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Assessment of the Eutrophic Status of Lake Burullus (Egypt) using Remote Sensing

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ABSTRACT
Eutrophication in water bodies is associated with growth of phytoplankton biomass which is easily detected by satellite sensors. Landsat imagery with a fine spectral resolution increases the accuracy of quantifying Secchi disk depth, chlorophyll-*a*.
Lake Burullus is one of the vulnerable Egyptian coastal lakes, suffering from dense blue green algae, caused by expansion of fish farming agriculture, increasing fertilizers and pesticides concentration, and turbidity. The aim of this work is to establish the eutrophication profile of Lake Burullus using remote sensing approach. Three Landsat Enhanced Thematic Mappers have been processed for estimation and mapping the reflectance response of chlorophyll-a and transparency, which are considered as Trophic Response Variables (TRV). The developed TRV regression model was defined, using in-situ nutrients measurements with correlation coefficients that ranged from 0.6 to 0.8 in two different seasons. The critical areas were defined based on the TRV concentrations. The results suggest that there is a change in the eutrophic profile of Lake Burullus caused by a set of environmental factors. These factors are related to increased human activity in utilizing the natural resources and as a result of a steady flow of the Nile water and drains. So, monitoring these rapid changes is important to have a complete picture of the lake eutrophic profile. Using a powerful technique such as the remote sensing in regular monitoring over large scale chemical processes rather than the expensive traditional techniques for investigating the water quality status has been discussed. Lake Burullus eutrophic status is thus recognized as an alarming situation for considering the practical implementation water management plans.

1. INTRODUCTION
Eutrophication in water bodies is associated with growth of phytoplankton biomass which can be detected by satellite sensors. Lake Burullus is one of the Egyptian coastal lakes suffering from high level of blue green algae, over fishing, expansion in fish farming and agriculture and increasing fertilizers and pesticides. In addition, fish production in Egypt depends largely on the Egyptian shallow water bodies such as Lake Burullus.

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The role of phytoplankton as a main source of fish nutrition is well known (Dumont and El-Shabrawy, 2007).

The remote sensing technique has a potential advance in mapping, modeling and quantifying quality parameters of shallow waters because their quality is particularly vulnerable to human-induced wastes. Landsat imagery with finer spectral resolution increases the accuracy of quantifying transparency, chlorophyll-*a* (Chl-*a*) concentrations and turbidity.

Remote sensing may therefore offer a satisfactory response to the challenge presented by the situation given by the spatial/temporal frequency of observation by satellite sensors, which capture image data above national borders. Number of studies are available represent the role of remote sensing for water quality monitoring.

Most of the northern lakes of Egypt are suffering from receiving high amount of pollutants due to increasing human activities and urbanization. Lake Burullus is suffering from blooming of blue green species *Microcystis aeruginosa* which is well-known for its toxin production and a signal of advancing eutrophication (Dumont and El-Shabrawy, 2007). Several studies have been conducted to investigate water quality status of Lake Burullus using landsat imagery using two sensors (TM, ETM) and mapping chemical parameters. Some of these studies were considered the radiance data of TM and ETM and in-situ measurement in modeling the water quality parameters. Moreover, these studies confirmed that remote sensing coupled with Geographic Information System (GIS) could offer an integrated scheme for mapping water quality (Dewidar and Khedr, 2005; Hereher *et al*., 2010).

The aim of this work was to develop an eutrophication profile for Lake Burullus using remote sensing approach considering the spatial and temporal distribution over the lake.

2. Review

2.1 Retrieval of water quality variables from satellite data

Water quality parameters that can be quantified by means of remote sensing fall into three groups: inorganic sediment particulates (Suspended sediment and turbidity), phytoplankton pigments (Chlorophyll concentration) and color dissolved organic matter (CDOM), (Doerffer *et al*., 1999).

2.2 *Suspended sediment and turbidity* it is relatively easy to remotely sense suspended sediments in a water body because of their strong backscattering of the incident radiation. Suspended solid concentrations have been commonly determined from MSS data, TM, SPOT data and even color and color IR photographs (Liu *et al*., 2003).

2.3 *Chlorophyll concentration* is consist of phytoplankton pigments consist mainly of chlorophyll *a*, *b* and *c*, of which chlorophyll *a* is derivable by means of remote sensing. Sun-stimulated natural fluorescence of chlorophyll *a* is a good predictor for phytoplankton, even in waters with varying suspended matter and yellow substance concentrations (Fischer and Kronfeld, (1990). The detection and assessment of chlorophyll *a* concentration and its variations within a water body require narrow bands of imagery (Liu *et al*., 2003).

2.4 *Color organic dissolved organic matter (CDOM)* encompasses algae, yellow substance and organic plumes. Algae are simple, variously one-celled organisms containing chlorophyll and other pigments. Remote sensing of algae in inland waters should be based on increased scattering by the cells and not increased absorption by chlorophyll (Quibell, 1992). The upwelling spectral signatures for algae were determined by the reflectance of the particles themselves, and by the absorption by the water surrounding the particles (Quibell, 1991).

2.5 *Secchi disk depth SDD* is a crude measure of water clarity or transparency. It increases with the decrease in reflected radiance, SDD is significantly correlated to atmospherically corrected satellite radiance (Choubey, 1998).

