BALANCE Interim Report No. 12

Evaluation of satellite imagery as a tool to characterise shallow habitats in the Baltic Sea

Baltic Sea Region
INTERREG III B

BALANCE

<table>
<tr><td colspan="2">Title

Evaluation of satellite imagery as a tool to characterise shallow habitats in the Baltic Sea</td><td colspan="4">BALANCE Report No.

12</td></tr>
<tr><td colspan="2" rowspan="2">Authors

Ulf Bergström[1]
Joakim Evertson[2]
Peter Karås[1]
Alfred Sandström [1]
Göran Sundblad[2]
Sandra Wennberg[1]

1 Swedish Board of Fisheries, Institute of Coastal Research, P.O.Box 109, SE-74071, Öregrund, Sweden.

2 Metria Miljöanalys, P.O. Box 241 54, SE-10451 Stockholm</td><td colspan="4">Date

May 2007</td></tr>
<tr><td colspan="4">Approved by

Johnny Reker</td></tr>
<tr><td>Revision</td><td>Description</td><td>By</td><td>Checked</td><td>Approved</td><td>Date</td></tr>
<tr><td>1</td><td>Final report</td><td>SW</td><td>JYR</td><td>JYR</td><td>31/3-06</td></tr>
<tr><td>0</td><td>Draft report</td><td></td><td></td><td></td><td></td></tr>
<tr><td></td><td>Front page illustration: NERI</td><td></td><td></td><td></td><td></td></tr>
<tr><td colspan="2">Key words

BALANCE; remote sensing, marine habitats, Archipelago Sea,</td><td colspan="4">Classification

☒ Open

☐ Internal

☐ Proprietary</td></tr>
</table>

Distribution	No of copies
BALANCE Secretariat	3 + pdf
BALANCE partnership	20 + pdf
BSR INTERREG IIB Joint Secretariat	1
Archive	1

CONTENTS

0 PREFACE

This report is a BALANCE product and focuses on evaluation of remote sensing methods as a tool to characterise shallow marine habitats. The report has been compiled by:

- Sandra Wennberg and Ulrihca Malmberg from Metria Miljöanalys, P.O. Box 241 54, SE-104 51 Stockholm, and
- Göran Sundblad, Alfred Sandström, Ulf Bergström and Peter Karås from Swedish Board of Fisheries, Institute of Coastal Research, P.O. Box 109, SE-74071, Öregrund, Sweden.

This report is the final report completing BALANCE Interim Report no. 5 “Remote sensing as a method to characterise shallow coastal habitats in the Baltic Sea”. The study is a part of BALANCE is co-financed by the Swedish National Space Board, the Swedish Board of Fisheries (SBF) and the Swedish Environmental Protection Agency (SEPA). The majority of the evaluations, interpretations and analyses of remote sensing images are performed by Metria. The output from the study will form an important part of Work Package 2 by producing maps on environmental variables that are used for predicting the distribution of Baltic Sea habitats.

More information about BALANCE and electronic copies of this report can be found at http://www.balance-eu.org.

Alfred Sandström

Swedish Board of Fisheries, Institute of Coastal Research

1 INTRODUCTION

1.1 Background

The Baltic Sea coastal zone hosts a large variety of environments. In the near-shore shallow areas both production and diversity are usually high, which makes these habitats both ecologically and economically valuable and important for several organism groups. For several fish species these shallow areas function as spawning, feeding and recruitment habitats. The vast majority of both marine and freshwater fish species in the Baltic Sea utilise shallow coastal areas (depth 0-10 m) as nursery habitats. The threats to these environments are, however, many and there is a need to identify habitats with particularly high potential for fish recruitment in order to enable an efficient physical planning and thus a sustainable coastal zone management. Knowledge on the distribution of marine habitats is very fragmented today, mainly because of the high costs associated with conducting field surveys in marine areas. Remote sensing has the potential advantage of covering large areas and enabling a fast and resource-efficient method to map the characteristics of shallow habitats.

Mapping of fish nursery areas as well as the majority of other key biological habitats in BALANCE will mainly be conducted by combining statistical models describing the habitat requirements of the target organisms and using GIS to produce geographical predictions by combining several layers of habitat information. Since the access to high resolution maps that cover larger coastal areas currently is a significant bottleneck in all such efforts to model distribution of coastal habitats, the benefits from developing remote sensing techniques may be of fundamental importance for the long-term success of the project.

In this evaluation of the potential of remote sensing we mainly concentrated on three environmental variables: (i) coverage and composition of submerged and emergent vegetation, (ii) water depth and to a smaller extent (iii) light attenuation. These parameters were chosen since they are important for characterising coastal habitats in general and fish nursery areas in particular.

i. *Vegetation is the main provider of structural complexity in marine and freshwater ecosystems and its importance in facilitating predator-prey interactions and sustaining species diversity in aquatic ecosystems has been demonstrated in numerous ecological studies (e.g. Orth et al., 1984; Pihl, 1986; Christensen & Persson, 1993; Mattila, 1995; Eklöv, 1997; Grenouillet & Pont, 2001). Vegetated areas may offer spawning substrate, refuge for larvae and juveniles during predation-sensitive stages and foraging possibilities for many coastal fishes. Current studies conducted by SBF in Pilot Area 3 indicate that fish species with littoral larvae may be particularly dependent on vegetation (fig. 1). Studies within associated projects also show that loss of vegetated habitats and/or shifts in vegetation communities caused by physical disturbances and boating activities may affect the recruitment of near-shore fish species (Sandström et al., 2005).*

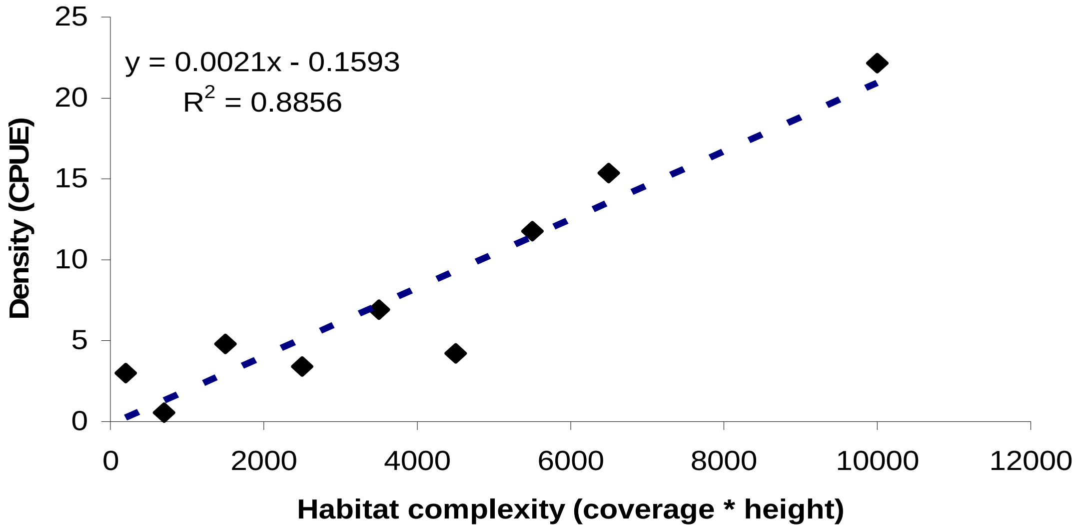

***Fig. 1**. Relationship between the catch per unit effort (CPUE) of juvenile fish and habitat complexity measured as the product of mean vegetation coverage (%) and height (cm). Data from the INTERREG IIIA financed project "Fish production in shallow bays".*

ii. *Water depth is one of the key parameters in modelling marine habitat distribution, both as a direct and as an indirect predictor variable. It is often highly correlated with other environmental variables such as vegetation, temperature, light climate and exposure to waves and ice-erosion. In order to use depth as a predictor variable for both fish recruitment potential and vegetation community composition there is a need for relatively detailed bathymetry maps, particularly for areas shallower than 5 m in depth (fig. 2). Such maps are not available at the moment and thus a successful attempt to use remote sensing techniques will be necessary to use depth as a parameter in the modelling of these as well as other organism groups.*

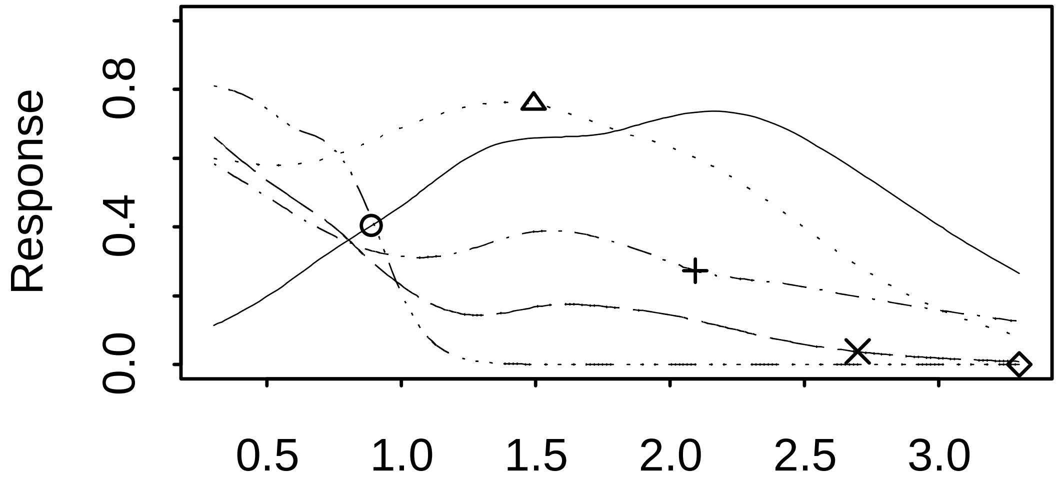

Fig. 2. *Species model response curves in relation to a depth (m) gradient. Data from Sundblad, G., Sandström, A., Mattila, J., Snickars, M., unpublished data. O = pike, Δ = roach, + = rudd, x = tench, ◊ = goby.*

iii. *Light attenuation or water turbidity may vary considerably within the archipelago areas in pilot area 3 partly due to natural causes but to a large extent also due to anthropogenic disturbances, e.g. eutrophication (Breukers et al., 1997), dredging (Gregory, 1990) and deforestation (Berube & Levesque, 1997). As a consequence water turbidity in many marine BS areas has been substantially elevated and the composition of suspended and particulate materials altered. Different substances absorb different parts of the light spectra, thus the intensity of remaining wavelengths will vary with both depth and the composition and abundance of absorbing agents. Visual conditions also affect the depth distribution of submerged vegetation as well as the interactions between all organisms relying on visual cues for perceiving their ambient environment. In addition, water turbidity is a strong indicator for system productivity. Turbidity is particularly well correlated to the distribution of fish juveniles of species equipped with sensory physiological adaptations that enhance foraging and anti-predator behaviour in dim and turbid conditions and/or species that are favoured by increased productivity (Sandström, 2004).*

1.2 Project goals

The objectives of the project are to:

i. evaluate remote sensing using satellite imagery from SPOT 5 as a method for mapping shallow coastal habitat characteristics, such as submerged and emergent vegetation, Secchi depth and water depth, in the Baltic Sea.

ii. evaluate if satellite based information can complement existing information and hence be incorporated in the strategies developed to protect the marine environment and to achieve a sustainable management of fish resources.

