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Change detection using remote sensing in a reef environment of the UAE during the extreme event of El Niño 2015–2016

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ABSTRACT
Coral reefs of the United Arab Emirates (UAE) are living in the world’s hottest sea. Recently, corals harbouring Symbiodinium thermophilum, a thermotolerant microalga, were found to be prevalent among UAE reefs and were reported to endure extreme sea-surface temperatures. Late 2015–early 2016 was marked with the strongest El Niño on record worldwide, which caused massive coral bleaching (loss of symbiotic microalgae from reef-building corals). In September 2015, the waters flanking UAE coasts were identified to be among the areas facing a thermal stress reaching its highest level liable to cause massive coral bleaching. However, the effect of this thermal stress on UAE corals remained largely unknown. Here, multi-temporal DubaiSat-2 satellite images were used to show that changes in the reef environment of Dalma Island, UAE, between 2014 and 2016, occurred in macroalgae-dominant habitats, whereas live corals remained unaltered. Furthermore, extending the study to a larger area helped in discovering a continuum of live and pristine corals, which was not reported or studied before. While sea-surface temperature anomalies of 1°C were reported to significantly damage coral reefs around the world, the live coral habitat was observed to exhibit no-change despite four consecutive months of +2°C to 3°C anomalies reported during the study period. These findings point to the tolerance of UAE live corals faced with extreme climate conditions.

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1. Introduction
The United Arab Emirates (UAE) coasts are 1318 km long (CIA 2009), bordered by the Arabian Gulf, and host a reef area of 1190 km² approximately (Spalding, Ravilious, and Green 2001). UAE ranks 38th out of 80 countries in terms of coral reef size (Spalding, Ravilious, and Green 2001). UAE coral reefs are exposed to local and global
environmental changes (Rezai et al. 2004). UAE corals are living in what is known to be the world’s hottest sea and seem to endure extremes in salinity and sea-surface temperatures (SSTs) (Riegl and Purkis 2012).

A recent study (Hume et al. 2016) reported that corals that are harbouring a thermo-tolerant microalgae, of the species Symbiodinium thermophilum, are tolerant to high salinity and temperature levels. Another recent study (Hume et al. 2015) reported that this association is prevalent in UAE waters and is exhibiting tolerance to continual high SST. Exceptional positive SST anomalies (SSTAs), however, led to bleaching (the loss of symbiotic microalgae from reef-building corals) and mortality across UAE corals in the late 1990s and early 2000s that were associated with 1997–1998 and 2009–2010 strong El Niño seasons (Wilkinson 2000; Riegl 2002; Riegl 2003). El Niño was found to significantly affect several hydro-climatic variables in the UAE region; variables such as precipitation (Ouarda et al. 2014; Kumar et al. 2016), temperature and soil moisture (Basha, Ouarda, and Marpu 2015), wind (Naizghi and Ouarda 2017), and SST (Niranjan Kumar and Ouarda 2014).

During late 2015 and early 2016, SST were driven by the strongest El Niño event on record (Science 2015). During this 2015/2016 El Niño, positive SST first appeared off the South American Coast during boreal spring 2015 then extended westward during the developing phase of the event to reach their peak intensity in late 2015 (Paek, Jin-Yi, and Qian 2017). Late 2015 was marked by night-time SSTAs of approximately +2°C to 3°C in data sets of the National Oceanic and Atmospheric Administration’s (NOAA’s) Coral Reef Watch (CRW) (NOAA-CRW 2016). CRW’s SSTAs are useful in assessing El Niño’s development and observing major shift in coastal upwelling (Liu et al. 2013). Several media releases reported confirmations by scientists of a global bleaching event for 2015 (Survey 2015; NOAA 2016; WWF-Australia 2016). In September 2015, CRW has identified the waters flanking UAE coasts to face a thermal stress reaching its highest level liable to lead to massive coral bleaching (NOAA-CRW 2015c, 2015d) (Figures 1(a) and (b)). The corresponding SSTAs were +2°C to 3°C (NOAA-CRW 2015e) and gave another indication on potential thermally induced coral reef bleaching in UAE (Figure 1(c)). The duration and accumulation of this thermal stress was evidenced by CRW’s Degree Heating Weeks (DHW) product. DHW is a cumulative measure of thermal stress intensity and duration during the most recent 12 week period used for monitoring the accumulation of instantaneous thermal stress (Skirving et al. 2006; Liu et al. 2013). Sample charts of CRW’s twice-weekly 50 km DHW product (Figure 2) show accumulated thermal stress in the Arabian Gulf and UAE waters in particular. The range displays 11.0°C to 15.0°C-weeks approximately during late summer from 31 August 2015 to 2 November 2015 with a peak around 21 September 2015 (NOAA-CRW 2015a).

