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Monitoring of lake water quality along with trophic gradient using landsat data

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ABSTRACT: Effect of differential trophic states on remote sensing-based monitoring and quantification of surface water quality is an important but understudied context. Landsat ETM+ data-based multiple linear regression models were conducted to quantify dynamics of lake surface water quality along oligotrophic-to-eutrophic gradient and to explore the influence of trophic state on the detection of water quality dynamics by the best multiple linear regression models. The best multiple linear regression models of dissolved oxygen, chlorophyll-*a*, Secchi depth, water temperature, and turbidity had R^2_{adj} values ranging from 36.2 % in water temperature to 93.1% in dissolved oxygen for eutrophicYenicaga Lake and from 36.1 % in Secchi depth to 99.7 % in water temperature for oligotrophic Abant Lake. The difference in the trophic state between Lakes Abant and Yenicaga , significantly affected the composition of the nine Landsat ETM+ spectral bands included in the multiple linear regression models as well as the predictive power of the multiple linear regression models. Remote sensing-based monitoring of lake water quality variables appears to be promising in terms of devising adaptive management decisions towards sustainability of water resources.

Keywords: *Modeling; Remote sensing; Spatio-temporal dynamics; Surface water*

INTRODUCTION

Monitoring and modeling the quality of surface water in lakes is a crucial issue in making management decisions towards sustainability of water quality (Girgin *et al*., 2010). Readily available data from remote sensing, reduces expensive and labor-intensive *in situ* measurements by providing a spatially and temporally continuous coverage of environmental processes (Koponen, 2006; Vignolo *et al*., 2006; Alparslan *et al*., 2007; Giardino *et al*., 2007). Lake water quality variables that directly influence optical properties of water such as turbidity, Secchi disk depth (S_{depth}), chlorophyll-*a* (Chl-*a*), suspended matter, water temperature (T_w) and Colored dissolved organic matter (CDOM) have been monitored using remotely sensed data by numerous studies (Brivio *et al*., 2001; Dekker *et al*., 2002; Zhang *et al*., 2003; Kutser *et al*., 2005; Sudheer *et al*., 2006; Nouri *et al.,* 2008). However, the related literature has a relatively limited number of studies about remote sensing-based monitoring of optically inactive lake water quality variables such as total phosphorus (PO_4-P), Dissolved oxygen (DO), Biological oxygen demand (BOD_5), Total organic carbon (TOC), nitrite (NO_2-N), and nitrate (NO_3-N) (Lavery *et al*., 1993; Dewidar and Khedr, 2001; Wang *et al*., 2004; Sass *et al*., 2007; Nouri *et al.,* 2009). In the related literature, *in situ* measurement values of lake water quality variables were compared to reflectance values of spectral bands of various satellite data without the inclusion of spatio-temporal components in regression models (Pulliainen *et al*., 2001; Bilge *et al*., 2003; Sawaya *et al*., 2003; Giardino *et al*., 2007; Gitelson *et al*., 2008). The objectives of this study were: 1) To monitor dynamics of multiple water quality variables (DO, Chl-*a*, S_{depth}, T_w, and turbidity) for Lakes Abant and Yenicaga along oligotrophic-to-eutrophic gradient, respectively, using Landsat ETM+ time series data in 2009, and 2) To explore effects of trophic gradient on detection by landsat-based Multiple linear regression (MLR) models of dynamics of water quality variables.

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MATERIALS AND METHODS

Study areas

Lakes Yenicaga and Abant are located in Bolu in the northwestern Black Sea region of Turkey under the influence of a warm temperate climate regime with a

