

Estimation of chlorophyll «A» on the Mediterranean coast using a QuickBird image

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Abstract

Remote sensing has proved a useful tool for monitoring and assessing water quality. However, little research has been conducted using satellite images with high spatial resolution to analyze coastal areas with high variability near shore. The objective of this research was to develop a model for estimating chlorophyll-a concentration on the Gandia coast (Western Mediterranean) by means of a high resolution QuickBird image. Several linear regressions were calculated to find the best chlorophyll-a model. The optimal model was found when blue and red bands were used. The retrieval accuracy (R^2) was 0.92, while the root mean square (RMSE) was 0.34 mg/m³. The selected model was validated with an independent data set and the estimation of chlorophyll-a was reasonably accurate ($R^2 = 0.90$). The results obtained in this study suggest that using a QuickBird sensor is an effective technique for monitoring the ecological status of coastal areas with an inherent high variability.

Key words: remote sensing, monitoring, chlorophyll, coastal waters.

Resumen

Estimación de la clorofila-a en la costa mediterránea mediante una imagen de satélite QuickBird

La teledetección ha demostrado ser una herramienta útil para el monitoreo y la evaluación de la calidad del agua. Sin embargo, pocas investigaciones se han llevado a cabo utilizando imágenes de satélite con alta resolución espacial para analizar las zonas costeras con alta variabilidad cerca de la costa. El objetivo de esta investigación fue desarrollar un modelo para estimar la concentración de clorofila-a en la costa de Gandia (Mediterráneo occidental) por medio de una imagen de alta resolución QuickBird. Varias regresiones lineales se calcularon para encontrar el mejor modelo de clorofila-a. El modelo óptimo se obtuvo cuando se utilizaron las bandas 1 (azul) y 3 (rojo) con un valor del coeficiente de determinación (R^2) de 0,92, mientras que el error medio cuadrático (RMSE) fue de 0,34 mg/m³. Se validó el modelo seleccionado mediante un conjunto de datos independientes obteniendo un valor de R^2 de 0,90. Los resultados obtenidos en este estudio sugieren que el uso del sensor Quick-Bird puede ser una técnica eficaz para el seguimiento del estado ecológico de las zonas costeras con una alta variabilidad inherente.

Palabras clave: teledetección, monitoreo, clorofila, aguas costeras, QuickBird.

Introducción

Coastal watersheds support more than 75% of the human population and are sites of large increases in nutrient loading associated with

urban and agricultural expansion. Increased nutrient loading has led to eutrophication problems which symptoms include increased algal bloom activity (including harmful taxa), accumulation of organic matter, and excessive

oxygen consumption (hypoxia and anoxia) (Paerl, 2006). In order to assess the eutrophication risk, chlorophyll-*a* (Chl-*a*) concentration, which is a proxy of phytoplankton biomass, has been used in monitoring programs such as the established by the European Water Framework Directive (WFD) (2000/60/EC). However, monitoring data characterizing the biological elements is imprecise due to spatial variations, temporal variations and sampling and analytical errors. Carstensen (2007) pointed out the need of sufficient monitoring data and the improvement of indicator bias and precision through modeling and further development of measurement techniques. In this sense, satellite monitoring is an alternative and efficient technology for water quality monitoring that can aid the application of these monitoring programs considerably (Chen *et al.*, 2004). Satellite sensor and airborne images have been extensively used to assess water quality parameters such as temperature, chlorophyll-*a*, turbidity and coloured dissolved organic matter (Oyama *et al.*, 2009; Zhang *et al.*, 2009; Santini *et al.*, 2010). While conventional water quality sampling is time-consuming, expensive and limited with the numbers of stations, remote sensing provides a synoptic view not otherwise attainable at a relatively low cost (Liu *et al.*, 2003; Chen *et al.*, 2010). These advantages are especially important in environments with a high degree of variability in physico-chemical characteristics (*i.e.*, salinity, temperature and oxygen) and nutrient inputs that is reflected in the ecological assemblage (Elliot and Quintino, 2007; Maier *et al.*, 2009). Among these environments, coastal and transitional waters represent one of the most relevant examples. In this sense, remote sensing has been tested for monitoring ecological water quality in Spanish inland waters (reservoirs and lakes) and transitional waters (coastal lagoons) integrated in the Intercalibration Exercise of the WFD and proved to be a useful technique (Domínguez *et al.*, 2010, 2011).