2.6 Application of Remote Sensing Technology in Monitoring the Lakes

Various studies have been done to monitor the water quality status of the lakes using remote sensing data. One of these studies has been carried examine Landsat-7 ETM+ could be used to measure water clarity across a large range of lakes and developing a regression model to estimate Secchi disk transparency (SDT) from Landsat data and calibrated using 93 lakes in Michigan, U.S.A. It was concluded that the regression model had a much lower r^2 value than previously published studies conducted on smaller datasets (Nelson *et al*., 2003). At Boreal Plain of northern Alberta a research study has been conducted to provide an alternative of remote sensing methodology to characterize the spatial and temporal variation of the trophic status of lakes in the relatively remote and pristine regions of the western Boreal Plain. Three optically active trophic indicators of lakes have been sensed from satellite platforms are Chl *a*, Turbidity, and Scchi Disk. Regression models were used to predict satellite-based Chl *a*, Turbidity, and Scchi Disk for the remaining archived images for the period from 1984 to 2003. Regression models were developed, the correlation analyses showed that B1, B2, B3, B3/B1, and B3/B2 were all significantly ($p<0.05$) correlated to the three selected indicators. B3 and B3/B1 exhibited the highest correlation coefficients for the indicators of trophic status that can be detected by optical imagery (≈ 0.8 for Chl *a*, ≈ 0.9 for Turbidity, and ≈ −0.7 for Secchi Disk) (Sass *et al*., 2007). Another study has been carried out at Lake Chagan represents a complex situation of major optical constituents and emergent spectral signals for remote sensing analysis of water quality in the Songnen Plain. As such it provides a good test of the combined radiometric correction methods developed for optical remote sensing data to monitor water quality. TM data and in situ water samples collected concurrently with satellite overpass were used for the analysis, in which four important water quality parameters are considered: chlorophyll-*a*, turbidity, total dissolved organic matter, and total phosphorus in surface water. Both empirical regressions and neural networks were established to analyze the relationship between the concentrations of these four water parameters and the satellite radiance signals (Song *et al*., 2011).

3. MATERIALS AND METHODS

3.1 Study Area

Lake Burullus extends along the northern part of the Nile Delta. It is the second northern lake in size. Around the early 1900s, it had a surface area of about 600 km^2; by 1974, land reclamation for agriculture in its southern sector had caused it to decline to about 460 km^2, and this decline continues today. Its long axis, about 65 km long, runs parallel to the adjacent Mediterranean shore; its width is between 6 and 16 km, with the average being 11 km (Radwan and Lotfy, 2002).

The lake is extremely shallow, with a depth between 0.4 and 2.0 m. The deepest part lies in the western sector, which also has the lowest salinity, while the eastern sector, which contains its outlet as a 250 m long canal connecting the lake to the sea (Bughaz), is shallow and saline (Doumont and El-Shabrawy, 2007). Fig. (1) shows general layout of Lake Burullus.

The water quality basic parameters have been measured in the field using CTD (model Turo T-611) at different strata of the water column. The measured basic parameters are water temperature, pH, salinity, dissolved oxygen (DO) and turbidity. Transparency and water clearance have been detected using three different methods. These are Secchi Disc, total suspended matter (TSS) and turbidity sensor inside the CTD. Nitrites, Nitrate, Ammonia, Total nitrogen, Orthophosphate, Total Phosphorus and Silicate have been measured using portable spectrophotometer (model DR 2800 – HACH Company).

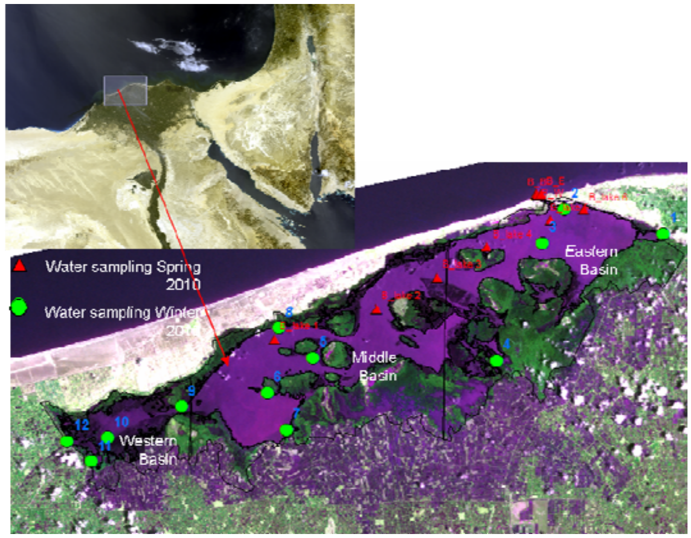

Fig. 1: Layout of Lake Burullus and water sampling locations.

3.2 Data Collection

Two types of data have been collected; the first is relevant to the measurements of the water samples, compared with the second one that was acquired from remote sensing technique. In order to study the water quality, samples have been collected from nine locations to represent most of Lake Burullus during spring 2010. The measured data were compared with published data collected during spring and winter seasons in 2009 and 2010, respectively. Five parameters have been analyzed. These are nitrite (NO_2), nitrate (NO_3), ammonia (NH_3), orthophosphate (PO_4) and total phosphorus (TP). Basic parameters were also measured such as pH, turbidity, salinity, electric conductivity, transparency and dissolved oxygen.

