Abstract
Remote sensing can provide information about the distribution of the sea bottom types (algae, seagrass, corals, sand, mud etc.) up to a certain extent of depth based on their spectral response. Of course, marine remote sensing is quite complex as the remote sensing signals have to pass through the intervening atmosphere as well as the water column, before hitting the sea bottom. The intensity of light penetrating water decreases with increasing depth and becomes zero after a certain depth. However, with the advancement of remote sensing techniques, it has become possible to map the sea bottom types with a considerable degree of accuracy. This paper deals with the marine habitat classification produced by integration of satellite remote sensing and traditional field survey data. The study area lies in the shallow sea near Fasht-Al-Jarim in the Kingdom of Bahrain. For this study, moderate resolution ASTER (Advanced Spaceborne Thermal Emission and Reflection Radiometer) image of August 2005 has been used. The marine habitat map was produced by automated classification of ASTER image. Before classification, the image was geo-corrected and subsequently correction for atmospheric as well as water column effects were performed. The ground surveyed point data aided in identification of different sea bottom types. Finally, the classified image was checked for accuracy with independent ground surveyed locations and average accuracy over 80% was achieved. The main advantage of this method is that the marine habitats identified at specified locations by the field survey can be extended to a large area with the help of image processing of remote sensing data which can minimize the field survey to a considerable extent.
Keywords: Marine habitat, remote sensing, ASTER, image classification

1.0 Introduction
Remote sensing has long been used as a tool for studying marine habitat and it has proven its potential in identifying various habitats and substrate types. Since the late 60s, aerial and spaceborne photographs have been used to detect submerged features, to study the seabed and to map bathymetry (Ackleson, 2003). With the advent of Landsat satellite, the use of remote sensing images for mapping and monitoring marine habitats has gained more popularity. Since then, numerous attempts have been made to categorize marine habitats utilizing Landsat MSS and TM (Khan et al. 1992, Luczkovich et al., 1993, Mumby et al 1998, Zainal et al. 1993, Zainal 1994, Hochberg and Atkinson 2003)., along with some of the studies concentrating on coral reefs monitoring and change assessment (Mumby et al. 1998, Green et al. 2000, Radiarta et al. 2002, Capolsini et al. 2003). However, detecting submerged habitats from remote sensing image is faced with a lot of challenge as the signal received at the sensor is a mixture of response from the atmospheric path between the sensor and the seafloor as well as the water column overlying the habitat. Most commonly cited difficulties with underwater remote sensing is the confounding influence of variable depth on the bottom reflectance (Cracknell et al. 1987, Ahmad and Neil, 1994, Green et al. 1996, Mumby et al, 1998). Removal of this influence of depth on the bottom reflectance has been attempted by various methods (Lyzenga, 1978; Maritorena, 1996; Bierwirth et al. 1993). Zainal (1994) put forward a regression method based on the critical depth range of each habitat using DEM of the seafloor. Lyzenga (1978, 1981) put forward a image-based approach to compensate for the effect of variable depth when mapping bottom features. Rather than predicting the reflectance of the seabed, this method produces a depth invariant bottom index from each pair of spectral bands. The attractive aspect of this approach of water column correction is that in situ or ancilliary data are not required. Considerable increase in accuracy of
image classification of coral reefs after this water column correction has been reported (Mumby et al. 1998).

The present paper demonstrates the effective integration of remote sensing images and field survey data for marine habitat mapping in the Fasht-al-Jarim area in the territorial water of Bahrain. Habitat mapping is the spatial representation of the classified habitat units. In general, habitats are identified as spatially recognizable areas where the physical, chemical, and biological environment is distinctly different from surrounding environments. In this paper, different types of habitats were identified with the help of remote sensing images and finally categorized through supervised image classification.

The marine environment in Bahrain was surveyed in detail by Vousden (1988). Extensive survey as well as remote sensing based mapping has been performed by Zainal (1994) in the Fasht-Al-Adhm. Under marine GIS projects (MARGIS I and MARGIS II) initiated by Bahrain centre for studies and research, Bahrain, extensive survey on marine habitat, substrates and marine animals was carried out (MARGIS, 2006). The present work was undertaken as a part of MARGISII.