In remote sensing oceanic waters are classified into one of two types: Case 1 or Case 2 (Morel and Prieur, 1977). By definition, Case 1 waters are those waters in which phytoplankton (with their accompanying and covarying retinue of material of biological origin) are the

principal agents responsible for variations in optical properties of the water. On the other hand, Case 2 waters are influenced not just by phytoplankton and related particles, but also by other substances, that vary independently of phytoplankton, notably inorganic particles in suspension and dissolved organic matter (IOCCG, 2000). Case 1 waters have been widely studied using ocean colour sensors with low spatial resolution image (around 1km), such as SeaWiFS and MERIS (Djavidnia *et al.*, 2010; Maritorea *et al.*, 2010). This scale is appropriate for oceans but insufficient for monitoring case 2 waters, which are mostly coastal waters and lakes. In this case, terrestrial observation satellites with moderate spatial resolutions such as LANDSAT, Terra ASTER (spatial resolution lower than 30 m) and MERIS (Liu *et al.*, 2003; Domínguez *et al.*, 2010, 2011; Focardi *et al.*, 2009; Oyama *et al.*, 2009; Song *et al.*, 2011) and high spatial resolution such as IKONOS (Ekercin, 2007; Ormeci *et al.*, 2009) and QuickBird (Wheeler *et al.*, 2012) have been used. Gohin *et al.* (2008) tested the capacity of using satellite data for assessing the eutrophication risk of coastal bodies according to the WFD with SeaWiFS and they found that the quality of the Chl-*a* satellite estimation decreased with the distance to the coast. The strong Chl-*a* gradient near shore was indicated as one of the possible causes of this loss of sensitivity and the use of a moderate resolution satellite was recommended. However, coastal water bodies may be very narrow to be studied from these satellites, according to the WFD definition (Gohin *et al.*, 2008). To overcome this disadvantage further research based on satellite images of high spatial resolution is necessary for detecting and portraying complex spatial distributions of chlorophyll-*a*, such as changes of Chl-*a* near shore in small areas. These changes are mainly due to nutrient inputs from point (streams, submarine outfall) and diffuse (urban and agricultural runoff) sources. Quickbird sensor has been successfully used for benthic habitat mapping (Mishra *et al.*, 2006) and for littoral remote bathymetry (Adler-Golden *et al.*, 2005). However, research with Quickbird image for estimating water chlorophyll-*a* concentration has been conducted mainly in inland waters (Wheeler *et al.*, 2012).

The Gandia coast is an ecologically and economically important coastal area and is a representative aquatic region of Spain's Mediterranean coast. However, no previous research has been developed in this area with satellite images. In this study high spatial resolution images are tested to map the coastal gradient of chlorophyll-*a*.

The objectives of this research were as follows: (1) to develop and validate a linear regression model to estimate chlorophyll-*a* concentration with a QuickBird image; (2) to analyze the spatial variation of chlorophyll-*a* concentration at high scale; and (3) to explore the feasibility of using remote sensing techniques to monitor small and narrow areas with high variability

Materials and methods

Study area

The study area (Fig. 1) is located in the southernmost sector of the Valencian Gulf (Mediterranean Sea) and it is defined by a 10 × 4.5

km rectangle which delimits the Gandia city coastline. The flat bottom morphology of this area (see isobaths in Fig. 2) is characterized by well graded sands and the absence of benthic vegetation such as seagrasses or macroalgae. Gandia is a populous coastal city with 1314 inhabitants/km², whose population triples in summer owing to beach tourism. 53% of the Gandia coast is considered as an urban area, including a small commercial, fishing and recreational harbour.

The study area receives freshwater inputs from point and diffuse sources that are rich in nutrients. At the northern end is the Vaca river mouth, which is a small river, 16.6 km in length, with a low slope. During the sampling period its flow was non existent. At the southern end the Serpis river flows into the Mediterranean. This river drains a basin of 752.8 km² and is 74.5 km in length. These rivers have a Mediterranean regimen characterized by a high seasonality, with a dry period during summer, and a wet period with episodes of torrential rain, mainly in autumn (Garófano *et al.*, 2009). Another point source is the subma-