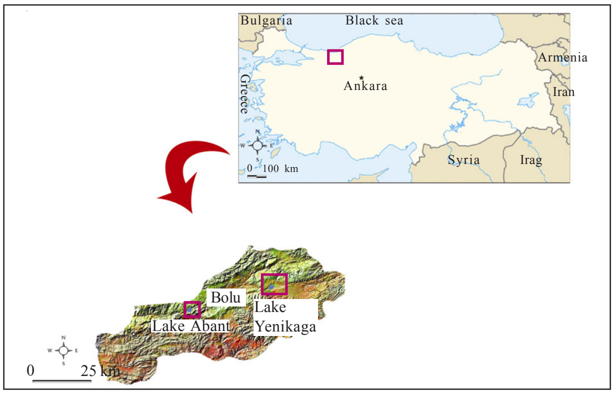

Fig.1: Location of study areas: Lakes Yenicaga and Abant

warm Summer season and a cool and rainy Winter season.(Fig. 1). Lake Abant (40º35'49"-40º36'54"N latitude and and 31º16'12"-31º17'42" E longitude) at altitude of 1350 m above sea level encompasses a basin area of approximately 15 km^2 surrounded by Abant and Mudurnu mountain ranges. Surface area of Lake Abant is 1.25 km^2, with a maximum depth and perimeter of 18 m and 6 km, respectively. Lake Abant is fed by underground water, Bespoyraz and Findikli streams and discharges water by Abant stream in the north. Lake Abant was declared as a natural park in 1988 and has about 1,221 plant and animal species at least 60 of which are endemic species (Dugel *et al*., 2008). Major environmental pressures on the lake include wastewater from the surrounding tourist facilities, erosion and sediment transport by grazing animals, and solid wastes. Lake Yenicaga (40º46'12"-40º47'24" N latitude and 32º00'36"-32º02'24" E longitude) consists of a basin area of about 180 km^2. Altitude of the lake is approximately 990 m. This shallow and non-stratifying lake has a surface area of 1.8 km^2 with an average depth of 4 m which seasonally fluctuates intermittently wetting the surrounding reed belt and peatland. The major environmental issues that the lake is currently facing include mining of peatlands, agricultural runoff, dry and wet atmospheric deposition from the nearby Ankara-Istanbul highway, unsanitary landfill leachates and discharges of untreated wastewater by surrounding domestic uses, slaughterhouse and animal farms.

Ground data

Lake Abant was randomly sampled from 16 geo-referenced measurement points each time of field visits on 26 May 2009 and 29 July 2009, while Lake Yenicaga was randomly sampled from 15 geo-referenced points each time of field visits on 11 June 2009 and 14 August 2009. Water quality variables monitored *in situ* during the local time of 09:00 AM to 12:00 PM in this study include S_{depth} (m), chlorophyll-*a* (Chl-*a*, µg/L), water temperature (T_w,ºC), dissolved oxygen (DO, mg/L), and turbidity (NTU, Nephelometric Turbidity Unit). All the water quality variables except S_{depth} were measured using YSI 6600 V2-2 multi-parameter water quality sonde (YSI Inc., USA) at a depth of 0.5 m beneath the water surface. For S_{depth} measurements, a standard 20 cm disk with alternating black and white equal quadrants was used. The standard methods of USGS were followed for washing, preparation, specification and preservation of sampling bottles (USGS, 2006).

Satellite data

A total of four cloud-free Landsat 7 ETM+ scenes (path: 178/row: 32) dated 26 May 2009, 11 June 2009, 29 July 2009, and 14 August 2009 were acquired from USGS (http://glovis.usgs.gov) temporally match the ground data collection and the satellite overpass. Landsat 7 ETM+ images consist of six spectral bands 1 to 5 and 7 (band 1: blue-0.45-0.52 µm; band 2: green-0.52-0.60 µm; band 3: red-0.63-0.69 µm; band 4: near infrared-0.77-0.90 µm; band 5: middle infrared-1.55-1.75 µm; and band 7: middle infrared-2.09-2.35 µm) at a 30-m spatial resolution and bands 6 (thermal infrared: 10.4-12.5 µm) and 8 (panchromatic: 0.52-0.90 µm) at 60-m and 15-m resolutions, respectively. Band 6 provides the low and high gain settings as two separate band files (B6L and B6H), respectively. Band 6L provides a more expanded dynamic range and lower radiometric resolution (sensitivity), with less saturation at high Digital number (DN) values than band 6H does. Mean DN values of the ground measurement points for each of the nine Landsat band images were extracted using a window of 3 x 3 pixels using ArcGIS 9.2 spatial analyst tool

(ESRI Inc., 2002) and used in the development of best MLR models. DN values were not converted to at-sensor reflectance values in order to improve simplicity and ease of use of remote sensing-based MLR models constructed, given the fact that a systematic conversion of DN values to reflectance ones does not change the empirical relationships between independent and dependent variables.

