Vol. 7 Issue 1

Meteorology Hydrology and Water Management
Research and Operational Applications

January 2019

Evaluating the potential of Sentinel-2 satellite images for water quality characterization of artificial reservoirs: The Bin El Ouidane Reservoir case study (Morocco)

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Abstract. Monitoring water quality in large dams is becoming a necessity for protecting stored water from various forms of pollution. This process requires analysis of several samples on a weekly or monthly basis. Our study aims to determine the relationship between water quality parameters (WQP) and digital data from the Sentinel-2 satellite to estimate and map the WQP in the Bin El Ouidane Reservoir. The in situ sampling was carried out in the Bin El Ouidane Reservoir (Azilal Province), followed by analysis of physicochemical parameters in the laboratory. These measurement results were compared with the reflectance in each sampling location to investigate the correlations between bands and laboratory chemical analysis results. The correlation results showed that all studied parameters have an R^2 greater than 0.52, and they can be transformed to predictive models by stepwise regression. The accuracy of our proposed models was tested using the Oum Er-Rbia Hydraulic Basin Agency data, and the results showed that only three parameters yield admissible verification results (Chlorophyll A, dissolved Oxygen and Nitrate). Those models were then used in geographic information system software to produce a thematic map of each parameter over the entire surface of the reservoir. As a conclusion, the Sentinel-2 images could help indicate the eutrophication stage in the Bin El Ouidane Reservoir, which is a major risk in major Moroccan reservoirs.

Keywords: Bin El Ouidane, water quality, sentinel, simultaneous, correlation, stepwise regression

Submitted 21 April 2018, **revised** 10 July, **accepted** 8 August 2018

1. Introduction

Lakes and reservoirs act as regulators of climate and carbon cycling (Tranvik et al. 2009). They provide water for multiple human uses ranging from drinking water to recreation, and they support high levels of biodiversity as well as agriculture (Brönmark, Hansson 2002). These roles reflect their importance in daily life and lead to a strong need for monitoring the water quality of reservoirs from local to global scales. There are approximately 117 million lakes greater than 0.002 km^2 in surface area in the world (Verpoorter et al. 2014), but only a small fraction of them is included in in situ monitoring networks, which are often limited in terms of frequency and spatial coverage.

Accurate information on reservoirs is an important task for water quality monitoring and prediction (Gray 2008), and the evaluation of water resources is important to human consumption and agriculture (Gleick, Palaniappan 2010). Often, this information is difficult to obtain due to the size of the reservoir, its hydrological dynamics, or its remote location in inaccessible terrain.

Remotely sensed data provide wide coverage of Earth's surface and can be obtained with frequent passing repetitions over the same spot varying from one to a few days. The capabilities of these satellite images can be exploited in several areas for the monitoring different phenomena over large spatial scales and for detecting variations that can be observed in soil or water (Ennaji et al. 2018).

Satellite remote sensing is a feasible way to monitor lakes and reservoirs when we are interested in ecological status (such as chlorophyll A augmentation and seaweed proliferation), or when water quality over large regions must to be monitored with reasonable frequency and at multiple sampling points.

The advantages that can be provided by remote sensing techniques are numerous, but the most important are extension of water quality parameter estimation over the whole lake (instead of at a single sampling point) and instantaneous water quality state determination without requiring field trips and sampling missions.

Many tests of water quality characterization of natural and artificial lakes using satellite images have been conducted since the 2000's, with an introduction of multispectral imagery techniques occurring only on water reservoirs with large areas (Yang et al. 1999; Basnyat et al. 2000; Pierson, Strömbeck 2000; Wang, Ma 2000). These tests demonstrated that some water quality indicators, such as chlorophyll A (Chl a), total suspended matter, turbidity, Secchi depth and color dissoluble organic matter, can be measured using remote sensing techniques (Dekker et al. 2001; Kallio et al. 2001; Giardino et al. 2007; Olmanson et al. 2008; Moses et al. 2009; Hunter et al. 2010).