2 STUDY AREA AND DATA

2.1 Study area

The study area covers three coastal types with different water characteristics. The northernmost scene covers the area around Holmöarna in the southern Bothnian Bay, the scene in the middle covers large parts of the coast and archipelagos in Uppsala County in the southern Bothnian Sea and the southernmost scene covers the northern part of Stockholm archipelago in the northern Baltic proper.

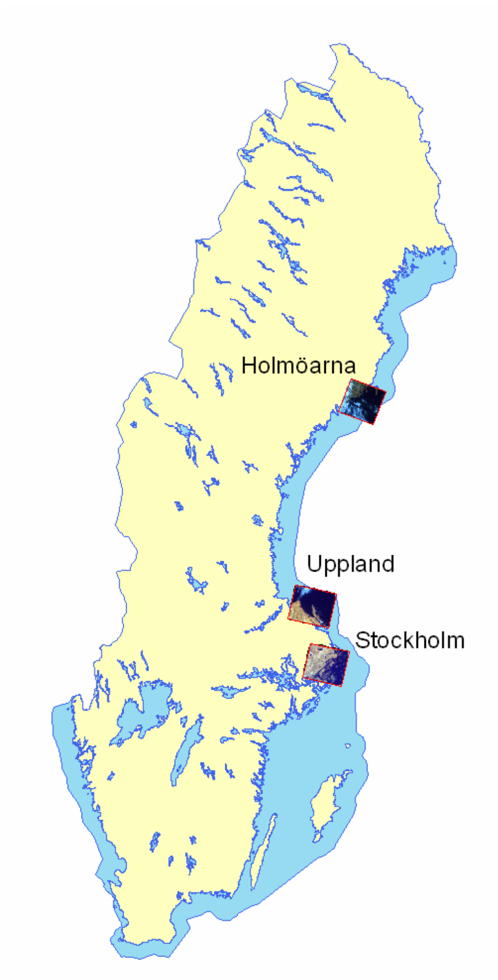

Fig. 3 *Study area.*

2.2 Data

2.2.1 Satellite data

The satellite SPOT 5 was launched in 2002 and circles the earth in 26 days. Four sensor channels have been used for the analyses, where channel XS1 is green (0.50-0.59 μm), channel XS2 is red (0.61-0.68 μm), channel XS3 is near infra-red (0.78-0.89 μm) and channel XS4 is shortwave infrared (1.58 to 1.75 μm). The scenes have a spatial resolution of 10 metres, except for channel XS4 (SWIR) with 20 m resolution. The images are shown in fig. 3.

One SPOT-5 scene was chosen for each of the three areas (table 1). The images were chosen among available summer images with no or little clouds. Only summer images were of interest since that was the time of year when the reference data was sampled and when the aquatic vegetation is most developed.

Table 1*. Three scenes from SPOT-5 were used in the analyses.*

Satellite, Scene id	Area	Date of registration
SPOT-5, 058/226	Uppland	2003-09-05
SPOT-5, 058/219	Holmöarna	2005-06-19
SPOT-5, 061/228	Stockholm	2004-08-08

2.2.2 *Reference data*

Point data on cover of submerged and emergent vegetation, water depth and Secchi depth was collated from field surveys conducted in 2005-2006. The data was used for calibration in the satellite image analyses as well as for validation of the results.

Table 2. *Reference data for classification*

Producer:	Area	Date	Type of data
SBF and The Foundation for Uppland	Uppland	20050816 – 20050916	Field survey
SBF	Holmöarna	20050803 – 20050814	Field survey
SBF	Stockholm	20050808-20050902	Field survey

Table 3. *Other data for validation.*

Producer:	Area	Type of data
The municipality of Värmdö	Stockholm	Classification from aerial photo interpretation
Lantmäteriet	All	Aerial photos

2.2.3 *Cartographic data*

Nautical charts (scale 1. 25 000) and national maps (scale 1: 50 000) were used to outline the classification area.

3 METHODOLOGY

3.1 Overview

The methods used for classification of the satellite scenes are described below and in a conceptual model in figure 4.

1. Two masks are produced (1) cloud/cloud shadow mask and (2) open land and water areas within 0 – 6 meters depth.
   1.1. A study area is produced by applying the masks above. Clouds, cloud shadows and areas that are not open land or water within 0 – 6 meters depth is masked out of the satellite scene.
   1.2. A spectral separation is made in the SWIR channel (XS4) of SPOT 5 in order to separate land/emergent vegetation from open water.
   1.3. High and medium intensity pixels are separated into land/emergent vegetation.
      1.3.1. A segmentation operation is applied to the land/emergent vegetation area.
      1.3.2. A maximum likelihood classification is applied to distinguish common reed and other vegetation into spectrally homogeneous areas.
      1.3.3. An emergent vegetation classification is produced.
      1.3.4. The result is edited by deleting small and heterogeneous areas.
      1.3.5. The result is a map of emergent vegetation.
   1.4. Low intensity pixels are separated into open water.
      1.4.1. The open water area pixels are used as input to the production stage in the Artificial Neural Network (ANN) described in section 3.

2. The reference data and the satellite data is joined in a table for each point of reference data. The result is a table with spectral information as well as reference data of depth and vegetation cover/class.
   2.1. Data points within clouds or cloud shadows are deleted from the table as are points with incomplete data.
   2.2. A training data file is created with information about id, coordinates, XS1, XS2, XS3, depth, vegetation cover/class and Secchi depth if available.
   2.3. The training data is applied in the Artificial Neural Network (ANN)
   2.4. The Artificial Neural Network (ANN) is trained using 10 000 iterations.
      2.4.1. In the first run XS1, XS2 and XS3 are used as input and depth is used as output. In the Uppland scene, where Secchi depth data was available, Secchi depth is run first, with XS1, XS2 and XS3 as input. Thereafter the three spectral bands and Secchi depth is used as input when analysing depth.
      2.4.2. In the second run XS1, XS2, XS3, depth and/or Secchi depth is used as input and vegetation cover class is used as output.
   2.5. The result from the training stage in the ANN is tested on the training dataset. If the test has acceptable results (see e.g. Table 8 and 9) the network setting is saved while the connection to the training dataset is removed.

3. The network is connected to the open water area pixels (the production data set) and the resultant grids are produced.
   3.1. The estimation grids produced are depth, Secchi depth (only for Uppland) and vegetation cover classification.

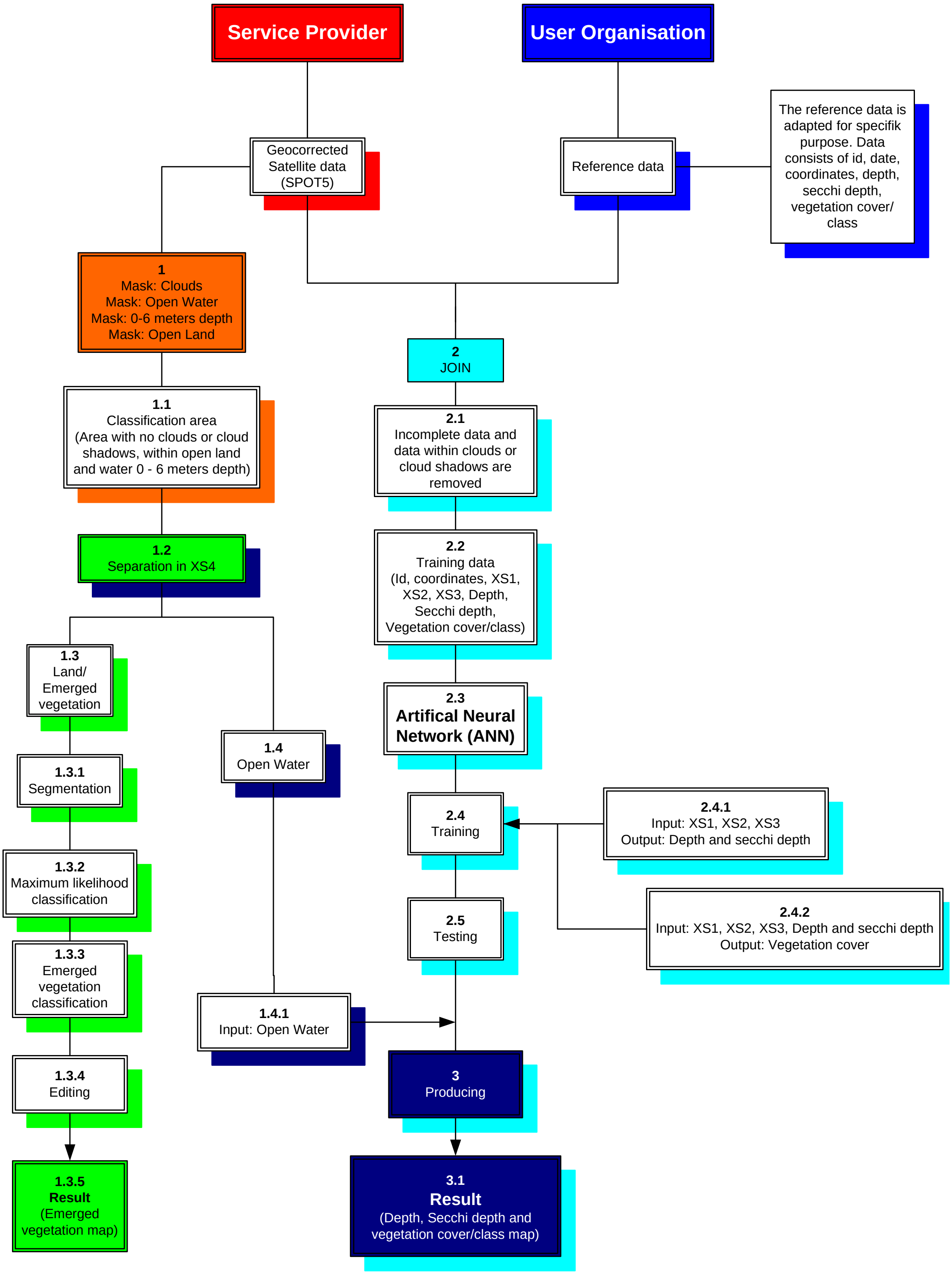

Fig. 4. *Flow scheme over the analyses performed in the classification of emergent vegetation, depth, Secchi depth, and submerged vegetation in the SPOT 5 scenes.*

3.2 Data pre-processing

3.2.1 Masks and classification area

A mask was created in order to only include areas of interest and to exclude areas covered by clouds or cloud shadows. The mask includes:

1. Water between 0-6 m depth (from nautical charts)
2. Open land lower than 5 meter (from map in scale 1: 50 000)

The mask excluded clouds and cloud-shadows that were visually identified.

Within the classification area, the SWIR (short-wave infrared) channel was used to separate emergent vegetation/land from open water based on a threshold. The two separate areas are classified by different methods.

