

Object-oriented classification of QuickBird data for mapping seagrass spatial structure

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Abstract

QuickBird satellite images were processed using object-based analysis to map the spatial structure of seagrass in sandy shoal habitat in the southern Baltic Sea. A three-level ecological model of seagrass landscape, composed of meadows, beds and patches/gaps, was implemented in the multi-scale object domain. Image segmentation was performed at different spatial scales. In order to determine representative scales for bed level and patch/gap level objects, histograms of delineated objects were analyzed. Using object-oriented classification methods, two hierarchically nested maps of seagrass spatial structure were created. The map of patches/gaps was created using the nearest neighbor classification method in the feature space defined by the mean value of band 2 and the value of the proposed seagrass index. Overall map accuracy was 83%. The second map, which depicted the cover density of seagrass beds, was created on the basis of hierarchical relationships between objects at two chosen spatial scale levels. Both maps were exported as vector objects to GIS. Vector-based mapping of seagrass landscape structures at two scales simultaneously provides new possibilities for using landscape metrics and time change detection methods.

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INTRODUCTION

Seagrasses are one of the most significant components of submerged aquatic vegetation (SAV), and therefore play a key role in coastal ecosystems. Seagrasses support high species diversity and provide shelter, food and nursery ground for invertebrates and fish (Boström & Bonsdorff 1997, Pihl & Wennhage 2002, Pihl et al. 2006). They stabilize and trap bottom sediments, providing protection against coastal erosion (Ward et al. 1984, Sleeman et al. 2005). According to Constanza et al. (1997), seagrass beds have a value of \$US 19,000 per hectare, per year. Because seagrasses are sensitive to degraded water clarity and quality they are also often regarded as a good indicator of the ecological status of coastal waters (Sagert et al. 2005, Krause-Jensen et al. 2005, Foden & Brazier 2007). Due to the fact that coastal waters and sea bottom are protected using several legal systems (e.g. in Europe: Natura 2000 network and Water Framework Directive - WFD), there is a strong need to develop tools to create high-resolution continuous maps of SAV density cover. These maps can be used not only for management purposes but also for monitoring submerged vegetation areas. In order to create continuous high-resolution maps of seabed vegetation, which consists mainly of coral reefs, seagrasses and macroalgae, optical and acoustical remote sensing methods are supplemented with field surveys. Most of the recent studies are based on optical methods, analyzed satellite data received from Landsat, IKONOS and SPOT satellites (Andréfouët et al. 2003, Elvidge et al. 2004, Fornes et al. 2006, Pasqualini et al. 2005) or images from multi-spectral airborne cameras (Green & Lopez 2007, Lathrop et al. 2006). The images were usually preliminarily transformed using geometric and radiometric corrections. The effects of variable depth across the image (Lyzenga 1981, Mumby & Edwards 2002) and the effects of possible sea surface roughness were also removed (Andréfouët et al. 2003). Then the images were classified based on the spectral information and the classes determined in field survey points or transects (mainly using underwater photos).

Commonly used methods of classification were maximum likelihood classification (Dekker et al. 2005, Fornes et al. 2006, Mumby & Edwards 2002, Pasqualini et al. 2005) and various methods based on unsupervised classification (Andréfouët et al. 2005, Cuevas-Jiménez et al. 2002). The above-mentioned studies revealed two basic limitations in the application of satellite images for sea bottom mapping. First, the spatial resolution of Landsat or SPOT satellite images is often comparable with the size of habitat patches. Thus, mixed pixels are generated. Second, many benthic habitats (particularly seagrass species) are dominated by a mixture of photosynthetic organisms and the spectral differences between the species are too subtle to differentiate them (Mumby & Edwards 2002). Detailed maps of SAV provide basic information

