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BENTHIC HABITAT MAPPING USING REMOTE SENSING DATA AT HURGHADA REGION, RED SEA COAST, EGYPT

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The present research was designed to focus on the utility of Landsat 8-OLI multispectral data for identifying and classifying benthic habitats mapping of the Red Sea after applying atmospheric and water-column corrections at Hurghada city. Atmospheric and water column corrections were applied to the imagery, making it an effective method for mapping benthic habitats. Water column correction was achieved by deriving absorption and backscattering coefficients for each band of the image of clear water pixels. An unsupervised classification (ISODATA) algorithm was applied to generating 22 class habitats. The supervised classification was performed using machine-learning algorithm a maximum likehood and reference points to produce 7 classes of benthic habitat as the following, coral reefs (dense and patch), sea weeds (macro-algae), sea grass (dense and patch), deep water (more than 20 m), shallow water (less than 20 m), sandy bottom (mainly consist of calcium carbonates and silicates) and rocky bottom. Sea weeds (Macroalgae) and deep water areas showed the highest producer's and user's accuracies, when compared to dense seagrass, mixed: seagrass/sand, and mixed: coral/sand areas. Based on 1050 reference points overall accuracy of the benthic habitat assessment is 66.7 percent, with an overall Kappa coefficient value of 0.611.

***Keywords**:* Mapping; Benthic habitat; Remote sensing, Accuracy assessment.

1. INTRODUCTION

The Red Sea is one of the most important marine biodiversity repositories in the world. It has abundant and unique coastal and marine habitats including coral reefs, mangroves, sea weeds and sea grass beds which perform important biological, ecological, aesthetic, and economic functions. They provide key resources for coastal populations: food, shoreline protection and stabilization, and economic benefits from tourism development [1, 2]. The Red Sea is the habitat of over 1,000 invertebrate species, more than 1200 species of fishes, and 200 soft and hard corals. It is the world's northernmost tropical sea [3].

Hurghada was a fishing city and later, in the 1980s became the first tourist resort on the Egyptian Red Sea [4]. Its coast extends for about 46 km along the Red Sea, and it is mainly supported by tourism from water-based sports and activities [5]. Monitoring can provide valuable information on the benthic habitats condition derived from different data sources such as satellite images; field surveys; and local knowledge [6, 7]**.** Anthropogenic impacts on the seafloor alter benthic biodiversity [8], habitats [9], and modify ecosystem structures and functions [10].

Remote sensing is widely used to provide accurate and timely geospatial information describing changes in urban land use/land cover [11, 12]. The importance of remote sensing was emphasized as a ‘unique view’ of the spatial and temporal dynamics of the processes in urban growth and land use change [13-15]. Satellite remote-sensing techniques have been used in detecting, mapping benthic habitat and monitoring land cover change at various scales with useful results [16-18]. The combination of remote sensing with geographical information systems (GIS) and field data collection have been used to assess land cover change and mapping [19-22].

Satellite data has been suggested as a potential tool for monitoring coral-reef ecosystems with several researchers having **tested space-borne** sensor systems [6]. Spatial resolution of these systems ranges from 30 m for the Landsat Thematic Mapper (TM) to 4 m for the Ikonos multispectral data. Those evaluating the utility of the TM have mapped subtidal coastal habitats [23], delineated sand bottoms [24], digitally classified coral reef zones [25], evaluated the benthos [26], and performed time series analyses [15, 27]. Similarly, researchers have used SPOT (20 m) imagery to survey coral reef abundance [28] and apply a spatial statistical approach to multi-date SPOT data to identify coral stress [29].

Coral reefs consist of a mosaic of fine-scale features between 1 to 5 m in size with complex optical signatures that blend as individual fields of view become larger **[27]**. The relatively coarse spatial resolutions of TM and SPOT may have a limited effectiveness in coral reef studies. **Mumby *et al*. [16]** noted that although TM and SPOT can detect benthic signals through clear water to a depth of approximately 25 m, the coarse spatial and spectral resolutions of these systems limit classification results to broad-based geomorphological information, rather than biotic assemblages. The same authors concluded that a pixel size of 3 to 4 m is probably optimal for surveying tropical marine environments. High resolution satellite images such as Ikonos, QuickBird and WorldView would be deemed appropriate for evaluating coral habitats. Recent studies concentrated on using sensors with high spatial resolution such as Ikonos, QuickBird, and WorldView in shallow water mainly to classify and map coral reef communities. These previous sensors help to increase the ability to discriminate the benthic habitat into classes [30, 31]. The combination between satellite data and bathymetric data also assisted in increasing the accuracy of benthic habitat mapping [32]. Early Studies analyzing Ikonos data to assess coral reefs were applied [32, 33]. The previous authors concluded that Ikonos great than Landsat-7 in the benthic habitat classification. QuickBird may have significant potential for discriminating and mapping benthic habitats in tropical-coastal environments [34].