2.0 The study area
The study area consists of the fasht-al-Jarim and the adjoining area in the Arabian gulf, lying north west of the mainland of Bahrain (figure 1). It is bounded by longitudes 50°24’6.9”E and 50°37’52.2” E and latitudes 26°20’15.2”N and 26°34’30.2”N. It covers an area of about 555 sq km. Fashts are very shallow sea beds lying in the intertidal zone which are mostly exposed during low tides and submerged during high tides. The average depth of the seafloor in most of the fasht-al-Jarim is 2m. However, the depth in the surrounding area of the fasht reaches up to 10 m below ground level. Fashts generally supports variety of species of seagrass, coral, algae and fishes. This area is one of the most important known fishing grounds for large number of commercial fishing in Bahrain (Abdulqader et al, 2004). The Fasht also plays an important role in the
hydrodynamic regime of the area north of Bahrain, which in-turn supports the surrounding biological communities (Geomatec, 2006).

![Figure 1. The location map of the study area](image)

### 3.0 Data used

For the present study, moderate resolution ASTER (Advanced Spaceborne Thermal Emission and Reflection Radiometer) image of August 2005 has been used. ASTER is an imaging instrument flying on Terra, a satellite launched in December 1999 as part of NASA’s Earth Observing System. Out of its 14 bands, only the visible-near infrared (VNIR) bands were used for the present study.
ASTER has only 2 bands in the visible region of electromagnetic spectrum, which have good penetration into water. However, large part of the study area being shallow (fasht) area, the NIR band shows considerable reflectance from the sea floor and hence was utilized for classification. These three bands have a spatial resolution of 15 m

The field survey data used in this study were collected as a part of the MARGIS II project. About 100 sea survey sites data have been used for the present study, collected during May/June 2005. These field data have details about the presence of flora and fauna, their percentage coverage, type of seabed substrate and other parameters at a particular location. In order to reduce positional transformation errors, field data was collected from an area of 20 x 20 meter around the centre point. (Geomatec, 2006).

4.0 Methodology
The methodology for the present work can be discussed in three parts: preprocessing, water column correction and image classification. Preprocessing was carried out in order to minimize the geometric, radiometric and the atmospheric effects. The ASTER image was georeferenced to UTM projection zone 39N (WGS 84 coordinate system) with a sub-pixel accuracy. Similarly, the field data points were georeferenced to UTM projection zone 39N (WGS coordinate system) and converted to GIS database. Point maps have been prepared from these data and they have been used to help in image classification.

The image has been subjected to noise removal filter which reduces the periodic noise within the image. After the correction for noise, the next was to remove the influence from the atmosphere from the image data in order to obtain information about the spectral property of different habitats or the substrate. There are several methods of atmospheric correction. Sophisticated methods require accurate measurements of the atmospheric properties from the time of image
acquisition. For this study, dark pixel subtraction (Chavez et al. 1977) has been employed. This method is based on the assumption that somewhere in the image is a pixel with zero reflectance e.g. deep clear water. This method is widely used because it does not require the measurements of atmospheric parameters which are not available many a times. The noise removal followed by the atmospheric correction enhances the interpretability of submerged habitats many fold (Figure 2).

![Atmospherically corrected ASTER image of Fasht-Al-Jarim.](image)

The intensity of the light that penetrates a water body will decrease exponentially with increasing depth. This process is known as attenuation and caused due to scattering and absorption of the light by water itself and substances in the water. At a certain depth, all light has been absorbed and targets located below this depth will be invisible to any remote sensing sensor (Green et al. 2000). Due to
attenuation, the spectral response of habitats varies with depth. As for example, spectral property of sand at a depth of 2m and 10 m depth is different. On the other hand, the spectral property of deep sand may resemble to that of shallow seagrass, causing confusion in classification. As the effect depends on the depth and the substances in the water, a water column correction is often necessary in order make same substrates spectrally similar for different depths, times and locations. In order to compensate for the effects of variable depth, the model derived by Lyzenga, (1978, 1981) was used. Processing creates a single depth invariant band from each pair of spectral bands ($X_i$ and $X_j$). ASTER, with only two water penetrating spectral bands, produced a single depth invariant index band. In the deeper areas, this image revealed more details compared to the color composite of atmospheric corrected ASTER bands. Based on this observation, habitat classification was performed in two parts. Areas having a depth up to 2m were classified separately from the atmospherically corrected ASTER bands and

Figure 3. Bathymetric map of the study area.
for the rest of the area (depth >2m), the single depth invariant band was classified. The bathymetry map was generated through interpolation of the sea depth data (Figure 3) and the entire area was segmented into two parts based on depth (depth less than 2 m and greater than 2 m).