used in research of the seagrass landscape and its ecological role in the marine environment. It is generally accepted that seagrass habitat has a multi-scale structure. However, the model of the structure is ambiguous and consequently various definitions of their main elements like beds and patches have been formulated (Boström et al. 2006). Current maps of seabed cover are mostly in raster formats, i.e. divided into equal-sized cells constituting a raster mosaic. Hence, it is difficult to use such maps in the landscape pattern analysis based on objects, instead of single pixels (cells). Since seagrass landscapes are of great interest (Boström et al. 2006), it is essential to produce vegetation cover maps corresponding to natural seagrass landscape structures as closely as possible. The multi-scale character of the structure must be taken into account. An object-oriented approach enables one to analyze the study area as an object mosaic at different scales (Blaschke et al. 2004), which is not possible when pixel-based classification is used. Object-oriented classification is based on multi-scale segmentation of raster images, which leads to the extraction of spectrally and internally homogenous units at a particular spatial scale. This method has been used to create maps of SAV but only using images obtained from airborne digital cameras. Lathrop et al. (2006), following Robbins & Bell's (1994) approach, considered habitat structure at three different levels: (a) meadow - a spatially continuous area of seagrass beds of varying percent of cover composition; (b) bed - a spatially continuous area of overall similar percent of cover composition; and (c) patch - a small discrete clump of seagrass- or gap - an area within a seagrass bed not occupied by plants. They applied both segmentation procedures and object-based analysis in order to aid the manual creation of a seabed cover map. The map consisted of 6 classes including three manually encoded classes of seagrass cover (dense, moderate, sparse) based on the analyst's judgement. Green & Lopez (2007) applied segmentation techniques and classifications using regression tree analysis to create a map of benthic habitats. The aim of our study is to apply object-oriented classification with the goal of fully automating the mapping of spatial structures of underwater seagrass habitats. The three-level model of seagrass landscapes (Robbins & Bell 1994) was implemented in multi-scale object domain. Two maps of different spatial scales were created. The first map presents patch/gap structure whereas the second one presents SAV density of bed cover. The format of the maps allows one to analyze them in GIS software or in other scientific software programs used for landscape analysis.

MATERIALS AND METHODS

Study area

The study was carried out within an Area Of Interest (AOI) polygon of 2×2 km located at the Long Shoal in Outer Puck Bay which is a sheltered part of the Gulf of Gdańsk in the southern Baltic Sea. Sand shoals in the southern Baltic, sheltered from waves, are mainly occupied by seagrass meadows of *Zostera marina*, *Potamogeton* spp., *Zanichellia palustris* and *Ruppia maritima* (Pliński & Józwiak 2004, Kruk-Dowgiałło & Szaniawska 2008). It must be emphasized that underwater meadows constitute one of the most diverse coastal ecosystems in the Baltic Sea (Boström & Bonsdorff 1997). Seagrasses are essential for coastal zone management in the countries of the Baltic Sea region. What is more, the studied area is a part of Natura 2000 site (code: PLH220032). The sea bottom at the AOI is described as sandy, with optimal conditions for phytobenthos, with silt and clay less than 20%, a mean depth of 2-3 m, salinity higher than 7.5 PSU, maximum orbital velocity caused by waves lower than 0.3 m s^{-1} near the bottom, a water temperature range of 12.8°C and annual solar irradiance of $30\text{--}70 \text{ kW m}^{-2}$ reaching the bottom (Urbański et al. 2008).

Data acquisition

High-resolution QuickBird images covering the AOI were obtained by the standard tasking procedure on September 30, 2007. The spatial resolution of the images acquired by the QuickBird panchromatic band (spectral range 450–900 nm) and multi-spectral bands (spectral ranges: 450–520, 520–600, 630–690, 790–900 nm) are 0.6 m and 2.5 m, respectively. Data were geometrically and radiometrically corrected in coordinate system UTM-34 with datum WGS84 in GeoTIF format and then saved as a 16-bit standard imagery product with digital numbers (DN). Information concerning the type of benthic habitats present in the study area was obtained from underwater photographs and videos. Thirteen sampling stations were documented during August, September and October of 2007. Underwater photographs and short movies were captured by divers using an HP Photosmart R818 Camera. Each movie was examined precisely by means of VirtualDub Editor 1.7.6 software. The goal was to select the sharpest movie frames with elements of the seabed easily distinguishable. In order to gain comprehensive characteristics of the bottom on each point, 3-6 photographs of each sampling station were selected. Plants in the photographs were identified to the lowest possible taxonomic level using standard taxonomic keys. Scuba divers visually estimated seagrass and macroalgae cover.

