Change detection and mapping of mangrove using multi-temporal remote sensing data: a case study of Abu Dhabi, UAE

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(Received: January 12, 2013; in final form April 2, 2013)

Abstract: Decline in arid mangrove's area is one of the most serious problems of the United Arab Emirates coastal ecosystems. Tackling of these problems require precise mapping and understanding of the spatial distribution of mangroves on large scale. This is the first study to map and monitor changes in the mangrove eco-systems of Abu Dhabi Emirate, UAE. Fuzzy logic approach was used to map mangroves from multi temporal remote sensing data. The approach requires four precise parameters such as the scale Level, merge level, thresholding and computing attributes. The resultant maps were then enhanced by applying a 3x3 Sobel filter. This enhancement eliminated the noise and improved the quality of the mangrove maps at the density level. Post-classification accuracy assessment was performed using confusion matrix. Changes in mangroves were detected by computing the differences in the classified images. After that, change detection statistics for the periods 1990-2000 and 2000-2006 generated. The results show that the mangrove area has decreased during the periods 1990-2000 and 2000-2006. The decrease in mangrove area were -2.91 km^2 (-0.104%) during 1990-2000 and -2.17 km^2 (0.091%) during 2000-2006. The present study will be of great help to the environmental and coastal engineers and may be used as a background for generating mangrove maps at a finer level.

Keywords: UAE; Mangroves; LANDSAT; Change detection; Fuzzy logic

1. Introduction

TMangroves are reported to have covered up to 75% of the world's tropical coastlines (Spalding et al., 1997). The ecological value of these mangroves is acknowledged in many respects: (i) protecting the coastline from tidal waves and storm surges; (ii) acting as biological filters in polluted coastal areas; (iii) supporting aquatic food-chains; and (iv) shielding a large number of juvenile aquatic organisms (Barbier and Sathiratai, 2004; Hogarth, 1999; Linneweber and de Lacerda, 2002; Lugo and Snedaker, 1974). Mangroves at the moment are, unfortunately, in serious decline due to the expansion of human settlements, the boom of aquaculture businesses, the impact of tidal waves, industrial activity and storm surges (Barbier and Sathiratai, 2004; Linneweber and de Lacerda, 2002). The estimated global mangrove area has declined significantly from 19.8 million ha in 1980 to 14.7 million ha in 2000 (Orth et al., 2006).

In the UAE, mangroves are common in tidal lagoons between Tarif and near Ras Al-Khaimah Emirate. According to Embaby (1993), the environmental and geomorphologic conditions prevailing on the coasts of the UAE are favorable for the growth of Avicennia marina, which can apparently tolerate water of high salinity and dry weather conditions (Howari et al., 2009). The total areal extent of this species in the UAE is estimated to be 38 km2 (Blasco et al., 2001) with a standing biomass between 70 and 110t per ha (Dodd et al., 1999). Recently, the spatial distribution of mangrove forests and seagrass habitat has declined because of industrialization, urbanization and coastal engineering (Orth et al., 2006; Short and Wyllie-Echeverria, 1996). Mangroves play an important ecological role along this coast. They prevent soil erosion, provide natural habitats for a large number of fish and crustaceans and enable high primary productivity through litter fall and decomposition. The local authorities in the UAE encourage programs for mapping and monitoring to estimate the extent of decline of this important ecosystem over large scale. Remote sensing has become an alternative to the traditional field monitoring for large-scale tropical mangrove management (Blasco et al., 1998; Verheyden et al., 2002; Demuro and Chisholm, 2003), mainly because remote sensing technology allows information to be gathered from the inaccessible areas of mangrove forests that would otherwise be, logistically and practically, very difficult to survey.

Remote sensing applications such as change detection are based on a number of instruments on both aerial and satellite platforms, including visible and infrared photographic cameras (Sulong et al., 2002; Verheyden et al., 2002), video recorders (Everitt et al., 1996), synthetic aperture radar (Aschbacher et al., 1995; Held et al., 2003), and multispectral and hyperspectral sensors (Demuro and Chisholm, 2003; Gao, 1999; Green et al., 2000; Held et al., 2003; Ramsey and Jensen, 1996). Although remote sensing applications for mangrove mapping at the fundamental level are wellestablished (Aschbacher et al., 1995; Demuro and Chisholm, 2003; Gao, 1999; Green et al., 2000; Held et al., 2003; Ramsey and Jensen, 1996; Sulong et al., 2002; Verheyden et al., 2002), there is an increasing demand for mangrove maps over a regional scale using multi temporal remote sensing data.

