Remotely sensed sea surface salinity in the hyper-saline Arabian Gulf: application to Landsat 8 OLI data

Jun Zhao*, Marouane Temimi, Hosni Ghedira

Department of Chemical and Environmental Engineering, Masdar Institute of Science and Technology,
PO Box 54224, Abu Dhabi, United Arab Emirates

*To whom correspondence should be addressed: jzhao@masdar.ac.ae

Abstract

In this study, a multivariable linear algorithm was developed to derive sea surface salinity (SSS) from remote sensing reflectance (R_{rs}) in the hyper-saline Arabian Gulf. *In situ* measured R_{rs} at Operational Land Imager (OLI) bands 1-4 were involved in the algorithm development. Comparisons between estimated and *in situ* measured SSS produced R^2 s reaching 0.74 and RMSEs < 2%. The proposed algorithm was applied to OLI scenes collected in November 2013 and March 2016 to demonstrate SSS changes from normal conditions when extreme events were encountered. The good agreement between satellite-derived and *in situ* R_{rs} suggested that the algorithm uncertainties were primarily attributed to the algorithm parameterization and more measurements were required for performance improving. Compared with OLI-derived products, numerical simulations overestimated SSS by 3.4%. Our findings demonstrate the potential of high resolution satellite products to study short-lasting events and capture fine-scale features in the marine environment.

Keywords: Landsat 8, Arabian Gulf, sea surface salinity, ocean color, multivariable regression

1. Introduction

The Arabian Gulf (hereafter referred to as the Gulf) is located in the arid region of the Middle East. Salinity in the Gulf is high which can exceed 44 practical salinity units (psu) in summer resulting from several factors. These factors include high evaporation rate, low precipitation and fresh water discharge,

strong surface heat loss, limited exchange with the open ocean, and shallow water depth (with an average of ~35 m). Saline and dense water flows out into the Sea of Oman and fresher Indian Ocean surface water flows into the Gulf through the Strait of Hormuz (Al Azhar et al., 2016; Johns et al., 1999; Pous et al., 2004; Wang et al., 2013; Yao and Johns, 2010).

Due to the high reliance of the Gulf countries on desalinated water as the main source of potable water, it is required to regularly monitor the water quality surrounding the desalination plants. Remote sensing is a cost-effective and non-intrusive tool that allows continuous observations of the Gulf waters at large spatial and temporal scales. Although microwave remote sensing was frequently used to study ocean salinity at a global scale, the utilization of this technology for fine-scale studies was hampered by its low spatial resolution. For example, the Soil Moisture and Ocean Salinity (SMOS) provides data with a spatial resolution of 35 km at the center of field of view and Aquarius was designed to remotely sense salinity fields at a spatial resolution of 150 km. Current ocean color sensors, such as Moderate Resolution Imaging Spectroradiometer (MODIS) onboard Aqua and Terra satellites and Visible Infrared Imaging Radiometer Suite (VIIRS) onboard the Suomi National Polar-orbiting Partnership (S-NPP) satellite, provide data with coarse moderate resolutions (250-1000 m), which limit their use in the first nautical mile from the coast. This limitation is mainly caused by viewing factors such as adjacent effect and mixed water-land pixels as well as by stray light contamination (Vanhellemont and Ruddick, 2015). Therefore, satellite imagery with higher resolution will be more suited to monitor water quality in the Gulf, especially in coastal areas.

As a fundamental sea water quality parameter, salinity has a direct effect on the stratification and circulation of the global ocean (Yu, 2011). Variations in salinity also affect dynamics of tropical oceans and air-sea interaction (Li and Han, 2016). In sub-polar regions, variability of salinity can provide insights into changes in bloom timing (Gnanadesikan et al., 2011). Ocean salinity and its seasonal and inter-annual variability serve as key variables for hydrodynamic modeling such as Regional Ocean Modeling

System (ROMS) (Al Azhar et al., 2016) and Finite Volume Community Ocean Model (FVCOM) (Chen et al., 2003). Salinity-related information is also needed to run global water cycle and coupled ocean-atmosphere models (Durack, 2015). Furthermore, variability of ocean salinity has a direct impact on aquatic ecosystem and plays an important role in shaping coastal marine communities. Therefore, monitoring ocean salinity with a timely and efficient tool, such as remote sensing, is fundamental and of great importance for marine-related studies, policy making, and management of marine resources.