Image classification assigns the pixels to different thematic classes based on their spectral properties. Supervised classification approach was adopted to produce different habitat classes. This scheme relies on the analyst to define distinct areas with a unique spectral signature or training sites. The accuracy of the classification depends to many an extent on the generation of pure, distinct and accurate signatures for each class. The training sites have been selected from the field data, using this as a seed pixel where polygons are automatically drawn around contiguous area having similar spectral properties. Once the training sites are generated, the similarity of the signatures for each class has been measured using statistical methods. Contingency matrix was generated to test the reliability of the signature representing a particular class. The signatures are finalized when a satisfactory percentage of correctly classified pixels are achieved.

The conventional maximum likelihood classifier has been used to the atmospheric corrected bands because this both the variability of the classes and the probability of a pixel belonging to each class are taken in to account in calculating the distance between a candidate pixel and the mean of all classes (Green et. al. 2000). However, the depth invariant band was classified using minimum distance classifier as maximum likelihood classifier needs two or more bands. Finally, the two outputs were merged to produce the habitat map for the entire study area. The initial output of classification often exhibits speckled appearance due to small clusters of pixels. These clusters are identified defining a threshold and removed by majority filter.
5.0 Results and discussion

The habitat classification schemes are based on either ecological or geomorphological characteristics. Within this there can be different levels of details describing a habitat, based on the spectral and spatial resolution of the remote sensing image. Because of the relatively low resolution of the sensor (ASTER), a coarse level classification could be achieved. Finally, five classes of habitats were identified through the classification in the present area (Table 1). These are seagrass, intertidal sand, subtidal sand, rocky substrate and mixed habitat (Figure 4).

<table>
<thead>
<tr>
<th>Class name</th>
<th>Major component (&gt;50%)</th>
<th>Minor component (&lt;50%)</th>
<th>% of total area</th>
</tr>
</thead>
<tbody>
<tr>
<td>Seagrass</td>
<td>Seagrass</td>
<td>Sand, rock covered by algae</td>
<td>22.53</td>
</tr>
<tr>
<td>Intertidal Sand</td>
<td>Mixed sand</td>
<td>Fasht rock, algae, seagrass</td>
<td>8.71</td>
</tr>
<tr>
<td>Subtidal sand</td>
<td>Mixed sand</td>
<td>Rock pavement, algae, seagrass</td>
<td>19.63</td>
</tr>
<tr>
<td>Rocky substrate</td>
<td>Rock pavement, fasht rock, sand</td>
<td>Algae, seagrass, dead coral</td>
<td>42.81</td>
</tr>
<tr>
<td>Mixed</td>
<td>Algae, sand, dead coral, rock, coralline algae</td>
<td>Live coral (occasional), seagrass</td>
<td>6.35</td>
</tr>
</tbody>
</table>

Table 1: Major and minor components of the habitat classes identified from the classification

Sand as a pure habitat is rare in Bahrain’s water (Vousden, 1995). The sand classes represent a combination of medium to coarse sand and sand interspersed with algae and seagrass. Intertidal sand has a distinct bright signature, and readily identified on the color composite. A differentiation between intertidal and subtidal sand has been made because of the important spectral differences between submerged and exposed sandy substrate. The subtidal sand was classified from the depth invariant band and intertidal sand was classified from the atmospheric corrected ASTER bands. The subtidal sand being optically dark, exhibits spectral similarity with dense seagrass and also
rocky substrate. Contingency matrix generated from the training sites revealed that there was signature overlapping between subtidal sand, seagrass and rocky substrate. However, this was overcome to many an extent by using the depth invariant band.

The seagrass class comprises dense and sparse seagrass beds along with patches of sand in between, the coverage ranging between 50 to 100%. This area is dominated by seagrass. The mixed class does not exhibit dominance of any of the habitats but an assemblage of algae, sand, rock, dead coral as major components and seagrass and very little live coral as minor component. The field survey data and respective video reveal that there are small patches of mixed coral, mostly comprising dead coral. However these are not identifiable at this scale of study, partly due to the remote sensing resolution. This can also be explained by the optical similarity of the calcium carbonate skeleton of a dead coral to sparse seagrass within a sand background (Mishra et al. 2003). Malthus Karpouzli (2003), also reports patches of sparse seagrass being confused with fine sand.