3.2.2 Reference data from field surveys

Reference data (table 4) was prepared and provided by the Swedish Board of Fisheries (SBF). Field surveys were conducted by SBF and The Foundation for Uppland. The data include information about:

- position (Swedish national coordinate system RT90),
- depth
- Secchi depth (when available)
- vegetation cover
- vegetation type

The field data on vegetation and depth was collected by a free diver at sites with a depth ranging from 0 to 6 m. Two types of field surveys were conducted:

1. *A free diver investigated vegetation and water depth of a 10 × 10 m area.* The sites were randomly distributed and stratified along a wave-exposure continuum in each survey area. For each 10 × 10 m area the coverage of all species of underwater vegetation was estimated using five classes (0-4). Depth was measured at three locations at each site with a precision of 5 cm. Mean depth was used in all analyses. Positioning of the sample sites were conducted with a GPS (±10 m precision) at the center of each square.
2. *A free diver investigated vegetation coverage and depth of 10× 1 m areas in shallow lagoons*. Vegetation coverage of all species along with depth were surveyed at each site by diving along parallel transect lines (4-20 lines per site, length 20-340 m) drawn perpendicular to the length axis of the lagoons from one shore to the opposite, thus covering the entire site. The first line was placed 5 m from the innermost shore, the second line was placed at a distance of 50 m from the first one, and the rest of the lines 50 m from the previous one until the entire

area was surveyed. Depth and cover percentage of vegetation (cover classes, 0-4) was estimated at every ten metres, thus covering a 10 × 1 m sized rectangle (a total of 24-230 rectangles per site). Positioning of the sample sites were conducted with a GPS (±10 m precision) at the end-points of the transect lines.

The final ANN analyses were performed to distinguish between areas with high and low vegetation cover (all species together) and each sample point was classified into one of three vegetation cover categories: 0-20, 20-80 and >80% vegetation cover. Total per cent vegetation cover for each sample point was obtained by converting each species estimated cover class (0-4) into per cent cover (cover class 1 = 2.5%, cover class 2 = 15%, cover class 3, 40%, cover class 4 = 75%), and summarising the cover of all species.

Depth and secchi depth/turbidity data was also collected in separate surveys in two of the study areas. Secchi depth is the maximum depth at which a white disc (Secchi-disc) is visible from the surface. For shallow sites, where Secchi depth could not be properly measured, water turbidity was registered instead. Turbidity was measured in nephelometric turbidity units (NTU) with a turbidimeter (HACH 2100P) calibrated with formacin. NTU was later recalculated to Secchi depth using the following relationship obtained from parallell measurements of both variables: Secchi depth = 13,316 turbidity $^{-1,4402}$ (R^2 = 0.86).

Table 4. *Number of reference points used in ANN for each area.*

Area	Depth	Secchi depth	Vegetation
Uppland	36	36	729
Stockholm	81	81	750
Holmöarna	780	N/A	299

The field survey data was combined with the satellite data from the green (XS1), red (XS2) and infrared (XS3) channels to create training data for the artificial neural network (ANN). Table 4 presents the number of datapoints from the reference dataset that was used for training of the neural network.

3.3 Segmentation and classification of emergent vegetation

3.3.1 Background

In the study areas of Stockholm and Uppland emergent vegetation mainly consists of common reed belts (*Phragmites australis*), whereas in the study area around Holmöarna other species e.g. spikerushes (Eleocharis sp.), bulrushes (*Typha* sp.) and clubrushes (*Schoenoplectus* sp.) constitute a major part of the emergent vegetation (fig. 5). The delineation of emergent vegetation focused on common reed. Common reed is the largest grass in the region and normally forms large stands, making them relatively easy to separate from water using remote sensing. Reed belts are an important habitat providing food and shelter for many fishes, particularly for the early life-stages (Urho, 2002).

Segmentation of satellite data is a method that makes it possible to use other information of the objects than the pixels spectral value, e.g. shape, placement and texture. The method was chosen to solve the problem of separating common reed from grasslands as the reed-belts continue from the water on land and to be able to distinguish reed belts from pixels with a mixture of land and water.

Fig. 5. *The two dominating types of emergent vegetation in the study areas. Left: a dense patch of bulrush (Schoenoplectus sp.) at Holmöarna. Right: common reed (Phragmites australis) growing in a shallow bay in the Uppland area.*

3.3.2 Methodology

Emergent vegetation and land was classified using segmentation (see 3.2.1) and is based on all spectral sensor channels. Segments have no class but are polygons including pixels that are more alike inside the segment than towards its neighbouring segments. Segments were used as samples, i.e. given one of six classes: reed (i.e. all emergent vegetation), mixture of reed and water, mixture of land and water, forest, bare rock and other land. The samples for each class were selected using aerial photos as reference. Statistics of how well the classes can be separated were analysed in the classification program and serves as help for the operator to select additional samples or exclude samples. The samples were then used as input to perform a maximum likelihood classification.

The classification was rule-based where the output inherited one of two main classes; land and water, from a thematic layer. Classes without reed were reclassified to either land or semi-open water surface based on the main class. Reed classes were reclassified to either reed on land or reed in water.

The reed-classes were related to neighbours which, for example, created the class "reed on land intersecting reed in water". Reed on land that did not intersect water or reed in water was reclassified as land. Mixture of reed and water that did not intersect with reed in water or reed on land was reclassified as semi-open water surface. The remaining areas of reed (reed on land intersecting reed in water/water + reed in water) were analysed based on shape that gave additional classes of super objects; narrow reed belts (shape asymmetry > 0,85), small reed belts (< 5 pixels) and larger reed belts. This resulted in the classes described in table 5.

Small and narrow reed belts were evaluated. These areas had low classification accuracy and were therefore reclassified to either "Land" or "Semi-open water surface" based on their position in maps.

Table 5. *Resulting classes and inheritance in the segmentation analysis.*

Resulting class	Main class (Thematic layer)	Subclass 1 (ML-class)	Subclass 2 (shape/relation)
Semi-open water surface	Water	Bare rock / Mixture water and land	
		Reed / mixture reed and water	Small reed belt or narrow reed belt
Land	Land	Bare rock /Forest/Other land	
		Reed	Small reed belts or narrow reed belt
		Reed / mixture reed and water	Not intersecting reed in water
Reed on land	Land	Reed / mixture reed and water	Larger reed belt intersecting reed in water
Reed in water	Water	Reed / mixture reed and water	Larger reed belt

3.4 Classification of submerged vegetation, depth and Secchi depth using Artificial Neural Networks

3.4.1 Background

Artificial Neural networks (ANN) is a tool that can be used for classification or data modelling without assuming a certain type of mathematical relationship. The network is prepared with data representing input (here satellite data) and desired values (here depth, Secchi depth or vegetation cover). The training of the network is an iterative process where the network learns about the connection between input and desired signals. After training, the network is used to calculate desired data from input values.

Statistical correlation between two variables can be described with analytical statistical methods as regression analysis. More complex relationships between multiple input and outputs may be analysed with multivariate statistics. If non-linear relationship is assumed it requires that you decide the mathematical function for the non-linear regression. With an artificial neural network non-linear multivariate analysis can be performed directly from the input data without an a priori decision of the relationship between variables. In that case ANN can be described as a method to perform "non-linear multivariate regression”. The advantage of ANN is that it is flexible and can identify complex patterns, including interactions between variables. An inherent problem, on the other hand, is that it is difficult to describe the causal connection between input and desired data.

The training of ANN is an iterative process based on a selection of input values and desired values from the same location. The difference between output from the network and desired value is calculated and weights in the network are adjusted to minimise the error. The table is run through the network again, the differences are calculated and weights adjusted. The iteration is normally done thousands of times and the best weights are saved in the final network. This network can then be used to classify other input data, which in this case is the rest of the satellite scene.

An ANN is best described in a graphical model. The network is built on several nodes in multiple layers with nodes in one layer connected to all nodes in another layer. The number of nodes can vary; we have used one input layer, one hidden layer and one output layer. A larger number of hidden layers may increase the ANN:s capacity to fit input to desired values, but using many hidden layers may increase the risk of overfitting the model. In this study one hidden layer was used, to compromise between model flexibility and generality.

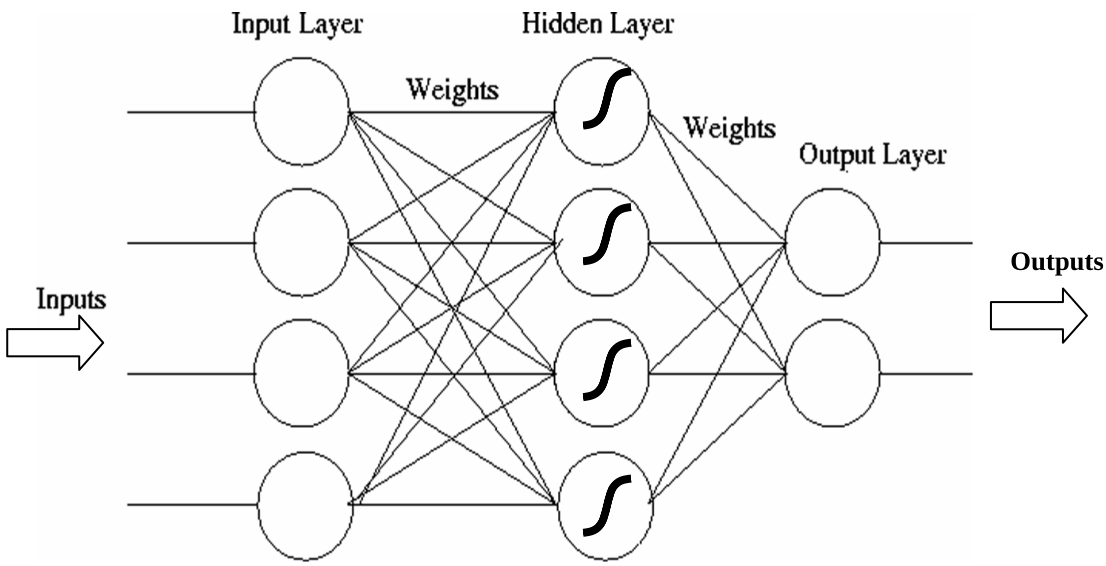

Fig. 6. *Schematic drawing of an Artificial Neural Network.*

3.4.2 Methodology

A back-propagation artificial neural network (ANN) was applied to classify multispectral remote sensing imagery data (SPOT5). The classification includes three steps: (1) training, (2) testing and (3) production. SPOT5 imagery data was used as input training data and field data was used as output desired data and for the accuracy assessment.

Selecting an efficient combination of satellite sensor channels for submerged vegetation classification, depth and Secchi depth is important for an effective refinement of an ANN. The contribution of each satellite sensor channel can be calculated from the weights of the neural network. For the neural network analysis the spectral sensor channels for green (XS1), red (XS2) and near infrared (XS3) light were selected.

Several attempts to use one or all sensor channels as well as an index between channel 1 and 2 were made. The project also tested several different steps of vegetation classification to optimise the results. The final method classified depth and Secchi depth if available in a first step; the values from the depth and Secchi depth classification were then used together with sensor data to classify vegetation.