The main objectives of this study were to (1) map mangrove and seagrass and (2) to monitor their changes using multi temporal remote sensing data.

2. Study area

The study area stretches between 24°15′ 12" N and 24° 39′ 48ˇ" N and between 54° 14′ 48" E and 54° 39′ 24" E. It is bound to the east and west by Abu Dhabi Emirate, UAE (Figure 1). It occupies an area of about 1,856 km^2 and extends from Mussafah area in the southwest to Ras Ghanadah in the northeast of Abu Dhabi Emirate. The terrestrial landscape is characterized by the presence of flat, salt-encrusted soil covered by a thin layer of blue–green algae and mangrove stands (Howari et al., 2009). The area belongs to arid region with air temperature ranges from a high of 47C° in summer, to a low of 12C° in winter. The mean annual rainfall is less than 40 mm and evaporation rate exceeds 124 cm yr^{-1} (Al-Sharhan and Kendall, 2003).

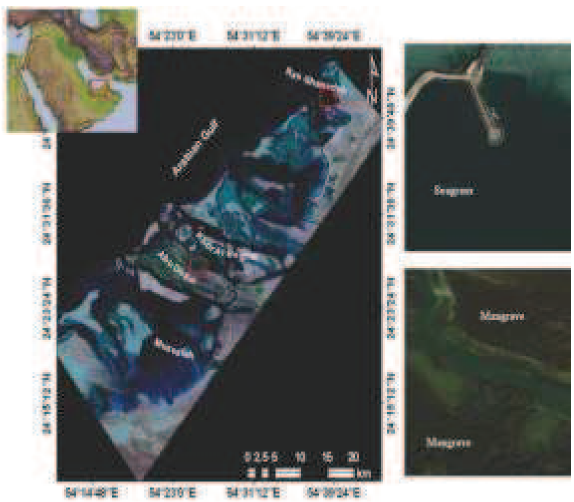


Figure 1: RGB LANDSAT image of the study area

3. Data sets

Three remotely sensed datasets were used in this study. The first data set was multispectral images acquired by the Landsat Themtic Mapper (TM) sensor of Landsat -4 satellite in an area of Abu Dhabi Emirate on 28 August 1990 (Figure 1a). The second data set used was multispectral image acquired by the Landsat Enhanced Thematic Mapper plus (ETM+) sensor of Landsat -7 satellite in Abu Dhabi Emirate on 23th August 2000. The third data set used was multispectral images acquired by Landsat Enhanced Thematic Mapper plus (ETM+) sensor of the Landsat -7 satellite in Al Ain area, Abu Dhabi, UAE on 25th September 2006. All remotely sensed data are in geographic (long/lat) projection, with the WGS84 horizontal datum currently available from the Tropical Rain Forest Information Center (TRFIC) database (http://landsat.org/ortho/index.php).

4. Methods

Before image processing and change detection, three steps are suggested to be performed sequentially for change detection analysis (Canty 2006, Richards and Jia 2006). They are (i) pre-processing. (ii) Image comparison and (iii) image processing and analysis. To decide whether radiometric and atmospheric corrections are needed or not, visual interpretation and histogram analysis were applied on all data sets. The results did not show significant changes due to absence of clouds, haze and rain during the overpass and data acquisition dates. Thus, no atmospheric correction was needed.

The fuzzy logic approach was applied on multi-temporal and multi-spectral remotely sensed data. The approach was found to be the most sensitive and realistic in classification. The approach was selected due to its ability to classify the mixed pixels and has not been reported widely in the literature of change detection applications. This approach begins segmenting the images corresponding to real world objects. The algorithm then simplifies the complex data thematically to delineate boundary of features and to group the small segments together. Finally, the algorithm computes attributes (spatial, spectral and texture) of each object prior to classification.

As a first step, the approach requires proper parameters input from the interpreter. The first parameter, the Scale Level, is related to the delineation of feature boundaries.

A higher Scale Level leads to more segments to be defined. For example, Scale Level of 85 is much better than Scale Level of 55 because the higher Scale Level delineates the boundaries of features better. The second parameter, the Merge Level, is related to the aggregation of small segments within larger areas or grouping the small segments together. For example, Merge Level of 65 is much better than Merge Level of 40.

