The Dynamic Monitoring and Management of the Portuguese Coastal Zones with Remote Sensing Technologies

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Abstract: It is recognized that the coastal zone and its environments are complex and specialized areas. Advances in sensor design and data analysis techniques are making remote sensing systems practical and attractive for monitoring natural and man-induced changes. The objective of this paper is to review and compare remote sensing technologies for the assessment of costal ecosystems that are cost-effective and practical and to illustrate their use through two case studies. The results of the case studies show that analysis of satellite imagery allows researchers to effectively identify beach features/patterns and to mapping the spatial distribution of coastal lagoon habitats.

1. Introduction and Background

The coastal areas are zones of primary importance from human and ecological perspectives. However coastal ecosystems have been exposed to a range of stress-inducing modifications, including land use and land cover changes, dredge and fill operations, hydrologic transformations (impacts on global sea level rise), pollutant runoff, eutrophication and impoundments (Klemas, 2011). In recent years, a number of Remote Sensing (RS) techniques are available to resource managers for developing effective marine ecosystem management initiatives, including the use of information technology for analyzing and understanding an ecosystem as a whole and not simply the targeted resource or a specific area. The wide applicability of RS techniques has allowed researchers and managers to take a broader view of coastal ecosystem assessment and management (Klemas, 2011). Ecological patterns, processes and changes in composition and structure of coastal ecosystems can be quantified using satellite imagery. When these RS tools for generating, organizing, storing, and analyzing spatial information are combined with mathematical and data mining models, marine resource planners and managers have the means for accessing the impacts of natural events, anthropic and alternative management practices on pattern and process on coastal areas. RS provide not only photographic representation of the coastal and marine surfaces, but also physical (absorbency, reflectance and emissivity) measurements of various properties of these ecosystems. These spectral characteristics can be used to access the major factors affecting water quality in coastal water bodies (e.g. Total Suspended Matter (TSM) and dissolved organic matter (DOM)) (Teodoro *et al*., 2007); to identify, characterize and analyze river plumes (Teodoro *et al*., 2009a); to extract estuarine/coastal sandy bodies (Teodoro and Gonçalves, 2011); to identify beach features/patterns (Teodoro, 2015); and to evaluate the changes and integrity (health) of the coastal lagoon habitats (Gutierres, 2014), at various scales. In fact, the RS creates new opportunities for identifying which parameters function as regulators of marine/costal ecosystems at local and regional levels and how these variables differ across spatial and temporal scales. The objective of this paper is to review RS techniques for studying coastal ecosystems that are cost-effective and practical and to illustrate their use through two case studies.

1.1 Status and Improvements for Assessment of Coastal Ecosystems

1.1.1 – Remotely sensed data

Today, and given the numerous RS satellite imaging systems available, it is a challenge to choose the most appropriate satellite images for observing marine/coastal ecosystems – for technical details of the classification of remote sensors, readers can refer to Klemas (2011). The digital systems can be grouped into four different types of resolution: spatial, spectral, radiometric, and temporal. In this paper will be highlighted some RS data that can be used in studies of marine/coastal ecosystems, applied to the Portuguese coastal environment. Depending on the research to carry out it is important to consider the temporal or spatial characteristics of the RS satellite imagery used in each analysis. In the work developed by Teodoro *et al*. (2009a) and Teodoro and Gonçalves (2011), it was used the TSM concentration retrieved from MERIS scene, which allowed the extraction of objects corresponding to river plumes. The medium spatial resolution of MERIS data is enough to estimate the river plume size. Gutierres (2014) showed that LANDSAT sensor has been an effective source for land cover data (Figure 1). Its 30m resolution and spectral bands have proved adequate for observing land cover changes in 'Santo André' coastal lagoons in south west of mainland Portugal. Other similar satellites with medium-resolution imagers, such as SPOT4/5 can also be used for change detection in water and wetland environment. However, finer details such as wetland habitats and species cannot be reliably differentiated at these resolutions. In this sense, several progresses is being made using high resolution sensors (GeoEye-1 and WorldView-2), with spatial resolutions of 0.5-1m. These sensors have consistently demonstrated the ability to classify features at detailed levels. Thus Worldview-2 improves the segmentation and classification of land and aquatic features beyond any other space-based RS platform.