4 RESULTS AND DISCUSSION

4.1 Emergent vegetation

The results for the three different study areas are raster layers with four classes (fig. 6). The class “Water, semi-open surface” includes pixels with a mixture of land and water, bare rock or sand just beneath the water surface and bridges, jetties and boats situated within the water area in maps. It may also include some emergent vegetation with a low coverage (< 20 %). Reed was separated into two classes, as the class “reed in water” has a higher accuracy than “reed on land”. Reed on land is partly mixed up with other grasslands (mainly high grass in moist areas).

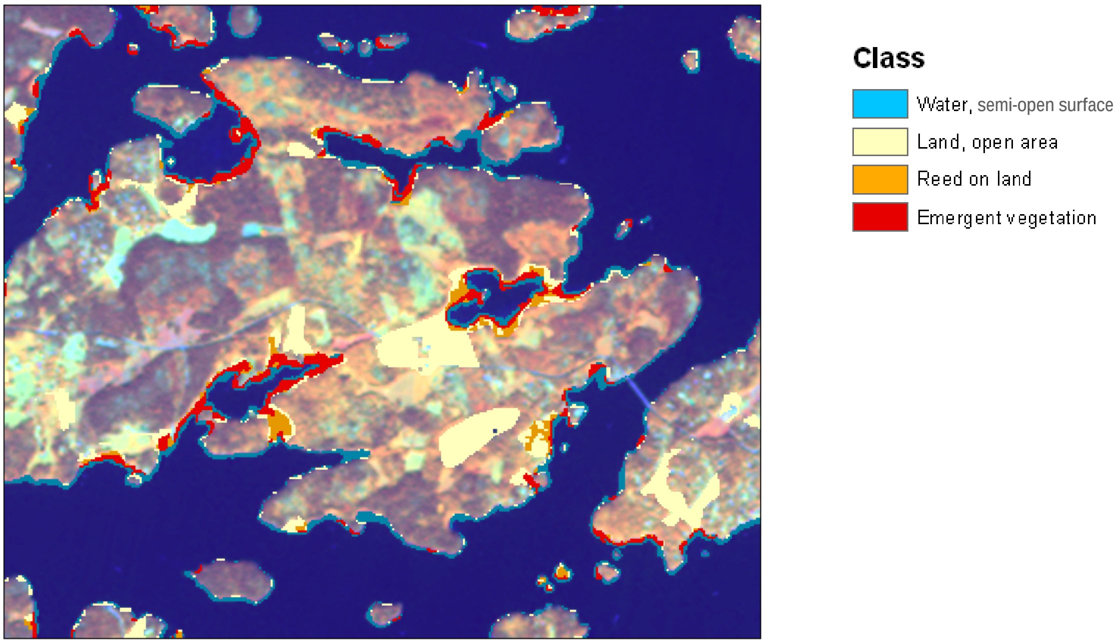

Fig. 7. *Example of the classification results of emergent vegetation around the island of Svartnö, Stockholm.*

The accuracy assessment was made on a random sample of points stratified by class in Uppland and Stockholm. The points were then evaluated against interpretations of orthophotos (Table 6 & 7). In Stockholm, reed on land was not separated from reed in water in the orthophoto interpretations. The satellite scene interpretation for Holmöarna was not evaluated since the orthophotos available were taken before the vegetation period.

Evaluation results for Uppland and Stockholm are given as i) overall accuracy (total number of correctly classified / total number of reference pixels), ii) user accuracy (correctly classified per class / total number of reference pixels classified as that class) and iii) producer accuracy (correctly classified per class / number of reference pixels of that class).

The classification of emergent vegetation, that is, “reed in water”, was successful for both scenes (Table 6-7). The user accuracy of that class was lower for Uppland than for Stockholm mainly due to that areas classified as reed was found to be semi-open water surfaces in the interpretation of ortophotos. The difference may be explained by that the Uppland scene is from September when the vegetation may be more developed than in the photos or that floating vegetation covers shallow areas in the satellite scene. In the analyses, reed was not separated from other emergent vegetation, such as bulrushes and clubrushes, as there was no reference data available on these species.

Table 6. *Accuracy assessment of the segmentation classification of the Stockholm scene.*

	Classified						
Reference data	**Open water**	**Water, non open surface**	**Reed**	**Land**	**Total**	**User acc. (%)**	**Producer acc.(%)**
Open water	33	3			**36**	91,7	89,2
Water, semi-open surface	4	11	4	2	**21**	52,4	73,3
Reed on land			5	8	**13**	38,5	
Reed in water		1	14	1	**16**	87,5	79,2
Land			1	9	**10**	90,0	45,0
Total	**37**	**15**	**24**	**20**	**96**		

Table 7. *Accuracy assessment of the segmentation classification of the Uppland scene. Overall accuracy 71 %.*

	Classified							
Reference data	Open water	Water, semi-open surface	Reed on land	Reed in water	Land	Total	User acc. (%)	Producer acc.(%)
Open water	16	1				**17**	94,1%	84,2%
Water, semi-open surface	2	12		1	7	**22**	54,5%	48,0%
Reed on land			7	1	12	**20**	35,0%	87,5%
Reed in water	1	10		14	2	**27**	51,9%	87,5%
Land		2	1		47	**50**	94,0%	69,1%
Total	**19**	**25**	**8**	**16**	**68**	**136**		

4.2 Secchi depth

The classification of Secchi depth covers shallow open water between 0-6 meters depth and is based on sensor channel XS1, Xs2 and XS3 as input. Based on the ANN analysis, a grid of continuous Secchi depth values was produced for the Uppland scene (fig. 8). The analysis of predicted versus observed values of Secchi depth showed that the major patterns of Secchi depth variations were captured in the analysis (fig. 9).

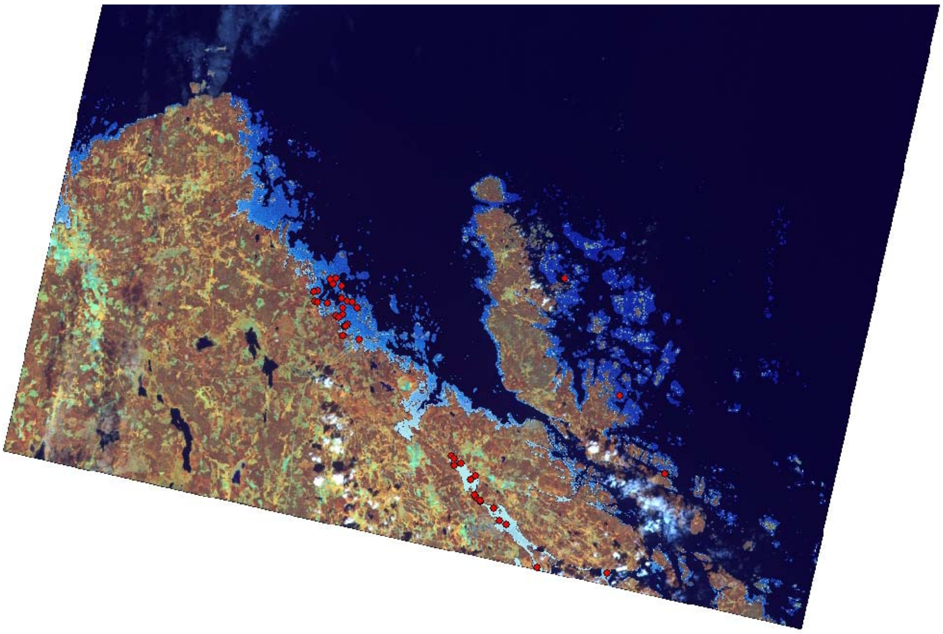

Fig. 8. *Secchi depth classification for the Uppland scene (light to dark blue corresponds to 1-6 m Secchi depth) and the position of the reference points (red dots). Only areas shallower than 6 meters were classified.*

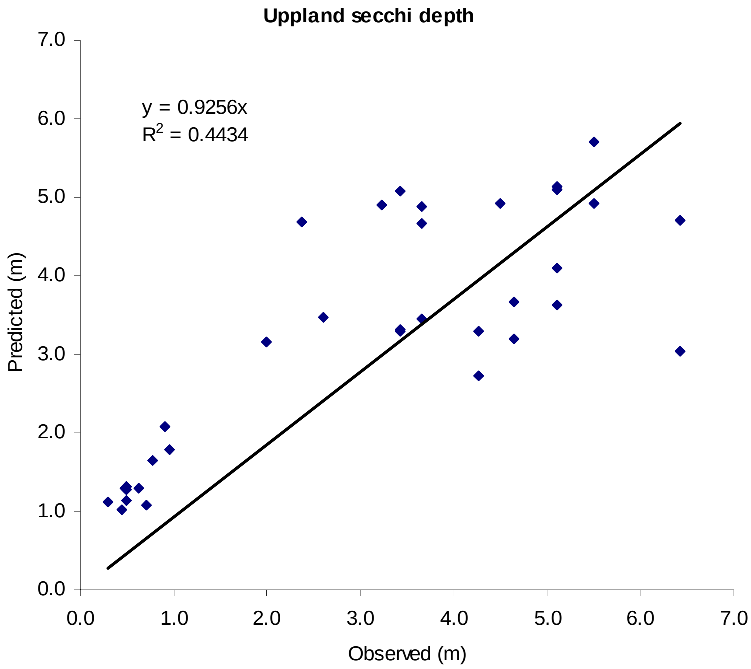

Fig. 9. *Predicted versus observed Secchi depth for the Uppland scene.*

For the Stockholm scene the Secchi depth prediction was not good (fig. 10-11). This might be due to a limited number of sites with low Secchi depth, a mismatch in time of sampling of reference data and the satellite scene and/or no reference data in the inner-most and outer archipelago to obtain an efficient ANN analysis.

For Holmöarna no reference data for the variable Secchi depth was available, hence no Secchi depth classification was made for this area.