Pixel versus object-oriented classification, seagrass model definition

An object-oriented approach to image analysis is based on objects defined as a group of pixels reflecting real-world features (Blaschke et al. 2004). The objects can be extracted from multi-spectral images based on their internal homogeneity and spectral separability. Objects form a hierarchical and scale-dependent structure. This means that any object, in contrast to a pixel, has not only neighbors but also sub-objects and super-objects at different scales. Groups of pixels, due to their hierarchical structure, are able to include many attributes which can describe objects' intrinsic characteristics (using physical features like color, texture, and shape), typological characteristics (relations to other objects, sub-objects and super-objects) and context (eCognition, 2005). These object characteristics allow one to classify objects using a complex cognitive process more akin to the human way of image recognition. The hierarchical and scale-dependent structure of objects can be applied to define the object-based seagrass model as shown in Fig. 1. It presents a meadow (a spatially continuous area of seagrass beds of varying percent of cover composition). The meadow constitutes the highest level of the structure. Subsequently, the meadow is divided into objects reflecting the second structure level – beds (spatially continuous areas of overall similar percent of cover composition). Furthermore, each bed object is split into smaller objects - patches and gaps - composing another level of the structure. The lowest level consists of pixels. Generally, this model can be extended by adding other levels, e.g. dividing the entire image into zones representing different depths or types of sediment. In order to perform object-based analysis and classification an appropriate tool is necessary. The present study utilized Definiens Developer 7 software. Previous versions of the software have already been used to analyze seabed cover based on optical (Green & Lopez 2007, Lathrop et al. 2006) or acoustical data (Lucieer 2008). The workflow is as follows (Definiens Developer 7, 2007). First raster layers, vector layers and metadata are entered. They include the information needed during the analysis and classification processes. As a result of segmentation process of raster layers (multi-spectral satellite images) and, if needed, vector layers objects are delineated. The segmentation is performed at different spatial scales and leads to the creation of a hierarchical structure of the objects. Finally, the feature space describing objects is applied in order to generate rule sets which classify objects. The rule sets are created by means of Cognition Network Language utilizing algorithms of the software.

Segmentation

Image segmentation leading to extraction of objects determines further analyses. In the present study multi-resolution segmentation was applied. This is

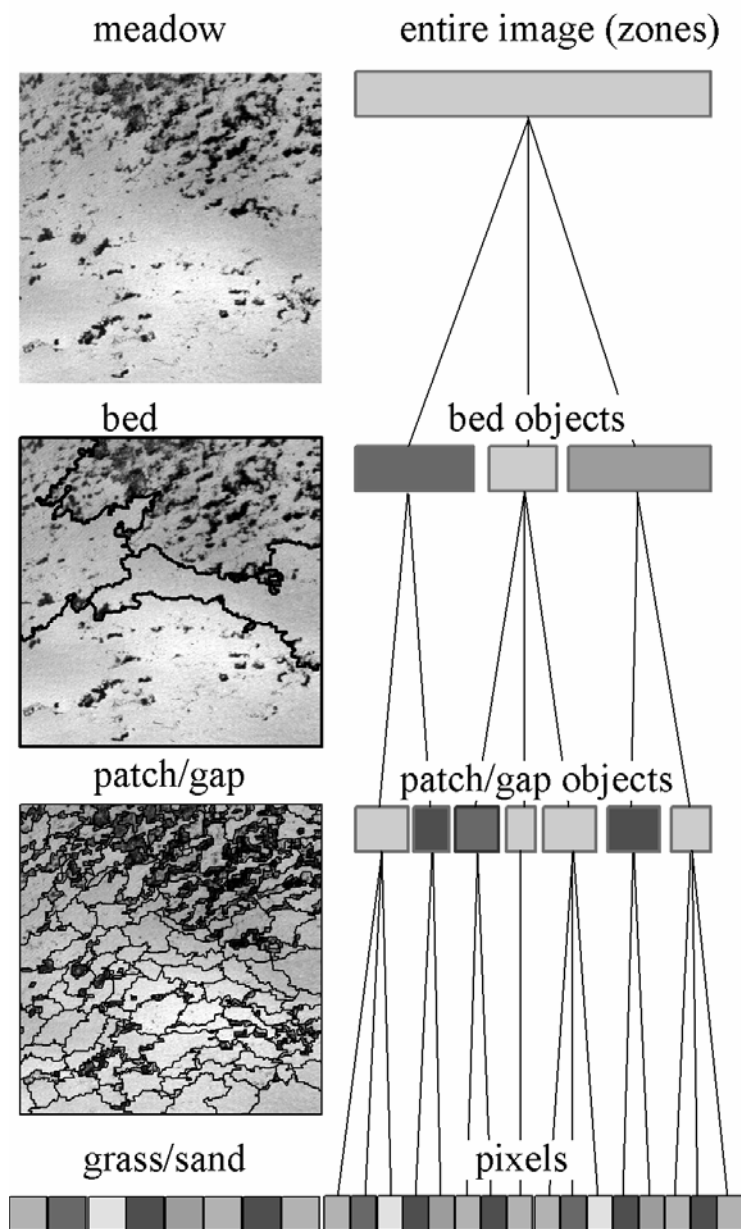


Fig. 1. Object-based model of seagrass meadow and its implementation in multi-scale object domain.