MLR models

Best MLR models were selected using best subsets procedure based on a combination of highest R^2_{adj} values, significant P values of each term used in a MLR model and Mallows' C_p values. Mallows' C_p criterion considers a regression model to be properly fit when C_p value approaches the number of explanatory variables that have entered the model and is expressed as follows (Helsel and Hirsch, 1992):

$$C_p = p + \frac{(n-p)(s_p^2 - \sigma^2)}{\sigma^2} \quad (1)$$

Where n is the number of observations, p is the number of coefficients (number of explanatory variables plus one), S_p^2 is the Mean square error (MSE) of the prediction model, and σ^2 is the minimum MSE among the possible models. MLR models were built using Minitab 15.1 in the following form:

$$Y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 \ldots \beta_v x_v + \varepsilon \quad (2)$$

Where Y refers to the response variables of S_{depth} (m), Chl-*a* (µg/L), T_w (ºC), DO (mg/L), and turbidity (NTU); x_n refers to the explanatory variables of each of the Landsat ETM+ spectral bands (mean DN values within a window of 3 x 3 pixels), Julian Day of year (DOY), easting (E, m) (UTM coordinate as a distance to the east) and northing (N, m) (UTM coordinate system as a distance to the north); β_n are the regression coefficients, and ε is the error term. Root mean squared error (RMSE) values were also expressed for each of the best MLR models constructed.

RESULTS AND DISCUSSION

In situ measurements revealed that Lakes Yenicaga and Abant differ in their trophic state in that Lake Yenicaga is eutrophic (nutrient-rich) ecosystem, whereas Lake Abant is an oligotrophic (nutrient-poor) ecosystem. Tukey's test following one-way Analysis of variance (ANOVA) showed that Lakes Yenicaga and Abant differed significantly in terms of DO, Chl-*a*, turbidity, S_{depth}, and T_w ($P < 0.01$) (Table 1). Landsat ETM+ data-based regression analyses resulted in the best MLR models with R^2_{adj} values ranging from 36.2 % in T_w to 93.1% in DO for Lake Yenicaga and from 36.1 % in S_{depth} to 99.7 % in T_w for Lake Abant. The resultant MLR models for Lakes Yenicaga and Abant are as follows:

DO (mg/L) for Lake Yenicaga = -2192 - (0.06237* band 1) - (0.21934*band 5) + (0.5226*band7) - (0.0002365*E) + (0.0005075*N) + (0.053166*DOY) (3)
(R^2_{adj}=93.1 %; RMSE=0.50mg/L; n=24;P=0.001);

DO (mg/L)for Lake Abant = 839.5 + (0.02275*band 3) -(0.02617*band 4) + (0.07607*band 5) + (0.013989*band 6L) - (0.12285*band 7) + (0.0000803*E) - (0.00019037*N) -(0.023993*DOY) (4)
(R^2_{adj}=96.7 %;RMSE=0.11 mg/L; n=24;P=0.001);

Ch1-a(µg/L) for Lake Yenicaga = -4465 - (0.7893*band 1) + (0.7776*band 2) + (0.4159*band 3) - (0.25935*band 4) + (0.889*band 6L) - (0.0022079*E) +(0.0011729*N) - (0.07193*DOY) (5)
(R^2_{adj}=96.7 %; RMSE=0.11 mg/L; n=24; P=0.001);

Ch1-a (µg/L)for Lake Abant = 21.6 - (0.0368*band 1) + (0.04391*band 2) + (0.0205*band 3) - (0.0344*band 4) + (0.03633*band 5) -(0.002347*band6H) + (0.035882*DOY) (6)
(R^2_{adj}=97.7%;RMSE=0.16 µg/L; n=24;P=0.001);

Turbidity (NTU) for Lake Yenicaga = 2320 - (2.846*band 1) + (4.298*band 2) - (2.383*band 3) -

Table 1: A comparison of Lakes Yenicaga and Abant for water quality (mean ± standard deviation) based on one-way ANOVA Tukey's test

Lake water quality	DO (mg/L)	Chl-*a* (µg/L)	Turbidity (NTU)
Yenicaga	10.00 ± 1.91	4.24 ± 2.20	8.42 + 8.2
Abant	9.18 ± 0.65	1.92 ± 1.08	0.59 ± 0.2
Statistically significant difference at $P < 0.01$	0.05	0.001	0.00