Previously, water quality detection in lakes has been hampered by the lack of appropriate satellite sensors (Palmer et al. 2015). Satellites, such as the Medium Resolution Imaging Spectrometer (MERIS) and the Moderate Resolution Imaging Spectro-radiometer (MODIS), have a frequent recording time of 1-3 days and sufficient image gray scale resolution (12 bits) for dark objects such as lakes, reservoir dams, and watercourses. However, the spatial resolution of these sensors ranges between 300 and 1 000 m, which is only suitable for very large lakes and reservoirs, whereas the majority of lakes and reservoirs on Earth have small to medium areas (Verpoorter et al. 2014). Previous Landsat satellites (Landsat 1-7) had good spatial resolution (30-90 m) but limited gray scale resolution (8 bits) that could be used in some way to map a limited number of water quality parameters in lakes and reservoirs (Dekker et al. 2001; Brezonik et al. 2005; Kallio et al. 2008; Olmanson et al. 2008; Kutser 2012).

In this study, we tested the ability of Sentinel-2 sensors (high-resolution images) to detect the instantaneous minimal variation in water quality parameters. The Sentinel sensors (launched on April 3, 2014) opened up new potential for research on environmental phenomena requiring high spatial resolution. The images from the Sentinel sensors have 10 m, 20 m and 60 m spatial resolution, meaning that even small reservoirs and local phenomena can be studied (Duvet et al. 2014; Li 2015). This ability was tested by the correlation between field measurements on the downstream part of the Bin El Ouidane Reservoir and the reflectance values in the equivalent pixel of each sampling location.

2. Methods

The Sentinel-2 data were downloaded for free from the official website of the European Space Agency (ESA). The satellite images were captured on the same date as the field data (26 May 2017), thus ensuring that both sets of measurements were made under the same weather conditions.

To meet the required standards, the Water Quality Department within the Oum Er-Rbia Hydraulic Basin Agency (ABHOER) periodically conducts in situ sampling in all rivers and reservoirs in its administrative boundaries, especially during the spring and summer periods when the presence of algae constitutes a considerable problem.

To test the correlation between the remote sensing indexes and laboratory analysis data, more scattered samples were collected in the Bin El Ouidane Reservoir during a field trip on 26^{th} May 2017.

The analysis of physicochemical parameters was conducted according to Morocco standard methods (MEE 2002). The pH, conductivity, temperature and dissolved oxygen were measured in situ using a calibrated pH-meter (ThermoWorks 8000), a conductivity meter (Pico Conductivity Meter), a digital Ox-meter (YSI Prodo), and a thermometer with a precision of 0.2°C. The remaining chemical parameters were analyzed at the Oum Er-Rbia Hydraulic Basin Agency Laboratory using volumetric dosage methods, flame photometry, and spectrophotometry.

2.1. Study area

The Bin El Ouidane Reservoir is located in the center of the northern part of Morocco, in Azilal Province (Tadla-Azilal region). This reservoir is ranked third in terms of stored water quantity in Morocco. It was commissioned in 1953 in one of the major Oued Oum Er-Rbia tributaries (Oued El Abid and Assif N'Ahncal), and it was constructed to satisfy the needs for irrigation and the production of electricity for neighboring regions (Tadla plain) and citizen consumption (Fig. 1). The area of the Bin El Ouidane Reservoir is 36 km^2, and it contains 1 384 million m^3 of water according to an estimation of usable and sealed water storage (Sabri et al. 2017).

The hydrological regime is of the snow-rainfall type and can be divided into two periods. The wet winter–spring season lasts from December to May, when average monthly precipitation can reach 80 mm, with average monthly temperatures varying between 10 and 17°C. The dry season is from June to October, with an average monthly precipitation not exceeding 5 mm, and with average monthly temperatures between 17 and 28°C (Cherifi, Loudiki 1999).