an optimization procedure which minimizes average spectral and shape (described by smoothness and compactness) heterogeneity for a given number of image objects and maximizes their homogeneity (Definiens Developer 7, 2007). Then objects of comparable spatial sizes are created. Their number and size at the particular segmentation level depend on scale parameter. Thus, the crucial step is to choose suitable segmentation parameters so that the size of the object is associated with its physical and biological spatial structure. One of the solutions previously proposed is local variance (Kim & Madden 2006). Due to the fact that sizes of the objects of the particular scale parameter have statistical distribution, it was assumed that comparison of statistical distributions leads to the selection of the most representative scale parameters for spatial structure in reality. The segmentation process aims to retain objects of strong spectral and shape homogeneity. When comparing distribution histograms of different scale parameters, some scales of objects tend to be more stable. They are observed in the image as representative scales of distinct patterns. As a geometric measure of the objects, the length object feature was implemented. It is calculated using the length-to-width ratio derived from a bounding box approximation.

Segmentation of each panchromatic image was performed for the following scale parameters: 400, 300, 200, 100, 50, and 20; which constitute six levels of objects. The homogeneity criterion was set to 0.9 for colour, 0.1 for shape, and 0.5 both for smoothness and compactness. Text files including feature values for each object were then exported from the levels. Using R software (R Core Development Team), histograms of object lengths at each level were obtained (Fig. 2). After analysis of the results, suitable parameters were selected and segmentation at the bed level was performed. The lowest scale describes the patch/gap (Mumby & Edwards 2002) level.

Classification at patch/gap level

While classifying bottom as covered with submerged aquatic vegetation (SAV) or without submerged aquatic vegetation (notSAV) in pixel-based analysis three strategies were typically used; unsupervised classification followed by assigning of benthic category according to expert knowledge; supervised maximum likelihood classifier which is trained by ground-truthed polygons for each class; and the application of contextual decision rules. If there is a need to distinguish seagrass from sandy bottom, the fact that sand has higher reflectance value than SAV in the visible region of the spectrum may be used (Kutser et al. 2006). Also the difference between band 2 (Ch2) and band 1 (Ch1) is higher for sand than for seagrass species, e.g. *Zostera* sp. or *Ruppia* sp. (Dekker et al. 2005). As a result, the difference of DN between bands (Ch2 — Ch1) can be used to distinguish seagrass meadow from sandy bottom. Using

