in each band are analyzed through regression analysis. It is observed that the linear correlation between the SDD values and reflectance values obtained for each band are low (R^2 up to 0.24). In general, higher correlation is observed for the 3rd (red) and the 4th (near infrared) bands compared to others. This may be attributed to turbidity level in the lake and the shallow depth of water. Later on, by using 1x1, 3x3 and 5x5 pixel average values, empirical models given in equations 1 to 8 are used for the determination of SDD values. Calculated SDD values are then compared with the field measurements. The highest R^2 value is obtained as 0.16 for the empirical model given by Equation 2. This result is obtained when average pixel reflectance values from the 5x5 pixels are used. Lower R^2 quantities are obtained for 3x3 and 1x1 pixel average reflectance values. These results indicated that, empirical models developed for other sites for the estimation of SDD values from the remotely sensed images are not applicable to Eymir Lake. This may be due to the shallow depth of water and highly eutrophic characteristics of the lake.

Fig. 3. Lake Eymir and SDD Measurement Points

Following the test of empirical models, ANN modeling is applied to predict the SDD values in Lake Eymir. The set of data is divided into three portions. Eight of the sampling points are used to train the ANN models. Five sampling points are used for prediction and the remaining 4 are employed for testing of the model. Thirteen training algorithms with 2 different types of transfer functions, 2 different numbers of hidden layers, each having 1 to 13 hidden neurons (HNs) are tested to come up with the best ANN architecture. The training algorithms considered are BFG (Quasi-Newton back-propagation), CGB (conjugate gradient back-propagation), CGF (conjugate gradient back-propagation with Powell-Beale restarts), CGP (conjugate gradient back-propagation with Polak-Ribiere updates), GDA (gradient decent with adaptive learning rate-back propagation), GDM (gradient decent with momentum back-propagation), LM (Levenberg-Marquardt back-propagation) and SCG (scaled conjugate gradient back-propagation) [11].

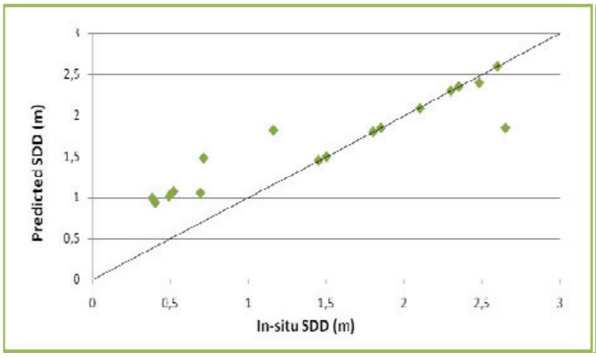
The results of the ANN modeling are summarized in Table 2 in terms of the R^2 values obtained for the relationship between the measured and predicted SDD quantities. The range of R^2 obtained is 0.65 to 0.92.

Highest R^2 are 0.92 and 0.85 obtained for the training algorithms of GDA and LM, respectively. For both, a single hidden layer is used. The numbers of HNs in the hidden layers are given in Table 2. The relationships between the predicted SDD via ANN models and measured SDD values at the field are depicted in Figures 5 and 6, respectively.

Reflectance of light from the lake bottom in the shallow lakes affects the pixel values in the satellite images. Besides, presence of macrophytes covering the lake bottom also impacts the light that will scatter from the bottom of the lake. Moreover, constituents in water may impact the pixel values as well. Yet these impacts would not be similar spatially. For example, chlorophyll-a contents of phytoplankton and macrophytes and sources and characteristics of the particles causing the turbidity and light scattering may be spatially variable in a given water body. In return, the relationships between the reflectance values and water constituents may be complicated. For this reason, if the data belonging to parameters that impact the pixel values are not considered, an empirical model derived through regression analysis for given water body may not show the same performance in another lake. However, since ANNs can handle the noisy data and modeling of the complex systems, it can be a highly useful tool in remote sensing applications compared to traditional approaches based on regression analysis used in the derivation of the empirical models.

Table 2. Results of artificial neural network model

ANN training algorithm	Number of neurons in the hidden layer	R^2	ANN Training Algorithm	Number of neurons in the hidden layer	R^2
BFG	31	0.67	LM	51	0.79
CGB	88	0.73	LM	74	0.92
CGF	20	0.75	RP	9	0.70
CGP	77	0.81	RP	35	0.65
GD	13	0.65	RP	77	0.78
GD	97	0.83	SCG	23	0.64
GDA	4	0.85	SCG	25	0.82
GDM	57	0.62	SCG	63	0.86



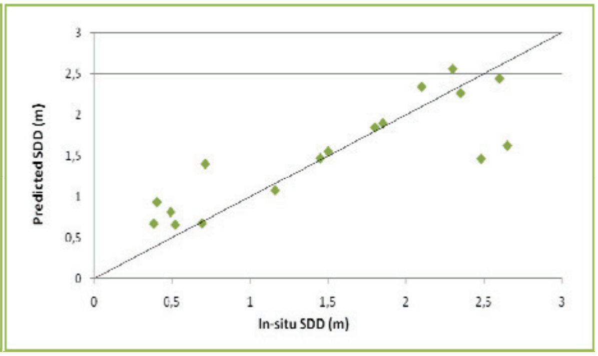


Fig. 4. Comparison of the results obtained from the ANN model trained with the LM training algorithm and the field SDD values (left),

Fig. 5. Comparison of the results obtained from the ANN model trained with the GDA training algorithm and the field SDD values (right).

