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EU Life algae

Remote sensing of filamentous algae in shallow waters along the Swedish West Coast

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EXECUTIVE SUMMARY

Conclusion

It is possible to detect areas with filamentous algae along the Swedish West Coast using satellite remote sensing. But it is not possible, with a Landsat-7 image, to quantify the algae cover. A regular monitoring of the growth of filamentous algae is thus not recommendable if one uses a satellite with a spatial resolution of 30m.

Materials

The image analysis was performed in the freeware program MultiSpec.The satellite image was acquired in August 24th 1999. An air photo survey from the same week was used as a reference material.

Image evaluation

The pixels were divided into one of the categories algae or water. Two different approaches were used in the classification:

1. Supervised Classification.
2. Normalised Algae Index (NAI)

The NAI was developed in the study and is based on the characteristics of the spectral signature from the algae. The calculation of algae cover based on the supervised classification showed better correspondence with the algae cover in the air photo survey than the NAI. An advantage of the NAI method is that it is more objective and would be easier to use in automated classifications.

GIS

It is easy to transfer the estimated algae cover into a GIS system where further analyses can be carried out. In this study the relationship between land cover within the watershed and algae cover was studied. The arable land and algae cover showed correlation.

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1. INTRODUCTION

Over the past five decades, Scandinavia's coastal waters have received an increasing amount of nutrients from a number of different sources. These have included direct loads from surface and subsurface run-off and atmospheric fall out. As a result, today many coastal areas are regarded as severely eutrophic. Eutrophication has in turn resulted in extensive development of mats of filamentous algae that cover shallow bays along the Swedish West Coast. These mats now constitute a threat to biological diversity, and can be expected to have a long-term negative effect on fisheries and tourism.

In 1996 the County Administration of Västra Götaland joined a project called EU-Life Algae. The aim of the EU project is to study if removal of the algae will eliminate or reduce the threat to biological diversity caused by algae mats. If the conclusion of that study is that harvesting of algae is an appropriate method, which will be recommended, in a large scale there is a need to find a method to monitor the growth of algae in the bays. Within the EU-Life project two possible monitoring methods have already been used, field measurement and air photo survey.

The objective of this master thesis is to investigate and evaluate if satellite remote sensing is a feasible method of detecting filamentous algae in shallow bays. A satellite image covering the Swedish West Coast will be used for the analysis. The results from the image analysis will be transferred into a Geographical Information System, GIS, for further analyses. The central point is to investigate the accuracy of the method but other aspects such as time, costs, data accessibility and subjectivity will also be discussed. An exploration of suitable software to classify and present the results from digital classifications of satellite data has also been made as a part of our work. The majority of the work has been carried out in MultiSpec and ArcView.

1.1 EU-LIFE ALGAE PROJECT

During the summer season many areas along the coasts of Scandinavia are becoming covered with malodorous mats of degrading algae. As a result, swimming and other forms of recreation are no longer the pleasure they used to be. Moreover, the algae are a threat to biological diversity and, if measures are not taken to remedy the situation, we may soon be looking at dead shallow-water areas. Fast-growing filamentous algae of the Enteromorpha and Cladophora genera flourish on previously unvegetated shallow areas and also on long-lived algae and sea grass. When the mats are fully-grown they lift to the water surface and drift around in the archipelago. The mats of algae cause structural and functional changes in coastal ecosystems, such as a reduction in the settlement and recruitment of plaice and lowered feeding success rates among juvenile cod. During the degradation process, the mats give off an unpleasant smell. As a result the areas are seen as less attractive for recreational purposes. Tourism and recreation are important to the economy of these parts of Sweden and Finland.