Numerous studies have been conducted to derive sea surface salinity (SSS) from ocean color satellite data. These studies fall under two categories. The first category of studies tried to correlate satellite-measured radiance or reflectance with salinity using different approaches such as multi-linear regression (Khorram, 1982; Marghany et al., 2010; Qing et al., 2013; Wong et al., 2007), neural networks (Geiger et al., 2013; Urquhart et al., 2012), least square regression (Marghany, 2009; Wang and Xu, 2008), and Box-Jenkins algorithm (Marghany and Hashim, 2011b). The approach used in the second set of studies was based on the inversion of salinity from the absorption of colored dissolved organic matter (CDOM) that can be retrieved from ocean color satellite products (Garver and Siegel, 1997; Kutser et al., 2005). This approach works well for coastal and estuarine waters where terrestrial runoffs affect the inherent optical properties (IOPs) significantly (Ahn et al., 2008; Bai et al., 2013; Binding and Bowers, 2003; Bowers and Brett, 2008). Both types of approaches have been successfully applied to various satellite imagery, such as Landsat MSS (Khorram, 1982), MODIS (Marghany and Hashim, 2011a), Medium Resolution Imaging Spectrometer (MERIS) (Qing et al., 2013), and Sea-Viewing Wide Field-of-View Sensor (SeaWiFS) (Binding and Bowers, 2003). Urquhart et al. (2012) compared eight statistical models to predict salinity from MODIS-measured reflectance and demonstrated that multivariable models were more suitable in such applications compared with univariate models.

Landsat-8 carrying the Operational Land Imager (OLI) was launched on February 11 2013 as continuation for the previous Landsat missions (Roy et al., 2014). OLI bands 1-7 cover a wide spectral range, including

visible, near infrared (NIR), and shortwave infrared (SWIR) at a spatial resolution of 30 m. These high resolution imagery has been used in a wide range of ocean color applications such as assessing the impact of offshore wind farms on suspended sediments (Vanhellemont and Ruddick, 2014), detection of shipwrecks (Baeye et al., 2016), identification of oil spill (Zhao et al., 2014), and estimation of water clarity (Kabiri and Moradi, 2016), chlorophyll-a (Watanabe et al., 2015), and CDOM (Olmanson et al.; Slonecker et al.) concentrations. However, to the best of our knowledge, the capability of OLI to monitor SSS in the Gulf has never been assessed before.

The objectives of this study are twofold: (1) to develop an empirical algorithm to retrieve SSS from remote sensing reflectance (R_{rs}) and (2) to demonstrate the potential of high-resolution Landsat 8 OLI imagery for mapping SSS in the hyper-saline Gulf. In this study, a regional multivariable linear algorithm is proposed to retrieve SSS from R_{rs} using *in situ* measurements collected in the UAE coastal area. The developed algorithm is then applied to Landsat 8 OLI scenes. A thorough validation of satellite-derived R_{rs} is then carried out to insure data quality which supports the widespread utilization of the developed product.

2. Data and method

2.1 *In situ* data collection and processing

Field campaigns along the west coast of the United Arab Emirates (UAE) were conducted between June 2013 and November 2014. Figure 1 shows the stations where *in situ* measurements were collected. 52 stations were surveyed during the entire observation period. A Sea-Bird's 9 plus CTD was deployed at each station to measure temperature and salinity profiles. The CTD system was hand-lowered at a constant speed of 0.5 m s^{-1} during both downcast and upcast. At each site, the CTD system was warmed up for two minutes in the sea surface before deployment. Each station was surveyed twice almost at the same time for cross-check and validation. Surface salinity used in this study was obtained by calculating

the average of salinity at the surface from the two casts except the downcast during the first deployment. Details regarding field measurements can be referred to Mezhoud et al. (2016).

