Chapter 13

A Review of Remote Sensing Techniques for the Visualization of Mangroves, Reefs, Fishing Grounds, and Molluscan Settling Areas in Tropical Waters

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Abstract: Globally there has been tremendous progress in space technology especially in the field of satellite remote sensing applications during the past five decades. Satellite based sensors provide a repetitive and synoptic coverage of inaccessible / larger areas which generated a time series database useful in identification and mapping of environment and resources. These databases form a scientific tool for various stakeholders to device suitable strategies for management of coastal and marine resources. This chapter analyses the various applications of satellite remote sensing and numerical modelling on identification and mapping of mangroves, coral reefs, fishing and molluscan grounds in the coastal marine ecosystems with relevant case studies and illustrations. The mapping methods for mangroves explains the classification protocols, advantages in using different remote sensing techniques and the comparison of different mapping techniques. In case of reef mapping, the vulnerability mapping of reefs due to extreme events is also discussed. Fish movement in a dynamic environment and the mapping of these movements with the help of proxy indicators are also detailed. Molluscan mapping is done based on the biomass differences during different seasons and their physical attributes.

Keywords: Mapping, Satellite image, Mollusc, GIS

13.1 Introduction

Tropical coastal waters of the world are rich in diverse resources such as mangroves, coral reefs, fishes and other invertebrates. Proper monitoring and

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assessment of these resources are important for their management. With the advent of technologies in Satellite Remote Sensing (SRS), coastal resource managers utilize this technique for resource assessment and mapping in a geo-spatial platform which form a useful database supporting their decision making. The mapping technique required for each resource is different and various approaches are available for implementing such techniques. In this chapter, we are discussing the various approaches utilized globally for coastal resource mapping with the help of some case studies.

13.1Mapping of mangroves

Mangroves are unique ecotones (Dahdouh-Guebas 2001) occurring along the sheltered inter-tidal coastlines, mudflats and riverbanks in association with the brackishwater margin between land and sea, and whose biogeographic distribution is generally confined to the tropical and subtropical regions. Nearly 75% of the mangrove density is found in just 15 countries between 5° N & S latitude (Giri et al. 2007, Spalding 1997) and only 6.9% are protected under the existing protected areas network. They sustain diverse species of flora and fauna in large proportion. Their importance is recognizable in various ecosystem services specifically in:

I. Forestry (provision for wildlife reserves, medicinal plants, timber products, feed supplement) (Giri et al. 2007),
II. Fisheries (provision of fishing areas, supporting aquatic food chains, aquaculture and as breeding, spawning, hatching and nursing grounds for the juveniles of many commercial fish and crustacean species (Robertson and Duke 1987, Tong et al. 2004),
III. Environmental conservation (coastal protection from storm, reduction of shoreline and river bank erosion, sediment stabilization, absorption of pollutants, store floodwaters, recharge groundwater aquifers, carbon storage and exports), and
IV. Human inhabitation, recreational opportunities and aesthetics (Barbier and Sathiratai 2004, Saenger et al. 1983, Giri et al. 2007).

Historically, the extent of riparian vegetation has been mapped using simple aerial photograph interpretation (API) and field observation. These conventional techniques of mapping are time-consuming, costlier, subjective, and difficult to repeat on account of inaccessibility to muddy terrain and prevalence of a number of tidal creeks and channels in these ecosystems. These disadvantages limited the further applications of the traditional techniques to large catchments where continuous monitoring of riparian vegetation is required (Yang 2007).

13.2.1 Remote sensing of Mangroves

The remote sensing (RS) facilities provide timely and cost-effective data over inaccessible areas (Everitt et al. 1991, Mumby et al. 1999), complementing field surveys, which are of higher information content, especially in the case of mangroves (Giri et al. 2007). A combination of RS and ground-truth measurements, analysed within a geographic information system (GIS) platform, is found to be highly advantageous (Dahdouh-Guebas et al. 2005a, b, Satyanarayana 2007). The remote sensed data adopted for mangrove classification can be grouped mainly into Satellite (optical), aerial- based and photographic images (Dahdouh-Guebas et al. 2000).

13.2.1.1 Satellite Remote Sensing of Mangroves

Satellite Remote Sensing (SRS) of mangroves are economic, less timeconsuming, provides better coverage, repeatability, provide information on surrounding land uses and their temporal changes so that the wetlands can be monitored seasonally or yearly. Globally, SRS is a reliable tool for the estimation of mangroves (Dahdouh-Guebas et al. 2000; Kovacs et al. 2005, Dahdouh-Guebas et al. 2000). The quality of the satellite products is generally dependent on the weather conditions and nature of the vegetation examined (Blasco et al. 2001). SRS applications in mangrove management are used for three purposes: resource inventory particularly species identification (Vaiphasa et al. 2005) or leaf-area index estimation, change detection, selection and inventory of aquaculture sites (Green et al. 2000). Recently SRS evolved as the best technique for mangrove assessment and mapping, comparison of two appropriate techniques for accurate mapping of mangroves and to study the effects of shrimp farming to mangrove environments.