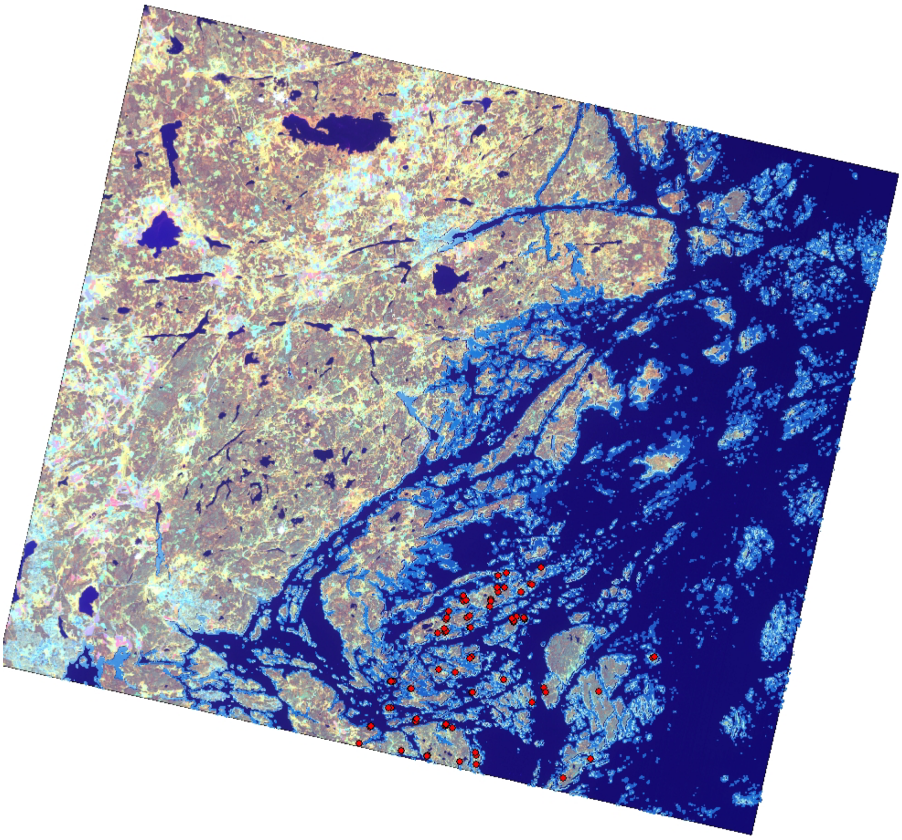

Fig. 10. *Secchi depth classification for the Stockholm scene (light to dark blue corresponds to 1-6 m Secchi depth). The reference sites (red dots) are mainly concentrated to the southern part of the scene.*

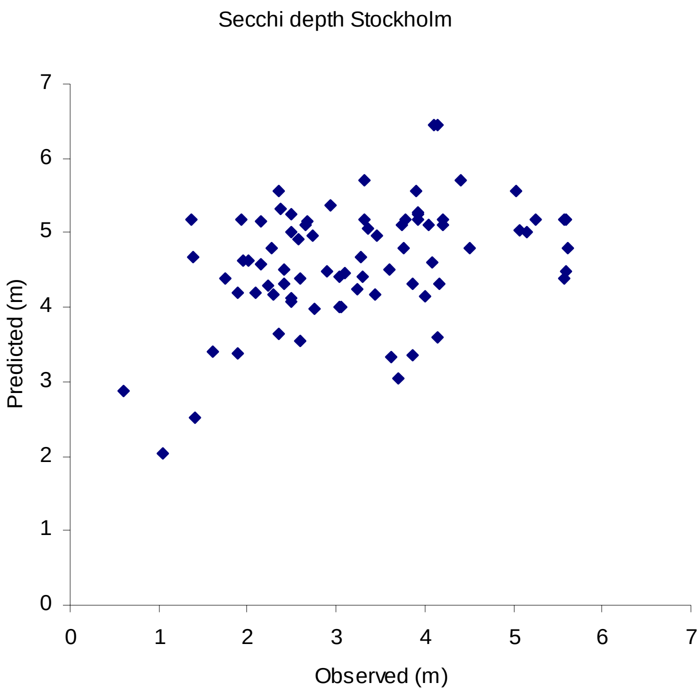

Fig. 11*. Predicted versus observed Secchi depth for the Stockholm scene.*

4.3 Depth

Water depth was analysed using ANN for all three areas. The analyses are based on spectral sensor channel XS1, XS2, XS3 as input variables. For the Uppland scene, a separate ANN that included predicted Secchi depth was also ran. The final predictions were evaluated against the observed data in all areas. The prediction of depth in Stockholm and Holmöarna worked well in areas down to 3m (Fig. 12-13 and table 8-9).

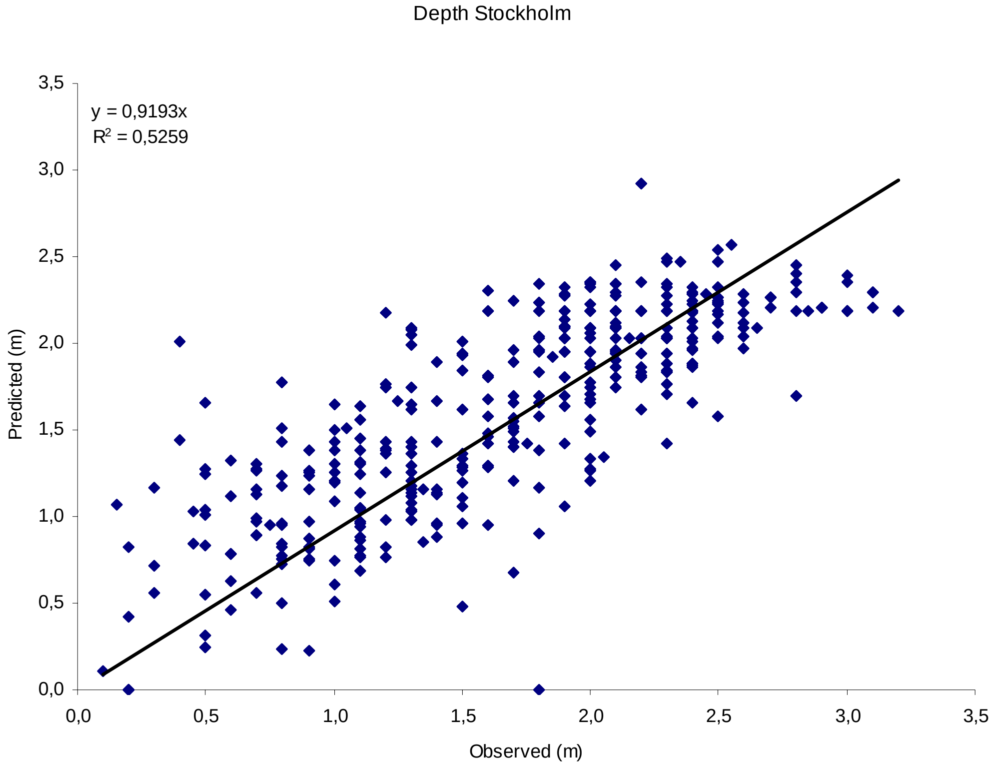

Fig. 12. *Predicted versus observed depth for the Stockholm scene.*

Table 8. *Evaluation of the depth classification in Stockholm. Mean squared error (MSE) per depth interval (reference points used in the classification and additional reference points from SBF), maximum overestimate (classified depth deeper than observed), maximum underestimate (predicted depth is more shallow than observed) and minimum squared error in the interval.*

Depth interval (observed)	Number of reference points	MSE	Max overestimate	Max underestimate	Min error
0 - 0,5 m	14	0,5	1,6	-0,2	0,0
0,5 - 1 m	52	0,3	1,2	-0,7	0,0
1 - 1,5 m	79	0,3	1,0	-0,5	0,0
1,5 - 2 m	80	0,3	0,7	-1,8	0,0
2 - 2,5 m	107	0,3	0,7	-0,9	0,0
2,5 - 3 m	36	0,4	0,0	-1,1	0,0
3 - 3,5 m	9	0,8		-1,0	0,6
All	**377**	**0,3**	**1,6**	**-1,8**	**0,0**

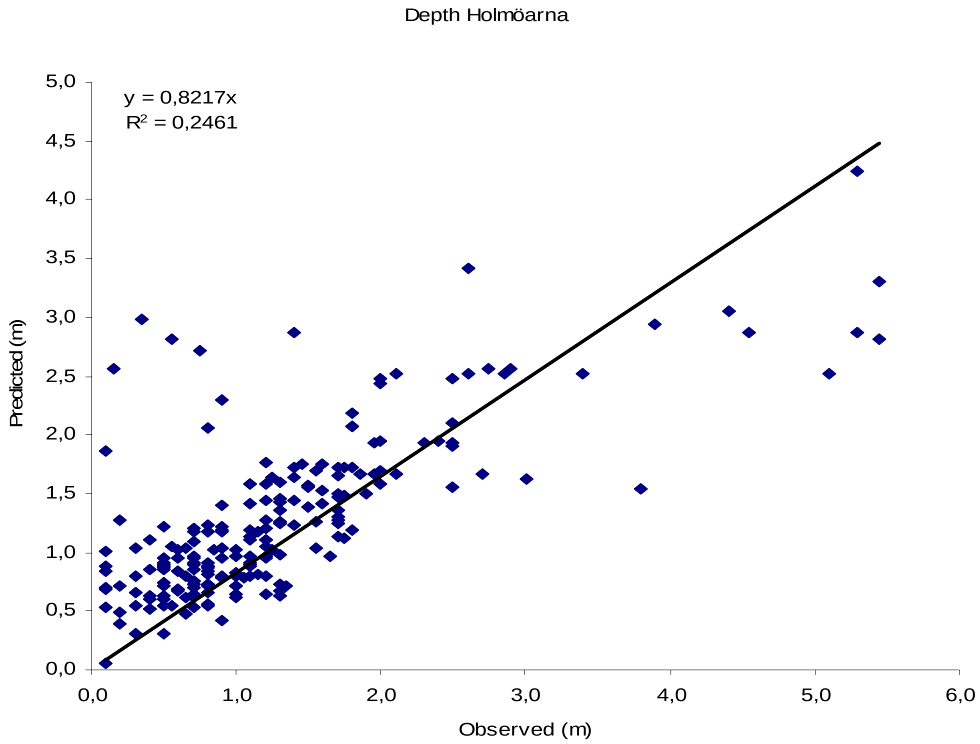

Fig. 13. *Predicted versus observed depth for the Holmöarna scene.*

Table 9. *Evaluation of the depth classification in Holmöarna. Mean squared error (MSE) per depth interval (reference points used in the classification and additional reference points from SBF), maximum overestimate (classified depth deeper than observed), maximum underestimate (predicted depth is more shallow than observed) and minimum squared error in the interval.*

Depth interval (observed)	Number of reference points	MSE	Max overestimate	Max underestimate	Min error
0 - 0,5 m	25	0,7	2,6	0,0	0,0
0,5 - 1 m	71	0,3	2,3	-0,5	0,0
1 - 1,5 m	54	0,3	1,5	-0,7	0,0
1,5 - 2 m	33	0,3	0,4	-0,7	0,0
2 - 2,5 m	9	0,4	0,5	-0,5	0,1
2,5 - 3 m	11	0,5	0,8	-1,0	0,0
3 - 3,5 m	2	1,1		-1,4	0,9
3,5 - 4 m	2	1,6		-2,3	1,0
4 - 5 m	2	1,5		-1,7	1,3
5 - 6 m	5	2,2		-2,6	1,1
All	**214**	**0,4**	**2,6**	**-2,6**	**0,0**

Prediction results for the Uppland scene using only spectral data in the ANN was poor. Including Secchi depth in the training dataset for Uppland slightly improved the correlation between predicted and observed data (compare table 10 and 11), however not enough for the results to be useful (fig. 14).