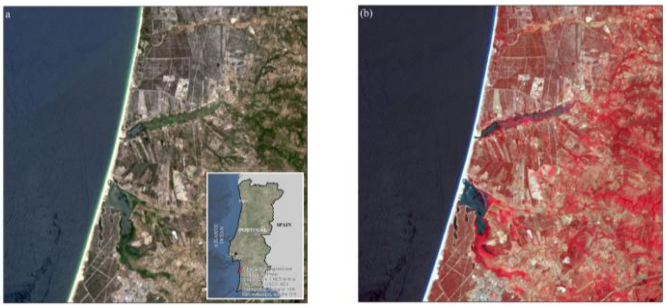


Figure 1 – Subset of Landsat 8 scenes from coastal lagoons in SW of mainland. Image acquired in 25 May 2015 over 'Santo André' lagoon. (a) Natural Color composite of the Operational Land Imager (OLI) red (0.64-0.67 μm), green (0.53–0.59 μm) and blue (0.45–0.51 μm). (b) Color Infrared (vegetation) composite of the OLI near infrared (0.85–0.88 μm), red (0.64-0.67 μm) and green (0.53–0.59 μm) Adapted from Gutierres *et al*. (2015)

1.1.2 – Object-Based and Pixel-Based Classifications

The literature regarding the discussion about the difference between Pixel-Based (Supervised and Unsupervised) and OBIA classification has been very active in the last years, and a large number of papers regarding the classification accuracy of this RS techniques have been published (e.g. Baatz and Schäpe, 2000). The most popular techniques are those based on group pixels – unsupervised and supervised image classifications – to represent land cover features such as wetlands and beaches. There are different image clustering algorithms such as K-means and ISODATA (Iterative Self-Organizing Data Analysis Techniques) (Gutierres *et al*., 2015). Instead, the OBIA classification generates objects of different shape and scale. OBIA is defined as a sub-discipline of GIScience devoted to partitioning RS imagery into meaningful image-objects, and assessing their characteristics through spatial, spectral and temporal scale (Gutierres *et al*., 2015). Several costal studies require the segmentation of natural spectral classes such as open water bodies (Lira, 2006), wetland habitats (Gutierres, 2014), river plume size (Teodoro and Gonçalves, 2011), physical differences (e.g. salinity) between the estuarine outflow and the ambient water (Dzwonkowski and Yan, 2005), sand spits (Teodoro and Gonçalves, 2011). So these objects are more meaningful than the traditional pixel-based segmentation because they can be classified based on texture, context and geometry (Teodoro and Gonçalves, 2011). Gutierres *et al*. (2015) compared OBIA and Pixel-Based classification, and showed that when merging a high-spatial resolution color infrared digital orthophoto with multitemporal (winter and spring) medium-spatial resolution SPOT-5 satellites images, an OBIA classification outperform both supervised and unsupervised Pixel-Based methods. Also the OBIA clearly reduced the "salt and pepper" effect presented in Pixel-Based classification, and may appear more visually attractive to the analyst. The research developed by Gao and Mas (2008) has shown that with satellite imagery of four different spatial resolutions (SPOT-5, LANDSAT 7 ETM+ and MODIS), OBIA obtained higher accuracies than those of the Pixel-Based one. Thus with the increase of the pixel size (10, 30 and 250 m), OBIA did not show more advantage over the Pixel-Based ones. The authors proved that OBIA has advantage over the Pixel-Based method but the higher accuracy only holds true for high spatial resolution images.