13.2.1.1 Mangrove Distribution vis-à-vis SRS:

Characterization of any vegetation pattern includes measurement of variations through time as well as across space (John 2011). Meza Diaz and Blackburn 2003 described the spectral-response signal variations of the mangrove canopy as a function of a series of optical (leaf area index, background reflectance, leaf inclination), biophysical (internal leaf structure, the number of cell layers, intercell spaces, air–water interfaces, cell size), chemical (water, cellulose, lignin, protein content, key leaf pigments chlorophyll a and b, carotenoids) and environmental (distance from the sea or the estuary bank, frequency and duration of tidal inundation, salinity, composition of soil) properties. Periodic climatic changes, species composition, distribution pattern, growth form, density, and stand height in mangroves are also responsible for the spectral response.

13.2.1.1 Change Detection in Mangrove Areas using SRS:

Tong et al. 2004 suggested that the physical and structural attributes of mangrove trees can be used for delineating the mangrove forests from mangrove mixed with shrimp farms utilizing *Système Pour l'Observation de la Terre* (SPOT) data. Attempts were made to estimate biochemical and biophysical parameters of wetland vegetation using satellite data (Artigas and Yang 2006, Filippi and Jensen 2006). Wang et al. 2004 inferred that greater spectral distinction between species found during periodic climatic changes may be considered as an attribute for mangrove species wise identification using remote sensing.

13.2.1 Aerial Photography of Mangroves

When the high spatial resolution of aerial photography is useful for discriminating substrates along narrow ecotones (Manson et al. 2001), their expensive data acquisition protocol/methods particularly for large-scale coverage, intensive pre and post-processing methods and the lack of global appeal (Lucas et al. 2002), compared to other sensors may be emphasized as their disadvantages. But, when the archives of aerial photographs which already exist for many coastal locations become the only source of data for assessing long-term, historical distribution changes of such study areas (Dahdouh-Guebas et al. 2000, Dahdouh-Guebas et al. 2004a,b), these data become invaluable.

Kanniah et al. 2007 remarked that accurate discrimination among mangrove species was possible using aerial photographs (Kairo et al. 2002) or images from airborne sensors such as CASI (Compact Airborne Spectrographic Imager) (Green et al. 1998, Wang et al. 2004), MASTER (MODIS/ASTER

Airborne Simulator) and AVIRIS (Airborne Visible/Infra-Red Imaging Spectrometer) (Vaiphasa and Ongsomwang 2004). Chavaud et al. 1998 mapped mangrove communities using colour aerial photography, multispectral satellite ASTER, and airborne hyperspectral AVIRIS data to find that aerial photography is the best mapping technique.

13.2.3 Different techniques employed in Satellite based Mangrove mapping

13.2.3.1 Multispectral Sensor Based Mangrove Mapping

Multi-spectral data acquisition sources such as Landsat Thematic Mapper (TM) and the SPOT satellite were used for coastal studies in countries such as Kenya (Brakel 1984), Bangladesh (Borel 1985), Ecuador (Terchunian et al. 1986), Thailand (Silapathong and Blasco 1992), Australia (Dale et al. 1996) and the Bay of Bengal (Blasco et al. 1994). SPOT is used for better discrimination and mapping of mangroves in most tropical and subtropical countries (Spalding 1997, Green et al. 1998, Gao 1999, Tong et al. 2004) TM and SPOT data have been used for studying water turbidity and depth in marshes, as well as the seasonal dynamics of inundation and turbidity (Bustamante et al. 2009), apart from land-cover mapping and changes in large coastal sheds (Klemas 2011a). Optical-based multispectral data, specifically Landsat TM images are the most common and important data source for wetland classification and monitoring (Harvey and Hill 2001, Phillips et al. 2005, Baker et al. 2006, Wright and Gallant 2007). Ahern and Teckie 1987 preferred Landsat TM over Landsat Multispectral Scanner (MSS) in detecting forest mortality that occurred due to forest fires and insect attack.

One of the major works in India on mapping of mangroves using Landsat MSS data and IRS-1A LSS data was carried out by Venkataratnam and Thammappa 1993 along the coastlines of Andhra Pradesh to monitor the areas of prawn farming. The commercial high spatial resolution (<5 m) multispectral satellite sensors such as IKONOS and QuickBird were used for discriminating mangrove species with an accuracy of 75.3% and 72.2% respectively to provide a baseline database for their future monitoring and management (Neukermans et al. 2008,Wang et al. 2004). Species specific distribution maps and species delineation maps along coast lines have been attempted to successful results using MSS by Green et al. 1998, Kovacs et al. 2001 and

Simard et al. 2006. Gao 1998 used a combination of aerial photographs at a nominal scale of 1:12500 and SPOT satellite image to identify the temperate mangroves.

13.2.3.1 Hyperspectral Sensor and Radar Based Mapping of Mangroves

Relatively low species diversity in mangrove vegetation makes them an ideal focus for development and calibration of new methodologies in SRS based classification using AVHRR (Advanced Very High Resolution Radiometer), MODIS (Moderate Resolution Imaging spectro radiometer) and WiFS (WideField Sensor). Hyperspectral remote sensing is also a wonderful tool used in detecting and mapping coastal vegetation species and in discriminating between multiple species (Vaiphasa et al. 2005). High-resolution imagery, which contain hundreds of narrow spectral bands located in the visible, NIR, mid-IR, and sometimes thermal portions of the electromagnetic (EM) spectrum (Jensen et al. 2007), is more sensitive to within-class spectral variance which adds to its efficiency in SRS (Ozesmi and Bauer 2002).