The National Aeronautics and Space Administration (NASA) ocean optics protocol was used for R_{rs} data collection and analysis (Mueller et al., 2003). R_{rs} data were measured by using an Ocean Optics spectrometer (USB 2000+) with a spectral resolution of 1 nm. Radiance signals reflected from the sea surface (L_{water}) including contributions from water-leaving (L_w) and sky-glitter, sky (L_{sky}), and a gray plaque (L_p) were measured. R_{rs} was calculated using the following equations:

$$R_{rs} = \frac{L_w}{E_s} \quad (1)$$

$$L_w = (L_{water} - \rho \times L_{sky}) \times F_L \quad (2)$$

$$E_s = \frac{\pi \times L_p}{R_p} \times F_L \quad (3)$$

where ρ is the Fresnel reflectance of the air-sea interface and an empirical value of 0.028 was adopted. F_L is the instrument response signal. R_p is the bidirectional reflectance function (BRDF) of the grey plaque when the instrument views the surface of the gray plaque at a fixed angle of 90° , which was provided by the manufacturer. E_s is the incident irradiance. Due to cloud cover and shallow bottom, R_{rs} data from 4 out of the 52 stations visited were excluded from the modeling dataset. More details about the field campaign and the data collection and analysis protocols can be found at Mezhoud et al. (2016) and Zhao et al. (2016b). It should be noted that R_{rs} is determined by inherent optical properties (IOPs) of optically active constituents in seawater including phytoplankton, non-algal particulate, CDOM, and pure seawater and that CDOM has an inverse relationship with salinity in coastal and estuarine waters and can be retrieved from R_{rs} , which forms the basis for the SSS algorithm development in this study.

2.2 Satellite data acquisition and processing

OLI level-1 georeferenced total radiance data with a spatial resolution of 30 m were acquired from U.S. Geological Survey (USGS). These data were processed by using the SeaWiFS Data Analysis System (SeaDAS, v 7.3), which is a comprehensive image analysis package developed by the NASA Ocean Biology Processing Group (OBPG). The default short-wave infrared (SWIR) atmospheric correction scheme was implemented. The output products included R_{rs} at bands 1-7 and level-2 (L2) flags. Chlorophyll-a concentration based on the generalized inherent optical property (GIOP) algorithm (Werdell et al., 2013) was also generated to indicate the occurrence of algal bloom in November 2013 (Zhao et al.). According to the findings from Tiwari et al. (2016), chlorophyll-a from the GIOP algorithm matched better with *in situ* measurements than from other two community-accepted chlorophyll-a algorithms, namely OC3M and GSM, in the Red Sea with similar optical properties to those in our study area. Considering the signal-to-noise ratio of OLI bands, only data in the visible domain, i.e. bands 1-4, were used in this study. For validation purpose, satellite-derived and *in situ* measured R_{rs} were matched following the criteria below: (1) In order to have as many matched pairs of satellite and *in situ* measurements as possible, a time window of ± 6 hours was used; (2) Satellite data were quality controlled using the L2 flags including atmospheric correction failure, cloud, stray light, high top-of-atmosphere radiance, low water-leaving radiance, large solar/viewing angles, and navigation failure; (3) Satellite data were extracted from a 3×3 window centered at each station. For the 9 pixels, data extraction was done only when at least half of them had valid values as defined in step 2 and the coefficient of variation (defined by the ratio of standard deviation to mean) was less than 10%. The matchup analysis resulted in 16 pairs of satellite and sea truth measurements (Figure 1).