1.1.3 – What Needs to Be Improved

Generally, coastal ecosystems, such as open sea, wetlands, estuaries, and coastal lagoons, presents high spatial complexity and temporal variability, their assessment can be improved from new satellite imagery and aircraft, to allow getting better systematic, spatial, spectral, and temporal resolutions. According to Gutierres *et al*. (2015), the assessment of marine and coastal ecosystems can be improved considering the launch in June 2015 of the sentinel-2 satellite within Copernicus project of the European Space Agency (ESA). This will be an Earth Observation (EO) operational mission providing continuity to Landsat data. It has a global coverage of the Earth's land surface every 10 days with one satellite and 5 days with 2 satellites that will able to monitor continuously the water quality and flood dynamics. Further studies with new sensors must be developed for monitoring the marine and coastal areas. The usage of Sentinel-2 sensor, time series of very high resolution imagery (e.g. WorldView-2), hyperspectral sensors, airborne light detecting and ranging systems (Lidar), Thermal infrared scanners, microwave radiometers, Radar images, scatter meters, altimeters, Unmanned Aerial Vehicle (UAV) and new data analysis techniques can provide the way forward for future prospects, such as, raise the accuracy of change detection in costal ecosystem health (e.g. wetland biomass change);

detailed mapping of sea surface temperatures, salinity and soil moisture; deep analysis of sea surface winds, elevation, currents, wave fields and oil slicks; improvement of shoreline position analysis and beach erosion studies; and a better performance high-resolution three-dimensional measurements of biological and physical ocean features. Also accurate field data collection approach using ships, buoys, and field instruments with a valid sampling scheme must be improved to calibrate and/or validate the remotely sensed information.

2. Management of Coastal Ecosystems through Remote Sensing Applications: Two case studies

2.1 Integration Remote Sensing in Natura 2000 Habitat Monitoring

According Gutierres *et al*. (2015), RS is seen as an important tool to obtain and analyze synoptic data on Natura 2000 habitats, but currently reflects some limitations for monitoring and reporting purposes. In fact, the application of RS tools for habitat mapping and monitoring offers multiple advantages over traditional field mapping, like faster map production, insight into remote and inaccessible terrain such as coastal wetlands, and improved repeatability of the habitat mapping process. This study aimed to produce a detailed Natura 2000 habitat map contained in the fluvial-lagoon system of Santo André-Monte Velho.

The study was carried out with Very High Spatial Resolution Satellite Imagery (VHSR) –WorldView-2 covering Santo André-Monte Velho lagoon system. In addition to the standard panchromatic and multispectral blue, green, red (visible) and Near InfraRed (NIR1) bands the WorldView-2 sensor has: (a) a shorter wavelength blue band, Coastal Blue, planned for bathymetric studies, can be used for water color analyses and substantially influenced by atmospheric scattering;(b) a Yellow band can be used for the assessment of the Yellowness of vegetation both on land and water; (c) a Red Edge band, centered at the onset of the high reflectance portion of vegetation response to potentially significant in the measurement of plant health; (d) a longer wavelength Near InfraRed band (NIR2), partially overlapping the NIR1 is sensitive to atmospheric water vapor absorption. Using a methodological approach based on Segmentation-based Supervised Classification of the WorldView-2 image data, it was possible to produce habitat maps with high definition and thematic detail. The accuracy of the classification map was estimated using a set of test fields randomly selected on the ground truth map.

This analysis showed that the 8-band sensor is extremely useful to better discriminate different spectral sub-signatures corresponding to the same habitat category. This means that the major capability of the new sensor resides in the capacity of determine the ground diversity underlying the apparent homogeneity of conventional habitat map. From the Segmentation-based Supervised Classification approach, it was possible to detect changes in the bathymetry for the Sea Water classes by using the Coastal Blue band; moreover, the lowest wavelength band appears to be significant for the recognition of mixed patterns of water and terrain. The Yellow band appears significant to elicit terrain composition, as characterized by a certain degree of yellowness. The Red Edge and the NIR2 bands seem useful for a better discrimination of ground sites characterized by a mixing of water and vegetation. The results obtained proved that the VHSR integration can contribute to the area (location and size) monitoring and also to assess the structure and function (particularly regarding structural features) of the Natura 2000 coastal habitats at local scale (Figure 2).