Hyperspectral imaging systems are available for airborne as well as satellite-borne applications, thereby assisting in species discrimination on a global scale (Pengra et al. 2007).

Table 13. 1 Comparison of the prominent hyperspectral sensors used in mangrove mapping.

Hyperspectral sensors used	Advantages in using the technology	References
Radar	All-weather capabilities, sensitivity to changes in canopy structure and density, increased spatial resolution, time series data source	Baghdadi et al. 2001, Novo et al. 2002
LiDAR	Measure vegetation structure, canopy height, biophysical attributes over large areas and mangrove colonization rates	Lefsky et al. 2005, 2002
AVHRR , MODIS and WiFS	Sensor-derived phenology studies	Jaganathan et al. 2010

Based on the above mapping technologies, a lot of application studies occurred at global level. Some of the research works using hyperspectral technology are summarized in Table 13.2

Table 13.2 Case studies on hyperspectral sensor based mapping of mangroves.

Hyperspectral sensor	Study area	Ecological	Cited

technique		significance	
Hyperion	Australia	8-class species communities	Demuro and Chisholm 2003
AIRSAR		Integration of ecological data to upgrade mapping accuracy	Vaiphasa et al. 2005 Lucas et al. 2002
Radar	Ganges delta of Bangladesh	Delineation of flooding boundaries within Mangrove stands	Wang and Imhoff 1993
Phased array L-band synthetic aperture radar (PALSAR)	Guinea, West Africa	Object-based image analysis (OBIA) approach in classifying and mapping	Fransisco et al. 2013
AVIRIS sensor	Everglade, Florida	Mapping to species level, Delineation of the invasive lather leaf	Hirano et al. 2003
CASI and AIRSAR	Daintree estuary, Australia	Mangrove zonation and green-biomass with accuracy of 71%	Alex et al. 2003
LIDAR	Hunter region, Australia	Delineation of invasive *Phragmites* from low marsh plants	Yang and Artigas, 2010
Lidar and IKONOS	Greater everglades	Estimation of the green biomass of mangrove vegetation	Chadwick 2011
INSAR and LIDAR	Columbia	Measurement of the 3-D vegetation structure and biomass	Simrad et al. 2008
MSS and LIDAR	Savanna river swamp forest	Detection of changes in vegetation cover	Jensen et al.1987

Though useful in many aspects, the hyperspectral remote sensing is disadvantageous in many ways. The high-dimensional characteristics of hyperspectral data causes low output classification accuracy. The high sensitivity to within-class spectral variance make separation of spectrally mixed land-cover types more difficult (Jensen et al. 2007). Apart from complicated image-processing procedures, low signal-to-noise ratios and voluminous data necessitating the use of specific software packages added to their disadvantages. The negativities will be added up more in tropical climatic conditions on account of a range of additional challenges related to prolonged periods of cloud cover, combined with low accessibility, high temperatures and humidity during ground validation campaigns.

Reviews of works from India is concentrated on the mangroves situated at Pichavaram & Muthupet estuary (Selvam et al. 2003), Ennore creek (Chaves and Lakshumanan 2008), Curtorim village in south Goa district (Pawar and Kolapkar, 2013), Indian coast as a whole (Nayar and bahuguna, 2001) etc. The majority of the studies revolved around change detection analysis (Ajithkumar 1998, Selvam et al. 2003, Chaves and Lakshumanan 2008) where in Landsat images and IRS images complemented with ground truthing were processed using supervised classification to discriminate the mangrove age group wise for strategic analysis from a conservation point of view.

13.2.3 Scientific protocols followed for mapping mangroves

The imagery obtained from various data acquisition sources needs to be classified based on the user requirement. Various classification methods have been used to distinctly separate the images to identify various species of mangroves (Fig.13.1). Green et al. 1997 used the classification methods such as visual interpretation, (after conversion to a vegetation index), pixel-based, and principal component analysis [PCA]) to identify mangrove habitat categories.

Fig. 13.1 Various classification protocols followed for mangrove mapping

13.2.4 Pixel-based techniques

Kanniah et al. 2007 in an attempt to classify mangroves of Malaysia using perpixel classification approaches, identified that Maximum Likelihood (ML) classifier is the most robust per-pixel classification method in accurate mangrove mapping. Saito et al. 2003, attempted to test and select the best methodological approach to discriminate and map the mangroves and related coastal ecosystems in the United Arab Emirates (UAE) by comparing three classifiers, namely Minimum Distance (MD) classifier, Maximum Likelihood (ML) classifier and Mahalanobis (MHB) classifier of which the latter gave satisfactory global results for coastal water content in the study area.

Sub-pixel classification (linear mixture modelling): Linear mixture modelling is an image classification technique to map the relative abundance of surface materials present within a pixel. The proportion maps of forest species derived from the LMM (**linear mixture modelling)** of remotely sensed data can be utilized for forest management such as harvesting plan and ecological conservation when such images are combined with age or stand maps of forest species (Kanniah et al. 2007).

13.2.4.1 Object based classification

Object-based classification methods incorporate spatial neighbourhood properties, by segmenting/partitioning the image into a series of closed objects which coincide with the actual spatial pattern and then proceed to classify the image. Fransisco et al. 2013 used object based classification to segregate different mangrove species in Guinea coast.

13.2.4.2 Fuzzy classification

Mangrove mapping can also be realized through fuzzy classification of the contrast-stretched multispectral image. This fuzzy method takes into account the affinity of a pixel and its neighbours to several image classes (Melagni et al. 2001).