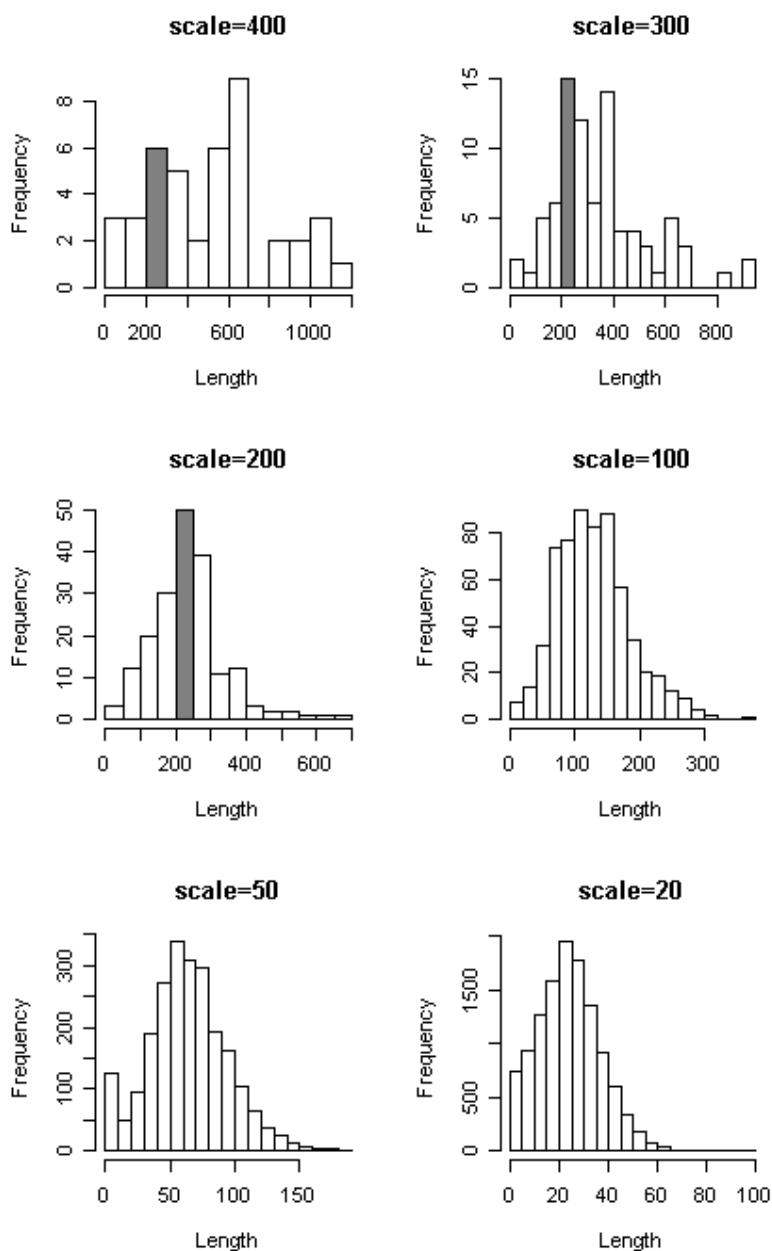


Fig. 2. Histograms of segmented objects' length at particular scale levels.

object-based analysis, many additional features describing objects can be implemented. In this project, the standard deviation (STD) of the second band signal was used. Values of STD (Ch2) were higher for patch objects than for gap objects. Using the difference of the mean values in the first and second bands together with standard deviation in the second band, the following Seagrass Index (SGI) was proposed:

$$\text{SGI} = [\text{Mean}(\text{Ch2}) - \text{Mean}(\text{Ch1})] / \text{STD}(\text{Ch2})$$

The SGI has low values (value of the numerator is lower and value of the denominator is higher) when the seabed is covered with vegetation or has high values (value of the numerator is higher and value of the denominator is lower) when only sand bottom is present. Beds were classified into 5 zones and then each zone was classified. Division into zones was based on depth, type of sediment and vegetation, including species composition and degree of algae cover. The process of division included image examination and analysis of field survey results as well. As a consequence, errors resulting from inconsistent radiometric response were smaller (Lathrop et al. 2006). Within each zone in the object layer with a scale parameter of 20 (patch/gap level), approximately 30 objects presenting vegetation cover (SAV_N where N is the zone number) and approx. 30 objects without vegetation cover (notSAV_N) were selected by manual sampling. The SGI index was calculated for the objects and results are shown in Fig. 3a. Then, using Definiens Feature Space Optimization software, analyses of a wide range of features were carried out in order to create optimal feature space for classification. The SGI index and mean value in Ch2 were chosen to form feature space discerning objects with or without seagrass cover (Fig. 3b). Further, these two features were used to perform classification using nearest neighbour (NN) method. NN was applied to every zone and was based on the condition of image object domain about existence of the particular super-object of the zone layer. Having performed the classification, SAV_N and notSAV_N classes were reclassified and assigned to SAV and notSAV classes. In order to perform accuracy assessments, samples from the patch/gap level were selected once more but for the scale parameter of 10. The samples were assigned to SAV or notSAV classes. Atypical, potentially difficult to classify objects were purposely chosen. Finally, the samples were exported to TTA (training and test area mask).

Classification at bed level

The aim of classification at the bed level was to create a map illustrating the density of patch/gap (Level 2) objects covered by SAV inside objects delineated