4. Conclusion

In this study, SDD values in Lake Eymir are modeled using the multi-spectral remotely sensed image obtained from the Quickbird satellite. Results indicated that it is not possible to obtain successful results when empirical algorithms provided in literature are employed. However, ANN modeling exhibited high R2 values between the predicted and measured SDD values. This study, once more, indicated that remote sensing can be an important tool in water quality management and monitoring. In addition use of ANN modeling can provide advantages over other empirical models provided in literature. Remote sensing can provide easier spatial analysis. Therefore, it would be easier to observe the spatial variation in the water quality parameters.

Acknowledgements

This study is financially supported by the Middle East Technical University (Project number: BAP-2004-03-11-03). We are thankful to Tarek Elahdab and Muhittin Aslan for their support in conducting the field study and ANN modeling, respectively.

References

[1] Alparslan E, Aydöner C, Tüfekçi V, and Tüfekçi H. Water quality assesment at Ömerli Dam using remote sensing techniques, Environmental Monitoring Assesment, 2007, 135(1-3): 391-398.
[2] Altınbilek D, Kutoğlu Y, Soyupak S, Yazıcıgil H, Usul N, Doyuran V, Göğüş M, Gökçay C, Günyaktı A, Özsan E, Sürücü G, and Merzi N. Water resources and environmental management plan for Gölbaşı Mogan-Eymir Lakes (In Turkish). Technical Report, Ankara Metropolitan Municipality Water and Sewerage Administration. 1995.
[3] Camur MZ, Yazicigil H, Altınbilek D. Hydrogeochemical Modeling of Waters in Mogan and Eymir Lakes Special Environmental. Water Environment Research, 1997. 69(6), 1144-1153.
[4] Choubey VK. Laboratory experiment, field and remotely sensed data analysis for the assesment of suspended soilds concentration and secchi depth of the reservoir surface water, International Journal of Remote Sensing, 1998, 19(17): 3349-3360.
[5] Ekercin S. Water Quality Retrievals from High Resolution Ikonos Multispectral Imagery: A Case Study in Istanbul, Turkey, Water Air and Soil Pollution, 2007, 183(1-4): 239-251.
[6] Elahdab T. Investigation of algae distribution in Eymir Lake using site measurements and remotely sensed data, M.S. Thesis, Department of Environmental Engineering, Middle East Technical University. 2006.
[7] Harma P, Vepsalainen J, Hannonen T, Pyhalahti T, Kamari J, Kallio K, Eloheimo K. and Koponen S. Detection of water quality using simulated satellite data and semi-empirical algorithms in Finland, The Science of the Total Environment, 2001, 268(1-3): 107-121.
[8] Hellweger FL, Schlosser P, Lall U. and Weissel JK. Use of satellite imagery for water qualities in New York Harbor, Estuarine Coastal and Shelf Science, 2004, 61(3): 437-448.
[9] Karakoç G, Erkoç FU, Katircioğlu H. Water quality and impacts of pollution sources for Eymir and Mogan Lakes (Turkey). Environment International, 2003, 29(1), 21-27.
[10] Marini F. Bucci R. Magri AL. and Magri AD. Artificial neural networks in chemometrics: History, examples and perspectives, Microchemical Journal, 2007, 88(2): 178-185.
[11] Moral H, Aksoy A, and Gokcay CF. Modeling of the activated sludge process by using artificial neural networks with automated architecture screening, Computers & Chemical Engineering, 2008, 32(10): 2471-2478
[12] Nelson SAC, Soranno PA, Cheruvelil KS, Batzli S, and Skole D. Regional assessment of lake water clarity using satellite remote sensing, Journal of Limnology, 2003, 62(1): 27-32.
[13] Phinn SR, Dekker AG, Brando VE, and Roelfsema CM. Mapping water quality and substrate cover in optically complex coastal and reef waters: an integrated approach, Marine Pollution Bulletin, 2005, 51(1-4): 459-469.
[14] Tan, C.O. (2002). The roles of hydrology and nutrients in alternative equlibria of two shallow lakes of anatolia, lake Eymir and lake Mogan: Using monitoring and modeling approaches, M.S. Thesis, Department of Biology, Middle East Technical University.
[15] Tan C, & Beklioglu M. Catastrophic-like shifts in shallow Turkish lakes: a modeling approach. Ecological Modelling, 2005, 183(4), 425-434.
[16] Yuzugullu O. Determination of Chlorophyll-a Distribution in Lake Eymir Using Regression and Artificial Neural Network Models with Hybrid Inputs, M.S. Thesis, Department of Environmental Engineering, Middle East Technical University, 2011.
[17] Zhang, Y. Water Quality Retrievals From Combined Landsat TM Data and ERS-2 Data in the Gulf of Finland, IEEE Transactions on Geoscience and Remote Sensing, 2003, 41(3): 622-629.
[18] Zhang Y, Pulliainen J, Koponen S. and Hallikainen M. Empirical algorithms for Secchi disc depth using optical and microwave remote sening data from the Gulf of Finland and the Archipelago Sea, Boreal Environmental Research, 2003, 8(3): 251-261.
[19] Zhiqiang C, Frank MK, and Chuanmin H. Remote sensing of water clarity in Tampa Bay, Remote Sensing of Environment, 2007, 109(2): 249-259.