Three coincidence Landsat Enhanced Thematic Mapper (ETM) have been processed for estimation and mapping Chlorophyll-*a* and transparency which are considered as the TRV. The images acquisition dates included the following: May 2009, Jan 2010 and May 2010.

3. 3 Retrieve of Chlorophyll from satellite data

This work had been done to investigate the relationship between the spectral properties of water bodies within the optical and near infrared portion of the electromagnetic spectrum. Bands 1 to 4 (from 450 to 900 nm) are in spectral range where light penetrates the water to a sufficient depth to extract information about water quality, (Brivio *et al.,* 2001). The presence of chlorophyll-a determine attenuation in the reflectance in bands 1 (blue) and 3 (red), and an increase in reflectance in band 2 (green). Chlorophyll values have been extracted according to (Brivio *et al*., 2001) equation (1) by subtraction of the reflectance of band 3 from band 1 and normalizing by the reflectance in band 2.

$$chl = 0.098 \times \frac{band\,1 - band\,3}{band\,2} \qquad (1)$$

The method of Akbar *et al.* (2007) was used to show the ratios between band 2 reflectance and band 3 or between band 1 and band 3 to quantify the chlorophyll-a as represented in equations (2) and (3).

$$chl = \frac{(B2)green(0.5 - 0.6\mu.)}{(B3)red(0.6 - 0.7\mu.)} \qquad (2)$$

$$chl = \frac{(B1)blue(0.4 - 0.5\mu.)}{(B3)red(0.6 - 0.7\mu.)} \qquad (3)$$

3.4 Water Mask Approach

To profile the chlorophyll concentration over water surface area of the lake, the water surface of the lake was delineated accurately. There are a lot of methods applied to separate the water to the inland. One of these methodologies is the modified normalized difference water index (MNDWI) which used to reach the goal of isolating water and non-water features. There are various definitions of normal difference water index (NDWI) that combines different pairs of bands (normally of TM or ETM), typically and originally including green and near infrared (NIR) (band 2 and band 4). Meanwhile, in the middle infrared MIR (band 5) the reflectance of urban features is much higher than that of green band, thus the use of band 5 instead of band 4 for NDWI calculation significantly avoids the confusion of water and negative value of other features including urban areas (Ho *et al*., 2010). Equations (3 & 4) represent the combined pairs of bands for NDWI and MNDWI.

$$NDWI = \frac{Green - NIR}{Green + NIR} \qquad (3)$$

$$MNDWI = \frac{Green - MIR}{Green + MIR} \qquad (4)$$

3.5 Developing a Chlorophyll Regression Model

Theoretically, it is impossible to extract water quality information from remotely sensed radiance because the boundary condition of the water–atmosphere interface and the characteristics of the atmospheric aerosol are unknown. Thus, feasible approaches to quantifying water quality have to be empirically or semi-empirically based. The empirical relationship may be established through regression analysis. It may also be determined from the known spectral characteristics of the water quality parameter of interest. This is known as the semi-empirical approach Liu *et al.* (2003).

The chlorophyll-a concentrations have been calculated mainly by the phosphorus-chlorophyll relationship in lakes as represented in equations 5 & 6. The exponential relationship between chlorophyll and phosphorus suitable testable hypothesis while chlorophyll is both a useful and a simple estimator of phytoplankton standing crop and is now more generally used than cell number or cell volume according to the method of Dillon and Rigler (1974).

$$\log_{10}(Chl) = 1.583\log(TP) - 1.134 \qquad (5)$$

$$\log_{10}(Chl_a) = 1.449\log_{10}(TP) - 1.136 \qquad (6)$$

The correlation between TRV remote sensing variables with the others calculated from empirical equation were tested over the two seasons. In addition, the chlorophyll regression model has been developed based on measured nutrients measurements concentrations.

In addition, a Trophic State Index (TSI) has been calculated according to the three equations (7, 8 and 9) cited by Carlson and Simpson (1996). TSI has been calculated from three sources, Secchi disc reading, chlorophyll-*a* and total phosphorus. The values of TSI helped to classify the eutrophic status of the parts under investigation of the lake into four categories; oligotrophy, mesotrophy, eutrophy and hypereutrophy.

$$TSI_{SD} = 60 - 14.41\ln SD \qquad (7)$$

$$TSI_{Chl} = 9.81\ln Chl + 30.6 \qquad (8)$$

$$TSI_{TP} = 14.42\ln TP + 4.15 \qquad (9)$$

3.6 Error percentage method

The error percentage between the estimated chlorophyll from regression model (C_m) and the predicted chlorophyll (C_s) from the remote sensing data was calculated to check the accuracy of the regression model equations as follows:

$$Diff = C_s - C_m$$

$$Error\% = \frac{\left(\frac{\sqrt{\sum (Diff.)^2}}{n}\right)}{\overline{C}_m}$$

Where, $\overline{C}_m$ is the average predicted corresponding chlorophyll from remote sensing data.

4. RESULTS AND DISCUSSIONS

The flow of the results of this work has been categorized as two pathways; one from analytical measurements and other from remote sensing prediction as shown in the flow chart (Fig. 2). They were matched together to identify the eutrophic zones in Lake Burullus and to validate using the remote sensing output data instead of the analytical one.

