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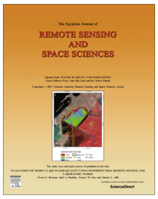

Research Paper

Development of an empirical model for chlorophyll-*a* and Secchi Disk Depth estimation for a Pampean shallow lake (Argentina)

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ABSTRACT

Shallow Pampean lakes are located in the most productive plain of Argentina. They are highly variable in salinity, turbidity and surface area. Laguna Chascomús has been monitored as a representative example of them. We developed a linear model based on satellite images validated against field measurements (2001–2011 period). A vegetation index and Landsat Surface Reflectance (Band 4) produced the best correlations with chlorophyll-*a* (Chl-*a*) and Secchi Disk Depth (SDD), respectively. In a second instance, a retrospective analysis (1986–2013) was performed. As a result, significant positive trends were observed for SDD and Chl-*a*. In addition, both variables displayed trends related to rainfall and site depth.

1. Introduction

Freshwater is one of the most valuable resources on Earth. Presently, the main risks for the water resource are human overexploitation (Christie, 2011), decreases of the value of the ecosystem services provided by the water bodies and changes related to climate variability (Andersen et al., 2006; Adrian et al., 2009). Monitoring of water quality of shallow lakes is an obvious prerequisite for developing mitigation programs.

Dörnhöfer and Oppelt (2016), in a review about remote sensing as a support for lake research, emphasized the importance of remote sensing technology for retrieving historical information about lakes, especially in regions where such information is scarce. Recent studies (Fuller and Minnerick, 2007; Moses, 2009; Bonansea et al., 2015; Doña et al., 2015) demonstrated that LANDSAT satellite data provide useful tools for monitoring surface waters over time. The 490–555 nm portion of the electromagnetic spectrum has been mostly used for chlorophyll-*a* (Feng et al., 2014) estimation whereas red and near infrared reflectance has been used for studies in turbid waters (Moses, 2009).

The Pampean region of Argentina is a heterogeneous landscape, including large plains, crossed by rivers and scattered with shallow lakes (Fig. 1). In this region lakes are typically shallow (~2 m) and highly variable in surface area, salinity and nutrient content (Dangavs, 2005). The hydrology of Pampean lakes is highly dependent on the rainfall regime (Kruse and Laurencena, 2005).

In a previous study (Diovisalvi et al., 2015) we compared Pampean shallow lakes vs. a large dataset of lakes worldwide (over 2700 lakes) as regards to some basic limnological variables. Interestingly, we found that Pampean lakes are, on average, more eutrophic than any other group of lakes considered in our study. Pampean lakes tend to display higher Chl-*a* concentrations and shallower SDD. Moreover, the analysis showed that, at comparable Chl-*a* concentrations, Pampean lakes have (on average) shallower SDD than any other grouping of lakes.

Laguna Chascomús is a typical Pampean shallow lake. This lake has been studied during long periods from different biological perspectives (Torremorell et al., 2007; Diovisalvi et al., 2010; Lagomarsino et al., 2015). Therefore, a long data series of SDD and Chl-*a* concentrations is available. Chascomús has remained in turbid state (non-vegetated) since 1980 (Barla, 1991), which

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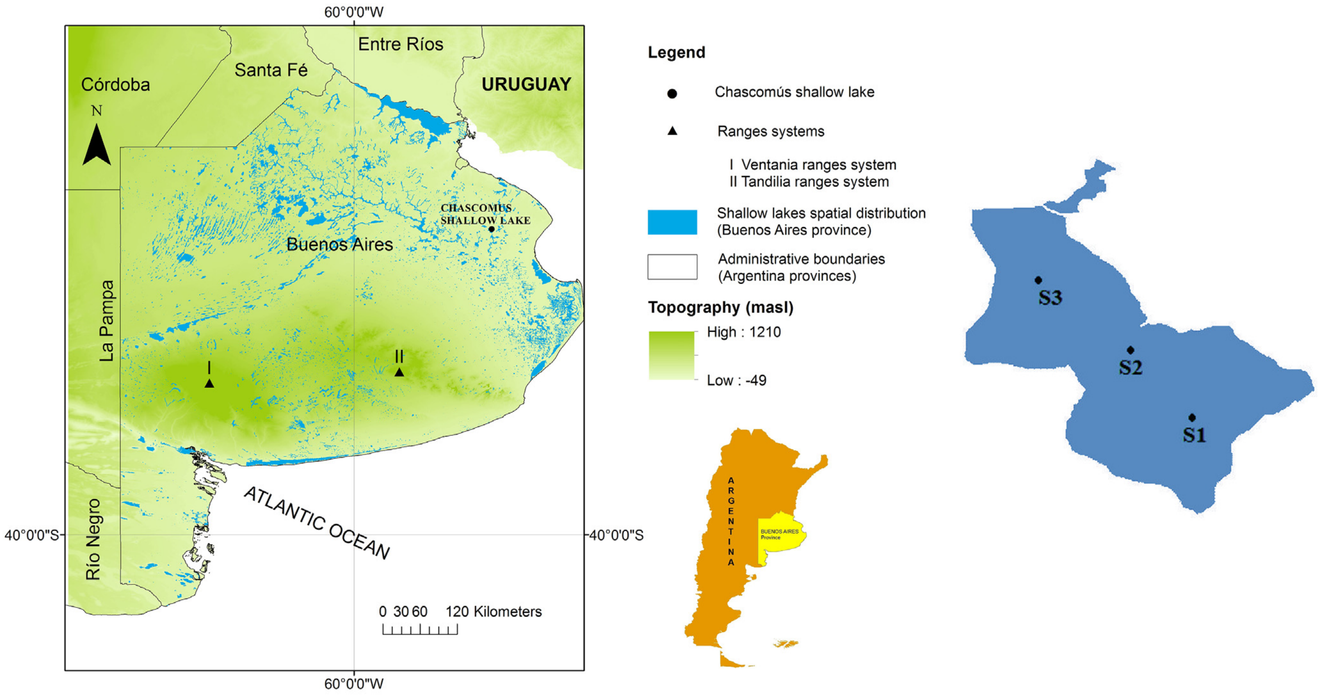