The production of coastal habitat distribution maps, at various scale levels, constitutes a promising new area for the development of RS applications, as Gutierres *et al*. (2015) indicated. The emergence of hyperspatial and hyperspectral sensors will enhance the analysis of related habitat types at very fine scales. The researchers need such maps based on RS data maps for estimating range and area of coastal habitats, but also to achieve a better definition and constant updating of the sampling frame for Natura 2000 habitats survey. Indeed, RS technologies represent an important opportunity for harmonizing Natura 2000 habitat mapping throughout Europe.

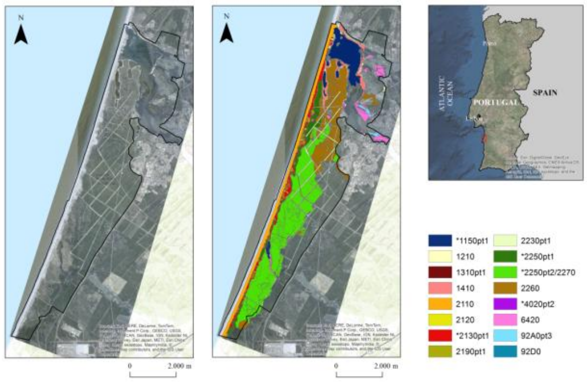
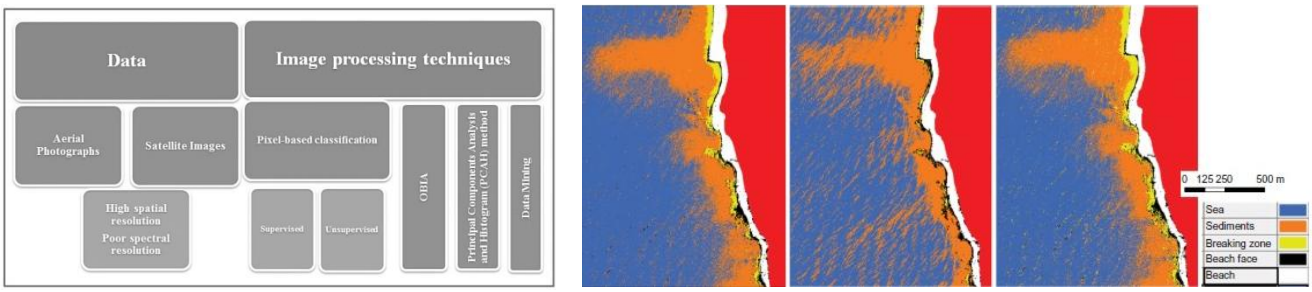


Figure 2 – Mapping the local variability of Natura 2000 habitats with WorldView-2 image data. Image acquired in 11 June 2011 over the fluvial-lagoon system of 'Santo André-Monte Velho' (Gutierres *et al.*, 2015)

2.2 Beach features/patterns identification

Beach morphological classification is a very complex task and was mainly established for Australian and American microtidal sandy environments (e.g. Short, 2006). Remote sensing is a very powerful tool for beach features/patterns identification, since it allows the collection of spatially continuous information over a vast area in a short time frame. Moreover, the availability of remote sensed data could be the unique alternative when in situ data/observations are not available. The main objective of this work was to improve and develop new techniques based in remotely sensed data and image processing techniques in order to identify beach features/patterns.

The methodology followed in this work, is presented in the Figure 3(a).



(a) (b) (c) (d)

Figure 3 – (a) Methodology followed in the beach features/patterns identification through remote sensing data; Results of (b) the parallelepiped (with maximum likelihood as tie breaker) and (b) the minimum distance and (d) maximum likelihood classifiers applied to the IKONOS-2 image (adapted from Teodoro et al. (2011))