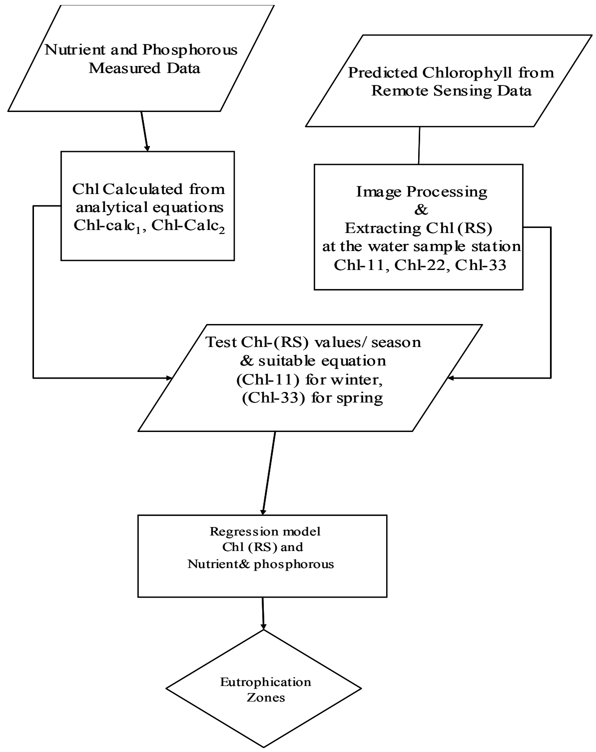

Fig. 2: Flow Chart of the Research Methodology

From reviewing the previous water quality sampling over the lake during winter and spring seasons, it was found that the total phosphors (TP) ranged from (1181.9) to (322.8) mg/m^3 in winter while it ranged from (1325.1) to (416.4) mg/m^3 in spring, the NH_3 values varied from (2350.2), (173.6) mg/m^3 to (2582.3), (81.6) mg/m^3 in winter and spring, respectively. The NO_3 values decreased from (268.2) to (416.6) mg/m^3 from winter to spring. The air temperature varied from 32°C to 21°C in spring and from 20°C to 10°C in winter, that may affect the eutrophication process. Figs. (3 & 4) represent the nutrients distribution over the lake in spring and winter seasons.

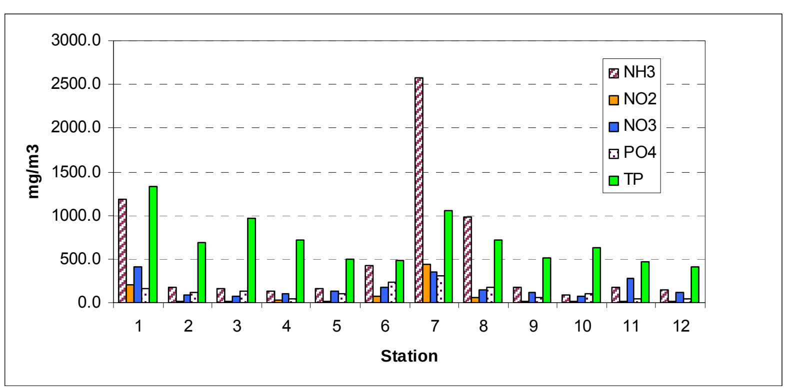

Fig. 3: Nutrients distribution over Lake Burullus, during spring 2009.

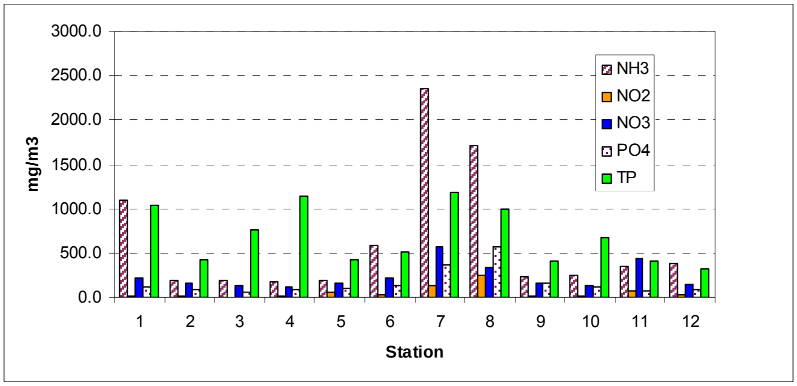

Fig. 4: Nutrients distribution over Lake Burullus, during winter 2010.

Water samples have been collected from 9 sites covering Lake Burullus and its outlet region along the Egyptian Mediterranean coast at spring 2010. The basic parameters results have been summarized in Figs. (5 & 6). The investigation of water temperature measurements revealed that there is irregular temperature distribution along the study area as shown in Fig. (5). An increasing trend of water temperature through the water column was observed in the lake starting from site B1 to B6. Generally, the water temperature of the outlet region was relatively higher than the Lake water temperature. This may be due to the differences of the time of sampling and the difference in depth. Fig. (5) showed also irregular distribution of DO along the water columns in the area under investigation. Hypoxia or anoxias were not detected at any site. The minimum DO value was 2.1 mg/L detected at B6 site of the Lake, while the maximum value was 7 mg/L detected at B5 site. Moreover, Fig. (1) shows the distribution of pH values along the area under investigation. It revealed that all the water samples have slightly alkaline nature as normal. Increasing trend of pH values was observed at the lake starting from site B1 toward site B6.