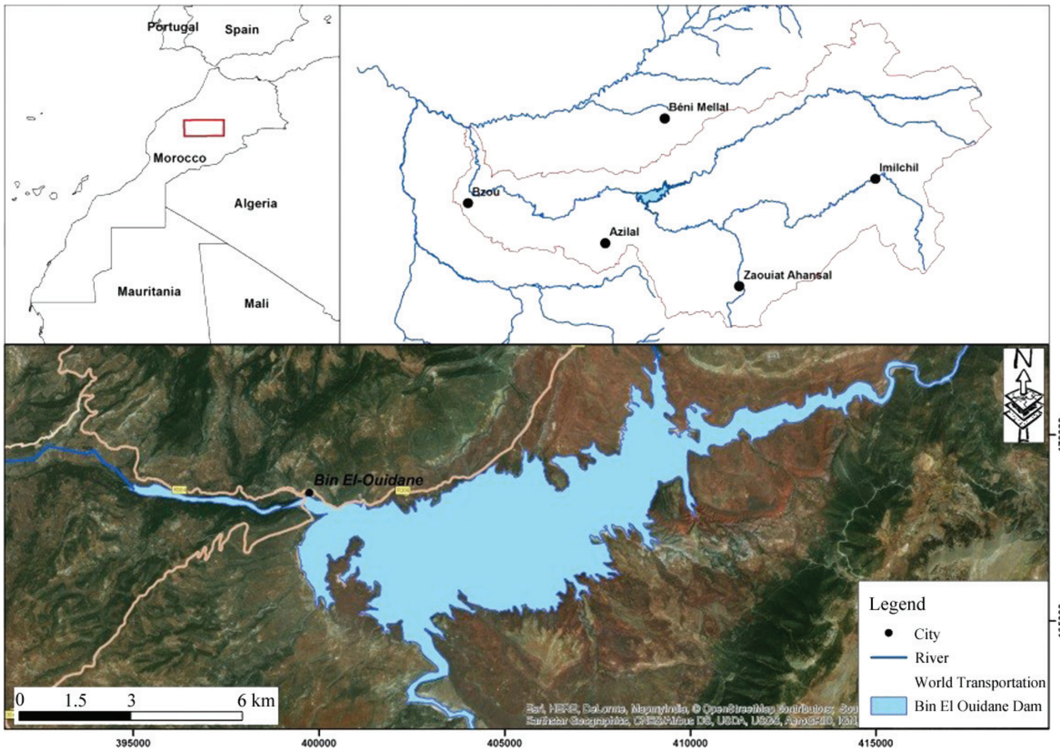

Fig. 1. Location of the Bin El Ouidane Reservoir

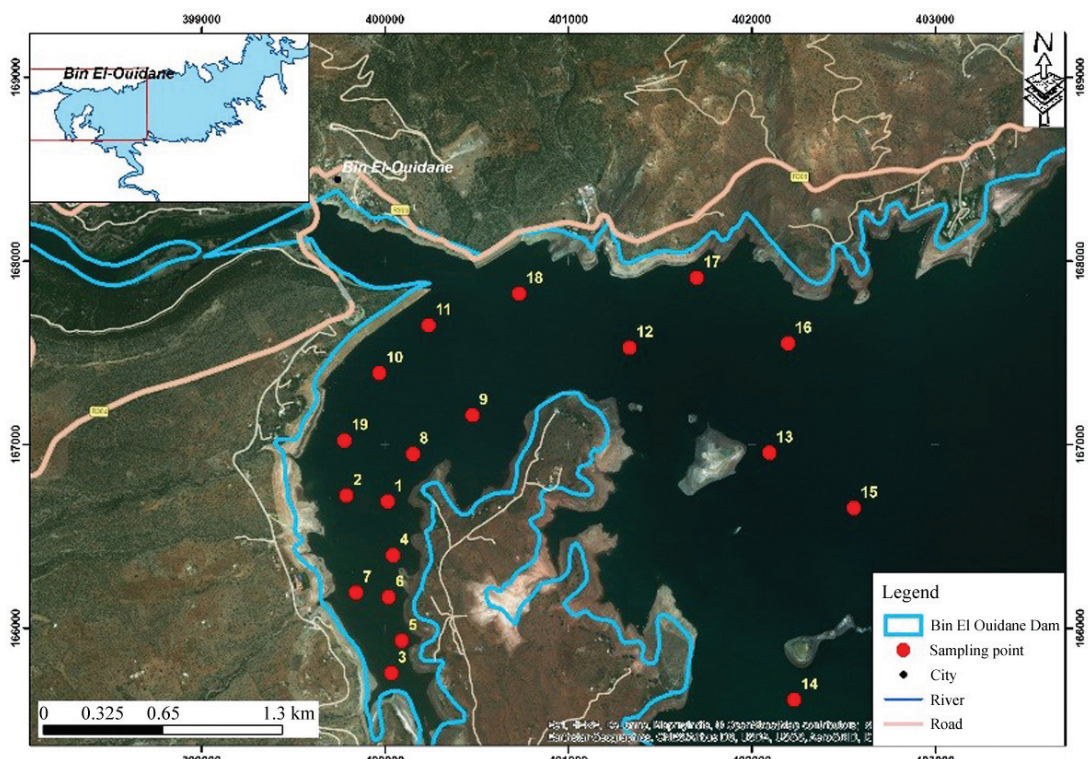

Fig. 2. Sampling points in the Bin El Ouidan Reservoir taken on 26 May 2017

2.2. Field data

During our field trip, we collected samples from the downstream part of the Bin El Ouidane Reservoir (Fig. 2). Samples were collected at a reasonable distance from the banks to avoid any influence of the solar radiation reflectance of the lake bottom. Because the quality values fluctuate rapidly with changes in temperature and wind conditions, samples were taken only on the downstream part so that sampling would coincide with the passing of the satellite over the lake. As a result, the dedicated sampling time was quite short (a few hours).

Nineteen samples were collected (Fig. 2). Dissolved oxygen (O_2diss), nitrate (NO_3^-), total phosphorus (PT), phosphate (PO_4^{3-}) and chlorophyll A (Chl a), were analyzed at the Oum Er-Rbia Hydraulic Basin Agency laboratory. Those parameters are defined as indicators of water pollution in the water quality simplified grid of lakes and reservoirs (MEE 2002).

2.3. Remote sensing techniques used for water quality assessment in Moroccan reservoirs

In Morocco, several reservoirs suffer from water quality degradation due to different sources of contaminants such as wastewater. One consequence of this is enrichment of water with nutrients (nitrogen and phosphate) leading to an advanced state of eutrophication. This phenomenon causes an imbalance of the ecosystem with a bloom of algae and an intense consumption of oxygen at the bottom of the lakes (El Ghachtoul et al. 2005). Monitoring water quality typically involves time-consuming, in-situ surveys and is costly when samples are returned to the laboratory for testing for water quality indicators such as chlorophyll A (algae indicator) and suspended solids. This method allows accurate measurement within a water body but only at discrete points (WHO 2008). However, satellite remote sensing has been a valuable tool for providing a complete and synoptic geographical coverage of water systems (Harrington et al. 1992; Gitelson et al. 1993; Dekker et al. 2001). Using correlation techniques and regression analyses, remote sensing indexes and water quality parameter measurements can be transformed into empirical equations that can describe the instantaneous water quality state in the Bin El Ouidane Reservoir as a case study.