In this study, several statistical parameters were used to assess the differences between *in situ* measurements and model estimates, including mean ratio, relative percentage difference (RPD), root mean square difference (RMSE), slope and intercept coefficients, as well as coefficient of determination (R^2) when linear regressions were applied.

2.3 Model configuration

This section describes the theoretical background of the multivariable linear regression model developed in this study. A linear regression model describes the relationship between the dependent variable, y , and independent variable or variables, X . A general form of a linear regression model can be written as

$$y_i = \beta_0 + \sum_{k=1}^K \beta_k f_k(X_{i1}, X_{i2}, \dots, X_{ip}) + \varepsilon_i, \quad i = 1, \dots, n, \quad (3)$$

where y_i is the i th response, β_k is the k th coefficient, β_0 is the constant term, $f(\cdot)$ is a scalar-valued function of the independent variables and could be in any form including nonlinear functions or polynomials, X_{ij} is the i th observation on the j th independent variable ($j=1, \dots, p$), and ε is the i th noise term that is a random error. A least-squares fit that is very efficient with the model's form known was constructed in this paper to estimate β_0 and β_k . With respect to this study, y corresponds to SSS and x corresponds to R_{rs} . Different combinations of R_{rs} for the model were tested. The best performance was produced by combining all 4 visible bands of OLI and using quadratic functions. The least-squares estimates were undertaken in Matlab (v2015b). Thus, equation 3 can be rewritten as

$$SSS = \beta_0 + \beta_1 \times R_{rs}(443) + \beta_1 \times R_{rs}(482) + \beta_1 \times R_{rs}(561) + \beta_1 \times R_{rs}(655) + \beta_1 \times R_{rs}(443)^2 + \beta_1 \times R_{rs}(482)^2 + \beta_1 \times R_{rs}(561)^2 + \beta_1 \times R_{rs}(655)^2 + \varepsilon \quad (4)$$

2.4 Model calibration and validation

For purposes of model calibration and validation, *in situ* collected 48 pairs of salinity and R_{rs} data were split randomly into two sets (33 for calibration and 15 for validation). Based on the model established above, the best-fitted regression equation was expressed as

$$\begin{aligned} \text{Salinity} = & 39.664 - 1233.1 \times R_{rs}(443) + 1067.5 \times R_{rs}(482) - 189.58 \times R_{rs}(561) + \\ & 1640.8 \times R_{rs}(655) + 23823 \times R_{rs}(443)^2 - 17844 \times R_{rs}(482)^2 + \\ & 1944.7 \times R_{rs}(561)^2 - 94613 \times R_{rs}(655)^2 \end{aligned} \quad (5)$$

Figure 3 shows the comparison between the simulated and *in situ* measured SSS for both calibration and validation datasets. The statistical results are summarized in table 1. It can be seen that the proposed model can estimate SSS with good accuracy as indicated by low RPD < 0.1%, low RMSE < 2%, slope close to 1, and mean ratio equal to 1.

3. Results

3.1 *In situ* measured salinity map

Figure 2 presents the spatial distribution of *in situ* measured SSS. The Data-Interpolating Variational Analysis (DIVA) tool was utilized for gridding (Barth et al., 2010), which is integrated in Ocean Data View (Schlitzer, 2002). The measured SSS values range between 38.54 and 44.7 psu. The highest value was measured in summer and the lowest value was recorded in winter (Mezhoud et al., 2016). The lowest SSS was found in November 2014 off Ras Al Khaimah (RAK) when there was an algal bloom. The measured SSS indicated a unique spatial trend that it decreased along transects from nearshore to offshore. This pattern was related to the stronger evaporation and weaker circulation in nearshore waters than in offshore waters, existence of desalination plants in nearshore waters, and the ocean circulation conditions in the Gulf that are characterized by outflow of highly saline water into the Sea of Oman and inflow of fresh water into the Gulf (Al Azhar et al., 2016).