(a) (b)

Fig. 1. Laguna Chascomús: a) hydrological system and localization; b) localization of sampling sites (SS).

reasonably allows an historical extrapolation back to the early 1980's given that it has not switched between alternative steady states. By necessity, *in situ* measurements in the lake are restricted to three sampling sites. A satellite application could be convenient to obtain knowledge of the spatio-temporal variations in the water quality parameters with a high frequency of monitoring and in the entire extension of the water body. Also, the aforementioned possibility could promote the generation of retrospective studies related to the environmental history of the lake.

The first objective of this work was to formulate and validate an empirical model to estimate Chl-*a* concentrations and SDD in a typical Pampean shallow lake by combination of satellite (LANDSAT ETM+(L7) and TM (L5)) and field data. A second objective was to use the model to reconstruct the lake history back to middle 1980′s and to map the spatial distribution of Chl-*a* and SDD during predefined dates.

2. Materials and methods

2.1. Study area

Laguna Chascomús is a shallow lake located in the "Pampean region" (Argentina), characterized by a plain landscape, except for two hill systems (Fig. 1). The Pampean region has a temperate climate (mean annual temperature: 14–20 °C) and it is characterized by a strong rainfall gradient, which decreases from the NE

Table 1
General characteristics of Laguna Chascomús.

Shallow lake parameter			Data
Morphometric parameters[1]	perimeter (km)		26.44
	area (km^2)		28.73
	Coastal Line Development (CLD)		1.39
	shape and origin by CLD		subcircular, deflation
Topographic features[2]	altitude (masl)		5
	regional slope (°)		<4
Climatological parameters[3]	mean annual precipitation (mm y^{-1})		900–1000
	mean annual temperature (°C)		14–16
	mean wind annual velocity (km h^{-1})		10.1
	evapotranspiration (mm y^{-1})		1100–1200
Limnological characteristics[4], 5	depth (m)	Min	1.5
		Max	1.9
	Chl-*a* (μg/L) (June 2005–May 2009)	Mean (SD)	328.5 (173.4)
		Range (Min–Max)	50.6–856.3
	SDD (cm) (June 2005–May 2009)	Mean (SD)	10.2 (3.1)
		Range (Min–Max)	5.0–18.3
Main use[2]			fishing, recreative activities

[1] Dangavs (2005). Estimations from LANDSAT TM 5 scene (224/085) 11th November 2009.
[2] IGN - Secretaría de Recursos Hídricos de la Nación – INA.
[3] Servicio Meteorológico Nacional (SMN).
[4] Diovisalvi et al., 2014. SD: Standard Deviation; Min: Minimum; Max: Maximum.

(1000 mm year^{-1}) to the SW (400 mm year^{-1}) (Viglizzo et al., 2009). There are five climatic subregions (Díaz and Mormeneo, 2002), covering a range from warm humid to cold sub-humid conditions. This region is one of the most productive of Argentina, in terms of agriculture and cattle breading. Chascomús belongs to a system of seven shallow lakes arranged as chained water bodies (Dangavs, 2005). The physical characteristics of Chascomús (Table 1) favor a state of continual mixing and lack of stratification (Torremorell et al., 2007).

2.2. Field measurements

Laguna Chascomús has been sampled every other week during the 2001–2011 period. A total of 29 sampling dates corresponding to this period, for which nearly simultaneous satellite images are available, were selected for this study. *In situ* measurements were done in three sampling sites (Fig. 1). In these 2001–2011 field campaigns, concentrations of Chl-*a* were estimated spectrophotometrically after extraction with methanol (Lopretto and Tell, 1995) and Secchi depth readings were measured *in situ*. Lake depth was measured during the June 2001–June 2012 period at a gauging station for which topographic altitude is known (IGN). The graduated scale is located in the dock of the Laguna Chascomús shallow lake.

2.3. Remote sensing data

Landsat 5 TM and 7 ETM + were the sensors used in this study. Landsat images (Land Surface Reflectance) were downloaded from the USGS Earth Resources Observation and Science (EROS) Center Science Processing Architecture (ESPA) on Demand Interface (https://espa.cr.usgs.gov/) webpage and from Glovis (http://glovis.usgs.gov/) visor (https://espa.cr.usgs.gov). Surface Reflectance data are generated from the Landsat Ecosystem Disturbance Adaptive Processing System (LEDAPS), a specialized software developed by NASA GSFC and the University of Maryland. The software applies MODIS atmospheric correction routines to Level-1 data products.