The choice of the most correlated bands was made based on the Root Mean Square Error (*RMSE*) and determination coefficient R^2. These two criteria provide a statistical evaluation of the relationship between water quality parameters and the reflectance values of pixels. Bands with better *RMSE* and R^2 values were selected and used to develop the weighting of the integration coefficients of each band in our proposed models.

3. Results and discussion

3.1. Water quality state in the Bin El Ouidane Reservoir

The laboratory results of the collected samples (Tab. 1) showed that, according to the Moroccan simplified grid, the water quality of the Bin El Ouidane Reservoir is of good to excellent quality for a large number of collected samples. The exceptions are the P13, P17 and P18 samples, where there was severe deterioration to very bad quality because the phosphate content exceeded the acceptable standards in Morocco. These values reached 5.45 mg/L, whereas the admissible value is a maximum of 0.5 mg/L. The values of chlorophyll A, dissolved oxygen and total phosphorus (PT) vary between 0.54 and 1.89 mg/L, 6.97 and 8.18 mg/L, and 0.01 and 0.02 mg/L, respectively, which are ranked in the excellent interval. The nitrate values are classified as good.

Table 1. Laboratory analysis results of collected samples

Sampling point	Dissolved oxygen [mg/L]	Total phosphorus (PT) [mg/L]	Nitrate [mg/L]	Phosphate [mg/L]	Chlorophyll A [mg/L]	Global quality
P01	7.01	0.01	11.21	0.11	1.89	Good
P02	7.01	0.01	10.99	0.12	0.54	Good
P03	7.01	0.01	10.79	0.12	1.12	Good
P04	6.97	0.01	10.14	0.07	1.00	Good
P05	7.38	0.01	12.48	0.09	1.00	Good
P06	7.45	0.01	9.94	0.08	1.65	Excellent
P07	7.31	0.02	11.29	0.03	1.73	Good
P08	7.56	0.01	10.73	0.44	1.77	Good
P09	7.49	0.01	11.51	0.05	1.72	Good
P10	7.49	0.01	11.14	0.06	1.85	Good
P11	7.56	0.01	11.04	0.46	1.86	Good
P12	7.27	0.01	13.23	0.05	1.89	Good
P13	7.75	0.01	13.16	2.04	0.54	Bad
P14	7.82	0.01	13.25	0.07	1.03	Good
P15	8.12	0.01	11.86	0.07	1.00	Good
P16	7.93	0.01	11.58	0.15	1.00	Good
P17	7.97	0.01	11.88	1.39	1.65	Bad
P18	7.71	0.01	11.68	5.45	1.22	Very bad
P19	7.31	0.01	11.90	0.20	1.00	Good