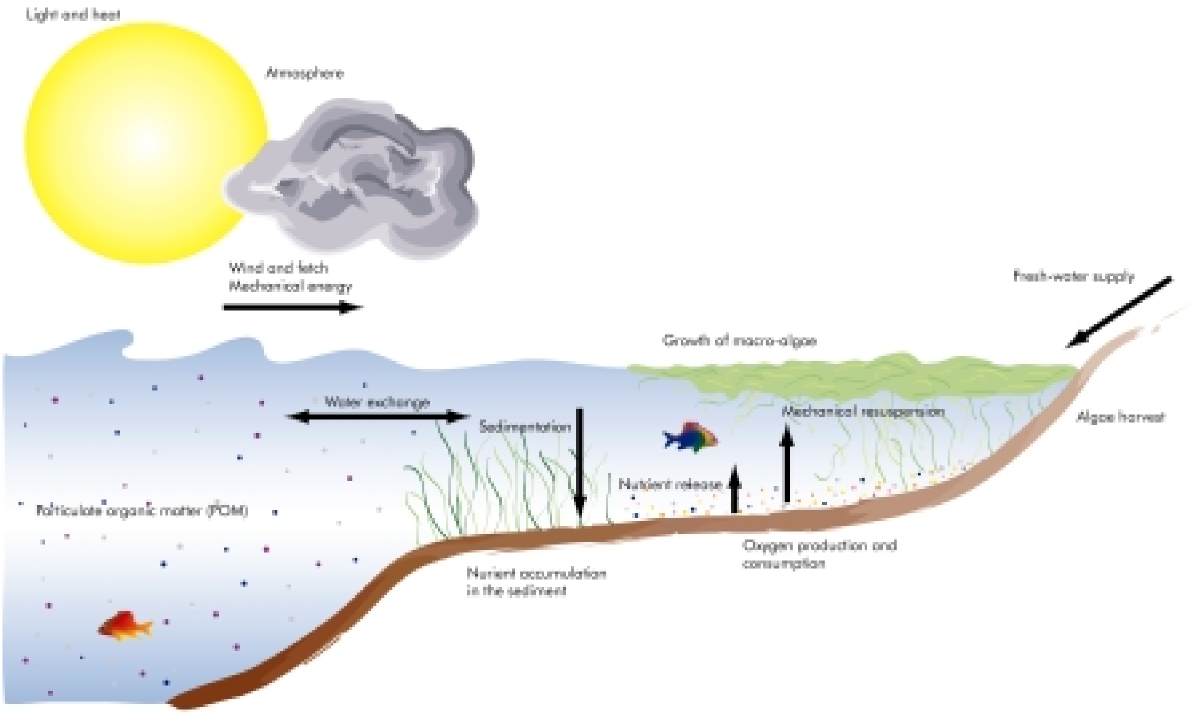

Figure 1.1 The growth of algae, Amelie Wintzell 2001.

To manage these problems the EU-Life Algae project was initiated. The project is based on the hypothesis that removal of the algae will have a positive effect on shallow-water areas. In the first place it has been shown that the structure of the algae mats has a negative effect on macro-fauna and fish. It is therefore possible that removal of the algae will result in important habitats being restored. Secondly, removal of the algae will also result in the removal of considerable amounts of nitrogen and carbon, very likely making it possible to reduce the pool of nutrients stored in the sediment, and thus the development of mats of algae in the future. Algae harvesting is carried out in two experimental areas, one on the Swedish West Coast and one in the Åland archipelago.

The EU-Life Algae project is funded by the European Union under the framework of EU-Life Environment[1]. The project started in December 1996 and is scheduled to run for 4 years but has been prolonged six months. The project budget comprise EURO 1 560 000. Half is funded by the EU-Life Council and half by the project partners.

Project activities

- The project includes identification of methods for removal of algae from shallow-water areas, which in turn includes construction of algae-harvesting equipment and methods of transporting harvest.

- Another important aspect is the identification of ways of putting algae masses to practical use.

- Experimental monitoring programmes, one in Sweden and one in Finland, are being carried out in shallow-water areas. The aim is to study the effects of algae removal on the biology and bio-geochemistry of the areas in question.

- Empirical models are also to be developed. These will present the presence and absence of mats of algae in shallow-water areas to the characteristics of the environment.

- Finally, based on the results of the project, guidelines will be drawn up for future management strategies.

Removal of algae

A machine has been constructed that is capable of removing mats of algae in shallow areas. This machine forms part of a complete harvesting system whose other aspects include transportation of algae to dry land and onward land transportation to final destination.

1.2 STUDY AREA, THE BOHUS COAST

The EU-Life Algae project focuses on mapping algae in shallow coastal bays with sediment bottoms of mean depths of less than one meter. The area of interest is along the Swedish West coast from Vrångö in the south to Idrefjorden in the north. In this master thesis the coastline from Sannäsfjorden in the south to Dynekilen in the north has been selected for analysis, see the rectangle in figure 1.2.