Finally, a benthic habitat can be defined as an area of anything associated with or occurring on the bottom of the deep water seabed [35]. **Brown *et al*. [36]** provided a comprehensive review of benthic habitat map types, data collection techniques, and habitat maps methodologies. Habitat-based approaches have been used for decades in landscape ecology [37, 38]. Due to the species environmental range preferences and requirements, many of these approaches focused on the structure and quantity of potential habitats, in addition to, the distribution of biological populations at the sampling time **[39]**. Habitat maps must be placed in context with the appropriate spatial, temporal, and thematic scales [40]. Scale is considered to be one of the most critical aspects in habitat mapping [41]. Scale is only briefly acknowledged in the extensive literature on benthic habitat mapping, often with little or no treatment of the role of spatial scale in the production of benthic maps and the interpretation of research results [42].

The main objective of the present research was to use Landsat 8-OLI multispectral data for identify and classify tropical-marine benthic habitats, after applying atmospheric and water-column corrections.

2. MATERIALS AND METHODS

2.1. Study area

Hurghada lies between 27° 25 to 27° 9 N and 33° 40 to 34° 8 E. It is the main touristic city of the Egyptian Red Sea which extends from El Gouna Resort to Magawish Resort (Figure 1). It covers approximately 46 km in length and 35 km in width .

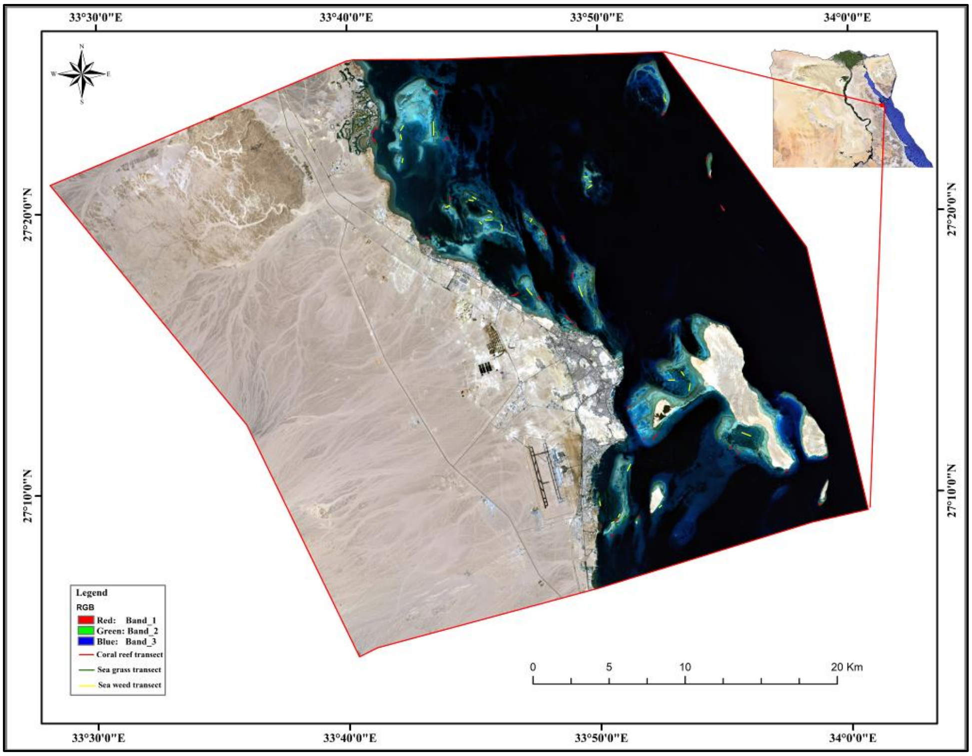


Figure 1: Landsat image indicating the studied location and benthic habitat transects.

2.2. Satellite Data

One Landsat 8-OLI multispectral image was collected for the studied site on 10 July 2015, which downloaded from the United States Geological Survey (http://earthexplorer.usgs.gov/). The Landsat 8-OLI sensor system has 11 bands; each band had slightly different spectral ranges (Table 1). The first four bands can be used for shallow marine applications.