13.2.4.3 ISODATA classification

An unsupervised Iterative Self-organizing Data Analysis (ISODATA) classification was used to discriminate mangroves from other types of vegetation to each Landsat image subset by Green et al. 1998. A case study is explained in Fig 13.2.

Fig 13.2 ISODATA Unsupervised classification of Puthuvypin mangrove patches. Landsat 8 is used here with OLI sensor multi spectral (11 Bands including PAN) and medium scale resolution (30 m; PAN 15 m) remote sensing data during 13 Jan 2015 and Survey of India Toposheet No.58 B8 scale1:50,000 data have been used in this study and plotting was done with ENVI and ArcGIS software.

13.2.4.4 Neural network classifications

Artificial Neural Networks (ANN) has been used in SRS applications to classify images, extract biophysical characteristics and incorporate multisource data (Benediktsson et al. 1993). The ability to incorporate non-normally distributed numerical and categorical GIS data and image spatial information, the considerable ease in using multidimensional datasets, and the efficacy in capturing some of the inherent nonlinearity in such data (Gopal et al. 1999) make the method more advantageous in classification. ANN was used to discriminate conifer stand age in southern Brazil and to measure photosynthetically active radiation (PAR) (Weiss and Baret 1999). They found that ANNs predicted biophysical variables more accurately than NDVI-based methods. Gopal et al. 1999 used ANNs and remote sensing to detect conifer forest change after a long drought in the Lake Tahoe Basin in California. Other ANN land cover mapping studies exhibited overall accuracy rates from 85 to 95% (Benediktsson et al. 1993, Yoshida and Omatu 1994).

Fig 13.3 Maximum Likelihood classification of Puthuvypin mangrove patches. In this study we modified the low resolution multi-spectral bands to high resolution (15 m) bands using PCA pan-sharping method. High resolution Landsat data are geo-rectified using SOI toposheet and ground control points. Landsat 8 data having spectral radiance is converted to reflection by using the formula: $\lambda' = \frac{\mathrm{M\rho Qcal} + Ap}{\mathrm{Sin\ (\emptyset SE)}}$ after radiometric correction and finally sub setting the mangroves.

Fig 13.4 Support vector machine supervised classification of Puthuvypin mangrove patches in Kerala is cited as an example.

In the case study presented above for Puthuvypin mangroves at Kochi in India, unsupervised and supervised classification were applied to mangrove patches. ISODATA unsupervised classification method used 60 classes to evaluate the mangrove patches. The features such as dense and sparse mangroves, associates, mud flats, buildings, water classes and unclassified classes present in the mangroves patches were estimated (7) and classified. The supervised maximum likelihood and support vector machine (SVM) classification methods were resorted to understand the performance in each class and maximum number of polygons were created using the supervised classification for good result. Both classifications estimated the different features and unclassified classes. All the three classifications resulted in some misclassification for buildings nearby coastal areas and mud flat because mangrove patches are in wetland area where there are some buildings and the pixel size available to differentiate them is only 15 m in resolution. Buildings and mud classes intersect at different pixels so that the polygon resulted in misclassification of these two classes. The SVM classification method resulted in misclassification of sparse mangroves into mud flats and buildings. The Maximum likelihood classification gave the best results for mangrove patches in the study area differentiating all the features into respective classes.

13.2.4.5 Indices

Vegetation indices are transformations of original multispectral data into a single channel that represents greenness and/or biomass. The ideal vegetation index is highly sensitive to vegetation dynamics, insensitive to soil background changes, and only slightly influenced by atmospheric path radiance (Richardson and Everitt, 1992). Most of the vegetation indices take advantage of the relationship between the red and near-infrared reflectance from healthy green vegetation (Bruce and Jensen 1998) to compute a greenness measure where higher values typically represent greater biomass. Though many vegetation indices such as near-IR to red ratio (Tucker 1979), NDVI (Rouse et al. 1974), perpendicular vegetation index (PVI), difference vegetation index (DVI), soil adjusted vegetation index (SAVI), transformed soil adjusted vegetation index (TSAVI) and Greenness vegetation index are used, the most common is NDVI.

The NDVI whose value varies between -1 and 1 stands as proxy for the above-ground biomass, primary productivity and vegetation health and in turn can reflect their health or photosynthetic activity. (Kovacs et al. 2005, Jensen et al. 1991). In remote sensing analysis, vegetation indices are often used to highlight wetlands. Many of these indices are highly correlated with one another, i.e. redundant in information content (Perry and Lautenschlager 1984).