The morphology along the coast displays a striking variation. In the selected study area between Strömstad and Havstenssund the islands are relatively big. On the flat undulating islands the pine trees face the sea. Flat rocks, blocky shores and sand beaches alternate with deep carved bays. Parts of the inner archipelago, in the shallow bays, are clay beds. These are important feeding grounds for juvenile fish. The land cover closest to the shore varies and may be bare precipitous rock or shores lined with reeds or just wetlands, sometimes above sea level, sometimes below. (Bondeson 2000)

[1] http://europa.eu.int/comm/life/home.htm

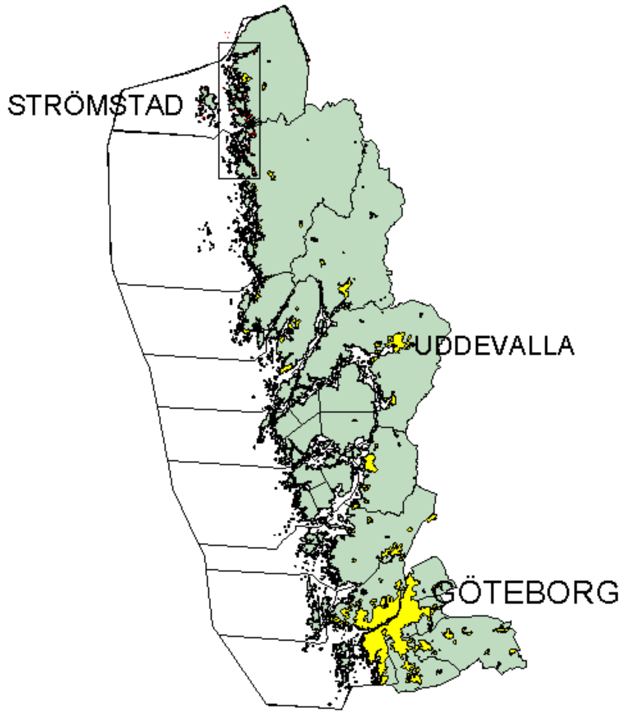

Figure 1.2 The Bohus coast and the study area in the upper left corner.

1.3 REMOTE SENSING

Remote sensing is the way of obtaining information about an object, area, or phenomenon through the analysis of data acquired by a device that is not in contact with the object, area or phenomenon under investigation (Lillesand, 1999). Here the term remote sensing refers to satellite remote sensing. The sensor is mounted on a satellite and registers the electromagnetic energy that various earth features emit and reflect. The sensor used in this study is called ETM+ and registers light in the visible, near, mid and thermal infrared part of the electromagnetic spectrum. The spectral characteristics of the ETM+ sensor are listed in table 1.1. For ETM+ and many other sensors, the sensed radiance is converted to digital numbers, DN. The DN range between 0 and 255 and represent a certain grey level. When three wavelength bands are displayed at the same time there are 256^3 possible colour combinations for each pixel.

1.3.1 General definitions

Landsat 7 ETM+

Landsat 7 was launched in April 1999. It is equipped with a sensor of the Enhanced Thematic Mapper Plus type. The satellite has an orbit of 16 days. Besides from being sensitive in the visible and infrared part of the spectrum, the ETM+ sensor also has a panchromatic band with better spatial resolution, see table 1.1.

Table 1.1 Characteristics of the Enhanced Tematic Mapper Plus (ETM+)

Band	**Sensitivity (μm)**	**Band name**	**Resolution (m)**	**Comments**
TM1	0.45-0.52	Blue	30	Good water penetration, strong vegetation absorbance
TM2	0.52-0.6	Green	30	Strong vegetation reflectance
TM3	0.63-0.69	Red	30	Very strong vegetation absorbance
TM4	0.76-0.9	Near IR	30	High land/water contrasts, very strong vegetation reflectance
TM5	1.55-1.75	Mid IR	30	Very sensitive to soil moisture and vegetation
TM6[a]	10.4-12.5	Thermal	60	Good geological discrimination
TM7[a]	2.08-2.35	Mid IR	30	
PAN	0.5-0.9	Visible	15	

TM1, the blue band, is normally useful for mapping water near coastal areas but in figure 1.3 it is almost impossible to see anything due to coherent noise (definition below) in this channel. TM2 is the green band and displays vegetation in white. In the red band, number 3, it is possible to identify the bay and the vegetation in white as in band 2. Band 3 is normally good for differentiating between plant species.