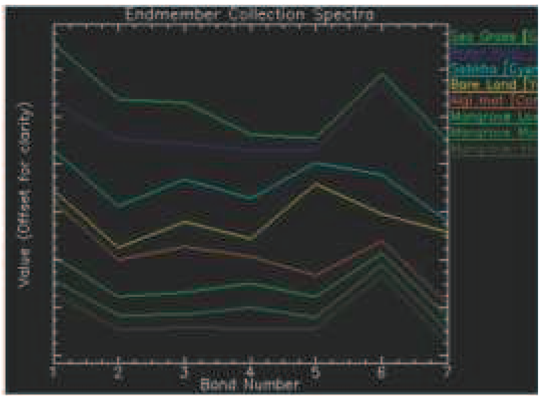
Higher Merge Level would be useful for improving the delineation of tree boundaries. The third parameter, thresholding, is related to the grouping of the adjacent segments based on their brightness to compute attributes. The fourth parameter, which computes attribute, is related to spatial, spectral and texture of each object. Classification was then generated using an image segmentation algorithm (Baatz et al. 2003). Finally, the resultant classification maps were then enhanced and noise was eliminated by applying a 3×3 non linear Sobel filter.

After performing the aforementioned steps, the accuracy assessment was performed on each classified image using confusion matrix by comparing classification result with ground truth information.

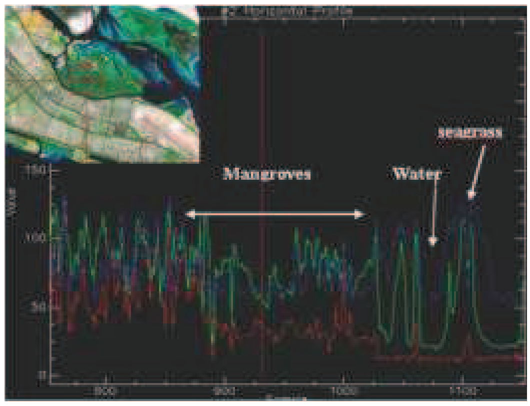
In each case, an overall accuracy, producer and user accuracies, kappa coefficient, confusion matrix, and errors of commission and omission (Congalton, 1991) were reported. The classified maps were corrected visually, using high resolution Quickbird images. After the accuracy assessment, change detection is done using classified images. Change detection statistics were generated. The result is in the form of subtractive maps and the features are represented in two different color codes to facilitate visual interpretation and discriminate new changes.

5. Results and discussion

Endmemeber collection spectra calculated from training sites using Spectral Angle Mapper (SAM) classifier and horizontal spectral profile are shown in Figure 2a. The spectral reflectance of each feature on the ground is very closely associated with leave water content, chlorophyll and leave size (Ramsey and Jensen, 1996). All mangrove classes showed subtle variation of spectral reflectance in visible and infrared regions. For example, dense mangroves showed low values for bands 2, 3 and 5 and slight high value for band 4. In turn, these classes exhibited high values for band 6 indicating a subtitle variation in thermal content of all classes. In visible range, the dense mangrove showed lower reflectance than scattered mangrove and sea grass (Figure 2b).



(a)



(b)

Figure 2: Graphs of end member collection spectra (a) and spectral reflectance of mangroves

The fuzzy logic classification maps extracted from multi-temporal and multispectral images are shown in Figure 3. The use of small value for threshold wasn't able to detect scattered mangroves that distributed in the isolated small islands and along intertidal channels. To overcome this problem, the threshold value was increased to 65. It should be noted that noise and shadows in the classified maps were removed when applying a 3×3 Soble filter and thresholding. The fuzzy logic performed well as compae to the image difference and transformation with regard to qualitative description of surface change .This is primarily due to the types of change that image difference wasn't able to detect and discriminate. To perform accuracy assessment for the produced classification maps, the program automatically picked up 450 random samples points and 50 ground-truth points. The accuracy assessments of fuzzy logic classification from multi temporal remote sensing data are summarized in table 1. The 2000 and 2006 classification image had an overall accuracy of 88.52 % and 89.82 % respectively. The 1990 classification image had the overall accuracy of 95.84 % and kappa value of 0.9429. The significant enhancements in the classified maps accuracy were also noticeable graphically by comparing the Figure 2 with Figure 3.

Post-classification change detection based on class comparison was accomplished using the three fuzzy logic classification images during the period of 1990-2000 and 2000-2006. The 1990 and 2000 classified images were combined together, resulting in eight change detection classes. The classification maps show that the dense mangroves increase in trunks and along intertidal channels where the sea water intrusion increases. The dense mangroves very closely associates with better tidal interchange (Allen, 1965). In turn, seagrass and algi mat had increased in shallow water of intertidal lagoons and channels.