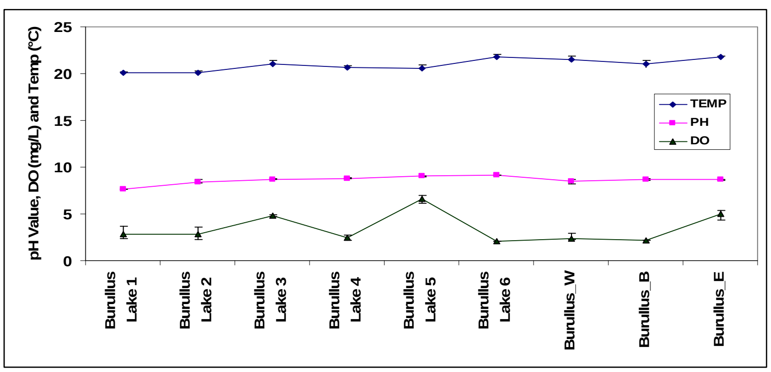

Fig. 5: Water temperature (°C), pH values and Dissolved oxygen (mg/L) in Lake Burullus during spring 2010.

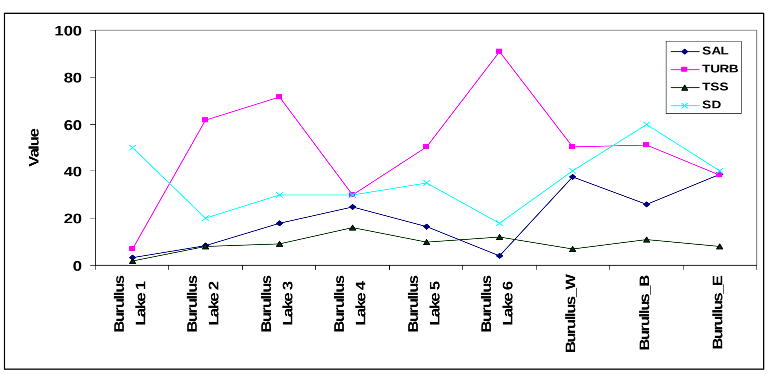

Fig. 6: Salinity (ppt), turbidity (ntu), TSS (mg/L x 100) and secchi disc reading (m x 100) in Lake Burullus during spring 2010.

Fig. (6) shows salinity measurements of the area under investigation which have very close values. The results of the salinity and conductivity measurements revealed that Lake Burullus is affected mainly by the saline seawater which could be exchanged with lake water through the outlet. Site B4 showed relatively higher salinity compared with other sites of the lake. This was because B4 is the nearest site to the lake outlet. Salinity was lower inside the lake at sites away from the outlet either at east or west directions.

Water turbidity has been expressed by three methods; CTD measurements, Secchi disc records and total suspended solids (TSS) measurements as shown in Fig. (6) Generally, the lake water can be divided into relatively high turbid water sites such as B2, B3 and B6 and relatively low turbid water sites such as B1, B4 and B5. The outlet sites had relatively more clear water than the turbid lake sites. TSS showed the same trend previous by mentioned but with some modification such as site B4 which appeared with higher station of TSS content (0.16 mg/l) than the other sites.

Concerning the eutrophication parameters, nitrogen and phosphorus have been measured in different forms. Nitrogen has been measured as nitrite (NO_2) and its oxidized form as nitrate (NO_3), ammonia (NH_3) and total nitrogen (TN). On the other hand, phosphate has been measured as dissolved inorganic phosphate "orthophosphate" (PO_4) and total phosphorus (TP). The results of nutrients concentrations and silicate distribution at the sites under investigation are shown in Fig. (7).

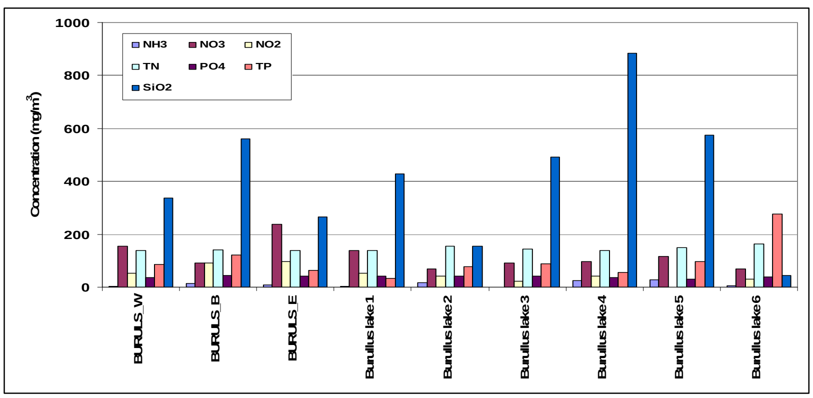

Fig. 7: Nutrient concentrations (mg/m^3) in Lake Burullus during spring 2010.

The investigation of Nitrite measurements along the area under investigation revealed that El-Burullus outlet region has relatively higher values (95.7 and 92.3 mg/m^3) of NO_2 especially at the outlet and the eastern sites comparing with the lake NO_2 values as shown in Fig. (7). The western sites of the lake observed as relatively higher than the other sites of the lake. Site B5 in the lake was observed as very low amount of NO_2 (1.01 mg/m^3) comparing with the other sites under investigation. Irregular distribution of nitrate (NO_3) and ammonia (NH_3) along the area under investigation has been recognized. The eastern site of the outlet region had the maximum value of NO_3 concentration (238.5 mg/m^3). Lake Burullus water had average NO_3 value 117.8 mg/m^3 with range from 170.8 mg/m^3. On the other hand, NH_3 distribution showed higher values inside the lake as in B4 and B5 (23.9 and 27.9 mg/m^3, respectively) than the other sites either in the rest of the lake or its outlet. Fig. (3) showed the distribution of total nitrogen along the area under investigation. The higher TN values were observed in the lake at B2 and B6 with 155.2 and 163 mg/m^3, respectively.