Relationship between biophysical variables to indices:

Several research works exploring the relationship between various vegetative indices and biophysical variables are summarised in Table 13.3

Table 13.3 Various vegetation indices used for classifying mangroves

Vegetation Indices	Significance/relationship	References used in classifying mangroves

In situ biophysical properties (LAI) and pixel-based	Positively correlated	Green et al. 1998, Fransisco et al. 2013
LAI estimated with Landsat Thematic Mapper (TM) data and NDVI	Positively correlated	Liu and Huete 1995, Lymburner et al. 2000
Simple NIR/Red ratio and LAI and TM data	Positively correlated Changes in canopy LAI can be detected using TM data.	Herwitz et al. 1990
LAI and NDVI	Positively correlated	Green et al. 1997
Simple NIR/Red ratio and NDVI and LAI	Positively correlated	Chen and Cihlar 1996
Stepwise regression combining six TM bands	Accurate method for green vegetation mapping	Lawrence and Ripple 1998
SPOT and four vegetation indices namely simple ratio, NDVI, perpendicular vegetation index, and the greenness vegetation index	Positively correlated	Jensen *et al.* 1991

Due to saturation at high levels of vegetation biomass and chlorophyll concentration (Gitelson and Kaufman 1998, Huete et al. 2002) and deviation in phenology curves with changing atmospheric conditions (Tanre et al. 1992), extracting reliable phenological information using vegetative indices is difficult (Weiss and Baret 1999). A better method was suggested by Jeganathan et al. 2010 wherein MERIS Terrestrial Chlorophyll Index (MTCI), which is a function of chlorophyll concentration and leaf area index was estimated, and was directly related to canopy chlorophyll content.

13.3 Monitoring and Mapping of Reefs Using SRS Techniques

The SRS data of SPOT, Landsat, IRS, LISS II, and LISS III are used for coral reef mapping also. Using the spectral data from the satellites, the coral reefs were identified and mapped as described in the case of mangroves described above. Individual/group of corals and reefs were identified using Landsat MSS data. There is an interesting case study done in the Great Barrier Reef. The reef was classified using this technique and analysed in micro-brain image processing system (Bastin 1988). Daniel et al (1986) mapped the shallow water in the Great Barrier Reef region using SRS data and illustrated it as a potential tool for coral reef mapping. There is a spectral difference between the living and nonliving corals which may appear in turquoise blue and greenish blue tone respectively on SPOT FCC of band combination 2, 3 & 4. In LISS III, the band combination of 3, 2, & 1 are found to be useful. More details of reef categories such as fringing, patch and reef spread could be mapped more accurately using IRS-LISS III data by visual analysis supported by proper ground truthing.

The Indian satellites IRS – 1C, 1D, P4 and P6 with their improved spatial resolution (PAN – 5.8 m, LISS III – 23.6 m, LISS IV – 5.8 m, WiFS – 188 m and AWiFS – 56 m), extended spectral range (inclusion of middle infrared band in LISS – III) and increased repeatability (5 days for WiFS data) have opened up new applications in coastal zone. The information available from merged PAN and LISS III, IV data about coral reef zonation, especially for atolls, patch reef and coral pinnacles, is valuable for coral reef conservation plans. Presently, the reef validation experiments using radiometers are happening at various locations to develop a database on spectral signatures produced by different reef groups, dead reefs and sand in different optical conditions and to develop sensors for hyperspectral satellites which can support reef mapping at an accurate scale (Fig 13.5).

Fig. 13.5 Radiometric measurements underwater for developing spectral signatures of corals and reef components

13.3.1 Mapping of Reef Vulnerability due to Extreme Events

Corals are known to be very sensitive to temperature rise. The large scale mortality and bleaching could be therefore attributed to increase in seawater temperature (Krishnan et al. 2011). The reefs in some islands of Andaman and Nicobar in India suffered severe damage following a tropical Storm in the Bay of Bengal off Myanmar coast during 13–17 March 2011(Krishnan et al. 2012). Surveys were conducted at eight sites in Andaman, of which five were located in the Ritchie's Archipelago where maximum wind speed of 11 ms^{-1} was observed; and three around Port Blair which lay on the leeward side of the storm and were not exposed to wind speed of more than 9 ms^{-1}. Corals in the shallow inshore reefs were broken and dislodged by the thrust of the waves. Significant damage in the deeper regions and offshore reefs were caused by the settlement of debris and sand brought down from the shallower regions. The fragile branching corals (*Acropora* sp.) were reduced to rubbles and the larger boulder corals (*Porites* sp.) were toppled over or scarred by falling debris. The reefs on the windward side and directly in the path of the storm winds were the worst affected. The investigation exposed the vulnerability of the reefs in Andaman to the oceanographic features which generally remain unnoticed unless the damage is caused to the coastal habitats.

Fast currents generated by eddies, tidal and ocean currents and gyres, quite close to coral islands are considered as physical factors that induce local water movements, flush toxins and remove thermal stratification in coral reef locations and hence are assumed as high reliability factors of resistance to coral bleaching. Physical damage to the coral reef structures due to eddies is not yet documented. Mesoscale eddies are quite common in the seas surrounding the Andaman and Nicobar Islands, however their presence in such close proximity to the coast as observed in this event has not yet been recorded. Eddies occurring in coral reef areas are known to cause thermal stress related bleaching due to the upwelling associated with the eddy circulation. Models evaluating the hydrographic effects of eddy on island waters have explained the dispersal of larvae due to high-velocity shear currents generated by the approaching eddy. Cross-frontal advection has been documented for cold core and warm core eddies.

13.4 Mapping of Fishing Grounds

Primarily, fish stock in a region is controlled by the 'spawning successes', 'growth' and 'recruitment'. At every stage in these controlling factors there is a withdrawal of fish biomass in the form of natural and fishing mortality. The

Cushing's triangle on fish migration explains various life cycle activities from recruitment to fishing as governed by physical oceanographic processes. (Fig 13.6). But in addition to this, there are various environmental factors affecting the fish stock too. Therefore, fishery managers tend to practice an ‘Ecosystem Approach to Fisheries’ (EAF). Numerical modelling and SRS has got numerous applications which can support EAF type of fisheries management (Grinson et al. 2011b, 2012) Spatially, the EAF approach indicates mapping of spawning, nursery and fishing grounds which may be different in space and time. Identification and mapping of these grounds or the resource is very important in managing the fishery.