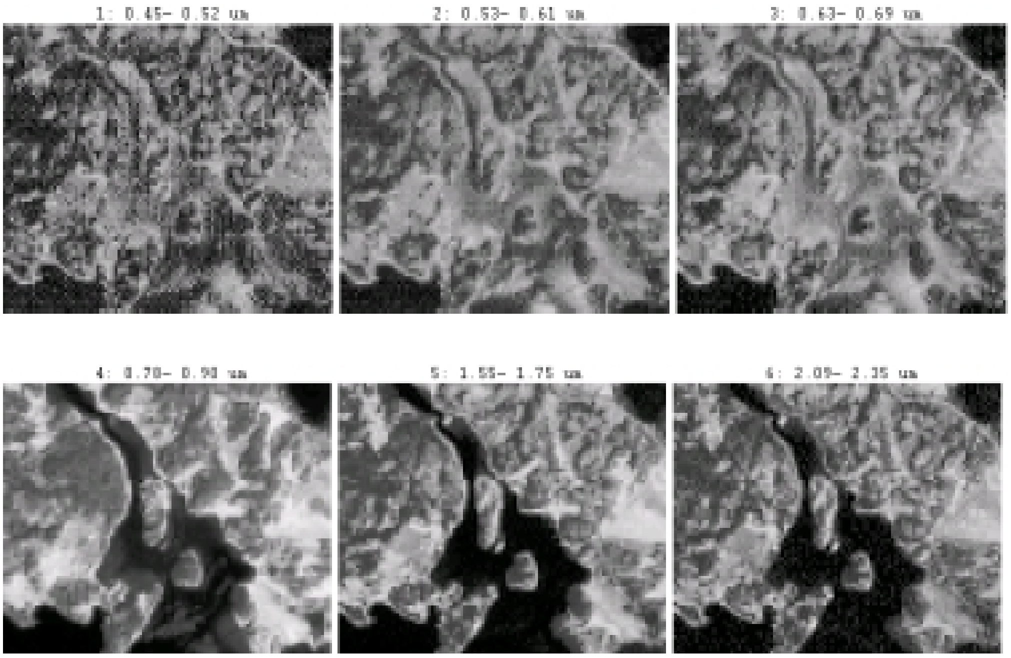

Figure 1.3 The satellite image over Galtöleran displayed as separate bands.

[a] Bands 6 and 7 are out of wavelengths sequence because band 7 was added to the TM late in the original system design process.

TM4, the near-infrared band, is good for discovering boundaries between land and water. Water absorbs almost all of the energy in this band and consequently appears black, an advantage when searching for mats of algae floating on the water. TM4 is the band that has been most widely used in this study. The mid-infrared band, TM5, is useful for determine soil moisture content. (GLOBE, 1997)

Spatial resolution

The limit for how small an object on the earth’s surface can be and still be detected by the sensor as being separate from its surroundings is called the spatial resolution. The visible bands of Landsat 7 ETM+ have a spatial resolution of 30 m. This means that each pixel, the smallest part building up the image, covers an area of 30x30 m. A full Landsat 7 scene covers an area of 185x185 km^2. The spatial resolutions for all the bands in Landsat 7 are listed in table 1.1.

An important effect of the sensor's spatial resolution is the occurrence of mixed pixels. Mixed pixels can be the result of that the sensor's IFOV[2] includes more than one land cover or feature of the ground. The extent to which mixed pixels are contained in an image is both a function of the spatial resolution of the remote sensing system and the spatial scale of the features in question.These mixed pixels present a difficult problem in image classification; their spectral characteristics are not representative for any of the single land cover types.

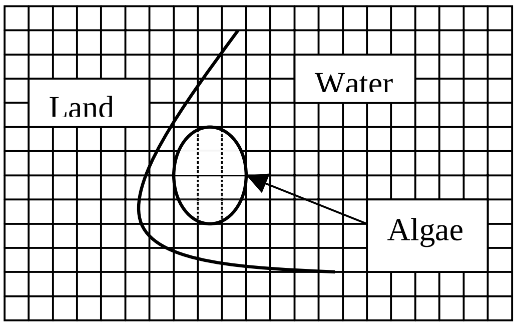

Figure 1.4 Mixed pixels are those pixels that include more than one land type.