2.4. Data processing and analysis

Two sets of satellite data were used in this study. In the first instance, the downloaded satellite images (n = 29) were selected according to sampling date (±3 days) (2001–2011 period). In the second instance, 103 satellite images were collected and processed to obtain the retrospective tendency of SDD and Chl-*a* for Laguna Chascomús (1986–2013). According to availability (data age, absence of clouds) an average of 4 satellite images per year were processed. Only 16.5% of this set of images were used also for the validation of the model. In summary, a total of 115 satellite images were analyzed in this study. Regardless of the specific objective, satellite images were digitally processed using ENVI 4.7 software. The analysis included the retrieval of Surface Reflectance values for every SS (Fig. 1) and for every date. As a result, a total of 83 pairs of data (satellite and *in situ* data) and 309 surface reflectance values for the model development and for the retrospective analysis were collected. The retrieval of a mean value around *in situ* sampling sites was considered more appropriate in both cases in order to reduce sensor and algorithm noise (Hu et al., 2001). Therefore, a region of interest (ROI) was defined for each of the three sampling sites. The ROI included a predefined number of pixels (5x5) which was proportional to the shallow lake size (~29 km^2) and considered appropriate for the number of SS. For each ROI, Landsat Reflectance values were retrieved. Paired *in situ* measurements (Log-transformed) and satellite band readings were considered appropriate (Sriwongsitanon et al., 2011; Bonansea et al., 2015) to develop the regression models for SDD and Chl-*a* estimation. For the first set of data, a table containing the totality (83 pairs) of *in situ* log-data and reflectance values (for all the spectral bands) was constructed. Moreover, several vegetation indices (Table 2) were calculated and added to the table. Water indices usefulness has been demonstrated in different studies for drought monitoring and early warming assessment (i.e. Ceccato et al., 2002; Haq et al., 2012; Memon et al., 2015). However, the vegetation indices and reflectance values (individuals bands and band ratios) application is highly encouraged for the estimation of water quality parameters (i.e. chlorophyll-*a*, transparency) in lakes (i.e. Kahru et al., 1993; Duan et al., 2010; Bonansea et al., 2015; Doña et al., 2015). For the second set of data, a table containing the values of surface reflectance of the bands 3 and 4 was constructed. NDVI was calculated from those values. Finally, the model equations (Eqs. (1) and (2), see Results section) were applied. As a result, SDD and Chl-*a* content were estimated for the 1986–2013 period.

Table 2
Calculated indexes between *in situ* log-data (83 pairs) and reflectance values: ρ_{NIR} Reflectance Near Infrared ρ_{Red} Reflectance Red; $C_1$and C_2 Coefficient to correct aerosol scattering in the Red band by the use of the Blue band; L soil adjustment factor; λ_1 and λ_2 center wavelengths of the red and infrared bands, respectively.

Index	Equation	Author
Normalized Difference Vegetation Index (NDVI)	$NDVI = (\rho_{NIR}-\rho_{Red})/(\rho_{NIR} + \rho_{Red})$	Rouse et al. (1974)
Enhanced Vegetation Index (EVI)	$EVI = G^{*}((\rho_{NIR}-\rho_{Red})/(\rho_{NIR} + (C_1^{*}\ \rho_{Red}-C_2^{*}\ \rho_{blue}) + L))$	Liu and Huete (1995)
Normalized Area Vegetation Index (NAVI)	$NAVI = (1-\rho\lambda_1/\rho\lambda_2)$	Carmona et al. (2015)
Ratio Vegetation Index (RVI)	RVI = NIR/red	Huete and Jackson, 1987

Infostat software (http://www.infostat.com.ar/) was used for statistical analysis. Each linear regression equation was based on two sets of data: calibration and validation data sets. Both included field data for 3 sampling sites in Laguna Chascomús. The calibration set involved 56 pairs of values and the validation set, 27, for each parameter (Chl-*a* and SDD). They were randomly selected.

In situ lake depth measurements and the Oceanic Niño Index (ONI) (http://www.cpc.ncep.noaa.gov) were used for the analysis of the physical temporal variations in Laguna Chascomús. Finally, for the purpose of verifying the developed regression models, standard regression assumptions were verified, both graphically and statistically. The prediction quality of the algorithms was validated by simple regression analysis using Landsat images randomly selected. These images were used only during the model validation process. The spatio-temporal distributions of Chl-*a* and SDD were mapped for representative dates of the retrospective analysis based on the linear regression equations generated in this research. Mapping of Chl-*a* concentrations and SDD was performed in ENVI 4.7 and ArcGIS 10.1.

3. Results

3.1. Model development

Regression models were obtained using 83 pairs (field and satellite) of data. For the Chl-*a* model 4 equations were evaluated, with the following independent variables: the NDVI, NAVI, EVI and RVI index. On the other hand, for the SDD model, the independent variable were the reflectance corresponding to Bands 2 and 4 of Landsat satellite images. Equation coefficients (and their associated errors) and r^2 are shown in Table 3, for each model. After

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Table 3
Equations and coefficients calculated for the Chl-*a* and SDD estimations in Laguna Chascomús.

Dependent variable	Independent variable	slope	constant	r2
ln(Chl-a)				
	NDVI	6.3167 ± 0.4884	5.0224 ± 0.0607	0.75
	NAVI	3.2712 ± 0.2718	5.1029 ± 0.0618	0.72
	EVI	22.5577 ± 1.7284	4.9363 ± 0.0631	0.75
	RVI	2.8729 ± 0.2116	2.0754 ± 0.2457	0.77
ln(SDD)				
	B2	−24.7211 ± 2.7637	3.8148 ± 0.1628	0.59
	B4	−15.204 ± 1.6394	3.3334 ± 0.1069	0.61

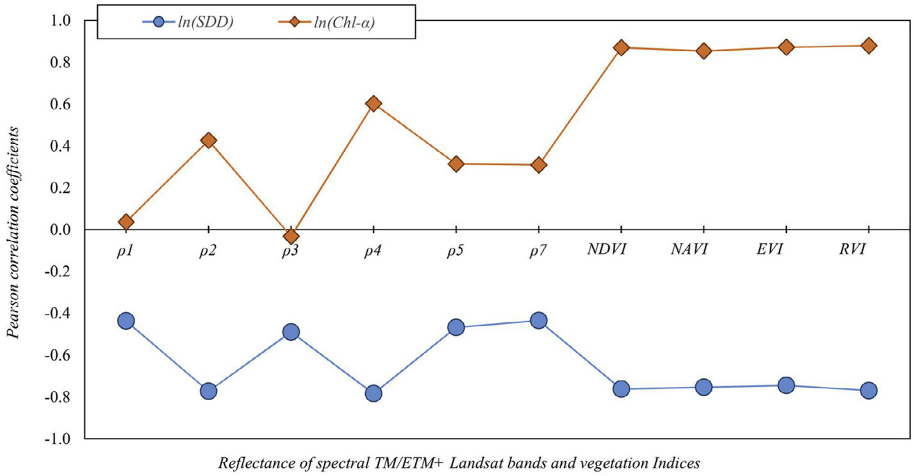

Fig. 2. Pearson correlation by bands and index analysis, p-value < 0.0001.