Fig. 13.6 The Cushing's triangle on fish migration.

Fig. 13.7 Schematic diagram explaining the **e**ddy process and its linkage to fish ground mapping.

13.4.1 Identifying and Mapping Fish Habitats Using Oceanographic Processes

Oceanographic processes such as fronts, eddies, meanders, rings and primary productivity linked to them are keys to the identification of Potential Fishing Zones (PFZ). Altimeter satellite remote sensing data could identify mesoscale features (Eddies). Such data products can supplement the SST-Ocean colour based PFZ and provide information in cloudy conditions too. Near Real Time and Delayed time maps of Mean Sea Level Anomaly (NRT & DT-MSLA) from the Archiving Validation and Interpretation of Satellite Oceanography (AVISO) (http://www.aviso.oceanobs.com/) can be used for the purpose. The merged SLA data from multiple satellite products are produced by Salto/Duacs and distributed by AVISO. SLA data are provided with spatial resolution of 1/3° latitude/longitude. Updated series is used for the study as this data keeps adding measurements up to four different satellites whenever a new satellite becomes available.

For the satellite-derived SST, MODIS Global Level 3 Mapped Thermal IR daytime SST from Aqua and Terra sensors, available at the Physical Oceanography Distributed Active Archive Centre (PODAAC) site of NASA (http://podaac.jpl.nasa.gov) can be used. For chlorophyll, MODIS Global Level 3 Standard Mapped Image (SMI) eight day composite maps from Ocean Colour Web of GSFC-NASA (http://oceancolor.gsfc.nasa.gov/) can be used (Fig 13.7). Both the maps have 4 km spatial resolution, sufficient enough to recognize changes in the study domain. The above data overlaid with SLA maps examined the productivity linked to eddies for a case study in Andaman Sea (Anand et al. 2014). A sample output mapping the eddy zones and fish availability as part of the case study is provided in the Fig. 13.8. Productive habitats and their quality can also be assessed using the satellite data based oceanographic processes for providing improved potential fishing zone (PFZ) advisories (Grinson 2011a).

Fig. 13.8 A schematic diagram indicating the relevance of mesoscale eddies for providing improved advisories in fishery.

Fig. 13.9 Science behind location of spawning, nursery and fishing ground.

13.4.2 Role of hydrodynamics in assessing fishing ground

Knowledge of local hydrodynamics is a pre-requisite to modelling coastal processes, given that physical drivers such as tides and currents control them. There is a major role of diffusion and related physical processes in dispersal and recruitment of marine populations. Tidal flows can move larvae passively in peak tidal velocities. Physical processes influence the distribution of larval fish on a variety of scales, ranging from few meters to thousands of kilometers. The basic idea in fish larval transport studies is to characterize the passive movement of larvae during the planktonic larval duration (PLD) phase of the species studied.

During the pelagic larval phase, the larvae may be dispersed or retained in passive response to physical forcing. It is a phase that larvae are considered as “poor swimmers” because the hydrodynamic (HD) forcing on them exceeds their swimming ability.

Biological processes such as fish larval transport can be modelled based on a clear understanding of the physics of a water body (Grinson 2014). There are few larval transport studies in the coastal waters in particular regions. A study combining observational data with a two-dimensional numerical model product had been carried out to determine the fate of fish eggs released in a semi enclosed basin (Grinson et al. 2011b). Fish eggs were treated as passive particles in the model, and were released from probable spawning sites identified during exploratory surveys (Fig 13.9).

Numerical modelling of fish egg dispersion at the Patos Lagoon estuary in Brazil was carried out by Martines and Toan. 2007. There are various HD models to provide the spatial and temporal current patterns. Digitized bathymetry maps were used for defining the study domain. Inputs such as tide and wind are given in the model as the major physical forces driving the current. Simulation will produce the HD variables as output at every grid point for the time interval required. The currents generated in these models can be validated using observed data at certain grid points to ascertain the model accuracy.

This HD input, along with the physical forcings, is applied to larval transport models to deduce the dispersion pattern of larvae. The role of currents in geological structures such as mounts in an open area such as Mangalore coast is explored to see the role of fish aggregation creating fishing and nursery grounds.Numerical and particle transport models was used for generating hydrodynamics and further for identifying areas of fish aggregation. Validations of the models were done with *in situ* observations. Likelihood retention areas of larval aggregations indicated formation of nursery grounds (Fig 13.10).

Fig 13.10 Mangalore fishing grounds mapped with the help of HD and fish larval transport models. The red colour indicates the aggregation of fishes in the fishing grounds, on release from spawning grounds at Mulki and Netravathi, after completion of their larval duration phase

13.5 Remote Sensing of Molluscan Settling Grounds

In the past, there were numerous studies based on observational data on species diversity pattern in benthic environment. Apart from their spatial complexity and extent, their burrowing mode of life and the associated difficulty in species level sampling were the major constraints in inventorising macro-faunal species. Despite their ubiquity, tremendous ecological and economic importance, very little is known about macro-faunal diversity relationships of these ecological engineers. The use of remote sensing and statistical analysis helped in identifying the relationships between various benthic macro-faunal groups on a spatio-temporal basis. Macro-faunal invertebrates are known as crucial barometer of the ecological values of coastal regions, since their habitat is strongly influenced by the benthic environment (Lee and Park 1998, Yap et al. 2003). Identification of changes in the macro benthos distribution is an important task for the conservation or rehabilitation of the economical and ecological properties of the tidal flats.