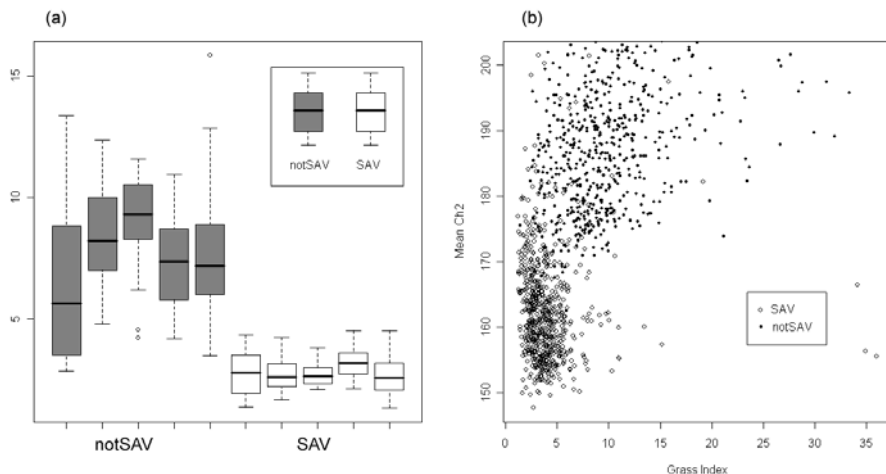


Fig. 3. Statistical analyses of samples: seagrass index (SGI) boxplots for the SAV and notSAV objects calculated for five zones (a); seagrass index and mean value of channel 2 scatterplot of SAV and notSAV objects (b).

on Level 1. At first, features defined as an area covered with sub-objects (at Level 2) assigned to SAV class divided by the area of image object concerned was calculated for each object at bed level (Level 1). Subsequently, values of calculated features were exported to *R* software and their histograms were generated in order to determine the classification scheme. Histogram analysis showed that the condition of a comparable number of objects in every class is fulfilled when the following ranges are used: 0 - 0.05, 0.05 - 0.1, 0.1 - 0.2, 0.2 - 0.4, 0.4 - 0.6, 0.6 - 0.8 and 0.8 - 1.0. The ranges defined as Boolean membership functions were applied to classify them. The entire process defining rule set was carried out by means of Cognition Network Language and is presented in Fig. 4.

RESULTS

The first stage of the analysis and classification process was multiresolution segmentation (Fig. 4) which delineated objects at three different scales. It is noticeable in Fig. 2 that objects about 200 m long have a tendency to maintain their size despite changes in scale. They constitute a maximum in histogram at a scale of 200 and 300, and a local maximum at a scale of 400. It was assumed that this scale is characteristic for seagrass beds. Beds were classified into 5 zones which allowed for zonal directed classification. Sandy sediments of the shallowest zone are covered by groups of vascular plants - mainly *Potamogeton*