2.3. Image processing

Satellite image was georeferenced and geometrically corrected to match a WGS 84 datum (world geographic system), UTM (Universe Transverse Mercator) Projection with Zone 36 North using ground control points verification using Guno Trimble GPS. This process was completed by using ERDAS software package with Root Mean Square Error (RMSE) of geometric corrected 0. 0035. The image data were radiometrically, atmospherically and water column corrected is based on linear relationship of the spectral radiance and the reflectance of objects on the bottom of the shallow waters using the FLAASH atmospheric correction module of the ENVI® software package (**Figure 2)**. Air-water interface correction was applied using coefficients extracted from **Andrefouet *et al*. [33]**. A manually digitized land

and deep-water mask, was applied to enable processing to focus on just the inter- and sub-tidal shallow waters.

Unsupervised classification (ISODATA) was performed on the image to yield **22** classes for water. The classes validation was conducted by selecting random points for each habitat in the area of the study around Hurghada. Ground truthing data collection was conducted over a period of **10 days in 2015**. About **150** reference points (**Figure 1**) were selected for each water classes in the study area using GPS points for the image data validation, data validation was gathered using georeferenced photo transects collected using snorkeling over the benthic habitat while taking photos with a digital housing camera at a set distance from the bottom, each photo was logged by Guno Trimble GPS and interpreted using Coral Point Count (**CPCe 4.0)** software. Locations of the logged photo were labeled based on common benthic habitat cover classes scheme (**Table 2**) similar to those defined by [43, 44].

A supervised classification and its accuracy assessment were then conducted by selecting specific training data for each benthic cover type. The supervised classification was performed using the model of machine-learning algorithm a maximum likehood and confusion matrix analyses (ENVI 5.2 software) for each image pixels, to calculate the overall accuracy of the classification result and kappa coefficient.

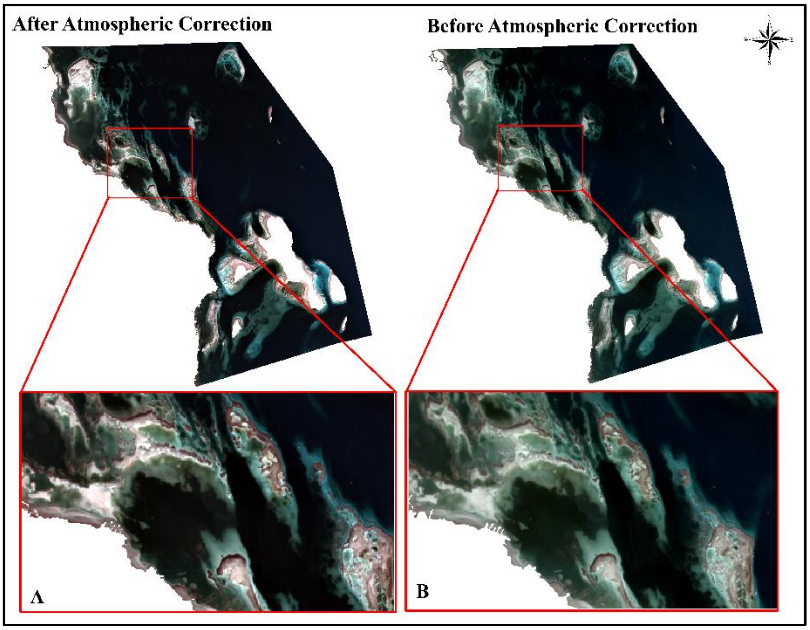
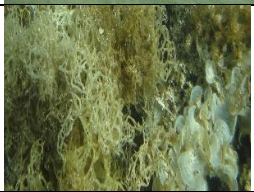
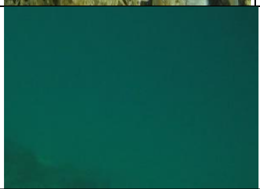


Figure 2: Landsat image before and after the atmospheric correction; (A) and (B) are the zoomed areas near Al Ahiaa district coral reef after and before the atmospheric correction.

Table 1: Landsat 8-OLI sensor spectral bands.

Band Number	**µm**	**Resolution**	**Band Number**	**µm**	**Resolution**
1	0.433–0.453	30 m	7	2.100–2.300	30 m
2	0.450–0.515	30 m	8	0.500–0.680	15 m
3	0.525–0.600	30 m	9	1.360–1.390	30 m
4	0.630–0.680	30 m	10	10.6-11.2	100 m
5	0.845–0.885	30 m	11	11.5-12.5	100 m
6	1.560–1.660	30 m			

Table 2: Benthic habitats classification scheme used in the study.