13.5.1 Remote Sensing of Molluscs

The seafloor and benthic habitats of molluscs have been mapped during the last 30 years using hydro-acoustic systems such as single-beam echo-sounder, sidescan sonar and multi-beam echo-sounder etc (Bartholomä, 2006). The pure depth information of the acoustic return signal of these systems along with backscatter information and waveform were used for acoustic seabed classification (Markert et al. 2013) as these signals are influenced by the benthic fauna such as blue mussel and oyster beds, shell debris etc.

Though acoustic techniques are considered as an efficient, low cost, easily repeatable remote sensing tool for mapping and monitoring of the seafloor over large areas, it is not efficient in monitoring the biological characteristics of the studied biotope. Since this section of the chapter focuses around the use of satellite remote sensing of molluscs, the use of acoustic remote sensing is not discussed in detail.

GIS has been emphasized to be made a part of the ecosystem-based approach to aquaculture (Aguilar-Manjarrez et al. 2010). Chlorophyll-a is a descriptor of the phytoplankton biomass which functions as a trophic resource explaining the variations in bivalve growth in most of the SRS based studies (Rosland et al. 2009).

Key temporal hyperspectral characteristics of oyster reefs were identified using spectral analysis techniques which are repeatable and less subject to human inconsistencies. High resolution LiDAR (Light Detection And Ranging) data have been used for identifying shellfish habitat by taking into account the ability to combine or relate the distribution of different oyster data sets such as oyster densities and reef bed quality to other types of remotely sensed data developed for phytoplankton blooms and sediment loads in the water (Steven 2006).

It is well known that hyperspectral SRS can acquire imagery at increased spectral resolution giving accurate mapping. Bolte (2011) prepared oyster habitat maps of Wolf Bay after habitat suitability analysis. Salinity, pH, temperature, dissolved oxygen, water depths and suspended sediments were used as variables to perform habitat suitability analysis. The study in turn emphasized that the difference in these variables' influence on the habitat classifications reflects the sensitivity of the variables themselves to climate change.

Thematic mapping, employing data from a variety of remote sensors coupled with decision support through GIS spatial analysis, provides more rigour and insight in aquaculture planning of molluscs. Using biophysical (SST, turbidity, chlorophyll and bathymetry) and logistic (distance to wharves, distance from river mouths) data obtained from satellite images. Radiarta and Saitoh. 2008 undertook constraint mapping of scallop culture areas in Funka Bay, to quantify site selection.

Thomas et al. 2011 observed that a method coupling dynamic energy budget approach with environmental data extracted from satellite images (i.e. chlorophyll-a concentration and temperature) is advantageous over traditional measurements for mapping molluscs as they are inexpensive, spatially extensive, automatically repeated in time and validated.

Radiarta and Saitoh. 2008, attempted to correlate scallop fisheries and aquaculture production to the spring bloom and its coincidence with departure of ice and wind stress along the Hokkaido coast. For the purpose, ice concentrations were obtained via passive microwave data and chlorophyll with SeaWiFS. Although inter-annual variations in these interactions were observed, their relationship to scallop production has not yet been examined. IOCCG (2009) examined temporal variation in chlorophyll, turbidity, and temperature in Funka Bay, Japan to explain seasonal trends in the spring bloom and relate them to scallop production. Nath et al. 2000 used shellfish module to indicate site capability indices using 14 biophysical variables with which the site suitable for the aquaculture of pacific oyster is mapped. Satellite data has been used in bivalve condition index studies, where in the condition indices data sets were correlated with remote sensed datasets such as temperature, chlorophyll and particulate organic carbon time series can be obtained from Goddard Earth Sciences Data and Information Services Center (GES DISC) from leased out land and wild.

Using a wide range of remotely-sensed data from Landsat, MODIS, MERIS, and AVHRR marine culture areas in Sanggou Bay (Yellow Sea) and Huangdun Bay (south of Shanghai) were characterized, by examining the distribution of chlorophyll and turbidity for the regions offshore of the bays. The selection of suitable sites for molluscan farming based on GIS and remote sensing as in prawn and fish farming would enhance the baseline information on the physico-chemical and topographic conditions as well as existing land use patterns, marketing channels etc.

Satellite data were used to test model predictions against measured mussel growth in cultivated areas and later on, the mussel growth model was applied to all the pixels to assess site potential at a wider scale. This study provided the first example of a cultured shellfish growth model coupled to oceancolour input (IOCCG 2009). Choi et al. 2011 used remote sensing techniques to examine the variables that influence the spatial distribution of macro-benthos in a tidal flat. Fulton et al. 2010 sought to predict the location of a mussel habitat by establishing correlations between mussel counts and hydraulics, using a GIS-based numerical model. The spatial relationships between species occurrence and species- related factors were derived via weights-of-evidence model to produce a species habitat potential map for the study area.