(0.5578*band 4) - (1.5344*band 5) - (4.038*band 6L) + (1.509*band 6H) + (5.671*band 7) + (0.000539*E) - (0.000488*N) - (0.0908*DOY) (7)
(R^2_{adj}=75.7 %; RMSE=4.0 NTU; n=24; P=0.001);

Turbidity (NTU) for Lake Abant = -339.3 - (0.05346*band 1) + (0.03704*band 2) + (0.03438*band 3) - (0.016424*band 4) + (0.02742*band6L) - (0.0246*band 6H) + (0.00919*band 7) + (0.004305*band 8) - (0.00001713*E) + (0.00007737*N) - (0.005491*DOY)
(R^2_{adj}=97.5 %; RMSE=0.04 NTU; n=24; P=0.001); (8)

S_{depth} (m)for Lake Yenicaga = 112 + (0.24329*band 1) - (0.27315*band 2) - (0.06228*band 3) + (0.05042*band 4) + (0.01556*band 5) + (0.207*band 6L) - (0.0433*band 6H) - (0.1222*band 7) - (0.000021*E) - (0.0000273*N) + (0.00946*DOY) (9)
(R^2_{adj}=85.1 %; RMSE=0.23 NTU; n=24; P=0.001);

S_{depth} (m)for Lake Yenicaga = 1157 - (0.03499*band 4) + (0.12429*band 5) + (0.004761*band 6H) - (0.17181*band 7) + (0.02412*band 8) -(0.0001439*E) - (0.0002447*N) - (0.009342*DOY) (10)
(R^2_{adj}=85.1 %; RMSE=0.23 NTU; n=24; P=0.001);

Tw(°C)for Lake Yenicaga = -138.61 - (0.11224*band 5) + (0.09993*band 6H) +(0.2187*band 7) - (0.03042*band 8) + (0.0003568*E) - (0.013418*DOY) (11)
(R^2_{adj}=36.2 %; RMSE=0.45°C; n=24;P=0.028); and

Tw(°C)for Lake Yenicaga = 895.8 - (0.1137*band 1) + (0.13349*band 2) + (0.01538*band 4) - (0.0583*band6L) + 0.05266*band 6H) -(0.0001276*E) - (0.0001869*N) + (0.058121*DOY) (12)
(R^2_{adj}=99.7 %; RMSE=0.12 °C; n=24; P=0.001)

Table 2: Comparisons of Landsat ETM+ data-based best multiple linear regression (MLR) models of dissolved oxygen (DO), chlorophyll-a (Chl-a), turbidity, Secchi depth (S_{depth}), and water temperature (T_w) for Lakes Yenicaga and Abant against in situ measurements (n = 24)

Lake	Performance test	DO (mg /L)	Chl-*a* (µg /L)	Turbidity (NTU)	S_{depth} (m)	T_w (°C)
Yenicaga	R^2 (%) of estimated vs. observed values	94.9	88.7	88.4	92.2	52.8
Abant	R^2 (%) of estimated vs. observed values	97.7	98.6	98.6	55.7	99.8

The RMSE values were consistently found to be lower for all the MLR models of the water quality in the oligotrophic Lake Abant than the eutrophic Lake Yenicaga. Comparisons of model estimates versus *in situ* measurements resulted in R^2 values ranging from 53 % for to 99.8 % for T_w of Lakes Yenicaga and Abant, respectively (Table 2). The best MLR models for the two lakes revealed that the trophic state significantly influenced not only the combination of the nine Landsat ETM+ spectral bands but also the predictive power of the MLR models used for the estimation of the five water quality characteristics measured in this study. The composition of the same independent variables used in the MLR models of the same dependent variables is as follows in increasing order of number of variables: T_w (band 6H) < DO (bands 5 and 7) < Chl-*a* (bands 1 to 4) = S_{depth} (bands 4, 5, 6H and 7) < turbidity (bands 1 to 4 and 6L/H to 8). The difference among the MLR models of the same dependent variables in R^2_{adj} values is as follows in increasing order of magnitude: DO (4 %) < Chl-*a* (15 %) < turbidity (21%) < S_{depth} (49 %) < T_w (64 %). The predictive power of the MLR models was stronger in the estimation of DO, Chl-*a*, turbidity, T_w and weaker in the estimation of S_{depth} for the oligotrophic Lake Abant than the eutrophic Lake Yenicaga. The most frequently used Landsat bands were bands 1, 5 and 7 (80 %) and bands 4 (100 %), 6H (80 %) and 7 (80 %) for the MLR-based estimation of the water quality of Lakes Abant and Yenicaga, respectively.