3.2. Correlation between bands and water quality parameters

The model quality was evaluated using the Root Mean Square Error (*RMSE*) and determination coefficient (R^2). Two basic criteria were respected in the development of the models:

- A minimum *RMSE* value, explained by a minimum difference between predicted model values and currently observed values. Note that a model was sometimes favored if it provided a slightly higher *RMSE* but involved more parameters relevant to the problem.
- A higher determination coefficients (R^2), indicating better models.

The stepwise regression model yielded results that are summarized in Table 2.

Table 2. Correlated bands and their R^2 and *RMSE* values

Parameter	Correlated bands	R^2	*RMSE*
Chlorophyll A	B03 (S2A_MSIL2A) B04 (S2A_MSIL1C) B05 (S2A_MSIL1C) B06 (S2A_MSIL1C)	0.78	0.037
Dissolved Oxygen	B08 (S2A_MSIL2A) B09 (S2A_MSIL2A) B10(S2A_MSIL2A) B11 (S2A_MSIL1C)	0.741	0.203
Nitrate	B01 (S2A_MSIL2A) B02(S2A_MSIL2A) B03 (S2A_MSIL1C) B09 (S2A_MSIL1C)	0.671	0.618
Phosphate	B01 (S2A_MSIL1C) B03 (S2A_MSIL1C) B04 (S2A_MSIL1C) B05 (S2A_MSIL1C) B8A (S2A_MSIL1C) B10 (S2A_MSIL1C)	0.544	1.024
Total phosphorus (PT)	B02 (S2A_MSIL1C) B04 (S2A_MSIL1C) B07 (S2A_MSIL1C) B1_TCI (S2A_MSIL1C)	0.521	0.001

MSIL2A and MSIL1C indicate the same image with two processing levels: levels 1C (named S2A_MSIL1C) or 2A (named S2A_MSIL2A). Level 1C corresponds to the original images after various automated processing and corrections, and Level 2A is the result of a classification and atmospheric correction of level 1C (BOA Reflectance).

The strength of correlation in our estimation models was estimated using the stepwise regression method in the *R* software. This regression consisted of predicting variables by an automatic procedure (Ennaji et al. 2018). In each step of the procedure, a variable is considered for addition to or subtraction from the set of explanatory variables based on some pre-specified criterion. Usually, this takes the form of a sequence of *F*-tests or *t*-tests, but other techniques are possible, such as adjusted R^2, the Akaike information criterion, the Bayesian information criterion, Mallows's Cp, PRESS, or false discovery rate (Bolboaca, Jäntschi 2013). Table 3 shows the different empirical equations used in our elaborated models.

To verify the accuracy of our proposed models, a comparison analysis was performed on a series of satellite images captured on the same days as the historical data given by the Oum Er-Rbia Hydraulic Basin Agency from 2016 to 2017 (Fig. 3).

The validation results analysis showed that the oxygen and chlorophyll A models provided estimates with average differences of 0.36 mg/L and 0.16 mg/L, respectively, and the correlation values between the Sentinel-2 bands and the laboratory results exceeded 0.78 and 0.74.

The proposed Nitrates, Phosphorus total and phosphate models provided estimates close to the laboratory results of January 6, 2016 for total phosphorus and May 26, 2017 for phosphate, identical to the laboratory results of July 28, 2017 for nitrates, and far from the laboratory results (May 26, 2017 for total phosphorus; December 30, 2016 for nitrates; and July 29, 2016 for phosphate). This is explained by the low values of the obtained R^2, which reflects the models non-ability to estimate the real values.