13.5.2 Case Study: Mapping of Clam Beds in Vembanad Lake Using GIS, SRS and in situ Data

Spatio temporal distribution of shellfish population and their habitats were carried out using SRS and GIS. The study was conducted at Vembanad Lake; the largest humid tropical wetland ecosystem of the southwest coast of India, famous for its live clam resources and sub-fossil deposits. Sampling was conducted during pre and post monsoon to see the variability of biomass during both the seasons. Ten and twenty one stations were chosen for sampling during the post and pre monsoon season for the study. The protocol followed in the study is explained in Fig: 13.11. Inverse Distance Weighted interpolation was used for delineating the most correlated physico-chemical factors with the clam biomass in the study area. The spatial shift was evident as explained in the Figure 13.12. The biomass variation in relation to the physico-chemical variables is explained in the Table 13.4 which indicates the difference between two sites during the study season.

Fig.13.11. Methodology adopted for mapping clam distribution in Vembanad Lake

Fig. 13.12 Clam biomass during pre-monsoon and post-monsoon in Vembanad Lake in Kochi, India

Table 13.4 Comparative analysis of physico- chemical parameters of dredged and Non dredged area during pre-monsoon period

Area	Dredged	Non dredged
Temperature (^{o} C)	31.5± .93	31.07 ± 0.56
Turbidity (cm)	87.94 ± 33.82	146.45 ± 40.80
Salinity (ppt)	9.31 ± 0.29	2.22 ± 1.33
pH	8.25 ± 0.42	7.5 ± 0
Biomass (g/sq.m)	381.78 ± 305.49	1014 ± 1165.63
Hardness (ppm)	16.16 ± 0.50	10.76 2.78

13.6 Conclusion

In marine environment, various life forms have acquired the potential for commercial application, utility and therefore face threat of excessive exploitation. The diversity is being eroded rapidly. There are various attempts to identify these resources spatially and monitor them as a conservation measure. The development of numerical modelling and a number of SRS tools will address the conservation challenges such as species distributions and levels of species richness in different geo spatial contexts. The SRS applications may be used for mapping the resources directly or indirectly for estimation of species distributions and richness levels, but of also shedding light on the processes underlying them. Aerial photography is best for mapping mangroves which extends along a narrow stretch and where accurate discrimination among mangrove species is a prerequisite. The MSS based mangrove mapping is advantageous for tropical as well as subtropical countries and is useful in studies related to seasonal dynamics of inundation, physical parameters of water sheds along with mapping of changes in coastal sheds. Hyperspectral resolution imagery, though widely accepted a wonderful tool for mapping and discriminating mangrove species, their utility becomes limited in tropical climatic conditions. Vulnerability mapping of the reefs using SRS is going to help the planners in identifying the stressed reefs and managing them with special care. Fishery and molluscan habitat detection using SRS and modelling will potentially benefit the fisher folk to identify their fishing location with less scouting. Thus, the chapter calls upon operationalizing the SRS data based mapping and monitoring for sustainable management of mangroves, coral reefs, molluscs and fishes.

Acknowledgement

The authors acknowledge the support from Dr. A. Gopalakrishnan, Director, Central Marine Fisheries Research Institute, India and the ChloRIFFS project which sponsored this work. Financial assistance from National Centre of Sustainable Coastal Management, Ministry of Environment and Forest, India is also acknowledged herewith. The first author would like to thank Dr. A.P. Sharma, Director, Central Inland Fisheries Research Institute for supporting the work.

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FIGURE CAPTIONS

Fig.13.1 Various classification protocols followed for mangrove mapping.

Fig 13.2 ISODATA Unsupervised classification of Puthuvypin mangrove patches. Landsat 8 is used here with OLI sensor multi spectral (11 Bands including PAN) and medium scale resolution (30 m; PAN 15 m) remote sensing data during 13 Jan 2015 and Survey of India Toposheet No.58 B8 scale1:50,000 data have been used in this study and plotting was done with ENVI and ArcGIS software.

Fig 13.3 Maximum Likelihood classification of Puthuvypin mangrove patches. In this study we modified the low resolution multi-spectral bands to high resolution (15 m) bands using PCA pan-sharping method. High resolution Landsat data are geo-rectified using SOI toposheet and ground control points. Landsat 8 data having spectral radiance is converted to reflection by using the formula: $\lambda' = \frac{\mathrm{M\rho Qcal} + A p}{\mathrm{Sin}\,(\mathrm{ØSE})}$ after radiometric correction and finally sub setting the mangroves

Fig13.4 Support vector machine supervised classification of Puthuvypin mangrove patches in Kerala is cited as an example.

Fig. 13.5 Radiometric measurements underwater for developing spectral signatures of corals and reef components

Fig. 13.6 The Cushing's triangle on fish migration.

Fig. 13.7 Schematic diagram explaining the eddy process and its linkage to fish ground mapping

Fig. 13.8 A schematic diagram indicating the relevance of mesoscale eddies for providing improved advisories in fishery

Fig. 13.9 Science behind location of spawning, nursery and fishing ground.

Fig 13.10 Mangalore fishing grounds mapped with the help of HD and fish larval transport models. The red colour indicates the aggregation of fishes in the fishing grounds, on release from spawning grounds at Mulki and Netravathi, after completion of their larval duration phase

Fig.13.11. Methodology adopted for mapping clam distribution in Vembanad Lake

Fig. 13.12 Clam biomass during pre-monsoon and post-monsoon in Vembanad Lake in Kochi, India