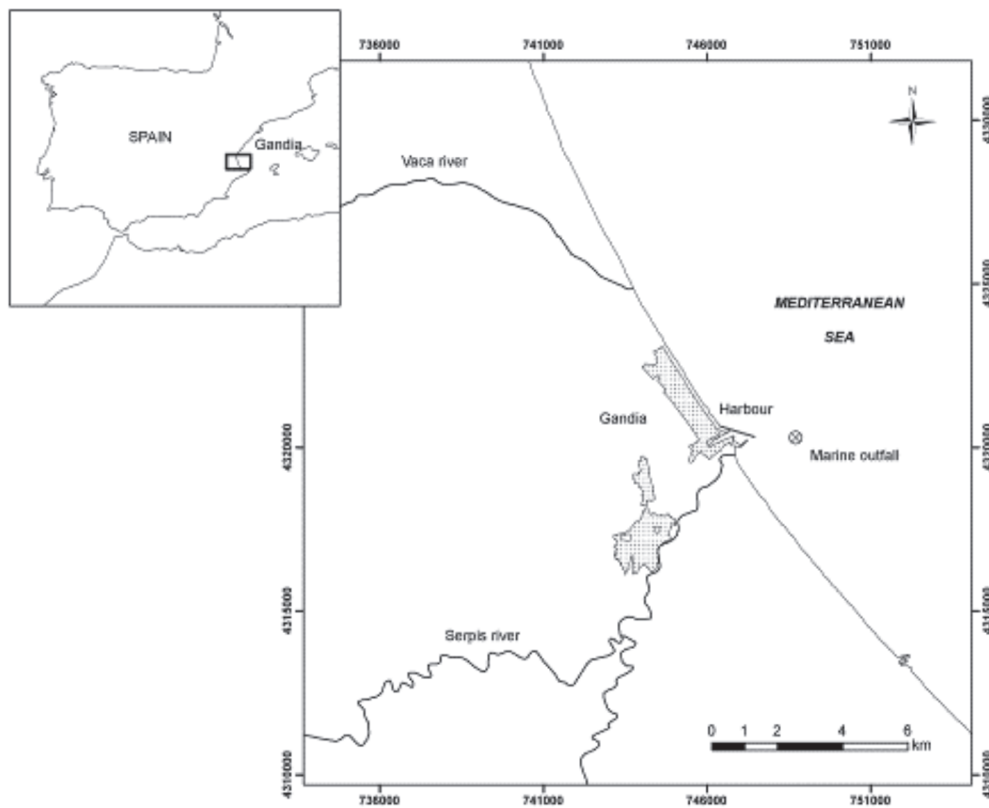


Figure 1. Location of the study area.

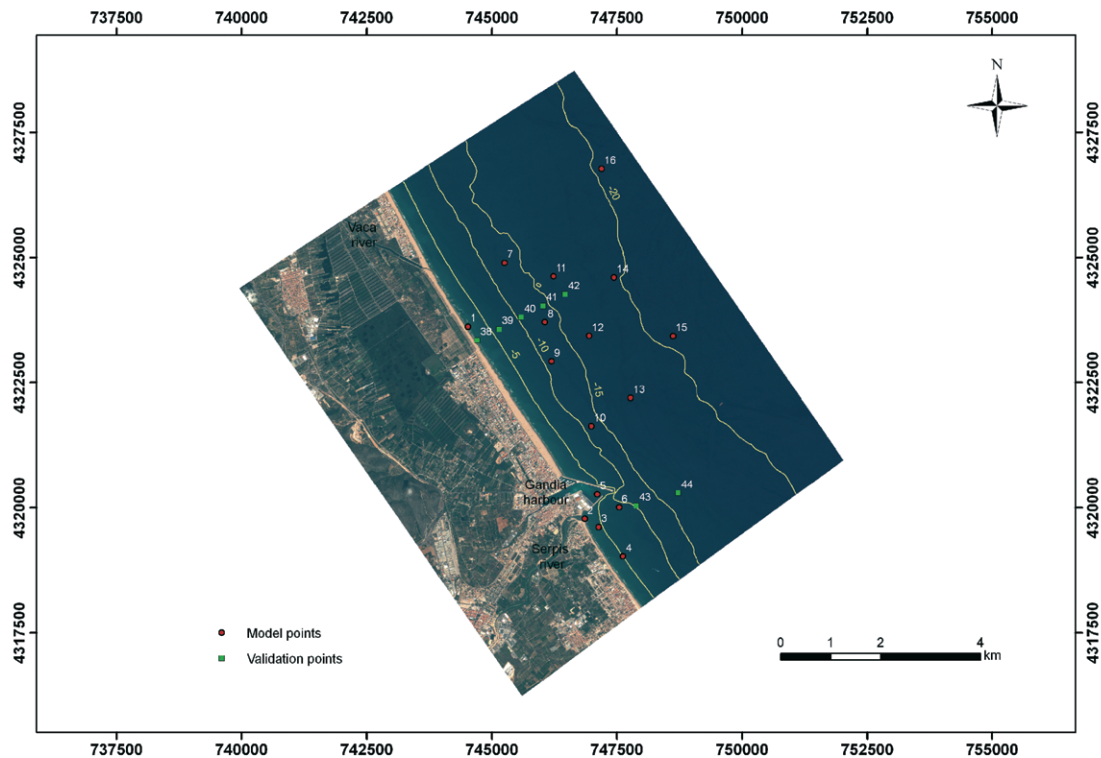


Figure 2. Location of the sampling points for model development and validation.