No	Class	Type	Description
1		Coral reef	Healthy, dead and infected coral reef included. Dominated by any life-form (digitate, branching, tabular, foliose, massive, submissive and encrusting) (>70%).
2		Seagrass	Seagrass bed mostly dense and patch dominated by *Halophila* sp. (>70%) and other species may be present in small quantity.
3		Sand bottom	Mainly calcium carbonate sand, white bright colour (>70%) and some small rubbles.
4		Sea weeds (Macro algae)	Area dominated by brown, green and mixed algae such as *Padina* sp., *Sargassum* sp., *Ulva* sp., *Caulerpa* sp., *Laurencia* sp., *Halimeda* sp., also turf brown algae (>70%).
5		Deep water	That's more than 20 m depth
6		Shallow water	That's less than 20 m depth
7		Rock bottom	Area of mainly rubble (>70%), with small portion of macroalgae, seagrass, or dead coral present.

3. RESULTS

Visually images before and after atmospheric correction revealed a sharp difference. The haziness depicted in the original Landsat image, attributed to Rayleigh and aerosol scattering, was eliminated resulting in a visually clear image as shown in the zoomed images (**Figure 2**). Radiance values of water over different bottom types were analyzed before and after the atmospheric correction.

A comparative evaluation of the classified image was performed against 1050 independents in situ points revealing an overall accuracy of 66.7 percent **(Table 3)**. The overall Kappa statistic, a discrete multivariate accuracy assessment technique described by **Congalton and Mead [45]**, was **0.611 (Table 3)**. This statistic estimates the percent of successful classifications compared to a random, chance classification assignment [46]. Sea weeds (Macroalgae) and deep water areas showed the highest producer's and user's accuracies, when compared to Dense seagrass, mixed: seagrass/sand, and Mixed: coral/sand areas. Sand (very bright), and deep water (very dark) are the two most spectrally distinct classes and yielded the lowest classification errors, whereas the mixed benthos areas had higher error because of the spectral similarities between various features.

The benthic habitat could be classified due to Maximum Likehood Algorithm and in situ data into seven classes as the following: coral reefs (dense and patch), sea weeds (macro-algae), sea grass (dense and patch), deep water (more than 20 m), shallow water (less than 20 m), sandy bottom (mainly consist of calcium carbonates and silicates) and rocky bottom according to scheme **(Table 2 Figure 3)**.

Based on the accuracy assessment, difference in accuracy can be seen in each benthic habitat class according to producers and user's accuracy. Producer accuracy using Landsat 8-OLI in mapping 7 benthic habitat classes of Sea Weed (S.W.), Deep Water (D.W.) and Shallow Water (Sh.W.) are above 80% which are 92%, **86.67**%, **85.33**%; respectively. While the other classes are above 60% of Rocky Bottom (R.B.), Sea Grass (S. G.) and Coral reef (C.R.) which are **69.33%**, **63.33**%, **61.33**%; respectively. Sandy Bottom (S.B.), show **8.67**% (**Table 3 and Figure 4**). The results demonstrated that atmospheric and water column correction can increase the quality of the benthic reef habitat map.

Table 3: Confusion matrix of 7 benthic habitat classes in the shallow waters of Hurghada city based on ground truthing points and Landsat 8-OLI imagery. Overall Accuracy = 66.7%, % and Overall kappa = 0.611.

C.D.	**R. D.**						
	C.R.	**D.W.**	**R.B.**	**S.B.**	**S.G.**	**S.W.**	**Sh.W.**
C. R.	**61.33**	0.00	0.67	22	18.67	4.00	1.33
D. W.	0.00	**86.67**	0.00	1.33	0.00	0.00	13.33
R.B.	0.67	0.67	**69.33**	1.33	1.33	0.00	0.00
S.B.	5.33	0.00	2.67	**8.67**	0.67	1.33	0.00
S.G.	8	0.00	26	20.67	**63.33**	2	0.00
S.W.	12	0.00	1.33	20.67	16.00	**92**	0.00
Sh. W.	12. 67	12.67	0.00	25.33	0.00	0.67	**85.33**

C.D.: classification data**, R. D.:** reference data**, C.R;** Coral Reef, **D.W.;** Deep Water, **R.B.;** Rock bottom**, S.B.;** Sand bottom**, S.G.;** Seagrass **S.W.;** Sea weed, **Sh.W.;** Shallow Water.