Phosphorus is an abundant element and one of the most important nutrients.

Concerning the results of PO_4 in Lake Burullus and its outlet revealed that PO_4 values were close to each other with some fluctuations as shown in Fig. (7). The average value of PO_4 was 39.2 mg/m^3 with range from 13.5 mg/m^3. Total phosphorus is composed of two principal components; the total dissolved form and the total particulate form. The investigation of TP measured values revealed that the relatively higher value (275.3 mg/m^3) was detected in the lake water at B6 site. The outlet site of the lake showed relatively higher TP (121.3 mg/m^3) than the other sites of the outlet region (86.7 and 62.7 mg/m^3).

The silicate distribution along the area under investigation revealed that irregular with average value of 415.6 mg/m^3. The minimum value (43.8 mg/m^3) was detected at B6 site in the lake and the maximum value (883.7 mg/m^3) was detected at B4 site as shown in Fig. (7).

4.1 Trophic Status Assessment

Lake Burullus was divided into four zones according to the nutrients load of the drainage waste discharged into the lake. EEAA & GEF (2002) and Okbah & Hussein (2006) and other reports stated that Lake Burullus is considered as an eutrophic area. On the other hand, El-Sayed (2010) assessed the eutrophication status of the lake by applying empirical models for Chl-*a* and nutrients, it was found that lake lies between oligo-trophic to meso-trophic states.

The trophic state of Lake Burullus has been assessed by estimating the TSI values at the water sampling sites. The TSI different values at the water sampling sites are presented in Fig. (8). The dots line (green) indicates the limit of mesotrophic state, the dashed line indicates the limit of eutrophic state and the solid line indicates the limit of hypereutrophic.

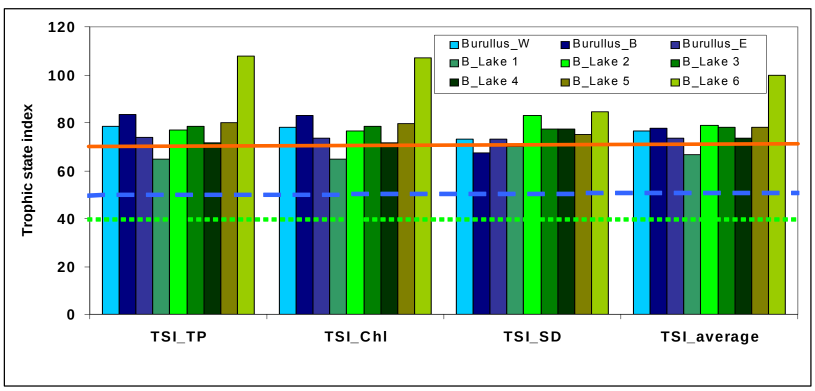

Fig. 8: The trophic state index of different parts of Lake El-Burullus during spring 2010.

4.2 Relation between (Chl) remote sensing and (Chl) calculated

Liu *et al.* (2003) reported that remote sensing of water quality parameters relies on the spectral properties of water leaving radiance. It refers to the light re-emerging from water after the incident solar radiation is selectively absorbed and backscattered by water constituents. According to Dekker and Peters (1993), the reflectance response of the sensor TM radiance could not be related directly to chlorophyll concentration. Hence, the expected relationship between the reflectance response of TM radiance as predictors of chlorophyll concentrations and the nutrients could be investigated, taking into consideration the temperature variation.

The chlorophyll values were calculated by substituting the phosphorous in the two empirical equations (5) and (6) to explore the correlation between the calculated chlorophyll with the values predicted from remote sensing data for each season. The chlorophyll predicted values were also tested with relevance to combined band ratio estimated. Calculated chlorophyll in spring season from equation (5) is abbreviated as ($Chl\_calc_1\_s$) and ($Chl\_calc_2\_s$) for equation

(6). It was found that the chlorophyll values predicted from remote sensing bands by substituting in equation (3) (Chl_3) has given a good correlation in spring and reached to r^2=0.75, 0.9 with relevance to (Chl_calc$_{1,2}$_s) as a result from equation (5), (6) respectively. Fig. (9) represents good correlation between calculated chlorophyll in spring season as calculated from substituting the total phosphorus in equation (6).