3.2 Application of the algorithm to OLI imagery

The proposed multivariable algorithm was applied to a satellite scene collected on November 7 2013, as shown in Figure 4a. The chlorophyll-a concentration based on the GIOP algorithm is illustrated in figure 4b. Chlorophyll-a concentration was as high as 15 mg m⁻³ in the area outlined in figure 4b, which indicates the occurrence of an algal bloom dominated by dinoflagellate *Noctiluca* in the eastern Gulf (Zhao et al., 2016a). The SSS in the bloom affected area varied between 40 and 41 psu. Satellite-observed pre-bloom SSS, i.e. for October 6 2013 shown in figure 4c, in the bloom-contaminated area

186 ranged from 40 to 41.5 psu. It seems that SSS was not correlated with the variations in the abundance of
187 *Noctiluca* in this study. A similar finding was reported by Turkoglu (2013). However, the preference of
188 high salinity for *Noctiluca* blooms corroborates the findings of Miyaguchi et al. (2006). It should be noted
189 that the salinity demands of *Noctiluca* are significantly variable (Turkoglu, 2013). High SSS patches along
190 the Iranian coast can be apparently recognized as annotated with green eclipses in figures 4a and 4c.

191 Examinations of ocean current data
192 (<http://coastwatch.pfeg.noaa.gov/erddap/griddap/index.html?page=1&itemsPerPage=1000>) indicated
193 that the high SSS patches were caused by advection of water with high salinity from the inner Gulf and
194 eddy-driven upwelling.

195 A severe storm hit the UAE between March 8 and 9 2016, when 300 mm of rain have been recorded in
196 less than two days. This amount is about three-fold the annual average precipitation rate of 100 mm
197 (<http://edition.cnn.com/2016/03/09/world/abu-dhabi-storm/>). In order to study the variations of SSS
198 pre- and post-storm, figures 5a and 5b show two satellite-derived SSS maps for February 8 and March 11
199 2016, respectively. It can be seen that significant differences in SSS exist between these two days. SSS
200 for March 11 2016 generally increased by ~3 psu especially in coastal waters compared with that for
201 February 8 2016. The post-storm SSS observed on March 22 2014 (figure 5c) was also compared with
202 normal conditions. The latter is similar to the pre-storm condition, except in southern coastal waters
203 where SSS increased by ~1 psu. Unfortunately, no usable data were available either in a similar period in
204 2015 or in late March 2016 due to the contamination of most of available scenes by sun glint or cloud
205 cover. Therefore, the unusual increase of SSS should be associated with the storm event in March 2016
206 over the southern part of the Gulf when strong winds stirred up the bottom water with higher salinity. It
207 can be concluded that high-resolution OLI-derived SSS data have contributed to have a better
208 understanding of the development of local events in the marine environment and their effects on the
209 marine ecosystem.

4. Discussion

4.1 Factors causing algorithm uncertainties in satellite applications

In order to assess the application of the proposed multivariable algorithm to the whole set of satellite data, factors causing uncertainties of the algorithm must be identified and addressed. There are two potential factors that contribute to the observed errors between estimated and measured SSS for satellite applications, i.e. satellite-derived R_{rs} and the algorithm design and parameterization.

Due to the revisit frequency of 16 days and the requirements of clear sky conditions for satellite measurements, there are very limited field measurements acquired during OLI acquisition times. Figure 6 shows the comparisons between OLI-derived and *in situ* measured R_{rs} at OLI bands 1-4 centered at 443, 482, 561, and 655 nm, respectively. The statistical results are listed in table 2. For all bands, the following results were observed: (1) R^2 is ≥ 0.97 ; (2) the mean ratio and the slope are close to 1; (3) R_{rs} was generally overestimated by satellite measurements except for band 4 and the absolute values of RPD is $< 30\%$; (4) RMSE is $< 41\%$. Additionally, the uncertainties in OLI-derived R_{rs} are relatively close to those obtained from the global open ocean waters (McClain, 2009). Compared with other bands, lower accuracy was observed for satellite-derived R_{rs} at band 4, which can be related to the low values of R_{rs} at this band. These results show that OLI-derived R_{rs} have a good agreement with sea truth data. Therefore, the mismatch between satellite-derived and *in situ* measured SSS is not due to satellite-derived R_{rs} , but primarily caused by the parameterization of the R_{rs} based inversion algorithm.