rine outfall (1,900 m in length), which discharges municipal wastewater from the treatment plant of Gandia. The alluvial plain next to the study area is 3 km wide and was totally occupied by the Safor wetland and crops until the seventies. Nowadays, this area shares its agricultural activity, mainly citrus fruits and vegetables, with the tourism of the urban areas. Due to the shallow phreatic level, freshwater is continuously pumped from the wetland to the Gandia Harbour to avoid crop and urban area flooding. Diffuse sources in the study area come from the groundwater discharge of the Plana Gandia-Denia detritic aquifer, quantified at 66 Hm³/year (2.1 m³/s) (Ballesteros-Navarro, 2003), although our sampling period was in the dry season, so discharge would have been lower than average.

Field sampling and laboratory analysis

Field work was timed to coincide with the acquisition of the QuickBird image on July 16, 2009, at 10:56 GMT. Weather conditions du-

ring the image acquisition included cloudless skies over the study area and low wind speed, less than 2 km/h. The water samples were collected for each site at 0.5 m beneath the water surface within 1.5 h of the satellite overpass. For model development 16 samples were collected (in Fig. 2 points numbered from 1 to 16). An independent data set was collected at 7 sampling points (in Fig. 2 points numbered from 38 to 44), and was used to validate the performance of the selected algorithm. For mapping nutrient water surface distribution, 21 extra samples were collected (points location not shown in Fig. 2, samples numbered from 17 to 37). The coordinates of the sampling points were determined using a global positioning system (GPS) model Garmin 60C with an accuracy of 3-5 m. Subsequently chlorophyll-*a* (Chl-*a*) was measured in samples used for model development and validation. Salinity, suspended solids and nutrients (nitrates, phosphates and silicates) were measured in all the samples. Chl-*a* concentration was selected for remote sensing analysis, while other parameters were used as secondary analysis.

Samples for chlorophyll a were filtered on GF/F fiberglass filters (25 mm diameter). The Chl-a was extracted using acetone (100%) and was measured using reverse-phase high-performance liquid chromatography (HPLC). The HPLC method employed was that proposed by Wright *et al.* (1991) slightly modified as per Hooker *et al.* (2000). Nutrients were analyzed colorimetrically using the method of Aminot and Chaussepied (1983). Salinity was determined by means of an induction conductivity meter Multi 340i/SET WTW.

Satellite image and model development

The remotely sensed data used for this study was a high resolution QuickBird multispectral image ordered from Digital Globe Corporation. This sensor has four multispectral bands with a 2.4 m spatial resolution. The wavelength of the respective bands is 0.45-0.52 μm (B1: blue); 0.52-0.60 μm (B2: green); 0.63-0.69 μm (B3: red); 0.76-0.90 μm (B4: near infrared). Prior to delivery, the imagery was radiometrically and geometrically corrected and rectified to the World Geodetic System 1984 (WGS84) datum and the Universal Transverse Mercator (UTM) zone 30 co-ordinate system. To improve the positional accuracy, 39 control points were selected using a rectified airborne image with a pixel size of 0.5 m. The root mean square error (RMSE) was 0.49 m. The digital numbers (DN) recorded at the sensor were converted to satellite radiance using the technical note from Digital Globe (Krause, 2003). Then, the module QUAC of ENVI 4.7 (ITT Visual Information Solutions) was applied to the radiance images to eliminate the atmospheric effects (Bernstein *et al.*, 2005). In addition, to remove the influence of depth on bottom reflectance upon chlorophyll-a retrievals, we calculated depth-invariant bottom indexes from each pair of reflectance bands as described in Green *et al.* (2000). This technique is only suitable where water clarity is good, such as in the study area. In this method a group of pixels distributed in shallow and deep areas with the same bottom type are selected. Then, a bi-plot is created from the reflectance values of two bands considering all possible band combinations. Six bi-plots are

created: band1-band2; band1-band3; band1-band4; band2-band3; band2-band4; band3-band4. The slope of each bi-plot represents the ratio of attenuation coefficients, k_i/k_j (equation [1]), between bands (Green *et al.*, 2000).