In this context, the present study aims to detect the changes in coral reef environment of Dalma Island, located approximately 42 km off the coast of Abu Dhabi, UAE, between 2014 and 2016, including the thermal stress incited by El Niño 2015–2016. Change detection is based on the analysis of multi-temporal and multispectral satellite images combined with in situ observations.

The coastal waters of Abu Dhabi are generally characterized to be shallow (<30 m) and optically complex (Sheppard et al. 2010). Optically complex coastal waters contain multiple types of constituents and are characterized by highly diversified optical properties (Shen et al. 2015). Coral reefs and seagrass beds in Abu Dhabi waters are mainly
present in the euphotic zone that mostly extends to 6–15 m (Sheppard et al. 2012), but that can stretch out to 20 m and more in less turbid areas (Purser 2012). Waters in this zone are, commonly, turbid and vertically well-mixed due to high wave action caused by strong winds (Sheppard et al. 2010; Riegl and Purkis 2012). Winds generate waves and then mixing occurs due to wave processes among other things. Coastal environments of similar complexity and heterogeneity are well-known to present several challenges for coral quantitative mapping, bleaching, and change detection using multispectral remote sensing (Lesser and Mobley 2007; Hedley et al. 2016).

Multispectral remote sensing has been widely used within seafloor mapping and monitoring studies and programmes (Mumby et al. 1999) as it covers large spatial (from reef to global) (Hedley et al. 2016) and temporal (>42 years) scales (Hochberg 2011) at relatively low
However, the similarity in reflectance characteristics of benthic features (classes of corals, seagrass and macroalgae) limits the effective performance of broadband multispectral sensors (Yamano 2013; Hochberg and Atkinson 2003). Progressively, advances in these technologies, e.g. increased spatial resolution (<1.8 m) (Hedley et al. 2016), have contributed to more detailed mapping and more accurate change detection of classes of corals and benthic habitats (>70% accuracy) (Yamano 2013; Botha et al. 2013). This accuracy improves with the integration of other remote sensing data such as in situ measurements (Scopélitis et al. 2009; Scopélitis et al. 2010; Roelfsema and Phinn 2010) and with statistical inferences of larger-scale patterns (Hedley et al. 2016).

The enhanced thematic accuracy of multispectral sensors has been demonstrated in the coral reef environments of UAE by a number of studies, e.g. Riegl and Purkis (2005) and Purkis and Riegl (2005). However, no studies have attempted to detect and analyse the changes in these environments to the knowledge of the authors. Digital change detection

Figure 2. NOAA’s satellite CRW Data sets – DHW product for last 12 weeks from 27 July 2015 to 17 December 2015. NOAA-CRW twice-weekly 50 km (0.5° exactly) satellite coral bleaching DHW product shows accumulated thermal stress, which can lead to coral bleaching and death (NOAA-CRW 2015b). The scale goes from 0°C to 16°C-weeks. DHW accumulates the instantaneous bleaching thermal stress during the most recent 12 week period. It is directly related to the timing and intensity of coral bleaching. Significant coral bleaching usually occurs when DHW values reach 4°C-weeks. By the time DHW values reach 8°C-weeks, widespread bleaching is likely and significant mortality can be expected. The displayed range shows 11.0–15.0°C-weeks approximately during late summer from 31 August 2015 to 2 November 2015 with a peak around 21 September 2015.
techniques using remotely sensed data have demonstrated significant potential to detect, identify, and map ecosystem changes through extensive review and evaluation (Singh 1989; Nielsen and Conradsen 1997; Coppin et al. 2004; Radke et al. 2005; Nielsen 2007; Bruzzone and Bovolo 2013; Marpu, Gamba, and Canty 2011). Several studies focused on coral reef environments using multi-sensor and multi-temporal data (Loubersac et al. 1988; Andréfouët et al. 2001; Palandro et al. 2003; Nurdin et al. 2015).

In this study, bi-temporal high spatial resolution DubaiSat-2 images were processed using Iteratively Reweighted Multivariate Alteration Detection (IRMAD) (Nielsen 2007) method in an object-based image analysis framework. Then, in situ data collected in November 2015 were used as ground truth to attribute physical description to the classes of change obtained from the image processing and analysis. Moreover, a thematic map of the reef environment was produced for the characterization of corals, other benthic classes, and classes of seabeds.