It should be noted that SSS used for the algorithm development in this study varied between 38.54 and 44.7 psu with only two data points with values lower than 39 psu. Therefore, more data covering a wider salinity range would help to improve the accuracy of the developed algorithm. Another source of error is that the used R_{rs} represents the integrated information of the surface ocean, while salinity data used were from a specific depth. As shown in Figure 5, sharp decrease in SSS can be seen, especially in

clear shallow waters around islands, which should not happen naturally. This phenomenon is very likely to be incurred by the bottom reflection that affects remotely sensed signal mainly in the green band. In this study, data from stations where the bottom can be clearly seen were excluded. More attention should be given in the application of the SSS-retrieval algorithm in clear shallow waters. Furthermore, special conditions like extensive algal bloom and high water turbidity may affect the accuracy of the algorithm. In very turbid coastal waters, the effects of atmospheric correction should also be taken into consideration (Ye et al., 2017). Nevertheless, although the performance of the proposed algorithm might be affected by several factors, it can still retrieve SSS with high accuracy especially in offshore areas. On the other hand, applications of the developed algorithm to other regions with different optical properties across the world must be cautious and recalibration with local *in situ* measurement should be considered.

4.2 Comparison with ROMS simulated salinity

Figure 7 shows the comparison between satellite-derived and Regional Ocean Modeling System (ROMS) simulated SSS for February 8 2016. A linear regression between simulated and satellite measured SSS resulted in a R^2 of 0.21 (N=963). Statistically analysis indicated that ROMS generally overestimated SSS by 0.02-5.05 psu with a relative error of 3.4% relative to satellite-retrieved SSS. The overestimation of ROMS-simulated SSS is clearly noticeable with higher values in coastal areas than in offshore areas. However, we haven't observed similar patterns when satellite retrievals were compared with *in situ* measurements. As shown in figure 3, most of the mismatch, both overestimation and underestimation, were observed in coastal and offshore areas. Those small scale features observable in OLI-derived SSS were smeared out in the ROMS modeled SSS. This could be related to the difference in the horizontal resolution of the two datasets. The spatial resolution of the ROMS-simulated salinity is 5 km while the spatial resolution of OLI measurements is 30 m, making OLI products more sensitive to small-scale features. Furthermore, it should be noted that the ROMS was forced by the 3-hourly evaporation and

precipitation data from the Global Forecast System (GFS) with a spatial resolution of $1/8^\circ$ (Al Azhar et al., 2016).

With advanced techniques, data collection over the global oceans has been carried out with different state-of-the-art platforms, such as gliders and Argo floats. They can provide valuable information for variability of seawater properties. Data from these platforms can be assimilated into numerical models to improve their performance (Moore et al., 2011). However, they are very costly and have limited horizontal coverage. In this regard, high-resolution OLI-derived SSS can provide better understanding of fine-scale phenomena in open ocean waters.

5. Conclusion

In this study, a multivariable linear algorithm was developed to retrieve SSS using *in situ* measurements in the hypersaline Gulf. Comparisons between estimated and measured salinity resulted in an R^2 of 0.74, which indicated the good accuracy of the proposed algorithm. The developed algorithm was then applied to OLI imagery. To assess the applicability of the proposed algorithm under different optical properties, the model was tested during an algal bloom event and before and after a storm event in the Gulf. Factors affecting the performance of the algorithm were identified and analyzed. Satellite-derived SSS was also compared with ROMS simulated data with the latter showing a general overestimation of 3.4%.