Despite the instability of the proposed models, the Nitrate model can be used to provide an instant global indicator of the current state of the Bin El Ouidane Reservoir in term of nitrates. The Moroccan standard limits the maximum allowable values to 50 mg/L (MEE 2002), and the nitrate model gives an estimate with a margin of ±5 mg/L. Thus, when using our model, and when the results approach the interval of 45-50 mg/L, it is necessary to signal an alarm indicating that the nitrates level is no longer acceptable.

The two other models (total phosphorus and phosphate) give gross overestimates of what happens in the reservoir. This overestimation exceeds Moroccan standards and subsequently indicates that the water quality of the Bin El Ouidane Reservoir is always very poor. As a result, these two models cannot be used to indicate or estimate the current water quality state of the reservoir (MEE 2002).

The validation process showed that dissolved oxygen and chlorophyll A are correlated and closely related to each other, such that a decrease in dissolved oxygen leads to an increase in algal levels (chlorophyll A) in the reservoir (Badran 2001; Peake et al. 2001; Morgan et al. 2006; Nezlin et al. 2009; Rocha et al. 2009). Generally, when we try to identify reservoir water quality, the most important parameter that should be identify is chlorophyll

Table 3. Proposed model equations for water quality estimation in the Bin El Ouidane Reservoir

Parameter	Model proposed equation
Chlorophyll A	0,0023***B03** – 0,0084* **B04** + 0,010***B05** – 0,0036***B06** + 0,903
Dissolved Oxygen	–0,0167***B08** + 0,0067***B09** + 0,0162***B10** + 0,0083***B11** + 9,577
Nitrate	0,095***B01** – 0,014* **B02** – 0,0262***B03** – 0,0126***B09** – 66,442
Phosphate	0,010***B01** –0,006***B03** – 0,022***B04** + 0,0388***B05** – 0,0105***B8A** – 0,0155***B10** – 8,507
Total phosphorus (TP)	0,0001***B02** – 0,0001***B04** + 0,0005***B07** + 0,002***B1_TCI** – 0,0433