the correlation by bands and index analysis (Fig. 2), the following equations (see also Table 3) were selected as the best alternatives for the Chl-*a* and SDD estimations, respectively

$$ln(Chl-a) = 6.317\mathrm{NDVI} + 5.022 \quad (1)$$

$$ln(\mathrm{SDD}) = -15.204\rho_4 + 3.333 \quad (2)$$

where ln Chl-*a* = natural logarithm of chlorophyll-*a* concentration (ug/L); NDVI = Normalized Difference Vegetation Index based on Landsat satellite data; ln SDD = Secchi Disk Depth (cm) natural logarithm and b4 = Surface Reflectance value extracted from the band 4 of Landsat satellite data. The formulated equations are ln (y) = a1 * x + b1, where X is the considered band or index and Y is the variable to estimate.

Regarding the relation between both variables, there was observed a negative correlation: when the SDD was higher, the chlorophyll-*a* concentration was lower. This phenomena allowed us to infer that the chlorophyll-*a* is a major cause of turbidity in the studied shallow lake (Fig. 3).

3.2. Validation

The model was tested by comparison between observed vs. estimated Chl-*a* concentrations (μg/l) and observed vs. estimated SDD values (cm) (Fig. 4). Chl-*a* and SDD were estimated using satellite values retrieved from images that were not used in the calibration instance. Chl-*a* and SDD estimates were obtained by using the best models obtained during the development process (Eqs. (1) and (2)).

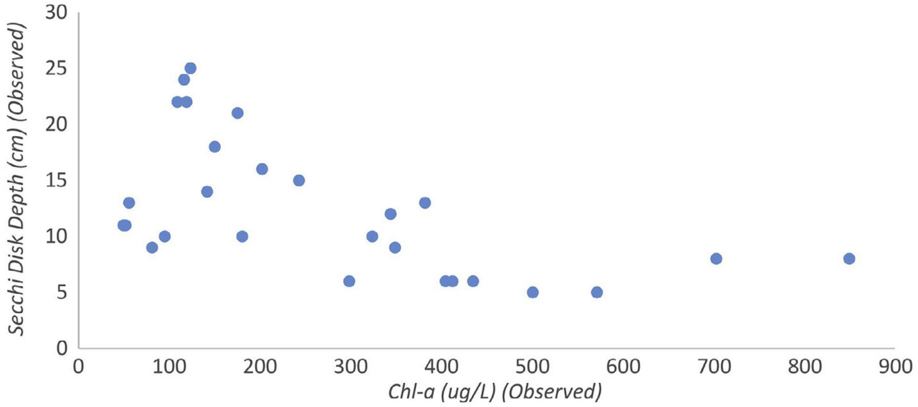

Fig. 3. Correlation between Chl-*a* and SDD (observed).

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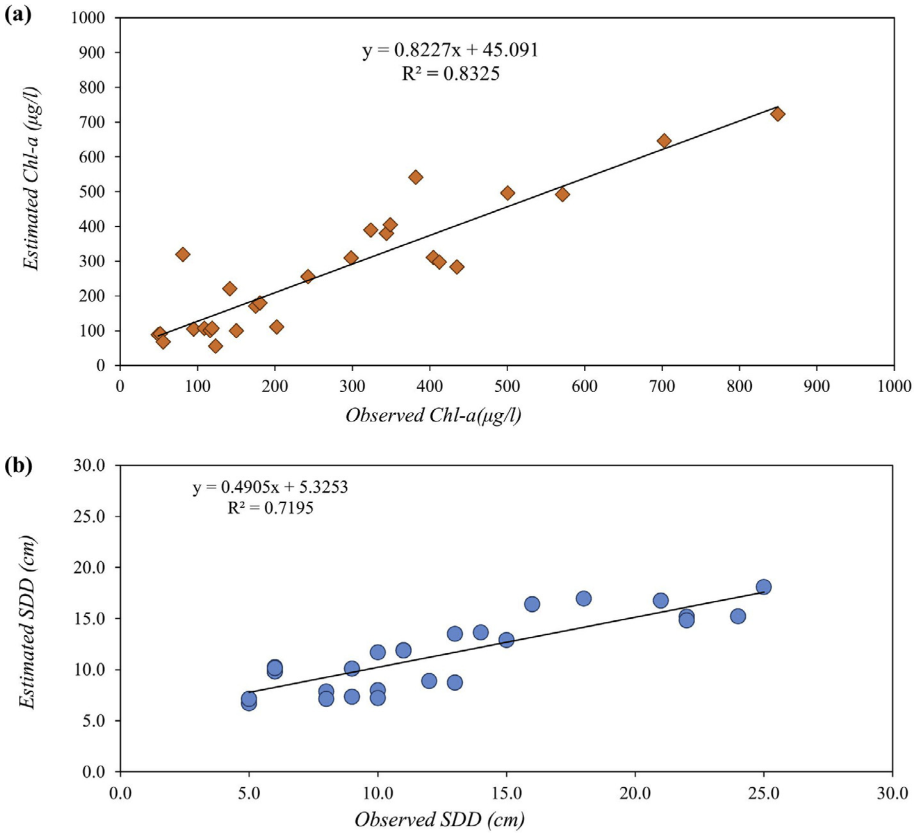

Fig. 4. Estimated values of Chl-*a* and SDD vs. Observed values of Chl-*a* and SDD for the selected models: a) NDVI (Chl-*a*); b) B4 (SDD).