Our findings demonstrate the value of satellite-derived high-resolution SSS maps, which have the potential to aid in studying the effects of short-term local events like storm and typhoon on the marine environment, interpreting the dynamics of periodical phenomena such as red tide, and establishing effective warning and mitigation systems for sensitive marine ecosystems. Assimilation of near real time (NRT) satellite-measured SSS into numerical models can improve their performance, which helps in better understanding the interactions between the ocean and the climate and the effects of

anthropogenic activities on the ocean. These cost-effective SSS maps can provide valuable information for shoreline protection and design of marine protected area. Furthermore, other commercial and industrial sectors such as fish farming, fishing, aquaculture, tourism, and desalination would also benefit from such synoptic satellite measurements.

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Figure 1 The upper panel shows a map of the Arabian Gulf. The red box outlines our study area which is enlarged in the lower panel. Bathymetry data from GEBCO are superimposed. Overlaid are stations investigated during field surveys conducted between June 2013 and November 2014 along the west coast of the United Arab Emirates (UAE). Black open circles denote all stations that have been visited. Black '+' signs indicate stations with simultaneous salinity and remote sensing reflectance (R_{rs}) measurements used for algorithm development and validation in this study. Red 'x' signs show stations with matched *in situ* and OLI measured R_{rs} . Station names are also annotated.

Figure 2 Spatial distribution of *in situ* measured sea surface salinity (SSS). The Data-Interpolating Variational Analysis tool integrated in Ocean Data View was used for gridding. The black dots denote *in situ* stations. Isolines of salinity from 40 to 45 are also overlaid. The inset figure shows SSS for the two stations off Ras Al Khaimah (RAK), i.e. RAK3 and RAK4 as shown in figure 1.

Figure 3 Comparisons between *in situ* measured and estimated SSS by implementing the algorithm developed in this study using the model calibration (a) and validation (b) datasets. The green and red dashed lines denote the best fitted relationships between measured and estimated SSS. The dashed blue lines show 1:1 relationships.

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Figure 4 OLI-derived SSS (a) and chlorophyll-a concentration (b) for November 7 2013. The generalized inherent optical property (GIOP) algorithm was utilized for the chlorophyll-a concentration. SSS for October 6 2013 is shown in (c). The red ellipse outlines the bloom affected area. High SSS patches along the Iranian coast are annotated with green ellipses.

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Figure 5 OLI-based SSS maps for February 8 2016 (a), March 11 2016 (b), and March 22 2014 (c).

Figure 6 Comparison between OLI-derived and *in situ* measured R_{rs} at OLI bands 1-4 centered at 443, 482, 561, and 655 nm, respectively.

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Figure 7 Satellite-derived (a) and Regional Ocean Modeling System (ROMS) simulated (b) SSS for February 8 2016 along the Abu Dhabi coast. Comparison between SSS from satellite measurements and ROMS simulations for February 8 2016 is shown in (c). The dashed line denotes a 1:1 relationship. The solid line denotes the best-fitted relationship. The statistical results are also annotated.

Table 1 Statistical results for the comparisons between measured and estimated salinity. Both calibration and validation datasets were used to calculate salinity using the algorithm proposed in this study.

Dataset	R ²	Mean ratio	RPD (%)	RMSE (%)	Slope	Intercept	N
Calibration	0.74	1	0.03	1.7	0.74	10.82	33
Validation	0.6	1	0.08	1.87	0.84	6.5	15

Table 2 Statistical results for the comparison between satellite-derived and *in situ* measured R_{rs} at Landsat 8 OLI bands 1-4 centered at 443, 482, 561, and 655 nm.

Wavelength	R ²	Mean ratio	RPD (%)	RMSE (%)	Slope	Intercept
443	0.98	1.27	27.34	35.76	0.98	0.0018
482	0.97	1.28	27.88	33.21	1.06	0.0018
561	0.98	1.13	12.97	22.09	1.07	0.0009
655	0.99	0.71	-28.95	40.95	0.7	0.00003