$$k_i / k_j = a + \sqrt{(a^2 + 1)} \quad [1]$$

where

$$a = \frac{\sigma_{ii} - \sigma_{jj}}{2\sigma_{ij}}$$

σ_{ii} is the variance of the band i , σ_{jj} the variance of the band j , σ_{ij} is the covariance between bands i and j . From k_i/k_j , a depth-invariant index (equation [2]) was calculated, which represents the y- intercept of the equation of a straight line

$$\begin{aligned} \text{Depth - invariant index}_{ij} = & \quad [2] \\ = \ln(\text{reflectance}_i) - (k_i/k_j) \cdot \ln(\text{reflectance}_j) \end{aligned}$$

where, i and j correspond to each band pair considered and (k_i/k_j) to the attenuation coefficient for the same band pair, and reflectance bands after applying an atmospheric correction. To calculate these indexes 180 pixels of each band were selected in shallow and deep areas with sand bottom type. The following ratios of attenuation coefficients for band pairs were calculated: k_1/k_2 , k_1/k_3 , k_1/k_4 , k_2/k_3 , k_2/k_4 , and k_3/k_4 . From these coefficients, six new images from each pair of spectral bands (hereafter referred to as Depth-invariant index) were generated (further information of this method can be found in Green *et al.*, 2000). The average digital number of pixels (a 3 × 3 window) surrounding the sample pixel was used in order to remove errors resulting from GPS measurements in the field work (Oyama *et al.*, 2009; Zhengjun *et al.*, 2008; Nas *et al.*, 2009).

A linear regression analysis was conducted between chlorophyll-a logarithm and depth-invariant indexes. When monitoring water quality, general methods are to find the best band combination. Thus the optimal index was judged by R^2 and RMSE (Root Mean Square Error) based on the comparison of simulated model outputs and actual observations (Zhang *et al.*, 2009). An independent data set, collected at 7 sampling points in the study area, was used to assess the performance of the tuned model.

Results and discussion

Results from field samples measurements (salinity, nutrients and chlorophyll-*a*) are shown in Table 1. In this table Chl-*a* values obtained from QuicBird image are also included.

Different approaches can be used to estimate chlorophyll-*a* from satellite data. The empirical approach, used in this study, is based on the development of a linear regression analysis between satellite image and measured water Chl-*a*. This approach has been widely used by many researchers (Zhengjun *et al.*, 2008; Ormeci *et al.*, 2009) and it has proven to be very effective in Case 1 waters (IOCCG, 2000). Despite coastal waters are mainly classified as Case 2 waters, according to Lee and Hu (2006), in summer, the Mediterranean shows values characteristic of Case 1 waters. The present study was carried out during Case 1 waters conditions, when freshwater discharges were minimal and average suspended solids values were 12 mg/L.

For linear regression analysis, the best model was obtained when B1 and B3 bands were used. When bottom reflectance correction was not performed the R^2 and RMSE values of the model developed were 0.76 and 0.61 mg/m³ respectively. After applying this correction the model estimation improved. The best model de-

veloped with the depth-invariant index13 showed a R^2 of 0.89 and a RMSE of 0.38 mg/m³. This result reveals the importance of applying the bottom reflectance correction. The bottom corrected model was selected for mapping Chl-*a* concentration in the study area and its equation was (see Fig. 3):

$$\log chl - a = -16.33 + 4.00 * k_{13}$$

In order to validate the applicability of the selected model, we used an independent data set of chlorophyll-*a* concentration, which ranged from 0.21 mg/m³ to 1.86 mg/m³. These values fell into the range of Chl-*a* concentration used to calculate the model. Measured and estimated Chl-*a* showed a great degree of concordance close to the 1:1 line (Fig. 4), with a

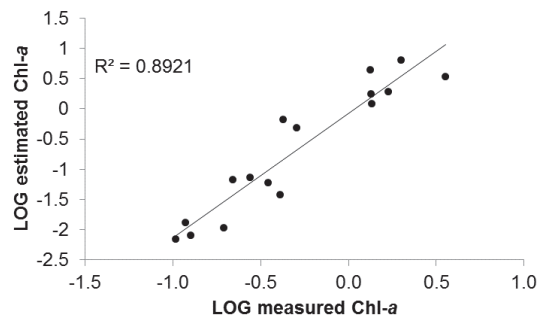


Figure 3. Comparison between logarithm of Chl-*a* satellite estimated and logarithm of *in situ* measured Chl-*a* for model development.