The change detection images (Figure 4) show that the new changes during the period of 1990-2000 are much higher than the period of 2000-2006. These changes include all classes such as mangroves and sea grass as well as sabkha and bare land. These changes very closely associate with industrial, natural process and urban development a (Howari et al., 2009).

The dense mangrove showed slight decreasing during the period of 1990-2000 and 2000-2006. The difference values were -2.91 km^2 (-0.104%) during the period of 1990-2000 and -2.17 km^2 (0.091%) during the period of 2000-2006. In turn, seagrass and algi mat showed significant increasing

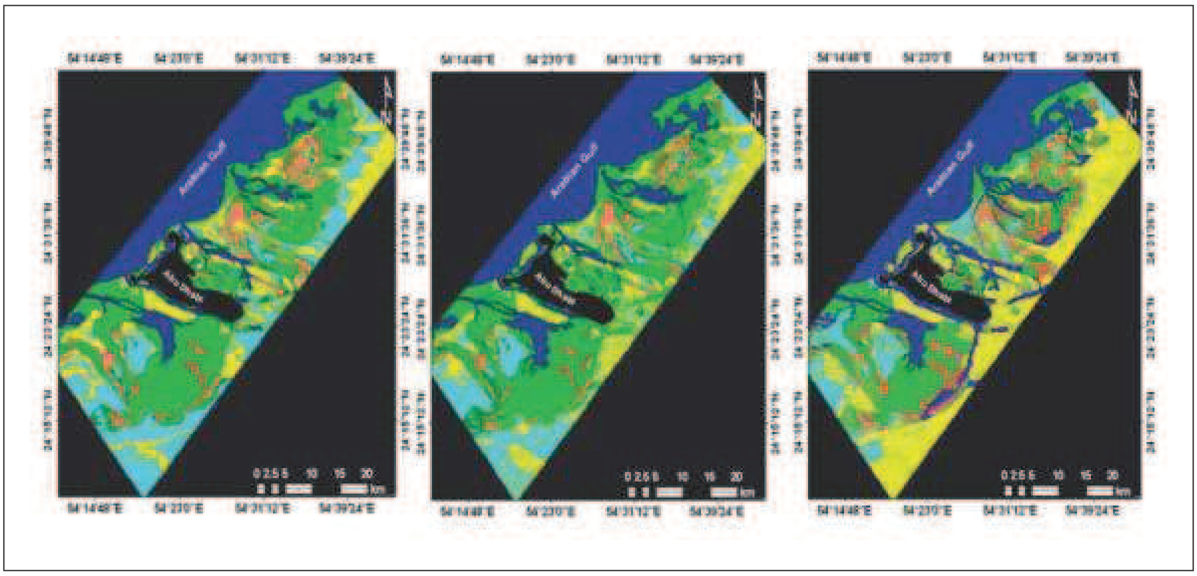


Figure 3: Classification maps derived from multi temporal remote sensing data using fuzzy logic approach

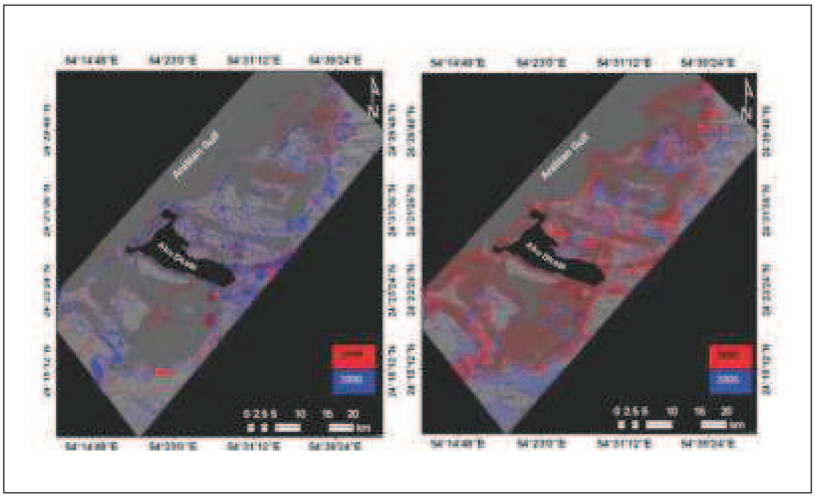


Figure 4: Computed image differences of the classified images of 1990-2000 and 2000-2006