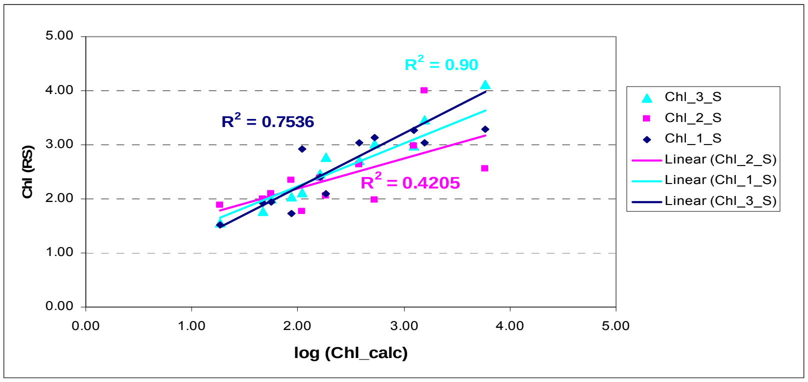

Fig. 9: Calculated chlorophyll (Chl_calc$_2$_S) from total phosphorus against chlorophyll predicted from remote sensing technique during spring season

The same correlation has been tested in winter season, where the chlorophyll values were predicted from remote sensing bands by substituting in equation (1) (Chl_1) gave a good correlation in winter reaching to r^2=0.74, 0.82 with relevance to (Chl_calc$_{1,2}$_w) as a result from equations (5) & (6) respectively. The correlation between calculated chlorophyll and predicted chlorophyll in winter season is represented in Fig. (10).

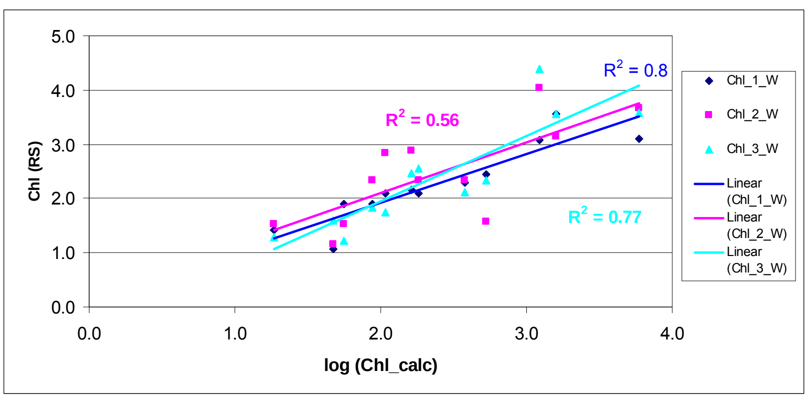

Fig. 10: Calculated chlorophyll (Chl_calc$_2$_w) from total phosphorus against chlorophyll predicted from remote sensing technique during winter season

4.3 Relation between (Chl) remote sensing and Nutrients measurements

The mechanism of seasonal changes in phytoplankton can be based upon physical, chemical and biological environmental factors of any water body. The distribution of phytoplankton in the lake is regulated mainly by temperature, light, nutrients, toxicants, parasitism, grazing and inter-specific competition. Maher *et al.* (2009) suggested that changes in phytoplankton distribution are probably due to seasonal variation in available nutrients and water temperature. The picture of chlorophyll a, b, and c of the lake water was slightly higher during the period of May-July. The highest value (34.12 µg/l) of chlorophyll-*a* was reported in May.

In order to develop chlorophyll regression model, the relationship between the Chl extracted values from Landsat images and nutrients measured data has been tested in winter and spring seasons. The results revealed a good agreement (r^2) between the remote sensing extracted values and the five predictors (NO_2, NO_3, NH_3, PO_4 and TP) that are higher than when compared with using two predictors (NH_3 and PO_4). Table (1) summarizes the good agreement between the predicted chlorophyll concentrations extracted from remote sensing data and the predictors by applying the reviewed winter 2010 image.

Table 1: Correlation coefficients among chlorophyll predicted from remote sensing technique with different types of nutrients during winter and spring seasons.

Chlorophyll Predicted from RS	All Nutrient parameters	Selected Nutrient parameters	All Nutrient parameters	Selected Nutrient parameters
	(r^2) Winter		(r^2) Spring	
Chl (1)*	0.970652	0.57083	0.870664	0.662909
Chl (2)*	0.987568	0.486189	0.960319	0.739735
Chl (3)*	0.986962	0.519197	0.940755	0.775446

*N.B. * refers to the number of equation applied for predicting the chlorophyll*

It was found that the developed relationship between the (TRV) and chlorophyll concentration showed a good agreement (r^2), that varied from 0.57 to 0.98 in winter and from 0.66 to 0.96 in spring. Regarding to the important role of temperature in changing the chemical processes and biological activities, the impact of temperature variation between spring and winter was detected. Also, Chl_1 predicted values against the two nutrients measured parameters (NH_3, PO_4) showed a good correlation reaching to o.6 in winter season while in Chl_3 the correlation reached to 0.77 in spring season. Two mathematical regression models have been deduced for each season, equations (10) and (11).

$$(Chl\_3\_S)_{RS} = 0.0081(PO_4) + 0.0005(NH_3) \tag{10}$$

$$\ln(Chl\_1\_W)_{RS} = 0.0096(PO_4) + 0.0002(NH_3) \tag{11}$$

Where NH_3 and PO_4 were measured in mg/m^3

By substituting measured nutrients (NH_3 and PO_4) in developed regression model in spring and winter seasons, the error percentage was calculated. The corresponding error percentage has approximately reached to 8% and 10% in spring and winter seasons, respectively.

4.4 Chlorophyll Profile

Developing a chlorophyll profile for the lake, it should separate the water from inland with the reliable methodology relevant to the natural condition of the lake and its surrounding area.

Ho *et al.* (2010) reported that the (MNDWI) can be used to identify moist surface or saturated areas to separate flooded and non-flooded areas. Moreover, the reflectance difference of water between band 2 and band 5 is much higher than that of moist soil features. Ho *et al.* (2010) mentioned also that in some cases if there is a great interference between the water areas and moisture soil, water mask could be developed by unsupervised classification of band 4 (near-infrared) which is characterized by the absorption of water which is very high in contrast to the surrounding land areas.