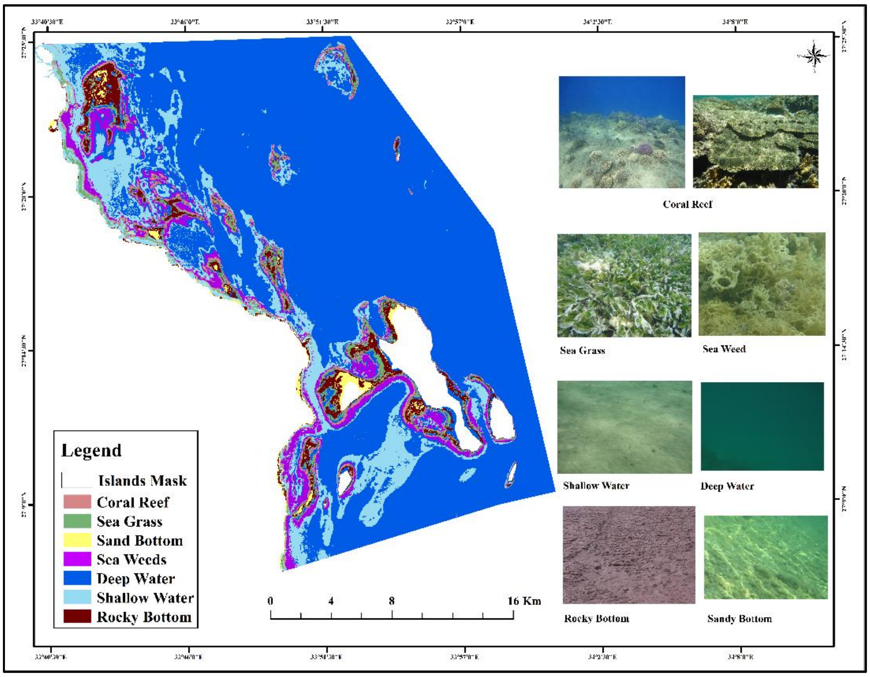


Figure 3: Shows different categories used for classification: dense sea weeds; patch coral; live coral; dense seagrass; deep and shallow water; rocky bottom and sandy bottom. Color coding represents habitat classes as described on Table (2).

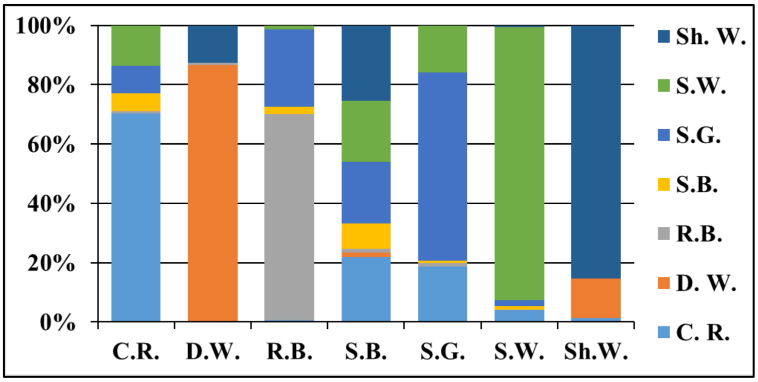


Figure 4: Benthic habitat classification scheme of Hurghada City. **C.R;** Coral Reef, **D.W.;** Deep Water, **R.;** Rock**, S.;** Sand**, S.G.;** Seagrass **S.W.;** Sea weed, **Sh.W.;** Shallow Water.

4. DISCUSSION

Remote sensing provides an important, complementary approach to in situ fieldwork for monitoring benthic habitats in shallow water environments. The study revealed that the near shore features as sand, macroalgae, seagrass and coral reef were mostly abundant. Each feature has different spectral characteristics and be separable as homogenous pixels. In reality, there is a significant amount of intermixing between these features. The complex benthic combinations of a mixed sandy/algal cover, mixed rocky/algal and dead coral/turf algae cover areas and error in depth estimation can also have a considerable impact on the classification results. The details deriving ecological and biological information for each field data point would increase the number of elements separable by a classification scheme.

The primary goals of this research were to assess the utility of the Landsat 8-OLI data and to determine the effects of water column and atmospheric correction on image processing techniques, to improve the benthic habitat classification accuracy. The present study showed the capability of increasing the number of benthic habitat classes due to the water column and atmospheric correction. So, the capabilities of the Landsat 8-OLI sensor were increased for benthic habitat mapping. Hyperspectral studies that may aid in discriminating between the mortality states of live and algae covered coral skeletons [47] can be used to develop baseline spectra to help minimize spectral confusion in satellite imagery.