Coherent noise

Coherent noise originates from a disturbance in the sensor system of the satellite. When studying the satellite image it is important to be aware of this effect. This is most easily seen in water and results in several digital numbers difference where one otherwise would expect a homogenous result. Thus these water areas are the best places for exploring the prevalence of coherent noise. Disturbances of this sort have also been a problem in earlier Landsat sensing systems. Before using the digital numbers of the bands it is recommended to explore the extent of the noise effects (Landgrebe, 2000).

[2] Instantaneous field of view, IFOV, is the area sensed at any instant in time. It could also be called the systems spatial resolution.

Spectral signature

Every object on the surface of the earth has a unique spectral characteristic, meaning that they are spectrally separable. How easily one can separate the classes depends on where one “looks”, spectrally. Some features may look the same in the visible bands while they show totally different appearances in other parts of the spectrum. The spectral characteristics are very often best to separate between the visible and the near infrared bands. By making use of this property one can from this piece of information find areas of similar spectral characteristics.

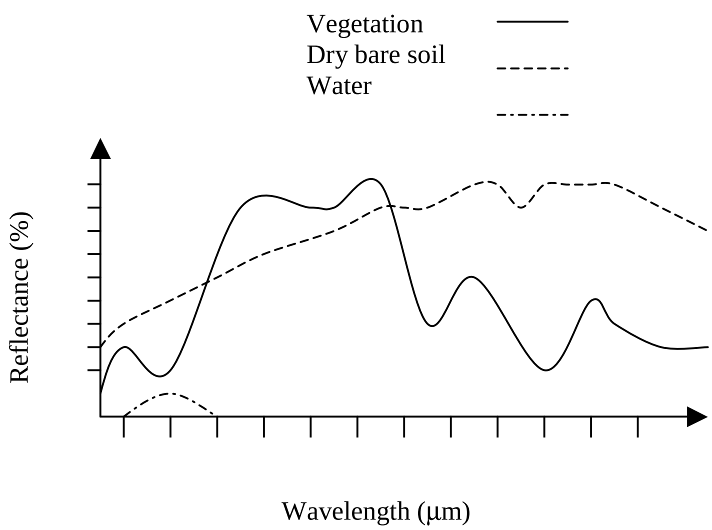

Figure 1.5 Typical spectral reflectance curves for vegetation, soil and water.

2. METHODOLOGY

2.1. CLASSIFICATION METHODS

The procedure of image classification is to categorize all pixels in the satellite image into defined categories.

2.1.1 Unsupervised classification

The unsupervised classification is not based on any kind of reference data as the basis for classification. This type of classifier involves algorithms that examine the unknown pixels in an image and aggregate them into a number of classes based on clusters present in the image values (reflectance). Each cover type has a specific spectral signature and pixels with similar signatures are put together. The classes that result from unsupervised classification are thus spectral classes, because they are based solely on the natural groupings in the image values. Initially the identity of the classes is not known but the analyst needs to compare the classified data with some form of reference data. (Lillesand, 1999)

2.1.2 Supervised classification

Supervised classification is the identification and selection of training areas in the image and there use in classifying the entire image. The process has two stages:

1. Training stage
2. Classification stage

The supervised classification always starts with defining suitable training areas, identified by the analyst. The areas are homogeneous and consist of the type of land cover of interest, thus forming a numerical description of the class. When one has enough representative training areas it is time to perform the classification, done by the computer. Each pixel in the image data set is categorized into the land cover class it most closely resembles. Supervised classification requires prior knowledge of areas within the scene.

Gaussian Maximum Likelihood Classifier

There are a number of different classifiers. In this study the Gaussian maximum likelihood classifier (ML) is used. When there is enough space for computational operations this is by far the most effective and accurate classifier. The ML classifier evaluates both the variance and covariance of the category’s spectral response patterns when classifying an unknown pixel. In order to do this is it assumed that the training data is normally distributed (Gaussian). From the mean vector and the covariance matrix it is possible to compute the statistical probability of a given pixel value being a member of a particular land cover class. The probability density functions are used to classify an unidentified pixel by computing the probability of the pixel value belonging to each category. That is, the computer can calculate the probability of the pixel value occurring in the distribution of the class “algae” and the likelihood of its occurrence in the class “algae”. After evaluating the probability in each category, the pixel will be assigned to the most likely class according to the highest probability value. (Lillesand, 1999)

Bhattacharrya distance

The Bhattacharrya distance measures the internal distance among the spectral classes. If the classes are far apart, having values greater than 1, it indicates that the classes are well separated and may be kept as separate classes. If the classes are close together one may have to consider revision of the classes and regroup the training areas.