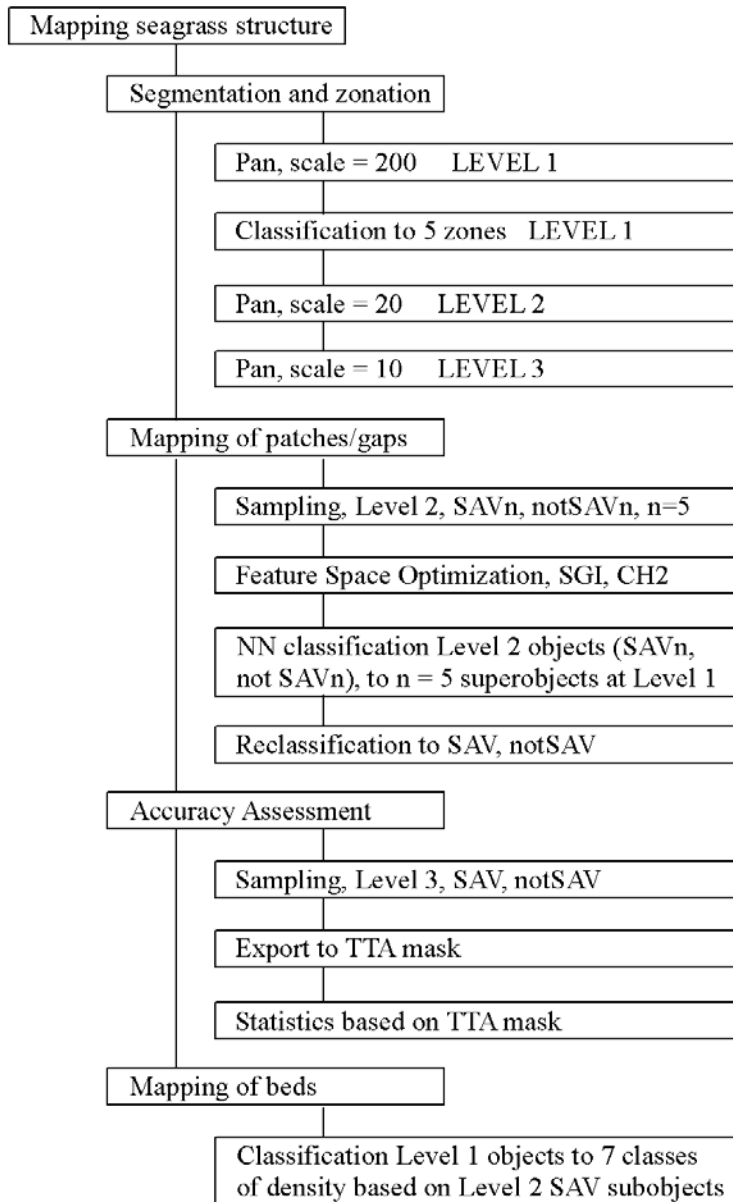


Fig. 4. The process tree defining all stages of object-based analysis and classification of submerged aquatic vegetation (SAV).

spp. and *Zannichellia palustris*. Plants are often covered by a blanket of filamentous algae. *Zostera marina* dominates in the two deepest sandy sediment zones. In the second stage patches and gaps were mapped using the seagrass index (SGI) combining pixel-based classification and object-oriented classification methods. Statistical analysis of index values for samples assigned to two classes of objects (SAV and notSAV) within five zones separately is presented in Fig. 3a. The analysis shows that the index values look very similar for seagrass presence (SAV class) in all zones, i.e. the means are similar and ranges are comparable. If, however, vegetation is not present, the index means and ranges show much higher diversity. The classification of patches/gaps was performed for five zones separately. The assessment of classification accuracy used additional samples selected by manual interpretation at Level 3 and placed in the TTA mask (Training or Test Area). Results are presented in Table 1.

Overall map accuracy is 83%. The producer's accuracy for seagrass is 93%, which means that 93% of the seagrass samples were classified as seagrass. The user's accuracy of 78% means that 73% of the seagrass within the polygons was

Table 1

The assessment of classification accuracy: SAV – Submerged aquatic vegetation, KIA – Kappa index of agreement.

User/Reference class	SAV	notSAV	SUM
SAV	19451	5413	24864
notSAV	1524	13790	15314
unclassified	0	0	0
SUM	20975	19203	40178
Producer	0.927	0.718	
User	0.782	0.901	
KIA per Class	0.809	0.545	
Overall accuracy	0.827		
KIA	0.651		

classified as seagrass. Overall Kappa index of agreement (KIA) is 65% and varies between categories (81% for SAV and 55% for notSAV). In the final stage, objects at Level 1 were classified based on density of Level 2 objects they contain classified as SAV. Consequently two vector layers were created enabling analysis in GIS. The vector layers were exported as polygon layers to ArcGIS 9.2 software. Polygons of the same class were merged together (dissolve) and their contours were simplified. In Fig. 5a, the map of patches presents 404 seagrass polygons (one class) unevenly distributed on the bottom. The areas of the polygons range from 5 to 250,000 m² which correspond to a scale of 10-20m in field survey. The diversity of area size results from

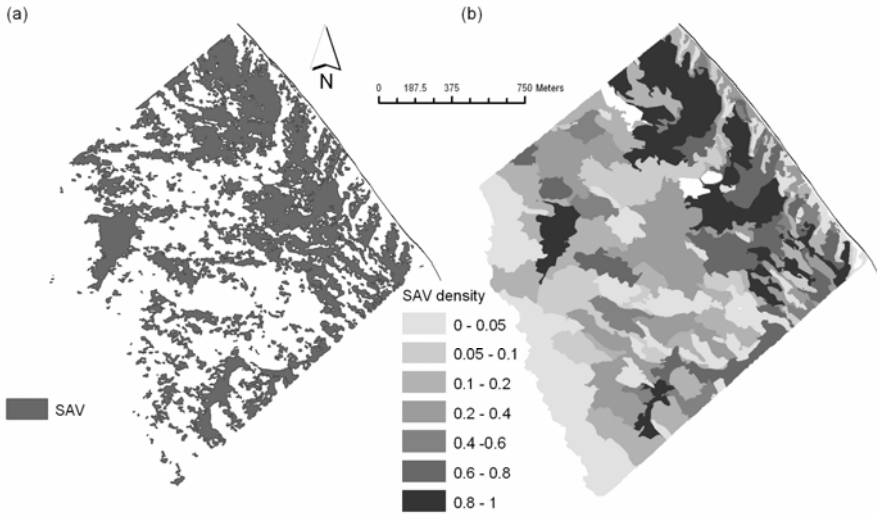


Fig. 5. Submerged aquatic vegetation (SAV) mapping: map of SAV patches at patch/gap scale (a); map of SAV density at bed scale (b).

merging neighbor objects of seagrass patches. In Fig. 5b, a map of beds constituting a mosaic of objects from 7 classes is presented. It consists of 115 objects which form a nearly continuous surface. Areas of the objects vary between 550-222,000 m², which represents the scale of 200-300 m in field survey.