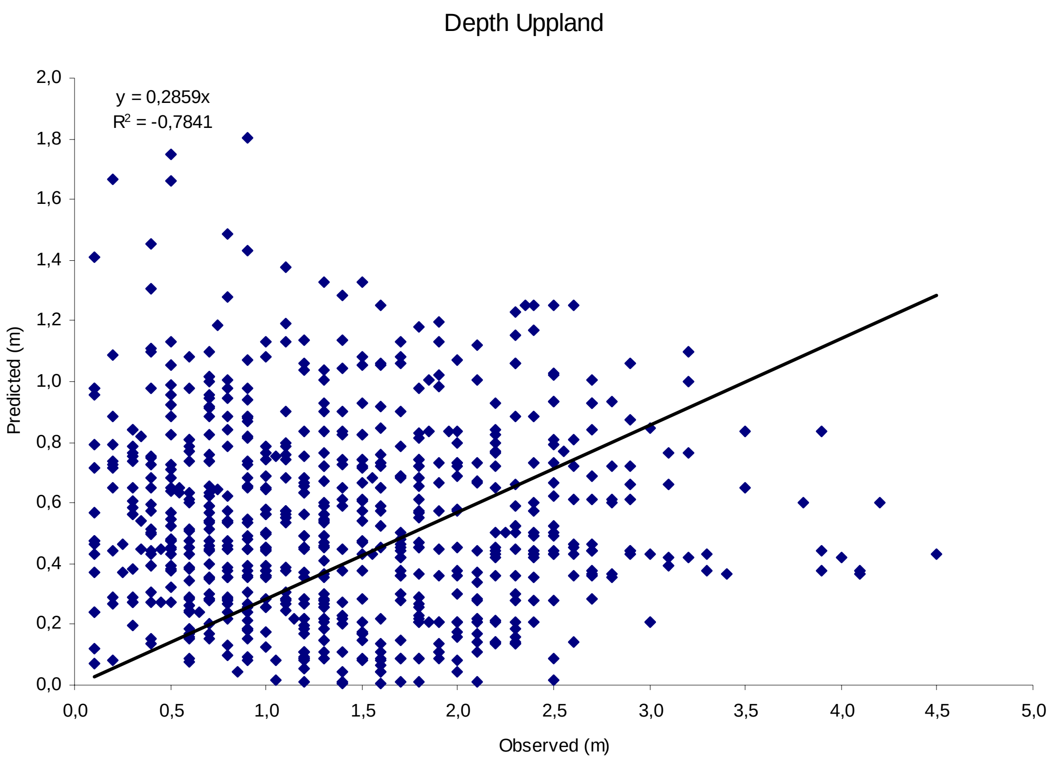

Fig. 14. *Predicted versus observed depth for the Uppland scene. The classification is based on XS1, XS2, XS3 and Secchi depth.*

Table 10. *Evaluation of the depth classification in Uppland based on XS1, XS2, XS3 and Secchi depth. Mean squared error (MSE) per depth interval (reference points used in the classification and additional reference points from SBF), maximum overestimate (classified depth deeper than observed), maximum underestimate (predicted depth is more shallow than observed) and minimum squared error in the interval.*

Depth interval (observed)	Number of reference points	MSE	Max overestimate	Max underestimate	Min error
0 - 0,5 m	74	0,4	1,5	-0,3	0,0
0,5 - 1 m	175	0,3	1,2	-0,8	0,0
1 - 1,5 m	157	0,7	0,3	-1,4	0,0
1,5 - 2 m	131	1,2		-1,8	0,2
2 - 2,5 m	94	1,7		-2,2	0,9
2,5 - 3 m	57	2,0		-2,5	1,3
3 - 3,5 m	15	2,6		-3,0	2,1
3,5 - 4 m	6	3,1		-3,5	2,7
4 - 5 m	5	3,7		-4,1	3,6
All	**714**	**1,0**	**1,5**	**-4,1**	**0,0**

Table 11. *Evaluation of the depth classification in Uppland based on satellite data only. Mean squared error (MSE) per depth interval (reference points used in the classification and additional reference points from SBF), maximum overestimate (classified depth deeper than observed), maximum underestimate (predicted depth is more shallow than observed) and minimum squared error in the interval.*

Depth interval (observed)	Number of reference points	MSE	Max overestimate	Max underestimate	Min error
0 - 0,5 m	75	0,5	3,3	-0,3	0,0
0,5 - 1 m	181	0,5	2,9	-0,8	0,0
1 - 1,5 m	174	0,8	2,4	-1,3	0,0
1,5 - 2 m	143	1,0	1,9	-1,8	0,1
2 - 2,5 m	106	1,6	1,1	-2,3	0,0
2,5 - 3 m	61	2,0	0,8	-2,8	0,1
3 - 3,5 m	15	2,9		-3,3	2,1
3,5 - 4 m	6	3,1		-3,8	2,2
4 - 5 m	5	4,0		-4,4	3,5
All	**766**	**1,0**	**3,3**	**-4,4**	**0,0**

The higher accuracy of the analyses in the Stockholm and Holmöarna scenes can probably be explained by the lower turbidity in these areas. In order to predict depth accurately it seems necessary that sufficient light penetrate to the bottom. In the Uppland scene, light penetration may have been further restricted by the lower solar elevation angle and poorer illumination conditions prevailing in September.

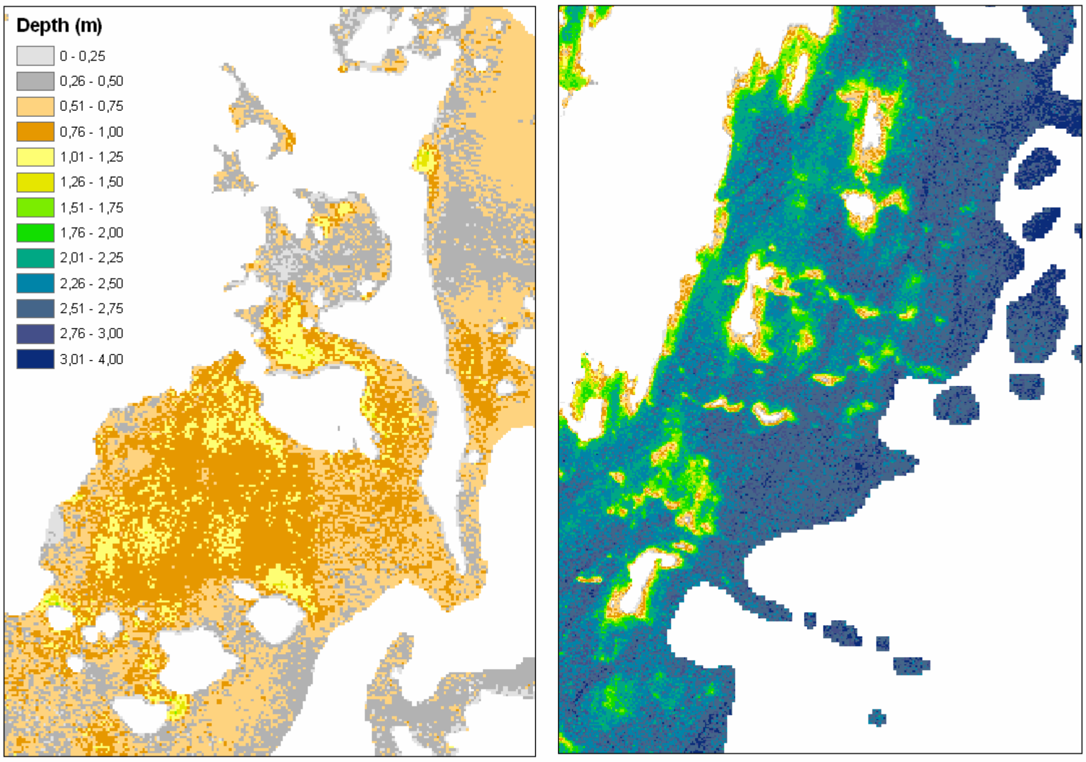

***Fig. 15**. Sub-samples of the predictions of depth. In Uppland (left, showing the inlet of Kallri-gafjärden) the predicted depth in general is too shallow and only depths shallower than 1 meter has a MSE < 0,5. In Holmöarna (right, showing the island of Grossgrundet to the left) and Stockholm the prediction was more accurate and depth down to 3 meters could be predicted with MSE < 0,5.*

4.4 Submerged vegetation

A number of different classifications of submerged vegetation were tested, including different classes of cover and colour of the vegetation. The species were classified into red, green and brown species (in analogy with Vahtmäe *et al*. (2006)), but analyses of the spectral information (fig. 16) as well as ANN analyses showed that it was not possible to separate between vegetation of different colour with satisfying result.

Including depth, as a predictor did not increase the accuracy of the interpretations, while including Secchi depth, which could only be done for the Uppland scene since no Secchi depth predictions were available for the other areas, seemed to be central for achieving adequate classification. Thus, the Uppland scene was the only one where the classification met the required accuracy level (Table 12-14). Although the overall accuracy was relatively low also for this scene , the predictions are probably useful as incorrectly classified pixels were as a rule classified to the adjacent class. Thus, the relative differences in vegetation coverage should be fairly well captured in the analysis. In interpreting these results it should be noted that the satellite scene and the field data are from different years, why small-scale changes in the distribution of the vegetation between years may have affected the accuracy of the predictions. A visual inspection of the classification showed that it was poor in the innermost bays (e.g. the inlet of Granfjärden in the image), most likely due to the very high turbidity of these areas. In the other areas the classification seems to be accurate.

The vegetation classification for Stockholm was not useful, as almost no vegetation was identified. For Holmöarna the High coverage class was captured to some extent, but not the other classes. However, a visual inspection indicates that the main patterns in the vegetation distribution were captured. The analysis of the Holmöarna scene was probably negatively affected by the large difference in data capturing date, as the satellite scene was from mid June while the reference data was from August, which means that different seasonal succession stages were compared in the analyses.

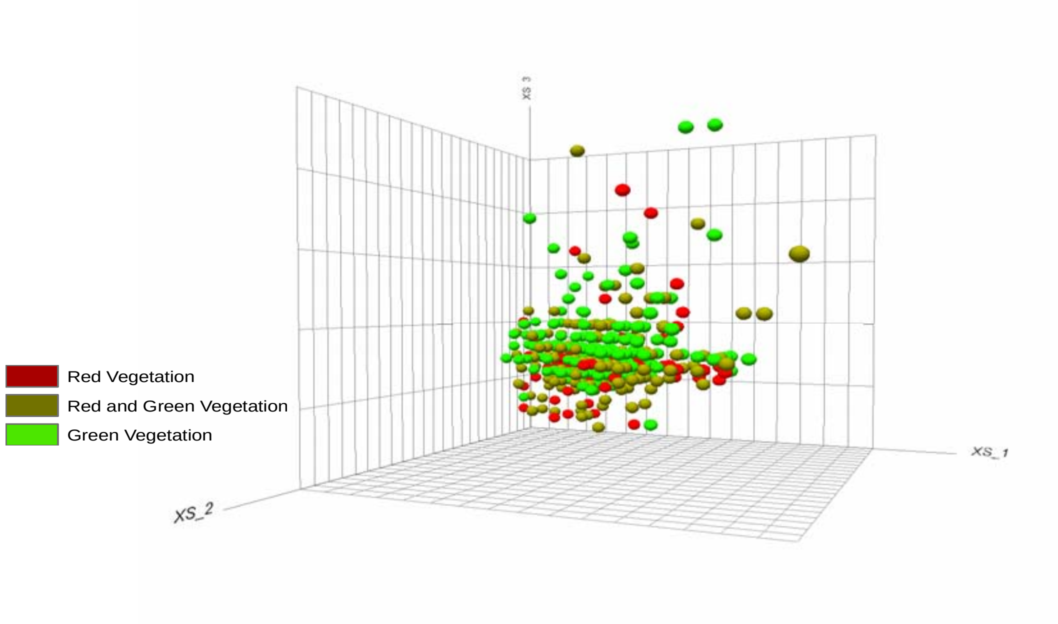

Fig. 16. *Correlation between spectral information (bands XS1-3) to reference points with red, green or red and green vegetation.*