Therefore, the NDWI, MNDWI and super classification of band 4 (near-infrared) were tested at the study area for developing the water area at the lake. The MNDWI has given better results than NDWI, the threshold of this study area is defined for each image to develop the water mask which ranged from 0.52 -0.56. Results are consistent with previous works that have been reported by Gao (1996) that separating the water from the moisture soil is difficult in depending on the threshold value and given no accurate output. Therefore, applying supervised classification method on band 4 near-infrared (NIR) and assisting of the ancillary data and field investigation provide a reliable water mask for the lake.

As the lake was classified before (EEAA and GEF, 2002) based on the geo-morphological characteristics, it was divided to three basins eastern, middle and western. In general, it was noticed that in winter the chlorophyll concentrations had slightly higher values at the defined trophic zones but the spread was more in spring. The chlorophyll concentrations could identify the trophic zones of the lake as three zones in winter (A, B, C) and four zones (A, B, C and D) in spring. It was found that zone C in the western basin has a high chlorophyll concentration value and it is considered hyper-trophic area, while zone A which is located in the eastern basin can be considered as eutrophic zone. For the middle basin zone, B is considered as a meso-trophic area in winter while in spring, it is eutrophic area due to increased chlorophyll concentrations. Figs. (11-a) and (11-b) show the chlorophyll profile over Lake Burullus in winter and spring seasons 2010.

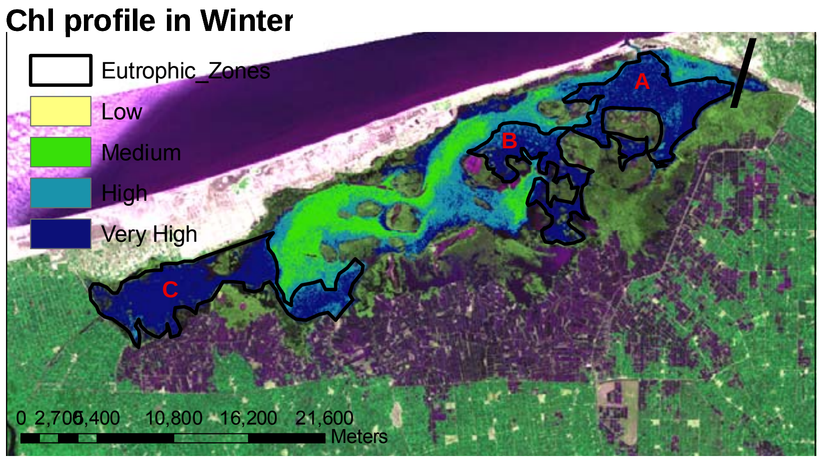

Fig. (11-a): Chlorophyll profile over Lake Burullus in winter.

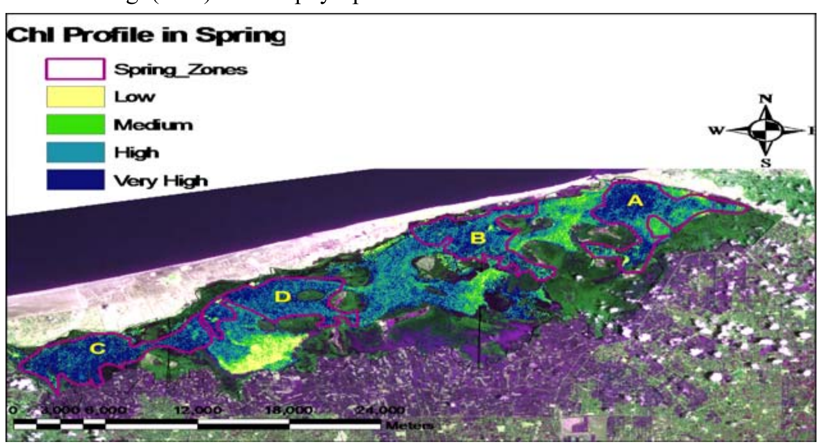

Fig. (11-b): Chlorophyll profile over Lake Burullus in spring

The use of remote sensing data to investigate the water quality of Lake Burullus was validated. The investigation of chlorophyll concentrations and TSI index of Lake Burullus revealed that its trophic status ranged from meso-trophic to hyper-trophic. Moreover, the hotspot areas in the lake were recognized. The parts of the lake affected by the agriculture discharge, polluted drainage waste and fish ponds areas were characterized by high chlorophyll concentration. The western basin is considered as the most trophic basin.

The results revealed that there is a change in the trophic profile of Lake Burullus due to changing the environmental factors affecting the lake. Such factors are related to the increasing of the human activities in utilizing the natural resources and as a result of a steady flow of Nile water and drains. Monitoring these rapid changes has become an important issue to have a complete picture of the lake eutrophication situation. Lake trophic status is recognized as alarming situation for considering the practical implementation of water management plans.

In future work, it is recommended to increase monitoring frequency and number of water sampling of the lake to enhance the regression model results. Developing a mathematical simulation of water quality models could help predict the changes of chemical concentrations reaching to the lake and affecting on its trophic status due to increasing development activities. That will be helpful for the decision maker and water resources planners for implementing future plans based on real understanding.

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