2. Materials and methods

2.1. DubaiSat-2: system capabilities and imagery

This study used Level Geo DubaiSat-2 images. DubaiSat-2 was selected for its high spatial resolution that advances the accuracy and potential of its sensor in benthic habitat mapping (Ben-Romdhane et al. 2016). DubaiSat-2 is an electro-optical satellite launched in a sun-synchronous orbit of 600 km altitude. Level Geo is the product corrected for radiometric, geometric, and sensor distortions; in addition, it is projected to UTM coordinate system (EIAST 2014). The used DubaiSat-2 bands are the 4 m 10-bit multispectral bands: red (R) (600–720 nm), green (G) (510–580 nm), blue (B) (420–510 nm), and near-infrared (NIR) (760–890 nm).

2.2. Study site

The study site is the coral reef environment of Dalma Island (24°28’ N, 52°19’ E). It was selected for its rich and important seafloor composition (e.g. seagrass beds, macroalgae), and in particular, for its coral community that was recently found to be particularly tolerant to high salinity and temperature levels (Hume et al. 2015). The island is relatively small (45 km²), and its population counts around 10,000 inhabitants (Salah 1996; Heard-Bey 2001). The island has witnessed several dredging and land reclamation activities due to the development and relative growth of its population, during the last decades. The main activities of the island’s inhabitants are based on farming, pearl fishing, and fishing activities that use traditional UAE gears such as deepwater fish traps ‘gargoors’ and fishing lines. Overall mean wind speed at sea level, in the region, is between 3 and 5 m s⁻¹ (Naizghi and Ouarda 2017). The tides are complex standing waves with the dominant pattern varying between being primarily semi-diurnal and diurnal (Hyder et al. 2013). The tidal range is large with amplitudes of more than 1 m (between the maximum high tide recorded in the tide tables of Dalma Island and surroundings, which is of around 1.7 m and a minimum height of around −0.1 m; referenced to Mean Lower Low Water). The study site was imaged on 18 June 2014 at 07:41 UTC and on 18 January 2016 at 07:18 UTC by DubaiSat-2 (Figure 4(a)). The wind and tide conditions were different
between the two acquisition dates/times. The wind speed and tide height were around 5.28 m s\(^{-1}\) and 0.7 m during the acquisition of the first image (Weather-Underground 2014; MSD-Bayanat 2014) and approximately 4.44 m s\(^{-1}\) and 1.1 m during the second image’s acquisition (Weather-Underground 2016; MSD-Bayanat 2016). However, the visibility and cloud coverage were nearly the same (around 10 km visibility for the two respective dates and <2% cloud cover in both instances) (Weather-Underground 2014; Weather-Underground 2016).

The corals surrounding Dalma Island shores were recently reported to have prevalent \(S.\) thermophilum, microalgal symbiont, which was proven resilient to positive thermal stress (Hume et al. 2015). Using the AquaTerra Moderate Resolution Imaging Spectroradiometer (MODIS) data, Shuail et al. (2016) established bleaching threshold temperatures for the Porites-dominated corals adjacent to the coasts of Dalma Island (Burt, Al-Harthi, and Al-Cibahy 2011), along with two other sites off the coast of Abu Dhabi during the 2012 bleaching event. Shuail et al. (2016) stated that 35.05°C was the bleaching threshold temperature for the hottest weeks between 2002 and 2014. Here, NASA’s MODIS Aqua data downloaded from the Physical Oceanography Distributed Active Archive Center (http://podaac.jpl.nasa.gov/) were used to reconstruct daily SST in Dalma Island reef environment from 12 July 2015 to 19 December 2015 during which the 2015–2016 El Niño was reported to have peaked. Figure 3 illustrates the temporal variation of these SSTs. Figure 3(a) shows the weekly mean SST (\(\mu_{\text{SST}}\)) along with the standard deviation of SST over each week (\(\sigma_{\text{SST}}\)) in comparison to the local bleaching threshold (\(T_{\text{SST}}\)) defined in (Shuail et al. 2016). Figure 3(b) shows the number of days during which this threshold was exceeded. Figures 3(a) and (b) highlight two instances at least, of local high heat stress. First, there were three consecutive weeks (from 12 September 2015 to 2 October 2015), then, six consecutive weeks (from 7 November 2015 to 18 December 2015) during which the

![Figure 3](https://example.com/figure3.png)