The rocky substrate class comprises of rock with a thin veneer of sand or mixed rock. This class is stretched around the fasht covering a large area and extends up to a depth of 10m towards the northeast. In the deeper areas, there was spectral overlap between rocky substrate and subtidal sand. In this area, algae or coral could not be identified as the dominant habitat, because occurrence of these is interspersed with sand and rock. Therefore mixture of algae, rock, mixed sand and dead coral in varying proportions are combine to define the mixed habitat. Live coral reported the field data under this class is of negligible coverage. In some areas, coralline algae has also developed. However, delineation of these components requires hyperspectral and high spatial resolution images.
It is universally accepted that the classification of marine habitat can never be 100% accurate. This is due to the fact that marine environment is by nature very complex. The boundaries of ecological habitats are not distinct line, but a gradational phenomenon. For the accuracy assessment of the classification, about 50 ground truth data were used which have not been used in the image classification. The overall accuracy is 80.39%. However, it should be mentioned that sufficient points were not available under the subtidal sand class, which can overestimate the accuracy for this class.

Figure 4: Marine habitat classification map produced from ASTER image classification
Rocky substrate covers the largest area of about 43%, followed by seagrass (22.5%), subtidal sand (19.6%). Intertidal sand and mixed habitat covers relatively smaller area of 8.7 and 6.35% respectively. The Kappa coefficient is suggested as a measure to summarise confusion matrix statistics. A value of Kappa of 0.75 or greater shows a very good to excellent classifier performance, while a value of less than 0.4 is poor (Mather 1999). The overall kappa coefficient for the present study is 0.72, which is considered as very good, considering the complexity of the marine environment in this area.

<table>
<thead>
<tr>
<th>ClassName</th>
<th>Reference Totals</th>
<th>Classified Totals</th>
<th>Number Correct</th>
<th>Producers Accuracy</th>
<th>Users Accuracy</th>
<th>Area (sq km)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Seagrass</td>
<td>15</td>
<td>14</td>
<td>11</td>
<td>73.33%</td>
<td>78.57%</td>
<td>124.90</td>
</tr>
<tr>
<td>Intertidal Sand</td>
<td>14</td>
<td>13</td>
<td>12</td>
<td>85.71%</td>
<td>92.31%</td>
<td>48.27</td>
</tr>
<tr>
<td>Subtidal sand</td>
<td>4</td>
<td>3</td>
<td>3</td>
<td>75.00%</td>
<td>100.00%</td>
<td>108.81</td>
</tr>
<tr>
<td>Rocky substrate</td>
<td>11</td>
<td>14</td>
<td>9</td>
<td>81.82%</td>
<td>64.29%</td>
<td>237.37</td>
</tr>
<tr>
<td>Mixed habitat</td>
<td>6</td>
<td>6</td>
<td>5</td>
<td>83.33%</td>
<td>83.33%</td>
<td>35.21</td>
</tr>
<tr>
<td>Totals</td>
<td>51</td>
<td>51</td>
<td>41</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Table 2. Accuracy report of the habitat classification map

**Overall Classification Accuracy = 80.39%**

6.0 Conclusion

The remote sensing of marine habitats is always very complex because of the optically similar behaviour of the habitats, the influence of the atmosphere and the water column and association of two or more habitats in the nature. However, remote sensing based methods can be quite effective in identifying the habitats through multispectral classification in conjunction with field survey data. Atmospheric correction followed by water column correction enhances the interpretability of the image to a great extent. The 15 m resolution ASTER bands have a good potential for mapping the marine habitats. The use of color composites from ASTER bands has helped a lot in delineating the habitats up a depth of 0-2 m. The absence of visible blue band restricts its opportunity of water column correction to a single depth invariant band. However, the single depth
invariant band has proven useful in identifying habitats up to a depth of 10m. The results from this study suggest that ASTER image having only two water penetrating band can be successfully used for a coarse level marine habitat mapping up to a depth of about 10m. However, higher resolution satellite images probably can provide fine level mapping.

**Acknowledgement**

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