Given the higher S_{depth} value of Lake Abant (4.2 $\pm$ 0.3 m) than that of Lake Yenicaga (1.7 $\pm$ 0.6 m) the lower predictive power of the MLR model for Lake Abant (R^2_{adj} = 36 %) than that of the MLR model for Lake Yenicaga (R^2_{adj} = 85 %) may be explained by the fact that Landsat TM/ETM+ sensors can not measure deep S_{depth} values of lakes as effectively as those of shallow lakes (Nelson *et al*., 2003; Brezonik *et al*., 2005). S_{depth} for Lake Abant had positive correlation coefficient (*r*) values with Chl-*a* (r = 0.6; P = 0.001) and turbidity (r = 0.53; P = 0.005) contrary to the expected relationship. This case points to a major control over S_{depth} by CDOM instead of Chl-*a*, and turbidity. As reported in the related literature, high levels of light-absorbing CDOM affects y, S_{depth}, and thus, satellite-based reflectance values (Brezonik *et al*., 2005).

In the related literature, surface water temperature is generally estimated using simple regression models of the thermal infrared band (band 6) of Landsat ETM+ (Zhang *et al*., 2002; Kay *et al*., 2005; Giardino *et al*., 2007;). However, in this study, a MLR model using a combination of the nine Landsat ETM + bands was developed to estimate T_w. The higher R^2_{adj} value (99.7 %) of the MLR for T_w of Lake Abant than that (36 %) of the MLR model for Lake Yenicaga may be attributed to the closeness of Lake Yenicaga to the highway with heavy traffic connecting the biggest two Turkish cities of Istanbul and Ankara as well as to settlements with a population size of around 5000 thereby, to negative impacts of atmospheric pollutants such as aerosols generated by these activities on the remotely sensed data. Atmospheric particles such as dust, ash, and smoke directly and adversely affect remote sensing of water quality due to backscattering and absorbing solar radiation (Slater *et al*., 2004). Although a considerable number of atmospheric correction algorithms are suggested to remove the effects of atmospheric particles (aerosols and molecules), an evaluation of their practical value and contribution based on comparisons of atmospherically corrected satellite-derived reflectance and *in situ* measurements-derived reflectance showed inadequacies in atmospheric correction algorithms over water bodies (Hadjimitsis *et al*., 2004; Hadjimitsis *et al*., 2010).

CONCLUSION

Remote sensing-based environmental modeling and monitoring assist in better understanding and capturing spatio-temporal variations in both optically active and inactive lake water quality variables. The present study applies this technique in order to detect the best linear combinations of Landsat ETM+ spectral bands in elucidating spatio-temporal changes in water quality along trophic gradient. Coupling of readily available satellite-based time-series data and MLR models can facilitate *in situ* measurements that are expensive and labor-intensive and enable adaptive management practices to be devised in response to spatially and temporally changing conditions in lake water. The Landsat ETM+-based MLR models developed for Lakes Yenicaga and Abant along the eutrophic-to-oligotrophic gradient appeared to perform considerably well in accounting for variation in spatio-temporal dynamics of the water quality variables except for S_{depth} (R^2_{adj} = 36 %) and T_w (R^2_{adj} = 36 %) of Lakes Abant and Yenicaga, respectively. The inclusion of spatio-temporal components in the MLR models in this study is first of its kind for the remote sensing-based quantification and monitoring of lake water quality in this region. A comparison of the Landsat-based MLR models for the two lakes indicated that the trophic gradient significantly altered the composition of the nine ETM+ spectral bands included in the MLR models and the predictive power of the MLR models for the estimation of the water quality characteristics. Using of remotely sensed time series data over a longer period and a wider spatial coverage of lakes and exploration of non-linear relationships among possible combinations of the independent variables are most likely to assist in further refining accuracy of remote sensing-based multiple regression models as well as in better devising adaptive management practices for water resources.

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