**Figure 3.** Temporal variation of SST data highlighting the heat stress in Dalma Island reef environment (24°30'1.35"N, 52°22'23.51"E) from 18 July 2015 to 19 December 2015. The SST are reconstructed from MODIS Aqua data (http://podaac.jpl.nasa.gov/). (a) Weekly mean SST (\(\mu_{\text{SST}}\)) along with the standard deviation of SST over each week (\(\sigma_{\text{SST}}\)) in comparison to the local bleaching threshold (\(T_{\text{SST}}\)) defined in (Shuail et al. 2016). (b) Number of days during which this threshold was exceeded. Local SSTs exceeded (\(T_{\text{SST}}\)) during the three consecutive weeks from 12 September 2015 to 2 October 2015. Local SSTs verged on or exceeded (\(T_{\text{SST}}\)) during the six consecutive weeks from 7 November 2015 to 18 December 2015. Local SSTs reached 45°C for a continuous week from 7 November 2015 to 14 November 2015.
SST in Dalma Island coral reef environment verged on or exceeded the local bleaching threshold; reaching 45°C for a continuous week from 7 November 2015 to 14 November 2015. These instances of local high heat stress corresponded to the reports of the global heat stress induced by El Niño event (Survey, XL Catlin Seaview 2015; NOAA 2016; WWF-Australia 2016) and suggested the occurrence of considerable bleaching among Dalma Island’s corals. A site visit and a remote-sensing-based approach were adopted in order to test this hypothesis.

2.3. **Ground-truthing**

The fieldwork was conducted in November 2015 with additional validation in May 2016. Over 30 locations surrounding Dalma Island were visited and verified (Figure 4(b)); via free diving for locations shallower than 10 m and via scuba diving in deeper sites. In each site, the dive included taking three photographs in left, right, and forward directions with a DSLR camera mounted to a 0.6 × 0.4 m quadrat frame (Figure 4(c)) providing a general description of the site. Depths were recorded using the boat sonar and dive computer. The quadrat frame helped unifying distance between the

![Figure 4](image-url)

**Figure 4.** The coral reef environment of Dalma Island (24°32′43″N, 52°18′11″E). (a) The images were captured on 18 June 2014 and on 18 January 2016 by DubaiSat-2. (b) 31 ground-truth locations distributed around the island were visited and described. (c) The photograph of the offshore eastern live coral habitat was taken on 6 November 2015 with a DSLR camera mounted on a quadrat frame. The frame is made of two rectangular shaped frames connected with vertical beams, the whole structure is made with 0.0254 m PVC pipes and connections. The main (lower) frame is 0.6 × 0.4 m; 0.24 m².
camera and the seabed in each photograph. It also helped to scale and identify the size of the objects in the photograph for a consistent characterization and classification of the benthic communities. Multi-resolution segmentation was performed at two levels using scale parameters 90 and 110. Shape and compactness were 0.3 and 0.5, respectively, in both levels. Scale parameter is an abstract value to determine the maximum possible change of heterogeneity caused by fusing several objects. It is used to control the average image object size. Shape parameter represents a weighting between the objects shape and its spectral colour (given by the pixel value). Shape includes compactness, which is a weighting for representing the closeness of pixels clustered in a formed object when compared to a circle (Baatz et al. 2004). Choices of these parameters were made based on the visual interpretation of the segmentation results. The two levels used ground-truth location points to generate the training and testing data sets independently, where each ground-truth observation (point) helped generating a region of interest (polygon). Eight classes were defined in addition to masked land and deep sea classes. Classes represented: classes of corals (live, damaged, and rubble), classes of corals with dominating macroalgal cover (damaged corals and macroalgae, rubble and macroalgae); and classes of seabeds without associated corals and/or macroalgae. These classes of seabeds are ‘bare sand’ (to refer to sandy and bare bottoms), ‘emerged seabed’ (to correspond to seabeds that were exposed during the satellite image acquisition due to low tide), and ‘unconsolidated seabed’ (when the substrate is of the gravel size or smaller; specified to be less than 0.004 m and as opposed to pebble-sized substrate or larger (EAD 2015)). The exposure of ‘emerged seabed’ out of the sea water was confirmed during the conducted fieldwork through direct observations and interactions with the island’s local community. Examples of categorized classes are given in Figure 5. The training and testing data sets are given in Figure 6. The classes’ labels as well as the number of pixels for each data set are illustrated in Table 1.

2.4. Methods

The adopted approach consists of three major procedures and is illustrated in Figure 7. First, Multivariate Alteration Detection (MAD) was used to determine the unsupervised change detection in the coral reef environment of Dalma Island (Figure 7(a)). Second, a spectral–spatial approach was adopted to classify this marine environment (Figure 7(b)). Third, a supervised change detection (Figure 7(c)) consisted in the relabelling of unsupervised classes of change using inputs from ground-truthing (Figure 7(d)) and from the classification map obtained using the spectral–spatial approach. The implementation of each of these three major procedures is detailed in the following sections.