Instead of using all the seven TM bands when classifying one can choose the best subset of spectral features for a specific classification. Sometimes it may be better to choose the best three of the seven bands for particular pairs of classes. It may both save time and provide higher classification accuracy. The best band combination is the one that has the smallest Bhattacharrya distance.

2.2 GEOMETRIC CORRECTION

Raw digital images usually contain geometric distortions so significant that they cannot be used as maps. The sources of the distortions range from variations in the altitude and velocity of the sensor's platform, to factors such as panoramic distortion, earth curvature, atmospheric refraction, relief displacement and nonlinearties in the sweep of a sensor's IFOV[1]. The intent of geometric correction is to compensate for the distortions introduced by these factors so that the corrected image will have the geometric identity of a map. (Lillesand, 1994)

The geometric correction process is normally implemented as a two–step procedure. First, the distortions that are systematic or predictable are considered. When buying a satellite image, those systematic distortions are already corrected. Secondly, random distortions are corrected by analysing well-distributed ground control points (GCPs) occurring in the image. GCPs are features of known ground location that can be accurately located in the digital image. In the correction process numerous GCPs appear both in the context of their two image coordinates on the distorted image and in the context of their ground coordinates. These coordinates are then subjected to a least-squares regression analysis to determine coefficients for two coordinate transformation equations that can be used to interrelate the geometrically correct map coordinates and the distorted image coordinates. Once the coefficients for these equations are determined, the distorted image coordinates for any map position can be precisely estimated. (Eklundh, 1999)

$$X = f_1(x,y)$$
$$Y = f_2(x,y) \qquad (2.1)$$

(X,Y) = disorted image coordinates (column, row)
(x,y) = correct map coordinates$f_{1,}$ f_2 = transformation functions

Transformations that are used in connection with rectification are commonly called "rubber sheet transformations". This means that the location of points in different parts of the image will not change uniformly.

[1] IFOV (instaneous field of view) is the area sensed at any instant in time, could also be called the systems spatial resolution

After the spatial transformation (above) an intensity interpolation follows. This is necessary for the allocation of grey levels in the rectified image. There are different methods to use depending on how important it is to keep the original grey level values (DNs).

Table 2.1 Interpolation – Resampling methods

Interpolation method	Advantages	Disadvantages
Nearest neighbour	Quick and simple No change in grey levels compared to original image	The resulting image is jagged
Bilinear	Smoother image than NN	Change the grey levels
Cubic convolution	Smoother than bilinear	Change the grey levels

If it is important to keep the grey levels the same as in the original image it is recommended to use nearest neighbour. The grey level that is closest to X in the original image is also placed in X in the rectified image. In figure 2.4 the value in the rectified image would be *c*. If it does not matter for further analysis if the grey levels are slightly altered it is better to use bilinear interpolation. The bilinear interpolation technique takes a distance weighted average of the digital DNs of the four nearest pixels labelled a, b, c and d in figure 2.2. This results in a smoother appearing resampled image. The cubic convolution works as the bilinear one but uses16 surrounding pixels instead.

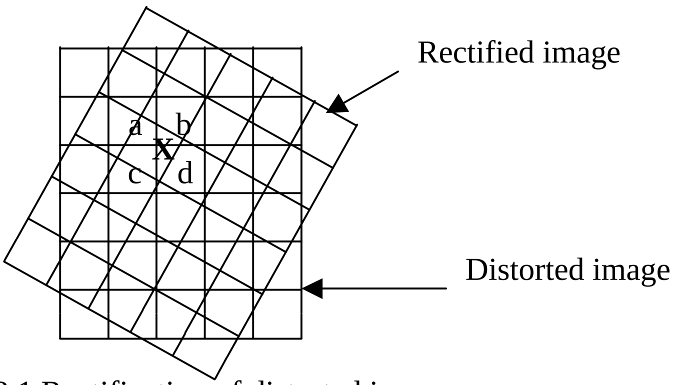

Figure 2.1 Rectification of distorted image

2.3 MATERIALS

2.3.1 Satellite image

The satellite data was available on CD-ROM distributed by Satellus AB in Kiruna. The CD consists of 15-m-resolution panchromatic data (0.52-0.9 μm) and six bands of data in the visible, near-IR and mid-IR spectral regions with a resolution of 30 m.