Based on the developed model, regarding the comparison between observed vs. estimated Chl-*a* concentrations (ug/L) for *in situ* data of Laguna Chascomús (November 2001 – September 2011 period), the results were: a) NDVI, $R^2 = 0.83$; b) NAVI, $R^2 = 0.79$; c) EVI and d) RVI, $R^2 = 0.84$. As a result, the option a) (NDVI equation) was selected as the best option. For this case, the root-mean-square error (RMSE) was 83 (μg/l). For the SDD, the best case was represented by the Band 4 equation which showed a RMSE and R^2 of 3.70 cm and 0.72, respectively. For the Band 2 equation, the R^2 was not acceptable ($R^2 = 0.51$).

As a result, the derived model for mapping Chl-*a* concentration was considered acceptable since it has adjusted R^2 values of 0.75 and 0.83 for the calibration and validation processes, respectively. Regarding to the estimation of SDD, the model was also acceptable since it has adjusted R^2 values of 0.61 (calibration process) (Fig. 2) and 0.72 (validation process) (Fig. 4).

3.3. Application of the regression model: a retrospective analysis

A retrospective analysis of the SDD and Chl-*a* was obtained from the application of the model developed in this study for the period January 1986–December 2013. As a result, a tendency of Chl-*a* and SDD was estimated for Laguna Chascomús during 27 years. In most dates, the estimates were homogeneous across SS (Fig. 5). According to the above mentioned tendency, a relation between Chl-*a* concentrations, SDD and depth/ONI index, was observed. For 2001–2012 years (the period in which the depth values were available), when the depth (Figs. 5 and 6) and ONI index were highest, the lower Chl-*a* concentration and the higher SDD values were shown. During the period in which the depth values were unknown (1986–2000), ONI index (Fig. 6) was as approximation of the lake depth. The following examples illustrate the usefulness of this approach. Laguna Chascomús showed a depth > 2 m and ONI index close to 0 during the 2001–2003 years in concordance with a Chl-*a* concentration < 200 μg/L and a SDD > 12 cm (Figs. 5 and 6). In contrast, during the 2009–2010 period, the lake showed a mean depth of 1.50 m, a Chl-*a* concentration > 400 μg/L and a SDD < 12 cm. The ONI index in this time frame was negative (Figs. 5 and 6). As an example of the cited relation during periods in which the depth values were not available, we could mention the 1987–88 and 1990 years. During those periods Chl-*a* concentrations were lower than 200 μg/L, SDD values were higher than 8 cm (peaks of 16 cm were detected) and ONI index was positive, suggesting that the lake remained relatively deep. In contrast, for the years 1998–2000 we could infer a shallowest condition taking into account the negative ONI values, Chl-*a* concentrations > 200 μg/L and SDD values ~ 12 cm (Figs. 5 and 6).

3.3.1. Chl-a concentration and SDD mapping

As an application of the satellite data, the validated algorithms were used in order to obtain a multi-temporal map series. These maps showed the space–time distribution of Chl-*a* and SDD in Laguna Chascomús for representative dates.

The spatio-temporal Chl-*a* distribution was estimated by the regression model developed previously, which was subsequently applied on 2 LANDSAT satellite images (none of which have been used for model development). The 2 satellite images were chosen to represent extreme and representative cases: March 1988 (Chl-*a* < 43 μg/l; SDD > 17 cm) (Fig. 7) and March 2007 (Chl-*a* ~ 700 μg/l; SDD ~ 8 cm) (Fig. 8).

As a result, the spatial distribution of calculated chl-*a* was homogeneous in the lake during the less turbid condition (Fig. 7) whereas during the most turbid condition the lake showed differences between the NW and SE zones (Fig. 8). In addition,