2.4.1. Unsupervised change detection using IRMAD

The aim of this step is to automatically identify changes in multi-temporal remote-sensing images. IRMAD, an unsupervised change detection method for multi-temporal multispectral images (Nielsen 2007), is used during this step. IRMAD is the iterative version of the MAD method (Nielsen, Conradsen, and Simpson 1998), which is based on canonical correlation analysis (Hotelling 1936). The principle of MAD is to identify a linear transformation that maximizes the change information contained in the two acquired images by minimizing the correlation between the canonical components of
the images. IRMAD is used for its potential to perform automatic radiometric normalization while mitigating side effects induced by different light conditions during image acquisitions (Falco, Marpu, and Benediktsson 2016). The principle of IRMAD is to iteratively reweight the MAD approach by attributing high weights on pixels exhibiting little change. At each iteration, more invariant (no-change) background is identified. The outputs from IRMAD are canonical variates (CVs) that are mutually uncorrelated. The MAD change components (MADC) are then derived as the difference images of the corresponding CVs.

In order to reduce the effect of spatial heterogeneity in the images that can affect the results of IRMAD, spatial smoothing was performed using image segmentation, where the median value of the pixels in the segment is considered as the common value for the segment. Segmentation of the images was performed using multi-resolution segmentation algorithm in eCognition® software (Trimble Germany

Figure 5. Examples of classes used for the change detection analysis.
During segmentation, objects that grouped pixels with similar spectral and spatial properties were extracted. In order to obtain better segmentation results, image dimension reduction using principal component analysis (PCA) was employed as a preprocessing step. The land and deep sea pixels were masked to obtain the area of interest for further processing. A new set of features was created based on the first principal components (PCs) that contained 99% of data variance, the normalized difference water index, \( \text{NDWI} = \frac{\rho_G - \rho_{	ext{NIR}}}{\rho_G + \rho_{	ext{NIR}}} \); where \( \rho \) represents the reflectance value of the band shown as a subscript (McFeeters 1996), and the normalized difference vegetation index, \( \text{NDVI} = \frac{\rho_{	ext{NIR}} - \rho_R}{\rho_{	ext{NIR}} + \rho_R} \) (Rouse et al. 1974), as it was done in Gao et al. (2011) where only PCs and NDVI were used. This enhances the spectral separability between different classes, thereby improving the segmentation results.
The obtained MAD change components were examined and analysed to quantitatively identify the changed pixels and classes of change. Each MADC was considered as a mixture of Gaussians (bimodal distributions representing change and no-change) and thresholds were identified using expectation-maximization (EM) algorithm (Canty 2014). EM algorithm provides the required statistics (means and the variances) for the decomposition of the MADCs. The identified thresholds were used to determine the value at which changed pixels could be isolated from unchanged pixels, and thus, the classes of change in each MADC. In practice, the Gaussian distribution with the mean value closest to zero is attributed to the no-change class. The variance of the no-change pixels is extracted from the relative covariance matrix. An example of MADC analysis is given in Figure 8, where the threshold was identified to be −0.29 after decomposing the third MADC (MADC3) data into two Gaussian components (GC). The total number of classes of change was based on the combination of all MAD components. A total of five classes were obtained at the end of the unsupervised change detection; one class of no-change gathering all unchanged pixels and four classes of changes corresponding to four types of changing pixels (Figure 9). The five determined classes were reclassified using ground-truth data and inputs from the
classification map obtained through the spectral–spatial approach detailed in Section 2.4.2. The final supervised classification of change reckoned ‘masked pixels’, ‘underlying seabeds’, ‘damaged corals and macroalgae’, ‘no-change’, and ‘reef rubble and macroalgae’ classes.

2.4.2. Spectral–spatial thematic classification
The thematic classification procedure is adapted from the method proposed in Ben-Romdhane et al. (2016). The spectral–spatial thematic classification is illustrated in Figure 10. During segmentation, objects that grouped pixels with similar spectral and spatial properties were extracted as explained in Section 2.4.1. A non-linear feature extraction method, the Kernel principal component analysis (KPCA) (Schölkopf, Smola, and Müller 1998), was then considered for classification as it provides better separability between classes than in original feature space to obtain more accurate results in comparison with other methods that use attribute profiles built using linear features (e.g. PCA) (Bernabé et al. 2014). The median values from the extracted features were then attributed to the multilevel image segments creating spectral–spatial profiles. These profiles were then used for classification using Random Forest (RF) (Breiman 2001). RF is an advanced non-linear model for subpixel classification that operates by constructing a multitude of decision trees at training time and obtaining the class label based on the outcome of all of these trees. The ground-truth data were divided into two separate sets. One was used to train the classification algorithm and the second set to assess the mapping accuracy of the resulting classification using user-, producer-, and overall accuracies described by Story and Congalton (1986). The user’s accuracy corresponds to the error of commission (inclusion), calculated for each class as the number of pixels correctly classified divided by the number claimed to be in that class. The producer’s accuracy is the indication on the error of omission (exclusion), calculated by dividing the number of correctly identified pixels in the reference plots of a given class by the number of pixels that are actually in that reference class (Story and Congalton 1986; Congalton 1991).
2.4.3. Supervised change detection

The final step consisted in the supervised classification of classes of change for a qualitative description of the change detection results. Benthic classes obtained through ground-truthing and from the thematic map were overlaid on the unlabelled classes of change for further interpretation of the changes detected using IRMAD as illustrated by Figure 9.