The dataset is composed by two aerial photographs (from 1996 and 2001, with a red–green–blue (RGB) colour composition) and one IKONOS-2 image (from 2005). The study area selected for this study is located in the Portuguese northwest coast, limited to the north by a small lagoon (Barrinha de Esmoriz) and to the south by Furadouro village, with an extension of 11.5 km. The study area is a plain sandy coast, formed by beaches and dunes with small elevations, with highly dynamic coastal patterns/forms that change continuously. The tide regime is semidiurnal (period or cycle of approximately one-half of a tidal day), reaching up to 4.0 m for spring tides (mesotidal coast). The littoral drift has a dominant north–south direction. Teodoro *et al.* (2009b) first applied pixel-based (supervised or unsupervised) and region-based (object-oriented classification) classifications to the dataset. In the supervised classification the image analyst "supervises" the selection of spectral classes that represent patterns or land/ocean cover features that the analyst can recognize (is a "prior decision"). In the unsupervised classification statistical, "clustering" algorithms are used to select spectral classes inherent to the data, more computer-automated (is a “posterior decision”). The signature separability function must be used to examine the quality of training site and class signature, before performing the classification. Three algorithms were tested: parallelepiped with maximum likelihood as tie breaker, minimum distance and maximum likelihood. In the unsupervised classification stage, two algorithms were tested: K-Means and ISODATA. More details about these algorithms could be founded in Richards (1995).

Object-oriented classification (OBIA- Object based Image Analysis) approach takes into account the form, textures and spectral information. Segmentation is the first stage of the object-oriented classification procedure, and its aim is to create meaningful objects (Benz *et al*., 2004). Latter, Teodoro *et al.* (2011) presented a novel approach based on principal components analysis and histogram segmentation (PCAH) aiming to identify and analyze morphological features and hydrodynamic patterns, also applied to the same dataset. The main concept of PCAH relies on principal component analysis (PCA). A preprocessing stage is performed prior to the PCA, which allows for an enhancement of the image. The preprocessing comprises histogram equalization, followed by Wiener filtering. A meaningful segmentation of each principal component can be performed independently, using histogram-based segmentation. The segmentation can be performed either manually or automatically. The automatic identification of classes in a histogram mainly consists of the detection of significant transitions from positive to negative values in a sequence formed by the consecutive slopes of the histogram. Recently, Teodoro (2015) presented a work focusing on the application of data mining techniques, particularly artificial neural networks (ANN) and decision trees (DT), to the same IKONOS-2 image in order to identify and classify beach features and their geographic patterns and to compare the performance of the ANN and DTs. Despite the fact that ANN and DT are well-known classification methods of remote-sensing high-resolution spatial data, they are not usually applied in the identification/classification of beach features/patterns. An ANN is a parallel-distributed processor that resembles the human brain by acquiring knowledge through a learning process and then stores the knowledge in the connection strength between computational units called neurons (Haykin, 1999). The back-propagation algorithm (BPA) is one of the most used neural network learning algorithms and has a simple internal architecture that can classify inputs into a set of target categories, and was used in this work (Russell and Norvig, 2002). In this work, the *nnet* package from *R* software was employed. The DT algorithm is one of the most popular data-mining techniques and has also been applied with success to extract forms/patterns from different types of satellite data. A DT is a classifier expressed as a recursive partition of the instance space. The DT consists of nodes that form a rooted tree, meaning it is a directed tree with a node called root that has no incoming edges. According to Breiman *et al.* (1984) the tree complexity has a crucial effect on its accuracy performance. The tree complexity is explicitly controlled by the stopping criteria used and the pruning method employed. The CART algorithm developed by Breiman *et al.* (1984) was implemented in this work, considering the *rpart* package found in the *R* software.

The supervised classification algorithms presented a very good performance (overall accuracy (OA) > 92% and Kappa >0.88). The good results of the supervised classification are also supported by the values of signature separability between the different classes defined, for both aerial photographs and the IKONOS-2 image (>1.8) (Figure 3 (b)-(d)). The object-based classification presented good results, but lower than the pixel-based classification procedure. The PCAH method was only applied to the IKONOS-2 image because the results obtained with the OBIA for the IKONOS-2 image were worse than those obtained for the aerial photographs. The proportion of variance explained by principal components 1, 2, 3 and 4 is, respectively, 94.5%, 3.9%, 1.3% and 0.3%. Each principal component allows for different identifications of the considered classes. The proportion of correctly classified pixels considering the second principal component were 98%, 92%, 43% and 99%, for the classes ‘sea’, ‘sediments+breaking zone’, ‘beach face’ and ‘beach’. Combining these proportions of agreement with the visual analysis the results shows that the PCAH method is a promising methodology regarding the identification of beach features/patterns through remotely sensed data (Teodoro *et al.,* 2011).