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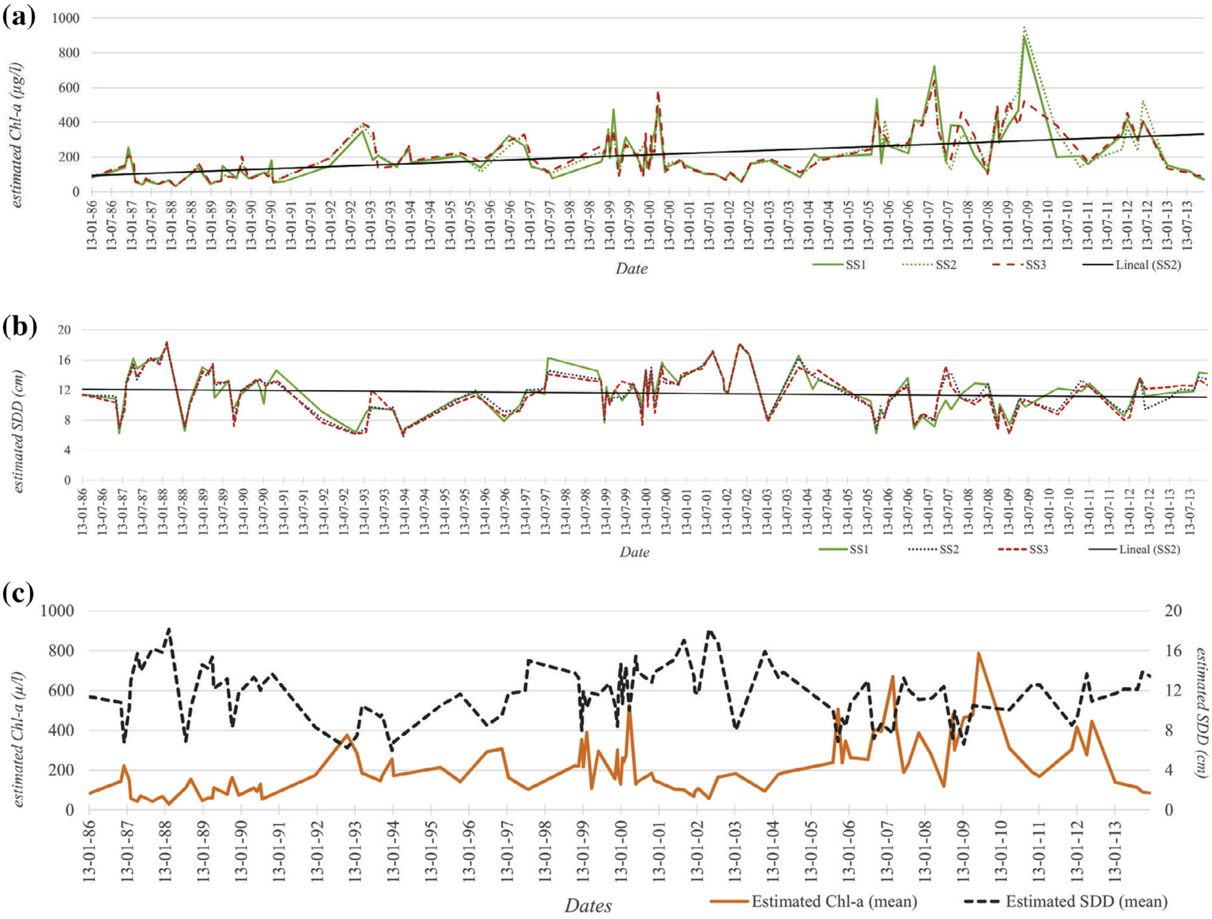

Fig. 5. Retrospective analysis of Chl-*a*: (a) SDD; (b) regression model application and (c) Mean values (between SS) of estimated SDD and Chl-*a* concentration. SS: sampling site, Date: dd-mm-yy.

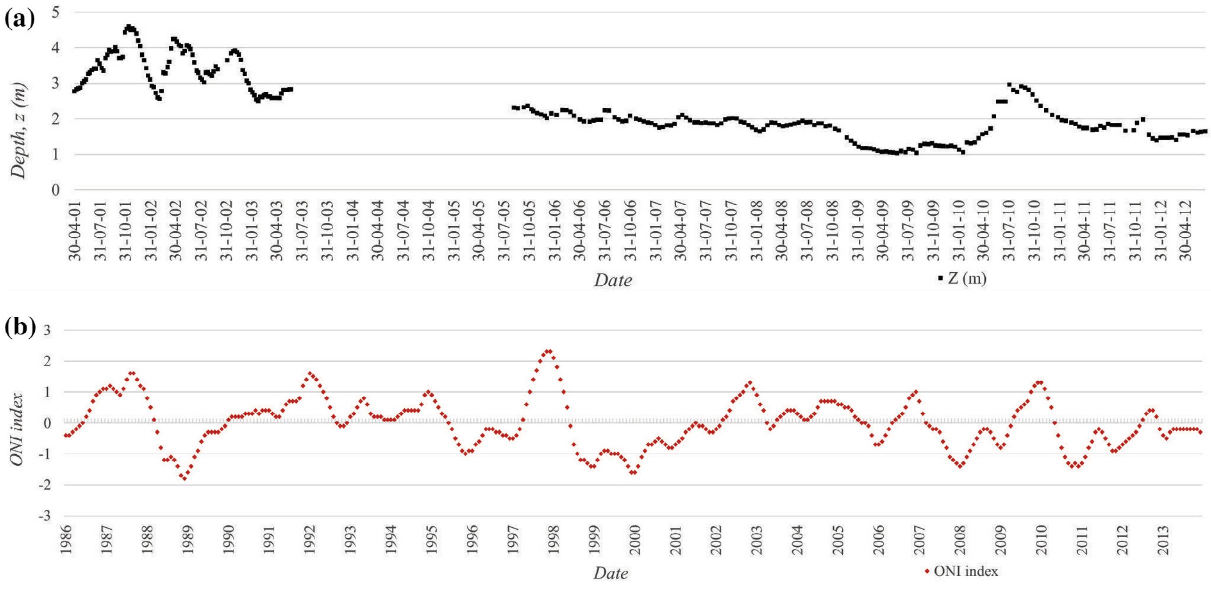

Fig. 6. Chascomús shallow lake: a) Lake mean depth for April 2001–April 2012 period; b) ONI Index evolution in the shallow lake region (January 1986–December 2013 period).

differences in values over time were detected. Remote sensing efficiency was also demonstrated for the estimation of transparency (SDD) of water in Laguna Chascomús. In all analyzed cases, transparency differed between NW and SE basins. In both cases, the same relation between the Chl-*a* concentration and SDD was observed: the higher concentration of Chl-*a*, the lower