**Figure 9.** Change detection map. Five unsupervised classes of change were distinguished using image segmentation and change detection methods. The classes of change were relabelled using ground-truth data and thematic classification of the surroundings of Dalma Island and the offshore live coral habitat. Final classes corresponded to ‘masked pixels’ (Class 1), ‘underlying seabeds’ (Class 2), ‘damaged corals and macroalgae’ (Class 3), ‘no-change’ (Class 4), and ‘reef rubble and macroalgae’ (Class 5).
3. Results and discussion

3.1. Spotting of unreported live coral habitat

The visual examination of DubaiSat-2 images acquired in 2014 discovered the existence of a benthic habitat 3.5 km off the eastern coast of Dalma Island (Figure 4(a)). This habitat was not reported before when referring to current Abu Dhabi and UAE official marine habitat maps (EAD 2015) or global maps (ReefBase 2016). A ground-truth survey, conducted in November 2015, confirmed the existence of this benthic habitat at 7–21 m depth and its main composition of live massive (approximately 4 m high and 5 m wide) Porites colonies (Figure 4(c)). This reef measures around 1 km$^2$ and represents a continuum of pristine corals that are not suffering from anthropogenic activities. The classification of this habitat as live corals was further delineated after the thematic classification of the coastal environment of Dalma Island using DubaiSat-2 images acquired in 2016.

3.2. Spectral–spatial thematic classification

As mentioned in Section 2.4.1, segmentation was performed as a preprocessing step for the thematic classification. Results from multi-resolution segmentation performed at three scale levels (5, 7, and 10) helped defining the optimal shape and compactness parameters to be 0.3 and 0.5, respectively. The selection of these parameters was based on the visual inspection of several segmentation attempts. Similarly, 2000 randomly selected samples were considered to derive the KPCA components. In the RF classification, 300 trees were used.

The classification map obtained after the application of the spectral–spatial method is represented in Figure 11. The producer’s and user’s accuracies of the classification map of
Dalma Island coral reef environment in 2016 are tabulated in Table 2. The live coral area off the eastern coast of the island, being referred to as ‘live corals’ class, was well-classified (81.68% producer’s and 58.25% user’s accuracies) in comparison to Andréfouët et al. (2003) that obtained 59% user’s accuracy for coral areas in Dubai. ‘Damaged corals and macroalgae’ class represented the lowest user’s accuracy (44.17%) when considering the rest of the classes. ‘Reef rubble’ presented a moderately better user’s accuracy (50.66%), however, lower than ‘reef rubble and macroalgae’ class. Relatively low accuracies in such habitats might be due to patches of algae-dominated habitats that appear in the same regions and

Figure 11. Thematic classification map of the study area obtained using DubaiSat-2 image.

Table 2. Producer’s accuracy and user’s accuracy of the developed spectral–spatial method.