Table 1. Summary of salinity (S), chlorophyll-*a* measured with HPLC and estimated from image, and nutrient measurements (nitrates, phosphates and silicates) in the study area

Sampling point	X UTM	Y UTM	Salinity (%)	Chl- <i>a</i> (mg/m ³)		Nitrates (μM)	Phosphates (μM)	Silicates (μM)
				Measured	Estimated			
1	744520	4323614	36.7	1.33	1.91	8.82	0.13	2.7
2	746858	4319776	33.8	1.69	1.32	27.74	0.18	12.7
3	747136	4319615	30.1	2.00	2.23	29.90	0.08	19.2
4	747622	4319025	36.6	1.35	1.28	8.45	0.05	4.2
5	747107	4320268	33.5	3.58	1.69	33.83	0.04	9.9
6	747542	4320007	37.0	1.36	1.09	8.72	0.08	1.1
7	745254	4324892	37.6	0.22	0.31	0.09	0.07	0.7
8	746058	4323701	37.6	0.28	0.32	0.32	0.04	0.7
9	746194	4322920	37.4	0.42	0.83	1.56	0.07	0.8
10	746991	4321630	37.5	0.51	0.73	0.42	0.02	0.8
11	746230	4324624	37.3	0.41	0.24	3.23	0.07	0.9
12	746950	4323430	37.4	0.35	0.29	5.62	0.06	1.5
13	747772	4322191	37.8	0.20	0.14	0.15	0.07	0.5
14	747442	4324601	37.8	0.12	0.15	3.97	0.06	0.8
15	748620	4323424	37.7	0.10	0.12	1.86	0.05	0.5
16	747193	4326775	37.7	0.13	0.12	1.69	0.02	0.8

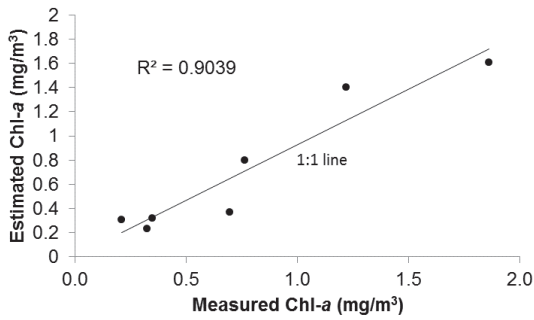


Figure 4. Comparison between satellite estimated and *in situ* measured Chl-*a* concentrations for model validation (1:1 line shown for reference).

highly significant linear relationship ($R^2=0.90$). The correlation obtained both for model development and validation is higher than the 70% correlation considered a good fit (Gregg and Casey, 2003; Santamaría-del-Ángel *et al.*, 2010).

The estimated chlorophyll-*a* concentration map is showed in Figure 5. Chl-*a* values range from 3.58 mg/m³ in sampling point number 5 located in the Gandia Harbour, to values around 0.10 mg/m³ in the sampling points furthest from the coastline (Table 1). It is important to highlight that the largest Chl-*a* variation occurs in the first kilometer from the coastline,

decreasing from values higher than 5 mg/m³ on the coast to values lower than 1 mg/m³. This Chl-*a* variation can be explained by the salinity and nutrient distribution showed in Figure 6, which are linked to the surface and subterranean freshwater discharges described below.

Figure 6 a) shows distribution of surface water salinity. Three zones show a salinity decrease: one in the north of the study area at the mouth of the River Vaca, one in the port, and the third one south of the River Serpis. The Vaca has reduced or non flow all year long, which, together with the low slope, contributes to the formation of a littoral sand spit that prevents river outflow. During July 2009 this sand spit was more than 30 m wide, so the salinity decrease could only be attributed to groundwater flow. Port salinity decrease is due to freshwater inputs from the Safor wetland, with a 0.3 m³/s flow during the sampling period. However, groundwater inputs have also been observed in the port (unpublished data). South of the Serpis river mouth, the salinity decrease was more accentuated. During July 2009 this river flow was below its minimum ecological flow, 0.1 m³/s (Garófano *et al.*, 2009). Dis-