The data mining algorithms employed in this work to identify beach features/patterns through an IKONOS-2 image presented a very good performance, demonstrated by the results of the individual class accuracy, overall accuracy (OA>98.5% for ANN, OA>98% for DT without pruning, and OA>96% for DT with pruning), and kappa (0.97 for ANN, 0.97 for DT without pruning, and 0.95 for DT with pruning). When applied to the validation dataset, ANNs performed successfully, with high-classification accuracies observed. Additionally, the ANN presented a classification more sensitive to rip currents (Figure 4). The accurate identification of rip currents (location, spacing, persistence, and size) is of extreme importance for coastal and marine researchers, because the sediment budget studies are primarily based on longshore and offshore transport rates.

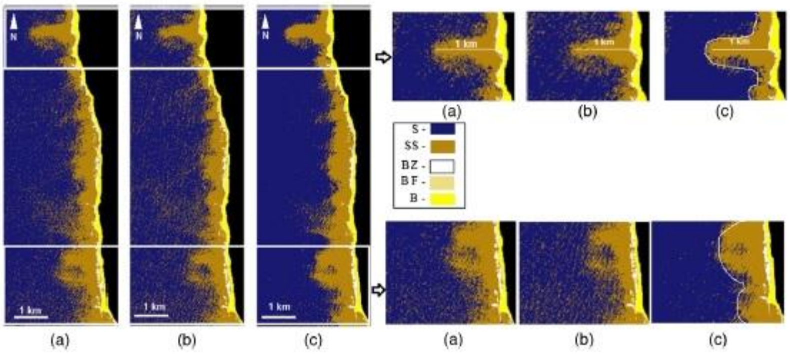


Figure 4 – Beach patterns/forms identification and two zoomed areas obtained through: (a) DT without pruning; (b) DT with pruning; and (c) ANN. Adapted from Teodoro (2015)

The use of ANNs and DTs for beach classification from remotely sensed data resulted in an increased classification accuracy when compared with traditional classification methods (pixel-based and OBIA), and the spatial resolution of the IKONOS image suggests this type of data is adequate for the identification of the considered beach features/patterns, through ANN and DTs techniques. This research demonstrated that the association of remotely sensed high-spatial resolution data and image classification algorithms is an effective methodology to identify beach patterns/forms.

3. Summary and Conclusions

Different methods in RS for determining the effect of spatial resolution on coastal ecosystems using different spatial, spectral and temporal resolution images can be applied. The two case studies presented in this paper clearly illustrate the main image classification techniques (Pixel-Based (Supervised and Unsupervised) and OBIA classification) to mapping the spatial distribution of natural habitats and to identify beach features/patterns. Making the right decision about which spatial resolution is optimal for the assessment of coastal ecosystems is not an easy matter. First, high spatial resolution images are more detailed than the low spatial resolution images. Second, some features can be identified clearly in high spatial resolution whereas some features can be recognized in low or moderate spatial resolution much clearer. Finally, the coverage using high spatial resolution is smaller than the coverage using low spatial resolution images. Therefore, the definition of a precise spatial and temporal resolution depends on the objectives of the research.

Enhanced efforts are required on the investigation of advanced algorithms and promote a higher usage of hyperspectral imagers and calibrated ship samples to identify accurately the effect of spatial resolution on the accuracy of thematic classifications, and support a better definition of the optimal resolution of remotely-sensed digital data for coastal ecosystems. It can be concluded that the application of novel RS techniques, combined with mathematical and data mining models, can help to overcome the shortcomings of satellite imagery and lead to satisfactory habitat map production and beach classification. This is a promising finding in the light of the development of operational methods for the dynamic monitoring and management of the coastal zones based on RS technologies.

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