Table 1: Accuracy assessment of the classified maps

	1990		2000		2006	
Class	**Prod. Acc. %**	**User Acc. %**	**Prod. Acc. %**	**User Acc. %**	**Prod. Acc. %**	**User Acc. %**
Mangrove High density	68.01	92.32	76.90	82.28	51.33	81.75
Mangrove M. Density	73.80	56.20	43.22	42.69	71.16	15.99
Mangrove Low Density	91.62	64.07	91.08	42.41	17.38	46.74
Algimat	98.81	99.63	93.80	99.10	96.19	91.63
Sea Grass	98.88	98.52	91.97	89.83	97.31	99.73
Water Body	99.37	98.23	99.30	97.53	97.30	100.00
Bare Land	95.49	97.45	81.53	93.20	93.72	97.39
Sabka	94.11	89.82	87.38	67.88	96.07	87.76
Overall Accuracy =	(112852/118194) **95.4803%**		(104632/118194) **88.5256%**		(59465/66200) **89.8263%**	
Kappa Coefficient =	**0.9429**		**0.8564**		**0.8756**	

during the period of 1990-2000 and 2000-2006 (Table 1).

Although dense mangrove can be discriminated from non-dense mangrove very accurately from LANDSAT images, these data can only discriminate three mangroves at the density level. This is due to the low spatial resolution of LANDSAT images (30m).

6. Conclusion

This study reveals potential and capability of remote sensing for coastal management, change detection and mangroves mapping. In brief, this study presented fuzzy logic approach to map and monitor changes in mangroves and seagrass from multi temporal remote sensing data. The results of change detection and classification using multi temporal remote sensing data show significant changes along the shoreline of Abu Dhabi Emirate during the period of 1990-2006. This study detected slight changes in mangroves and seagrass from multi temporal remote sensing data using fuzzy logic classifier. Mangroves had decreased in locations along the shoreline, creek banks of Abu Dhabi. In turn, mangroves had increased in other locations where they experience frequent tidal interchange, with their roots and lower trunks being normally covered at high tide (Al-Sharhan and Kendall, 2003).

From the point view of this study, using spectral signatures of mangroves alone was not adequate for mangrove classification if the study area is characterized by many species. Thus, ground truthing and field investigation are needed to resolve the spectral bias of mangrove and seagrass species.

Despite the low resolution of LANDSAT images and low discrimination of mangrove species, it was found that the fuzzy logic approach for mapping and detecting changes in mangroves at the density level in remote and inaccessible sites was worth as it considerably increased the mapping accuracy. The present study is of great help to the environmental and coastal engineers.

For the method to be more generally applied, more remote sensing data and ground truthing are needed. Future work will involve the application of hyperspectral remote sensing data and LiDAR in order to detect species and mangrove diseases.

References

Allen, J.F. (1965). Coastal geomorphology of Eastern Nigeria: beach ridge barrier islands and the vegetated tidal flats. Geologie en Mengib, 44, 1–21.

Al-Sharhan, A.S. and C.G. Kendall (2003). Holocene coastal carbonates and evaporites of the southern Arabian Gulf and their ancient analogues. Earth-Science Reviews, 61, 191–243.

Aschbacher, J., P. Tiangco, C.P. Giri, R.S. Ofren, D.R. Paudyal and Y.K. Ang (1995). Comparison of different sensors and analysis techniques for tropical mangrove forest mapping. In: editors (Eds.), Proc. Geoscience and Remote Sensing Symposium, IGARSS 95, Quantitative Remote Sensing for Science and Applications, Firenze, 10-14 July 1995, pp. 2109-2111.

Baatz, M., U.C. Benz, S. Dehghani, M. Heynen, A. Höltje, P. Hoffmann, I. Lingenfelder, M. Mimler, M. Sohlbach, M. Weber and G. Wilhauck (2003). eCognition object oriented image analysis user guide. Definiens, Munchen.

Barbier, E.B. and S. Sathiratai (2004). Shrimp Farming and Mangrove Loss in Thailand. Edward Elgar, Cheltenham.

Blasco, F., J.L. Carayon and M. Aizpuru (2001). World mangrove resources. Glomis Electronic Journal, 1(2), 1–3.