DISCUSSION AND CONCLUSIONS

The object-based model of seagrass meadows (Fig. 1) described in previous sections is another attempt, following Lathrop et al. (2006) and Green and Lopez (2007), to implement a classification seagrass structure model proposed by Robbins and Bell (1994). In contrary to these works the presented model is based on relationships between patch/gaps and beds constituting a hierarchical structure at two spatial scale levels. As a result, density of SAV cover at bed level could be determined by patch/gap sub-objects in a fully automatic way. In Lathrop et al. (2006) SAV cover was visually interpreted and manually encoded for three density classes whereas in Green and Lopez (2007), only a map of patch/gaps was created. In our project mapping of seagrass meadows was performed at two levels: bed and patch/gap. In comparison with raster data

based on pixels, which are artificial units, the elements of object-based models reflect real objects in the habitat. The selection of the scale for the analysis is essential to the results. The proposed method of interpretation of histograms showing spatial sizes of the objects for different scale parameters can be regarded as hypothetical and requires further studies. However further merging congruent objects of the same class together makes subjective decisions regarding the selection of scale parameters less important. As evidence, a comparable scale of the largest objects with surfaces of 220,000 and 250,000 m² at two levels can be given. Moreover, object-oriented analyses, compared to a pixel-based approach, provides an incomparably larger set of possible features which can be used for object description. The features are computed using subsets of pixels which belong to particular objects and therefore, contrary to the moving window technique, the subset is limited by the border of a real object, not an artificial one. The seagrass index (SGI) proposed in the study is an example of using both typical pixel-based spectral characteristics and object-based ones. The index was undeniably useful in the presented analysis but is not necessarily universal. Therefore further research should be carried out. The application of object-oriented classification is questionable when regarding ground-truth sampling conducted in order to perform supervised classification and accuracy assessment. The main problem during in situ sampling is the support size which is usually kept constant and which subsequently has to be referred to the objects of variable size which are often much bigger than the scale of applied methods of sampling or photo documentation. It is also highly questionable to assume that manual interpretation of objects identified in the image is completely accurate (Congalton 1991). This is why field samples should be taken and identification of the taxonomic composition of seagrasses should be carried out within the test area. However, selecting sampling points based on satellite or airborne images can significantly reduce the number of samples, which are expensive and time-consuming to collect and analyze. It seems essential to consider ground-truth data as containing some level of uncertainty. The accuracy errors can be estimated not as global (one value of error for entire map) but at the local level (for each object). The proposed zonal classification appears to solve to some extent the problems formerly mentioned by Lathrop et al. (2006) resulting from inconsistent radiometric response from image to image during the analysis of image mosaics. Additionally, a zonal approach to classification can facilitate the classification process when areas of different depths, types of sediment or vegetation cover are mapped. Object-based analysis enables supplementing classification rules with contextual analyses which can result in a robust automatic solution. The solutions can be implemented without in-depth knowledge of remote sensing methods and consequently can make such

methods widely applicable in coastal management, conservation and restoration projects. The methodology used in this study enables the creation of quantitative maps of SAV density at sea bottom (Fig. 5b). Until now, mainly semi-quantitative measures (e.g. sparse, moderate, dense, patchy, continuous) were used, for instance in studies by Lathrop et al. (2006), Dekker et al. (2005) or Pasqualini et al. (2005). Considering seagrass cover, mapping at the bed level is important for analyzing change as the seagrass species expand by rhizome elongation of terminal shoots. It is possible that seagrass spatial distribution at the patch/gap level varies annually and at the same time the density cover on the bed level is stable. Mapping of seagrass landscape structure simultaneously in two scales, since it is related to functional ecological models of the structure, using vector based data (polygons) provides new opportunities for applying landscape measures to ecological studies. It enables, for example, the monitoring of large-scale negative changes in shallow water marine ecosystems, which is a common phenomenon. Such large scale negative changes include habitat loss, fragmentation and decrease in density cover of seagrass beds. These changes in the seagrass landscape structure affect their function, thus affecting benthic fauna populations and communities (Boström et al. 2006, Jackson et al. 2006).

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