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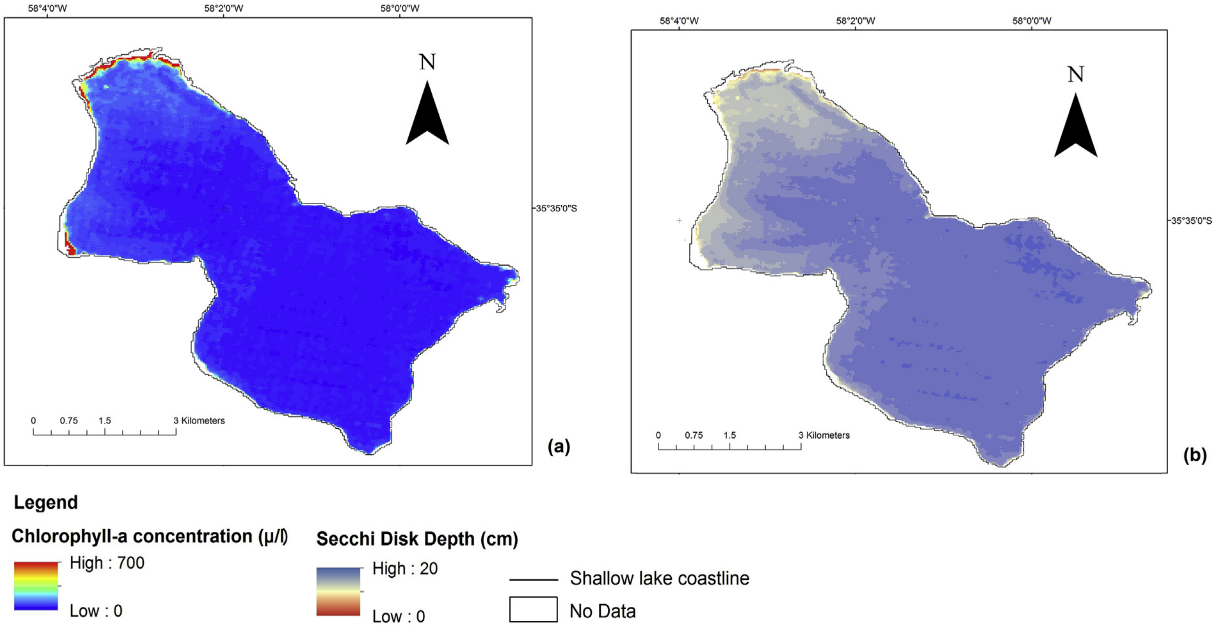

Fig. 7. Estimated Chl-*a* (a) and SDD (b) spatial distribution during a "lowest turbidity" condition in Laguna Chascomús.

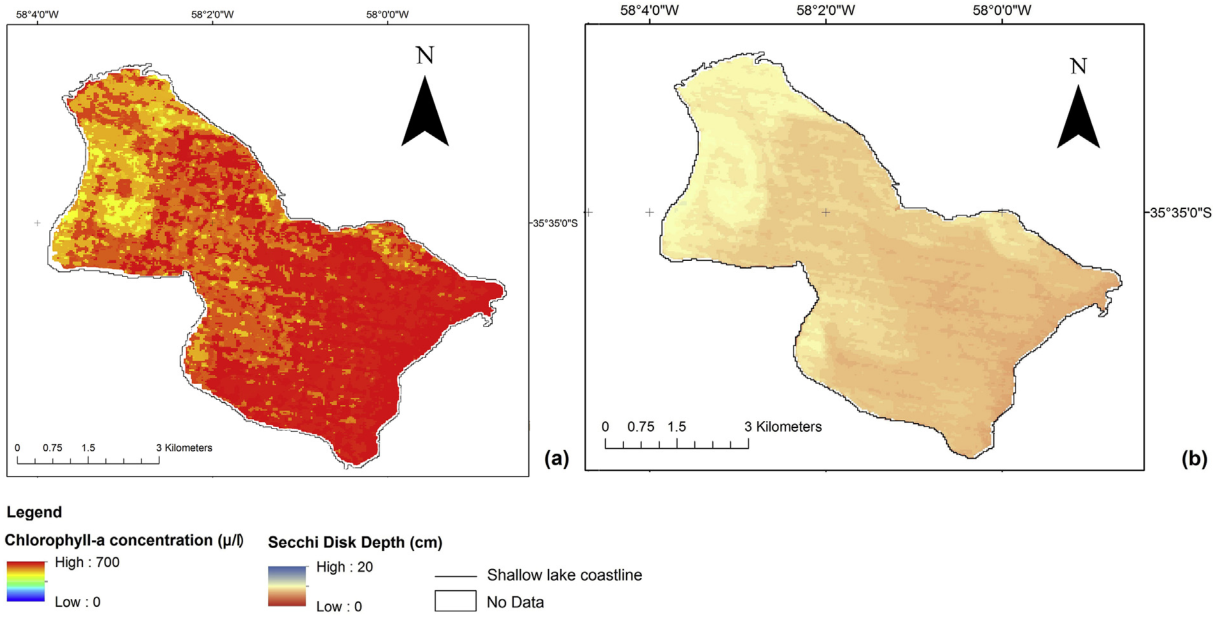

Fig. 8. Estimated Chl-*a* (a) and SDD (b) spatial distribution during a "highest turbidity" condition in Chascomús shallow lake.

transparency and vice versa. This may point to the strong influence of Chl-*a* (organic portion) on the turbidity of this shallow lake. During the two selected dates the area of the shallow lake was of 30 km^2 approximately.

4. Discussion

This research is one of the first studies that evaluate and compare data from satellite and *in situ* measurements of water quality parameters in Pampean shallow lakes (Argentina).

The results revealed that satellite-based monitoring data generally agrees well with *in situ* monitoring data, and that the operational satellite monitoring system is a rather reliable methodology. Although satellite data cannot be a replacement for field data, the quality of the information is much improved when satellite data is added to *in situ* generated data (Lindell et al., 1999). This work has demonstrated that remote sensing for water quality using traditional band ratio methods is especially relevant in shallow and highly dynamic water bodies and that its application is adequate for Chascomús shallow lake.