<table>
<thead>
<tr>
<th>Class</th>
<th>Producer’s accuracy (%)</th>
<th>User’s accuracy (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Bare sand</td>
<td>56.31</td>
<td>73.97</td>
</tr>
<tr>
<td>Damaged corals</td>
<td>73.61</td>
<td>79.58</td>
</tr>
<tr>
<td>Damaged corals and macroalgae</td>
<td>50.28</td>
<td>44.17</td>
</tr>
<tr>
<td>Emerged seabed</td>
<td>89.44</td>
<td>95.51</td>
</tr>
<tr>
<td>Live corals</td>
<td>81.68</td>
<td>58.25</td>
</tr>
<tr>
<td>Reef rubble</td>
<td>59.65</td>
<td>50.66</td>
</tr>
<tr>
<td>Reef rubble and macroalgae</td>
<td>85.88</td>
<td>59.82</td>
</tr>
<tr>
<td>Unconsolidated seabed</td>
<td>41.18</td>
<td>90.66</td>
</tr>
<tr>
<td>Overall accuracy (%)</td>
<td></td>
<td>83.38</td>
</tr>
</tbody>
</table>
at the same depths (Figure 11) as was predicted by Hochberg and Atkinson (2003). Misclassification of damaged corals and macroalgae, reef rubble, and reef rubble and macroalgae areas could be due to the spectral complexity of these reef components and/or to different conditions at the acquisition times of the image and comparative data. The class that contained damaged corals presented 79.58% user’s accuracy. This class was surrounding the western coast of the island and presented highly informative spectral–spatial profiles. User’s accuracies, then, increased with decreasing habitat complexity. Categories of seabeds (sandy, unconsolidated, and emerged) were well-classified (73.97%, 90.66%, and 95.51% user’s accuracy, respectively), which is aligned with previous studies. For instance, Andréfouët et al. (2003) stated 90–92% user’s accuracy for sandy seabeds in Dubai. ‘Unconsolidated seabed’ class presented the lowest producer’s accuracy (41.18%), however, followed by ‘damaged corals and macroalgae’ (50.28%) then by ‘bare sand’ (56.31%). Relative bias between producer’s and user’s accuracies, especially for unconsolidated and sandy seabeds, may be reflecting the heterogeneity of the reef floor especially at patch boundaries were ground-truth locations were selected to capture the extent of each class. Similar observations were made by Riegl and Purkis (2005) when they were detecting shallow subtidal corals using remote sensing halfway between Abu Dhabi and Dubai, UAE. The current classification hierarchy, i.e. eight classes, was more realistic and suited the reef environment of Dalma Island better in comparison to Ben-Romdhane et al. (2016).

The classification’s overall accuracy was calculated to be 83.38%. When compared to previous studies that evaluated the use of multispectral data for classification of similar coral reef environments in UAE (Andréfouët et al. 2003; Purkis and Riegl 2005), the obtained overall accuracy suggests that DubaiSat-2 data were suitable for coastal habitat mapping as similar or better results were obtained. In Ben-Romdhane et al. (2016), the eastern offshore reef was misclassified as ‘unconsolidated seabed’ and this was due to two reasons. First, the classification in Ben-Romdhane et al. (2016) was by reef type and discerned among five classes only. In contrast, the present classification scheme is based on defining eight benthic classes, including corals, macroalgae, and seabeds. Second, the former study used comparative data from published habitat maps (EAD 2015), whereas the current study integrated in situ observations. The importance of integrating field data with multispectral remote sensing is crucial as was highlighted in Yamano (2013).

### 3.3. Change detection

The results from the change detection procedure allowed to distinguish among three major zones (Figure 9): Zone 1 or the benthic habitat that flanks the western shore of the island, classified to be macroalgae-dominant; Zone 2 that represents the island’s eastern shoreline, zone of sandy, unconsolidated or emerged seabeds; and Zone 3, the distant live coral habitat, 3.5 km off the eastern shore of the island.

#### 3.3.1. Detecting the change in Zone 1

Results from the change detection analysis showed two main classes of change in the benthic habitat of Zone 1; as presented in yellow (Class 3) and orange (Class 5) in Figure 9. The overlying of ground-truth data with thematic classification results suggests that these two classes correspond to macroalgae intermixing with damaged corals and to macroalgae intermixing with reef rubble classes.
3.3.2. Detecting the change in Zone 2

This zone is characterized by sandy, unconsolidated, and emerged seabeds. Most changes occurred in the harbour area; shown in blue (Class 2) in Figure 9. This change is the result from dredging/reclamation activities, as introduced in Section 2.2. Indeed, such activities have led to the construction of a new seawall as encircled in red in Figure 4(a). The second class of change displayed in yellow (Class 3) in this zone would correspond to change in macroalgae-damaged corals class according to the supervised classification given for Zone 1.