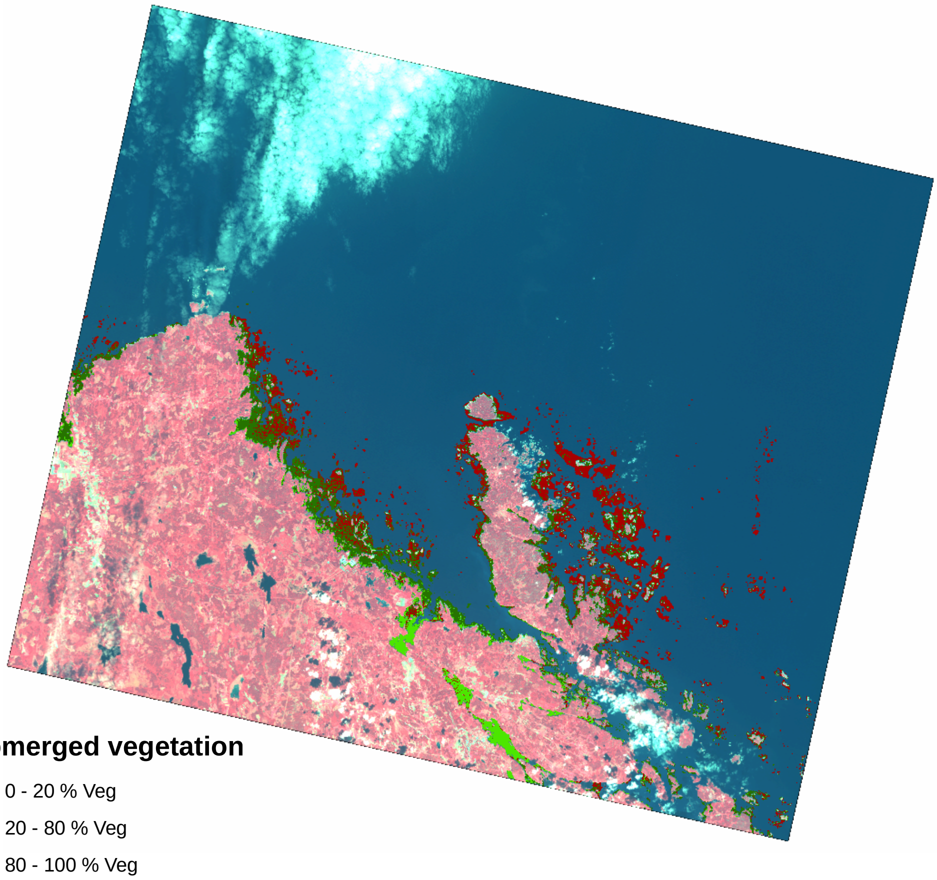

Fig. 17. *Vegetation cover image for Uppland. The classification is based on an analysis where satellite data and Secchi depth has been used as input.*

Table 12. *Accuracy assessment for the classification of submerged vegetation in Uppland. Spectral bands XS1, XS2, XS3 and Secchi depth have been used as input data. Overall accuracy 51.9 %.*

Uppland	Classified					
Reference data	Low coverage	Medium coverage	High coverage	Total	User acc. (%)	Producer acc.(%)
Low coverage	16	77	36	**129**	12.4%	57.1%
Medium coverage	10	135	157	**302**	44.7%	48.9%
High coverage	2	64	222	**288**	77.1%	53.4%
Total	**28**	**276**	**415**	**719**		

Table 13. *Accuracy assessment for the classification of submerged vegetation in Stockholm, where spectral bands XS1, XS2, XS3 have been used as input data. Overall accuracy 39.5%.*

Stockholm	Classified					
Reference data	Low coverage	Medium coverage	High coverage	Total	User acc. (%)	Producer acc.(%)
Low coverage	284	19	9	**312**	91.0%	41.0%
Medium coverage	197	5	5	**207**	2.4%	15.6%
High coverage	211	8	4	**223**	1.8%	22.2%
Total	**692**	**32**	**18**	**742**		

Table 14. *Accuracy assessment for the classification of submerged vegetation in Holmöarna, where spectral bands XS1, XS2, XS3 have been used as input data. Overall accuracy 36.4%.*

Holmöarna[1]	Classified					
Reference data	Low coverage	Medium coverage	High coverage	Total	User acc. (%)	Producer acc.(%)
Low coverage	55	89	9	**153**	35.9%	40.1%
Medium coverage	67	30	6	**103**	29.1%	24.6%
High coverage	15	3	23	**41**	56.1%	60.5%
Total	**137**	**122**	**38**	**297**		

4.5 Alternative methods (cost-benefit)

It may be beneficial to use other satellite or image data for mapping coastal features, such as depth, Secchi depth, and vegetation, as a higher geographic resolution or spectral resolution (including blue light) may be needed for more reliable classifications. Aerial photos have the additional benefit that atmospheric influence is less than in satellite images. The disadvantage of images with a higher resolution is that costs will increase as the number of images needed to classify the coastal area increases (table 15). Furthermore, the amount of reference data needed increases, as such data is needed for each image (Fig. 17). The increased costs of using higher resolution images has to be weighed against the potential benefits on a case by case basis.

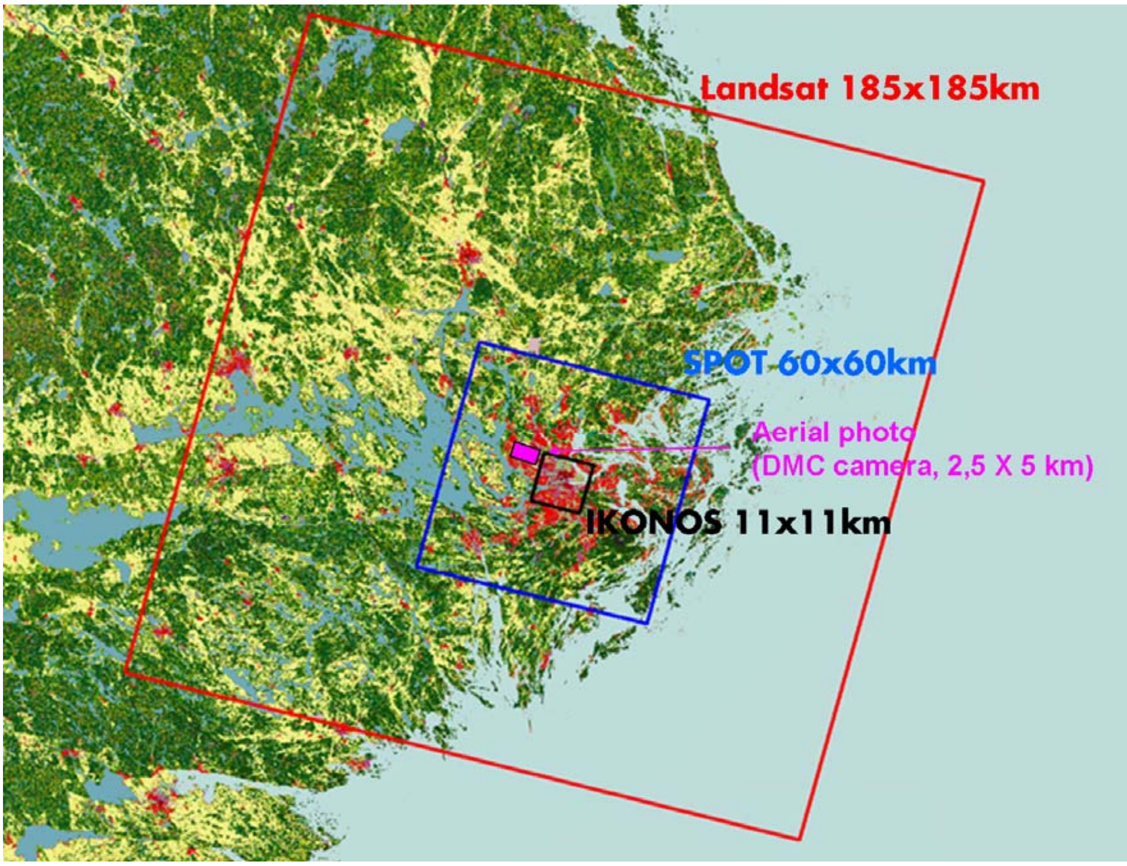

Fig. 18. *Relative size of alternative images.*

Table 15. *Image costs and estimations of time for analysis using alternative data sources. It is assumed that the time spent classifying one image whether it is SPOT or a digital photo is approximately the same.*

	Approximate number of images to cover Swedish coast	**Image cost (SEK/km^2)**	**Work time compared to SPOT**	**Costs compared to SPOT**
SPOT 5	60	6	1	1
VHR	360	60-100	6	10-16
Digital aerial photos	3600	60	60	10

5 CONCLUSIONS

5.1 SPOT 5 satellite data

The results of this pilot project indicate that SPOT 5 satellite images has the potential to identify depth and Secchi depth, as well as emergent and submerged vegetation in coastal areas of the Baltic Sea. The current lack of detailed, continuous maps of environmental parameters in shallow areas of the Baltic Sea is probably the main bottleneck for habitat modelling within the region. Therefore, additional efforts to enhance the interpretation of satellite images are highly demanded. The accuracy of the analyses in this study were quite variable, but still show that with further methodological development SPOT 5 images may be used for cost-efficient large-scale mapping of habitat characteristics of shallow coastal areas.

The spatial resolution of 10x10 meters in the SPOT 5 data may sometimes be to coarse for accurate analyses. For example, in this study many of the sample points in the reference dataset had to be omitted as they were situated close to land, and thus had spectral signatures that were influenced by land. Also, spatial variability of vegetation can be considerable, even at scales smaller than 10x10 m, why only large, relatively homogeneous vegetation patches can be identified using SPOT 5 scenes. The problems associated with the high level of small-scale heterogeneity in vegetation coverage may also be further accentuated due to inexact positioning of the reference data.

Using SPOT5 for analyses of underwater features is also limited by the lack of spectral information in the blue band. Blue light has the highest penetration capability in water, and information on blue light reflectance would thus probably increase the accuracy of the analyses. Alternative satellite data with higher spatial resolution and spectral information for the blue band exists on the market. This data is however more expensive and covers smaller areas, hence requiring more time to classify the same area as one SPOT scene. Using higher-resolution satellite scenes also sets a greater demand on the reference data when it comes to geographic positioning.

A temporal match in satellite data and reference data information is important for performing accurate analyses. In this study, reference data from the same time of the year but in other years than the satellite scenes were used in the analyses. The quality of the analyses is therefore most likely largely influenced by interannual variations in the studied variables. Still, the seasonal variations in both Secchi depth and vegetation cover is generally much larger than the interannual variations (when comparing the same months in different years), so using data from the same season should be more important than having data from the same year.