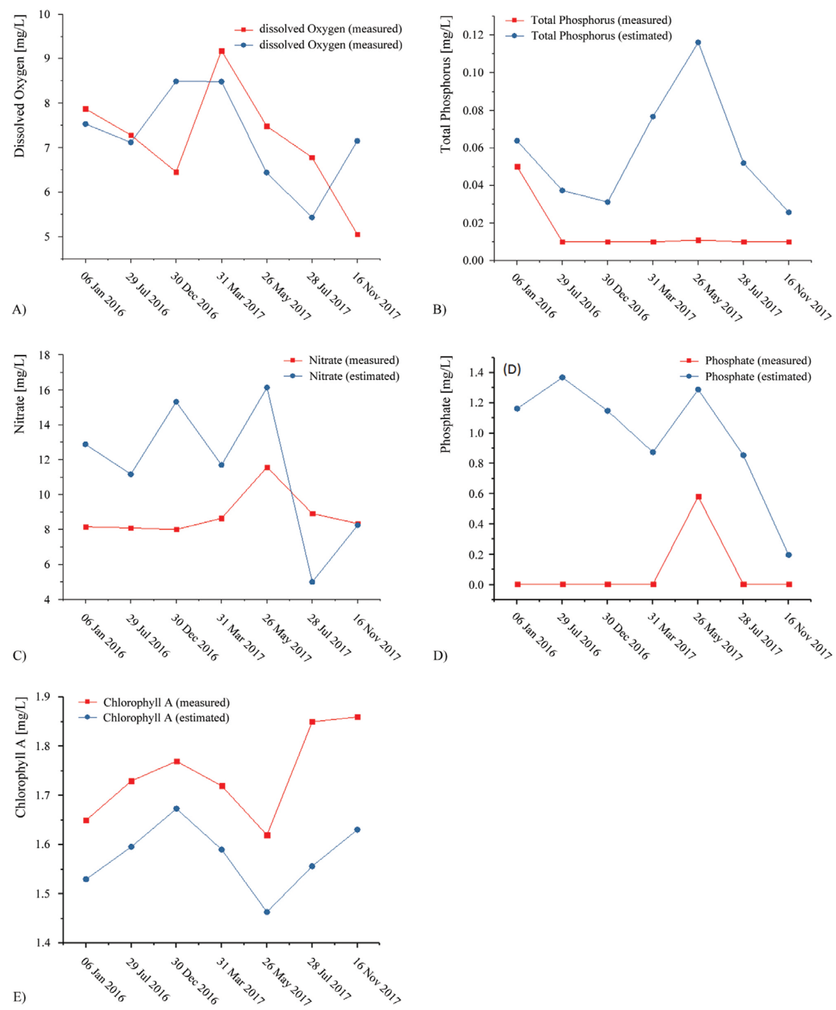

Fig. 3. Comparison of measured and estimated data between 2016 and 2017

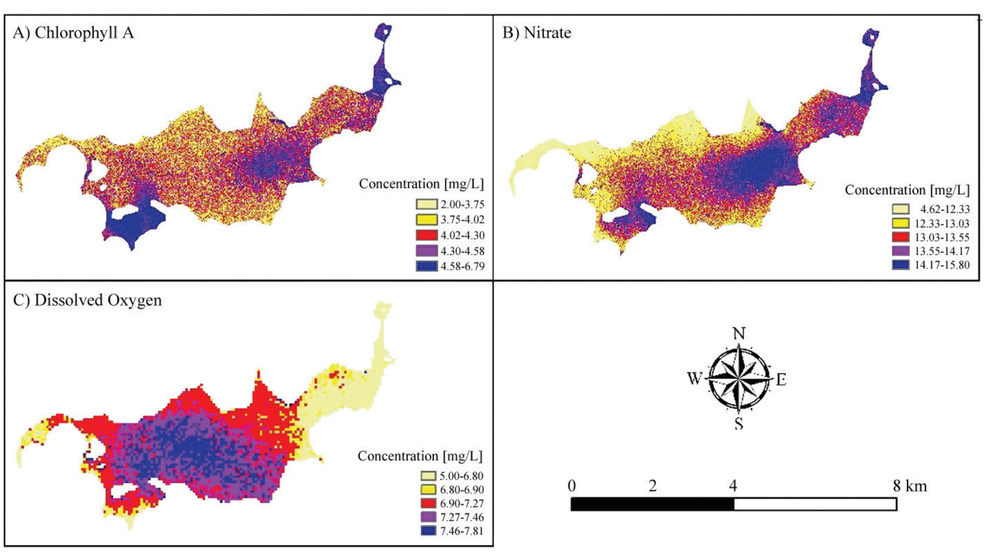

Fig. 4. Water quality variation on May 14th, 2018

A (de Ceballos et al. 1998; Çevik et al. 2007; Leigh et al. 2010; Straskraba et al. 2013). This parameter indicates the stage of eutrophication that could threaten reservoirs around the world (Arhonditsis et al. 2003; Cugier et al. 2005; Shen et al. 2013).

The three validated models were subsequently used in geographic information system software to elaborate thematic maps of the current situation (14 May 2018). Figure 4 indicates the variation of hlorophyll A, dissolved oxygen and nitrates over the entire Bin El Ouidane Reservoir.

Figure 4 shows the variation of the three parameters used in reservoir water quality characterization in Morocco. The chlorophyll A concentration (Fig. 4a) varies between 2 and 5.79 mg/L, and the zones where tributaries enter the reservoir have high chlorophyll A concentration compared with other areas. The chlorophyll A concentration over the entire reservoir is mostly less than 5, which is ranked as excellent quality in the Moroccan standards (MEE 2002). The nitrate concentrations (Fig. 4b) decrease to as low as 4.26 mg/L when approaching the dam, and they are 15.8 mg/L in the upstream area. Regarding the dissolved oxygen concentrations (Fig. 4c), high values are observed in the center of the reservoir (reaching 7.8 mg/L), and these concentrations decrease to 5 mg/L at the banks. When comparing these results with the chlorophyll A concentrations, it is found that this decrease in dissolved oxygen was always followed by an increase in the concentrations of algae, which consume oxygen (Badran 2001).

4. Conclusion

Based on the obtained results of this study, Sentinel-2 imagery data can be successfully used to map some surface water quality parameters (chlorophyll A, dissolved oxygen, nitrate) with high accuracy in the Bin El Ouidane Reservoir, whereas there is uncertainty in the detection of total phosphorus. The accurate mapping of water quality parameters can be exploited to obtain a general idea of the variation of their concentrations due to their high impacts on the water quality state. For the phosphate concentrations, despite the low correlation, the model can be used normally because the effect and variation of this parameter is negligible over the reservoir area as a whole.

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