The unsupervised classification gives more classes after masking, water column and atmospheric correction processes. The present investigation indicated that after completed processes of satellite data especially atmospheric and water column correction, total accuracy of coral reef habitat increased and the overall accuracy of the maximum likehood classification increased from 46% to 66.7% and the Kappa coefficient increased from 65.6% to 66.7%. Depending on the level of classification, previous studies using coarser resolution satellite data (e.g., Landsat TM) have normally achieved accuracies that have ranged from 37 percent [16] to 73 percent [48], even when compensating for the confounding effects of variable water depths. **Mumby** ***et al. [16, 49]*** found the overall accuracy of 4 classes increased from 55% to 73% for (Landsat TM) and 8 classes increased from 38% to 52% (Landsat TM), 13 classes increased from 21% to 37% (SPOT XS), CASI: increased from 72% to 93%**. Mumby** ***et al. [16]*** found the accuracy ranged between 89% and 81% for coarse and fine levels of habitat discrimination while **Roelfsema** ***et al.*** **[43]** mentioned the overall accuracy 62% increased from 11% to 82%. **Andréfouët** ***et al.*** **[33]** found the overall accuracy of the classification of IKONOS 77% for 4–5 classes, 71% for 7–8 classes, 65% in 9–11 classes, and 53% for more than13 classes, for Landsat: 56% for 5–10 classes. **Capolsini** ***et al. [50]*** found that the accuracy of Landsat ETM: increased from 48 to 81%. **Purkis** ***et al. [51, 52]*** mentioned that the overall accuracy was 53% without water column correction and it became 76% after water column correction for Landsat TM while **Nurlidiasari [53]** found the total accuracy of the images increased from 67% to 89% when the water column correction was considered. Finally, by implementing appropriate atmospheric and water-column corrections, and image classification techniques, coarser-resolution Landsat 8-OLI data become a great tool for mapping benthic habitats.

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Conflict of Interest
The authors declare that they have no conflicts of interest.

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تخريط البيئات القاعية باستخدام بيانات الاستشعار عن بعد بمنطقة الغردقة، ساحل البحر الأحمر، مصر

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تم تصميم البحث الحالي للتركيز على فائدة بيانات الاستشعار للقمرالصناعى لاندسات (- 8OLI)المتعددة الأطياف لتحديد وتصنيف وتخريط البيئات القاعية للبحر الأحمر بعد تطبيق التصحيحات الجوية والعمقية لمدينة الغردقة. تم تطبيق تصحيحات الغلاف الجوي وعمق الماء على الصور ، مما يجعلها طريقة فعالة لزيادة القدرة على تخريط البيئات القاعية. تم تحقيق تصحيح العمود المائي للأعماق عن طريق اشتقاق معاملات الامتصاص والتشتت الخلفي لكل نطاق من وحدات البكسل المائية الشفافة للصورة. بعد ذلك تم تطبيق خوارزمية التصنيف الغير مراقب خوارزمية التحليل التكراري الذاتي للبيانات (لإنتاج ٢٢ فئة من البيئات) . تم إجراء التصنيف المراقب باستخدام خوارزمية التعلم الآلية كخوارزمية التشابه القصوى والنقاط المرجعية (البيانات الحقلية) ذلك لإنتاج ٧ فئات من البيئات القاعية على النحو التالي ، الشعاب المرجانية (كثيفة وبقع) ، والأعشاب البحرية (الطحالب الكبيرة) ، والحشائش البحرية (كثيفة وبقع) والمياه العميقة (أكثر من ٢٠ م) والمياه الضحلة (أقل من ٢٠ م) والقاع الرملي (يتكون بشكل أساسي من كربونات الكالسيوم والسيليكا) والقاع الصخري. أظهرت الأعشاب البحرية (الطحالب الكبيرة) ومناطق المياه العميقة أعلى دقة للبيانات الآلية والمرجعية ، عند مقارنتها بالحشائش البحرية الكثيفة او المختلطة: الحشائش البحرية / الرمل ، والمختلطة: الشعاب المرجانية / الرمال. استنادًا إلى ١٠٥٠ نقطة مرجعية(بيانات حقلية) ، فإن الدقة الإجمالية لتقييم البيئات القاعية تبلغ ٦٦.٧ في المائة ، مع قيمة معامل كابا الإجمالية ٠.٦١١ .