5.2 Reference data

The quality of the reference data used for training the ANN largely determines how successful the classification of the satellite image will be. The reference data used in this project was mainly collected for other purposes than interpretation of satellite images. Substantial parts of the reference dataset in some areas were mainly collected in one specific habitat type (coastal lagoons). Some habitat types thus were under-represented which limited the possibilities of attaining accurate predictions for the entire areas. An important aspect, especially for classification of vegetation, is that for every satellite scene, specific reference data matching the area and the time of the image is required. Consequently, if larger areas should be covered with this method it would require extensive reference datasets. Such data is currently collected within the national surveys conducted in coastal Natura 2000 habitats. It would thus be valuable if these extensive surveys are designed in a way that facilitates the use of field data in remote sensing analyses. Our experience is that in order to obtain accurate analyses of satellite images, the reference data should:

- be distributed over the whole image to be classified, and cover major gradients in the variables that may affect the analysis
- preferably be collected as close as possible to the satellite image registration date. If this is not possible, it should at least be from the same time of year, thereby assuming that the spatial variability of the environmental variable in focus is comparative to the time of registration of the image
- sampled in a way that the data corresponds to the pixel which it represents

5.3 Emergent vegetation

Segmentation was an efficient method for classifying reed belts in water. Small or narrow reed belts were not captured in the classification as pixel size in the images was large (10x10 m). Since reed belts are important nursery areas for fish larvae, especially pike, burbot and cyprinids (Urho, 2002) the segmentation analyses can be essential in identifying recruitment habitats for these species.

5.4 Secchi depth

An analysis of Secchi depth using only SPOT 5 spectral bands as input data seems to work quite well under some circumstances, as it was successful for one of the scenes, but not for the other. Since the turbidity of the water may change substantially between seasons due to algal blooms etc, it is essential to have a good temporal match of the sampling effort and the satellite scene.

Presently, mapping of Secchi depth with remote sensing in the Baltic Sea region is mainly conducted via the MERIS and Terra/MODIS satellites which has rather coarse resolution (250x250m - 1x1 km). Using SPOT 5 thus could be a high-resolution alternative in near-coastal areas where land interference makes low-resolution alternatives unfeasible. The scene where the Secchi depth prediction was most successful also had the most accentuated gradient in Secchi depth, which probably enhanced the analysis. In the Stockholm scene, a large part of the reference data where obtained from shallower areas with a turbidimeter instead of a traditional Secchi disc, which due to the interaction between depth and vegetation composition in such areas, could have made the analysis less precise. In the Holmöarna area the spatial variation in Secchi depth is comparatively low, thus it is probably hard to conduct predictions of Secchi depth for this area, but it is also of less biological relevance.

5.5 Depth

Classification of water depth using only SPOT 5 spectral bands as predictor variables in the analysis seems to work well down to depths of around 3 m when water is relatively clear. As depth information of nautical charts is often inaccurate for these near-shore areas, satellite imagery may thus provide a tool for obtaining more accurate depth maps. These shallow areas have the highest diversity and coverage of vegetation and are also the most important nursery areas for many fish species, and more accurate depth maps would thus enable better mapping of these important habitats. Using satellite images containing blue light information, which penetrates furthest into the water, the depth classification could probably be further improved.

5.6 Submerged vegetation

The cover of submerged vegetation could be classified relatively well in one of the satellite scenes, despite the temporal mismatch between the satellite scene and field data. Information on Secchi depth in addition to the spectral information seemed to be needed for good performance of the model, as the level of turbidity has a large influence on the spectral signature. Inspired by the findings of Vahtmäe *et al*. (2006) we made an attempt to model vegetation types with different colours. The results indicated that it was not possible to separate spectral signatures from vegetation of different colour with the SPOT 5 satellite. This analysis however, was strongly limited by the lack of reference data for some of the colour types (particularly the red type).

For more powerful analyses of submerged vegetation, higher resolution satellite images and blue band information is probably needed. Since the interannual variability in vegetation may be high, matching field sampling efforts and satellite image acquirement is also needed for reliable analyses.

6 REFERENCES

Breukers, C. P. M., van Dam, E. M. & S. A. de Jong. (1997). Lake Volkerak-Zoom: a lake shifting from the clear to the turbid state. Hydrobiologia 342/343: 367-376.

Berube, P. & F. Levesque. (1998). Effects of forestry clear-cutting on numbers and sizes of brook trout, *Salvelinus fontinalis* (Mitchill), in lakes of the Mastigouche Wildlife Reserve, Quebec, Canada. Fisheries Management and Ecology 5(2): 123-137.

Christensen, B. & L. Persson. (1993). Species-specific antipredatory behaviours: effects on prey choice in different habitats. Behavioral Ecology and Sociobiology 32(1): 1-9.

Eklöv, P. (1997). Effects of habitat complexity and prey abundance on the spatial and temporal distributions of perch (*Perca fluviatilis*) and pike (*Esox lucius*). Canadian Journal of Fisheries and Aquatic Sciences. 54: 1520-1531.

Grenouillet, G. & D. Pont. (2001). Juvenile fishes in macrophytes beds: influence of food resources, habitat structure and body size. Journal of Fish Biology 59: 939-959.

Gregory, R. S. (1990). Effects of turbidity on benthic foraging of and predation risk of juvenile chinook salmon. In: Effects of dredging on anadromous Pacific coast fishes. Editor: Simenstad, C. A. Washington Sea Grant Program, Seattle, pp: 64-73.

Karås, P. & G. Thoresson. (1992). An application of a bioenergetics model to Eurasian perch (*Perca fluviatilis* L.). Journal of Fish Biology 41: 217-230.

Kirjasniemi, M. & T. Valtonen. (1997). Winter mortality of young-of-the-year pike-perch (*Stizostedion lucioperca*). Ecology of Freshwater Fish 6: 155-160.

Lek, S., & Guegan, J.F. (1999). Artificial neural networks as a tool in ecological modelling, an introduction. Ecological Modelling. 120:65-73.

Mattila, J. (1995). The effect of habitat complexity on predation efficiency of perch (*Perca fluviatilis* L.) and ruffe (*Gymnocephalus cernuus* (L.)). In: Biology and ecology of shallow coastal waters, Editors: Eleftheriou, A., Ansell, A. D. & C. J Smith. Olsen & Olsen, Fredensborg, Denmark, p. 261-268.

Orth, R. J., Heck, K.L. & van Montfrans, J. (1984). Faunal communities in seagrass beds: A review of the influence of plant structure and prey characteristics on predator-prey relationships. Estuaries 7: 339-350.

Olden, J.D., & Jackson, D.A. (2000). Fish-habitat relationships in lakes: Gaining predictive and explanatory insight by using artificial neural networks. Transactions of the American Fisheries Society. 130: 878-897.

Pihl, L. (1986). Exposure, vegetation and sediment as primary factors for mobile epibenthic faunal community structure and production in shallow marine soft bottom areas. Netherlands Journal of Sea Research 20: 75-83.

Sandström, A. (2004). The influence of visual conditions on young percids (Percidae spp.). PhD-thesis. Department of Biology, Åbo Akademi University.

Sandström, A., Eriksson, B. K., Karås, P., Isaeus, M., Schreiber, H. (2005). Boating and navigation activities influence the recruitment of fish in a Baltic Sea archipelago area. Ambio. Volume 34, Number 2.

Sundblad, G., Sandström, A., Mattila, J., Snickars, M., unpublished data.

Urho, L. (2002). The importance of larvae and nursery areas for fish production. PhD-thesis, University of Helsinki, pp: 215.

Vahtmäe, E., Kutser, T., Martin, G. & Kotta, J. (2006). Feasibility of hyperspectral remote sensing for mapping benthic macroalgal cover in turbid coastal waters; a Baltic Sea case study. Remote Sensing of the Environment 101(3): 342-351.

About the BALANCE project

This report is a product of the BSR INTERREG IIIB project "BALANCE".

The BALANCE project aims to provide a transnational marine management template based on zoning, which can assist stakeholders in planning and implementing effective management solutions for sustainable use and protection of our valuable marine landscapes and unique natural heritage. The template will be based on data sharing, mapping of marine landscapes and habitats, development of the blue corridor concept, information on key stakeholder interests and development of a cross-sectoral and transnational Baltic zoning approach. BALANCE thus provides a transnational solution to a transnational problem.

The BALANCE partnership is composed of the following institutions based in 10 countries: The Danish Forest and Nature Agency (Lead), The Geological Survey of Denmark and Greenland, The National Environmental Research Institute/University of Aarhus, The Danish Institute for Fisheries Research, WWF Denmark, WWF Germany, Institute of Aquatic Ecology at University of Latvia, Estonian Marine Institute at University of Tartu, Coastal Research and Planning Institute at Klaipeda University, Metsähallitus Natural Heritage Service, The Finnish Environment Institute, The Geological Survey of Finland, WWF Finland, The Swedish Environmental Protection Agency, The National Board of Fisheries – Department of Research and Development, The Geological Survey of Sweden, County Administrative Board of Stockholm, Department of Marine Ecology at Gothenburg University and WWF Sweden.

The following institutes contribute as consultants to the partnership: The Geological Survey of Norway, Norwegian Institute for Water Research, DHI Water & Environment, The Leibniz Institute of Marine Sciences, The Sea Fisheries Institute, The Finnish Game and Fisheries Research Institute, Metria Miljöanalys and The Nature Conservancy.

The **BALANCE Report Series** included on 1th of July 2007:

BALANCE Interim Report No. 1 "Delineation of the BALANCE Pilot Areas".
BALANCE Interim Report No. 2 "Development of a methodology for selection and assessment of a representative MPA network in the Baltic Sea - an interim strategy".
BALANCE Interim Report No. 3 "Feasibility of hyperspectral remote sensing for mapping benthic macroalgal cover in turbid coastal waters of the Baltic Sea".
BALANCE Interim Report No. 4 "Literature review of the "Blue Corridors" concept and its applicability to the Baltic Sea".
BALANCE Interim Report No. 5 "Evaluation of remote sensing methods as a tool to characterise shallow marine habitats I".
BALANCE Interim Report No. 6 "BALANCE Cruise Report - The Archipelago Sea".
BALANCE Interim Report No. 7 "BALANCE Cruise Report - The Kattegat"
BALANCE Interim Report No. 8 "BALANCE Stakeholder Communication Guide"
BALANCE Interim Report No. 9 "Model simulations of blue corridors in the Baltic Sea"
BALANCE Interim Report No. 10 "Towards marine landscapes of the Baltic Sea (June 2007)"
BALANCE Interim Report No. 11 "Fish habitat modelling in the Archipelago Sea"
BALANCE Interim Report No. 12 "Evaluation of satellite imagery as a tool to characterise shallow habitats in the Baltic Sea"
BALANCE Interim Report No. 13 "Harmonizing marine geological data with the EUNIS habitat classification"
BALANCE Interim Report No. 14 "Intercalibration of sediment data from the Archipelago Sea"
BALANCE Interim Report No. 15 "Marine spatial planning in the Baltic Sea – an interim report"
BALANCE Interim Report No. 16 "The stakeholder - nature conservation's best friend or its worst enemy?"

For more information please see www.balance-eu.org and http://maps.sgu.se/Portal.