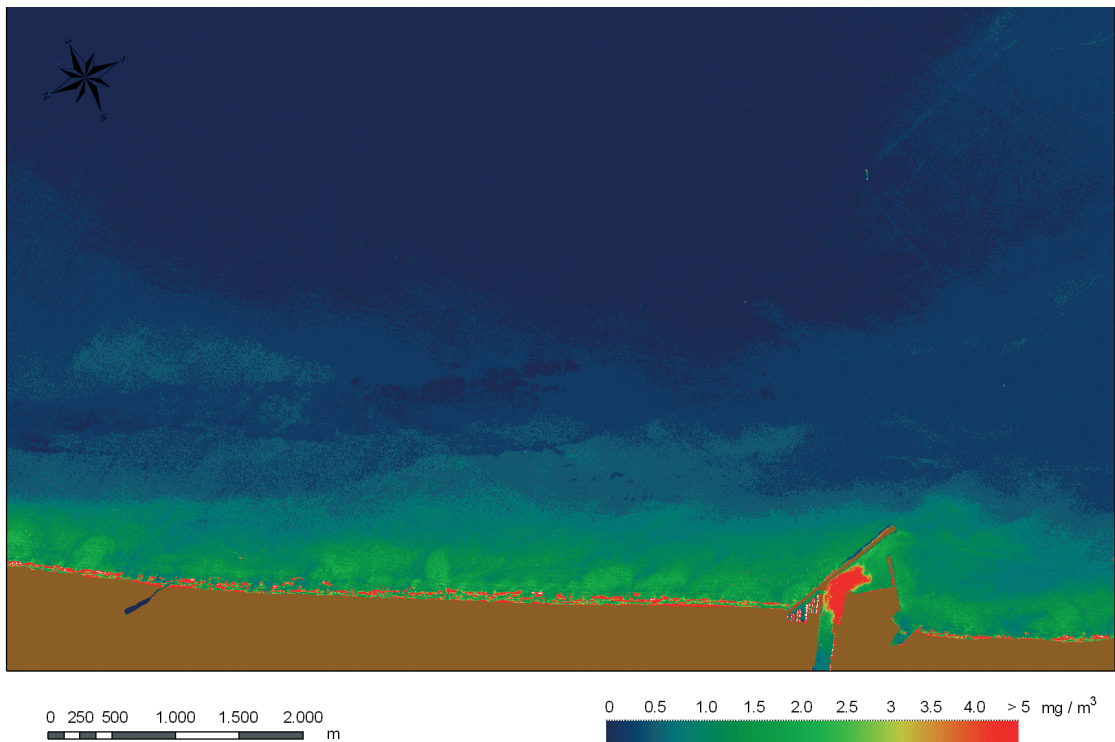


Figure 5. Estimated chlorophyll-*a* (mg/m³) concentration map.