Importantly, the depth of a shallow lake can be subject to strong fluctuations resulting from climate variability. Numerous observations highlight the importance of the water level for shifts between a vegetation dominated state and a turbid state in shallow lakes. Also a very low water level may have more complicated pronounced effects. For instance, desiccation of the lake bottom may in some cases damage the vegetation sufficiently to push a lake to a turbid state (Scheffer and van Nes, 2007). Maximum and minimum depth showed their influence in the chlorophyll-*a* concentration and SDD in Chascomús shallow lake (Argentina). This phenomenon has been previously detected during floods alternance by traditional sampling (Torremorell et al., 2007).

Remote sensing introduction in the study of the dynamic of biological and physical parameters in Laguna Chascomús is encouraging. This method allowed studying the spatial distribution of the analyzed parameters as a complement to site-based traditional studies. This spatial analysis provides possible research lines about the hydrodynamics of the shallow lake for the future. The high correlation achieved between *in situ* values and satellite information in both images confirms that SDD and Chl-*a* can be readily mapped using Landsat satellite data. The results presented here, taking into account the low level of error, are comparable to other studies (Bonansea et al., 2015; Doña et al., 2015).

The empirical spectral band ratio method is the most commonly used method for retrieving water quality using remote sensing and it has been shown to be effective in the retrieval of many water quality parameters. It has been found that the ratio of two bands reduces the effects of factors such as measurement geometry and atmosphere on the retrieval of water quality (Koponen, 2006). A semi-log regression has also been used in most other inland water quality band ratios.

In this paper, we show the potential for estimating chlorophyll-*a* content for past situations. Even though there are several water indices (i.e. the Normalized Water Index (NDWI), Gao, 1996) in this research only vegetation indices were evaluated for the chlorophyll-*a* concentrations estimation. Several authors have demonstrated that the water indices are an appropriate alternative for delineating water bodies and developing wetland inventories (El-Asmar et al., 2013; Rawat and Manish, 2015; Ahmed et al., 2016). However, vegetation indices appeared as a best alternative to model chlorophyll-*a* and transparency, principally when the transparency is highly affected by phytoplankton (Kahru et al., 1993; Novo et al., 2013). In this research, like other authors (Doña et al., 2015; Bonansea et al., 2015), we could showed the high correlation between the predicted values and the observed values of SDD and chl-*a* concentration. Vegetation indices and Landsat band ratio (notably B1, 2 and 4) were mostly used for estimation of chlorophyll-*a* in lakes and reservoirs (Brezonik et al., 2005; Olmanson et al., 2008; Fadel et al., 2016).

In this research, the NDVI was used in relation to Chl-*a* estimation for its optical characteristics and because it is sensitive to the pigment absorption. It was an appropriate descriptor for the Chl-*a* content estimation in Laguna Chascomús. NDVI is very sensitive to changes in the environment (Kahru et al., 1993). Moreover, the application of this index is more successful in zones with moderate wind speeds without developing or waves shortage, such as Laguna Chascomús (Table 1).

Chl-*a* is a variable of great ecological importance but probably one of the most difficult to map accurately (Lindell et al., 1999). The clarity of lake water is reduced by the presence of suspended sediment, organic particulates, free-floating algae, and zooplankton. Algae are often the dominant influence on transparency of lake water (Fuller and Minnerick, 2007). The SDD is probably the most commonly used water variable as indicator of water quality in limnology (Meijer et al., 1999). There have been many efforts to map this variable from satellite imagery. As SDD is highly correlated to different turbidity concepts we can expect rather good results. It is therefore also fairly simple to model SDD from satellite data. Many algorithms in the literature are based on some logarithmic relation of the reciprocal of the SDD. Lindell et al. (1999) have found that the use of spectral TM bands gives an acceptable correlation for its estimation. The presented method provides an inexpensive tool for monitoring SDD and has the potential to fill-in during periods in which field data is not available (Harvey et al., 2015). It gives the possibility to extrapolate the data in a retrospective way in order to analyze past eutrophic conditions of the lake as well as in order to predict the future environment dynamics in the studied shallow lake.

Our model limitation is in their application for the Chl-*a* and SDD mapping. There were detected mixed values in the coastline. The effect of reflection from the lake bed near the margins was seen as elevated erroneous chl-*a* and SDD predictions as well as in previous studies (Allan et al., 2007). Therefore, our model was more appropriate for open waters.

Regarding the correlation between observed and estimated values our results were comparable with those found by Doña et al. (2015). In the case of the Chl-*a* variable, our result showed a $R^2 \sim 0.83$ whereas the R^2 for the SDD was of 0.72. As well as several authors (i.e.: Fuller and Minnerick, 2007; Moses, 2009; Dalu et al., 2015; Fadel et al., 2016) we recommend the application of Landsat as a satisfactory and cost effective method for monitoring chlorophyll-*a* and SDD in shallow lakes.

5. Conclusions

Remote sensing, in combination with *in situ* data, provides information about water quality. In our study there was demonstrated that the combination between *in situ* and satellite data allowed an estimation of water quality parameters in Pampean shallow waters. In the present study, correlation between *in situ* data with reflectance values of Band 4 (SDD) and the NDVI (Chl-*a*) was appropriate.

The generated maps provided information about the spatio and temporal patterns of Chl-*a* and SDD. They emphasize the importance of extreme event occurrence in the control of algal production and transparency of water in Laguna Chascomús. Satisfactory values were obtained for the estimation of Chl-*a* and SDD, with high correlation between predicted and observed values. Maps showed the temporal variations of SDD and Chl-*a* concentration with an error of 3.7 cm and 83 μg/L, respectively. This method supplied information pixel-by-pixel in opposition, for instance, to a simple interpolation of SS. Moreover, it allowed not only to obtain an estimation for dates for which *in situ* data are unavailable, but also to monitor shallow waters at low cost. The introduction of other parameters related to water quality as well as the extrapolation of this method to other shallow lakes in a regional scale, could be useful in order to extend this study.

6. Conflict of interest

None.

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