3.3.3. Identifying the invariability in Zone 3

The live coral habitat spotted offshore the island was characterized to be predominantly unchanged as displayed in grey (Class 4) in Figure 9, while moderate thermal stress and SSTAs of 1°C were reported to cause significant deterioration of coral reefs around the world (Goreau and Hayes 1994; Wilkinson 2008; Fujise et al. 2014). The invariability of this live coral habitat assumes its tolerance to thermal stress. This assumption is supported by recent observations, from April 2016, reporting no bleaching in the waters of UAE flanking Abu Dhabi Emirate including the study site (I. Bugla, personal communication, 10 May 2016). Such tolerance can be explained by the pristine setting of this habitat and its relatively remote location from anthropogenic stress (the island that is 42 km offshore and the actual reef that is 3.5 km off the coast of the island). In fact, local stress and pre-existing human impact reduce coral fitness and resilience to episodic and global warming-related events (Carilli et al. 2009; Hughes et al. 2003). Moreover, Polidoro and Carpenter (2013) studied reef resilience and recovery at isolated locations and reported that recovery and resilience are enhanced when anthropogenic threats are minimized. Though, more recent studies, e.g. Hughes et al. (2017b), suggest that frequent, repeated, and extreme thermal stress can affect even the most protected and near-pristine reef areas. Thus, the tolerance of the studied reef can also be attributed to the Porites-dominant aspect that was considered by several authors, e.g. Marshall and Baird (2000), Loya et al. (2001), Roff et al. (2014), and Lenz and Edmunds (2017), to increase the thermotolerance of reefs. Another explanation might be due to the nature of UAE marine environment. In fact, Dalma Island’s corals being accustomed to the world’s hottest temperatures might have developed a natural change in responding to elevated temperatures by progressively altering their species mix via the loss of the more thermo-sensitive species in favour of the resilient ones. Around the world, similar observations have been made reporting the change from diverse and mixed growth form assemblages to specialized and massive growth-dominated communities, as environmental conditions become less than optimum (Kenyon et al. 2006; Hennige et al. 2010).

Concerning major changes detected, they were mainly associated with the western shore of the island (Zone 1), where ground-truth and thematic classification demonstrated a macroalgal predominance. The observed changes might be the result of a significant variation in the macroalgal community that is due to different conditions during the image acquisition times and/or tidal variation. Macroalgal blooms, common in naturally nutrient enriched coastal waters, were reported to often outcompete corals (Jompa and McCook 2003; Ritchie 2012). Moreover, previous studies have shown the negative effects of a number of macroalgal species on the physiology and health of...
corals (McCook 1999; Nugues et al. 2004). This could be one explanation to the major occurrence of damaged corals and reef rubble in this area, i.e. Zone 1. Besides, the changes detected along the eastern shoreline of the island (Zone 2) are suspected to be due, first, to dredging and man-made activities around the harbour area, and second, to inevitable misregistration of the two images and/or tidal effect as highlighted in Sections 2.2 and 2.4.

Furthermore, with regards to major highlights of this study, it is essential to keep in mind that in situ light measurements were, unfortunately, not available. DHW product, such as the data set used for this study, has successfully generated satellite bleaching warnings and alerts since 2000 (Goreau et al. 2000; Wellington et al. 2001; CRW 2003; Liu, Strong, and Skirving 2003; Skirving et al. 2006; Eakin et al. 2010). However, it does not comprise light measurements, thus, does not dwell on the effect of light stress, which was proven to lead to coral bleaching when modulated by high temperature (Franklin, Cedres, and Hoegh-Guldberg 2006; Jones and Hoegh-Guldberg 2001; Lesser 1997; Smith, Suggett, and Baker 2005). NOAA’s light stress damage product is based on coral physiology and combines satellite measurements of light and SST (Skirving et al. 2016), however, is not yet available for the studied region.

4. Conclusion

The key aspect of this study relies on an environmental stress related to El Niño 2015–2016 event. Contextually, it was primarily aimed to detect the changes occurred in the coral reef environment of Dalma Island using a combination of in situ observations, DubaiSat-2 images, SST, and DHW derived from NOAA’s CRW database. Coral change was presumed to be coral bleaching and damage driven by high positive SSTAs. Analysis of the collected data and the thematic classification emphasized the presence of a continuum of live and pristine corals located 3.5 km off the east coast of Dalma Island (Zone 3), which was not reported or studied before. Outcomes from the adopted approach have shown changes in predominantly macroalgal habitats, whereas the live coral habitat was observed to exhibit no-change facing +2°C to 3°C SSTA reported during the period of this study.

This observed response makes this reef habitat an intriguing case of adaptive response to climate change. This would require further scientific understanding and investigation on possible genetic adaptation and/or shifts in composition of these corals as indicated by studies reviewed by Putnam et al. (2017). In fact, the symbiont diversity that is liable to help coral reefs survive extreme conditions was reported and assumed for moderate climate change (Baker et al. 2004; Baskett, Gaines, and Nisbet 2009). Rarer was the case for pristine coral reefs faced with more extreme change such was the case for the coral reef investigated in this study.

Coral sampling out of the newly spotted reef and study of water quality parameters such as light penetration, nutrient composition, and water circulation are urging consequent steps. Demonstrated cases of evolutionary potential and processes by corals, in response to strong climate change, could apprise about recent reef ecological dynamics, thus reshaping management decisions as indicated by Oppen et al. (2017) and Hughes et al. (2017a). This offshore continuum of pristine corals presents a regional and
international significance as it provides a unique living laboratory for assessing the effects of highly elevated SST and climate change on corals.

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