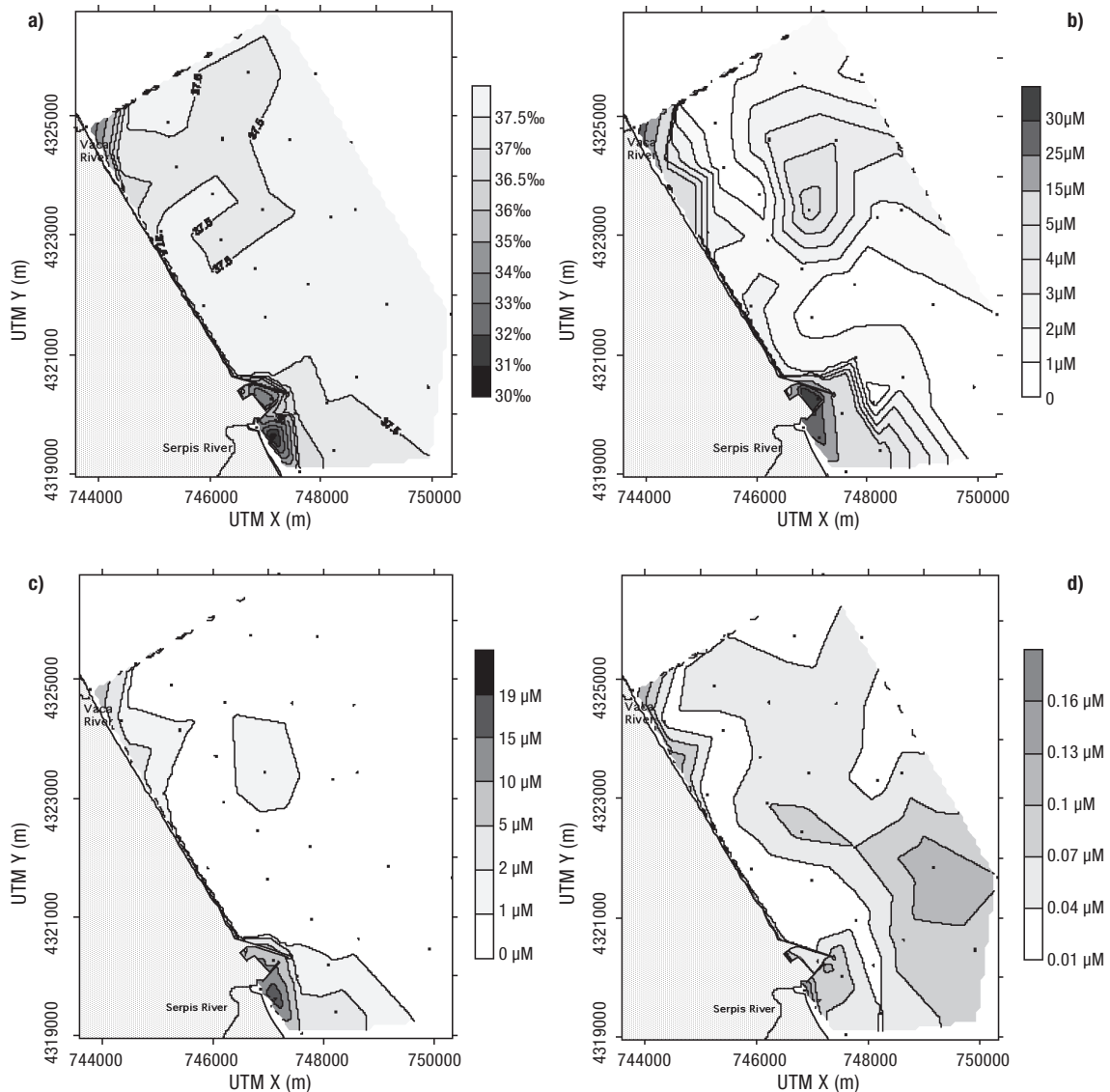


Figure 6. Distribution of nutrients in the surface waters. a) Salinity. b) Nitrates concentration (μM). c) Silicates concentration (μM). d) Phosphates concentration (μM).

charges from the wastewater treatment plant must be added to this river flow value. It should be highlighted that the submarine outfall discharges ($0.7 \text{ m}^3/\text{s}$) were diluted because no changes in surface water salinity were detected nearby. In the surf zone, salinity was always lower than in deeper water probably due to the groundwater inputs.

Figure 6 b), c) and d) shows nitrate, silicate and phosphate surface distribution respectively. Nitrates and silicates showed higher values where salinity was lower. In Spain, it is usual to find high nitrate values in freshwater. Spain is a country with a strong tradition of farming

and livestock, and water resources contain increasing levels of nitrate. This is mainly due to the abuse of fertilizers, poor management of livestock waste, and to a lesser extent, domestic wastewater (Pinilla, 1997). Silicates are associated with freshwater inputs due to the weathering of soil and rocks, so inputs of this nutrient depends more on geological formations than on any anthropogenic influence (Nedwell *et al.*, 1999). Phosphate levels were lower than $0.2 \mu\text{M}$ in all of the study area. In the Mediterranean Sea, phosphorus is the limiting nutrient for phytoplankton growth, which is normally the case in freshwater ecos-

systems, and contrasts with other seas, where it is nitrogen (Krom *et al.*, 2004). Phosphates (Fig. 6 d) show higher values near the coast in the north and the south of the study area, and also in a deeper less well-defined zone. This spatial distribution could be because dissolved phosphate concentration can be notoriously modified as a result of adsorption/desorption and reduction/oxidation processes, as well as by biological assimilation (Howarth *et al.*, 1995).

Estimated chlorophyll-*a* distribution is closely related with the nutrient inputs described above, with the exception of the high phosphate levels in the deeper zone where chlorophyll-*a* levels are lower than on the coast. According to Fang *et al.* (2006) and Smith (2006) this disparity can be explained because different phosphate levels and irradiance stimulate the growth of different phytoplankton groups. Depending on the chlorophyll cellular quote of these groups chlorophyll-*a* concentration can finally be lower despite the higher phosphorus availability. An independent research was conducted simultaneously in this study area to analyze the spatial variation of nutrients, chlorophyll-*a* and phytoplankton groups. Its results confirm the spatial distribution of Chl-*a* obtained with the Quickbird image (Sebastiá *et al.*, 2012; Sebastiá unpublished).

Conclusions

The results of this study show how chlorophyll-*a* estimation and mapping for the Gandia coast (Western Mediterranean) can be obtained using the depth-invariant index13 of a Quickbird image ($R^2 = 0.89$). The most important result of this study is on the feasibility of high spatial resolution Quickbird image to detect the high chlorophyll-*a* gradient of coastal areas. Despite the restrictive spectral resolution of this sensor, its high spatial resolution (2.4 m) makes it suitable for chlorophyll-*a* mapping in this type of areas. Compared to traditional field measurements and laboratory analysis, QuickBird data can provide detailed spatial distribution information on the ecological status of water bodies and multi-temporal evaluation at a relatively low cost, which

makes it suitable for monitoring programs such as the WFD one. In spite of the good results obtained, further research could be required to extend the approach applied in this study to more scenes (other days and other areas).

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