Blasco, F., T. Gauquelin, M. Rasolofoharinoro, J. Denis, M. Aizpuru and V. Caldairou (1998). Recent advances in mangrove studies using remote sensing data. Marine and Freshwater Research, 49 (4), 287–296.

Canty, M.J. (2006). Image Analysis, Classification and Change Detection in Remote Sensing, CRC Press, Taylor & Francis.

Congalton, R.G. (1991). A review of assessing the accuracy of classifications of remotely sensed data, Remote Sensing of the Environment, 37, 35-46.

Demuro, M. and L. Chisholm (2003). Assessment of Hyperion for characterizing mangrove communities. Proc. the 12th JPL Airborne Earth Science Workshop, NASA Jet Propulsion Laboratory, Pasadena, CA. 24–28 February, 10 pp. on CDROM.

Dodd, R.S., F. Blasco, Z.A. Rafii and E. Torquebiau (1999). Mangroves of the United Arab Emirates: ecotypic diversity in cuticular waxes at the bioclimatic extreme. Aquatic Botany, 63, 291–304.

Embaby, N.S. (1993). Environmental aspects of geographical distribution of mangrove in the United Arab Emirates. In: Lieth, H., and Al Masoom, A. (eds.), Towards the Rational Use of High Salinity Tolerant Plants, Volume 1. Dordrecht, The Netherlands: Kluwer Academic Publishers. pp. 45–58.

Everitt, J.H., F.W. Judd, D.E. Escobar and M.R. Davis (1996). Integration of remote sensing and spatial information technologies for mapping black mangrove on the Texas gulf coast. Journal of Coastal Research, 12 (1), 64–69.

Gao, J. (1999). A comparative study on spatial and spectral resolutions of satellite data in mapping mangrove forests. International Journal of Remote Sensing, 20(14), 2823–2833.

Green, E.P., C.D. Clark and A.J. Edwards (2000). Image classification and habitat mapping. In: Edwards, A.J. (Ed.), Remote Sensing Handbook for Tropical Coastal Management. UNESCO, Paris, pp. 141–154.

Held, A., C. Ticehurst, L. Lymburner and N. Williams (2003). High resolution mapping of tropical mangrove ecosystems using hyperspectral and radar remote sensing. International Journal of Remote Sensing, 24 (13), 2739–2759.

Hogarth, P.J. (1999). The Biology of Mangroves. Oxford University Press, Oxford.

Howari F.M, R.J, Benjamin, N. Bouhouche and S.W. Echeverria (2009). Field and Remote-Sensing Assessment of Mangrove Forests and Seagrass Beds in the Northwestern Part of the United Arab Emirates. Journal of Coastal Research, 25(1), 48-56.

Linneweber, V. and L.D. de Lacerda (2002). Mangrove Ecosystems: Function and Management. Springer, Berlin.

Lugo, A.E. and S.C. Snedaker (1974). The ecology of mangroves. Annual Review of Ecological Systems 5 (1), 39–64.

Orth, R.J., T.J. Carruthers, W.C. Dennison, C.M. Duarte, J.W. Fourqurean, K.L. Heck, A.R. Hughes, G.A. Kendrick, W.J. Kenworthy, S. Olyarnik, F.T. Short, M. Waycott and S.L. Williams (2006). A global crisis for seagrass ecosystems. Bioscience, 56(12), 987–996.

Ramsey, E.W. and J.R. Jensen (1996). Remote sensing of mangrove wetlands: relating canopy spectra to site-specific data. Photogrammetric Engineering and Remote Sensing, 62 (8), 939–948.

Richards, J.A. and X. Jia (2006). Remote Sensing Digital Image Analysis, 4th ed., Springer-Verlag, Berlin.

Short, F.T. and S. Wyllie-Echeverria (1996). Natural and human induced disturbance of sea grasses. Environmental Conservation, 23(1), 17–27.

Spalding, M.D., F. Blasco and C.D. Field (1997). World Mangrove Atlas. International Society for Mangrove Ecosystems, Okinawa.

Sulong, I., H. Mohd-Lokman, K. Mohd-Tarmizi, A. Ismail (2002). Mangrove mapping using Landsat imagery and aerial photographs: Kemaman District, Terengganu. Malaysia Environment, Development and Sustainability, 4 (2), 135–152.

Verheyden, A., F. Dahdouh-Guebas, K. Thomaes, W. De Genst, S. Hettiarachchi and N. Koedam (2002). High-resolution vegetation data for mangrove research as obtained from aerial photography. Environment, Development and Sustainability, 4 (2), 113–133.