Table 2.2 General information about the image

Satellite	Landsat 7
Sensor	ETM+
Registration date	1999-08-24
Upper Left Corner	59'43'32'N, 9'09'13'E
Upper Right Corner	59'14'25'N, 12'24'57'E
Lower Left Corner	58'08'23'N, 8'14'48'E
Lower Right Corner	57'40'33N, 11'22'29E
Path	197
Row	019
Scene	Full standard
Format	Fast
Level	SYSCOR
Cal	Pre-flight
Resample	Nearest Neighbour

There is also a seventh, thermal-IR band (10,4-12,5 μμ) with a resolution of 60 m. See table 1.1 for further information about the bands and their spectral and spatial resolution. The image is free from clouds in the near coastal area but is rather cloudy in the interior, see figure 2.2. TM1 and TM6 in the selected Landsat 7 image are disturbed by noise.

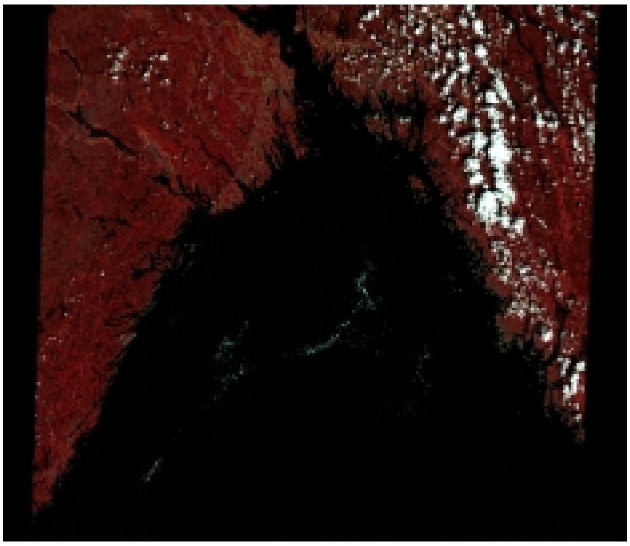

Figure 2.2 The satellite image.

2.3.2 Reference data

Anders Svensson at Kristineberg Marine Research Station in Fiskebäckskil provided a number of air photos shot in week 35 in August 1999. The photos were used as a reference material to check the accuracy of the results from the satellite image. The photos were taken on an altitude of 100-200 m with a Nikon system camera. For further information see Pihl, (1995).

2.3.3 Computer software

This study is divided into two parts, one that includes the image analysis and one that includes the data merging and GIS integration. Different softwares have been used in the different parts. The work has been carried out on PC-computers at the County Administration in Västra Götaland. Besides from not being too expensive the software also had to match the computer platforms at the County Administration. The software programmes that we finally chose to work with are listed below, see table 2.3. The majority of the work has been devoted to image analysis and we used the program MultiSpec. The advantages of MultiSpec are that it is a freeware program and that it can easily be downloaded from the Internet. The main reason for choosing this software was the limited budget. Unfortunately there are no handbooks or help functions to this program, but some people who have used it have made tutorials that are available on the Internet. We have made some cribs on the operations that we have used in the image analysis process. Those cribs are found in appendix 2.

Table 2.3 Software used

Software	Description	Advantages	Disadvantages	Field of application
MultiSpec	Image processing program	Freeware, User friendly, also available for Mac	No support ,under construction, does not work with copies	Image analysis
ArcView[12]	GIS program Display and Analysis	Support in Sweden, user groups on the internet, produces maps suitable for display	Expensive, must have access to extensions	GIS applications
MINITAB[1]	Statistical program	Straightforward, easy to learn	Costs money	Evaluation of data
Excel	Spread sheet	Easy to carry out calculations and displays results in tables and graphs		Evaluation of data

[2] Used together with the two extensions Spatial Analyst and Image Analysis

2.4 CLASSIFICATION

The methods in this chapter are developed for answering the question: “How do the results agree with the reality?” That is, how well does the estimation of algae cover in the satellite image correlate with the real algae cover. For answering this question the pixels are classified according to different methods and the percentages are thereafter calculated and compared with the air photo survey. Two established classification methods, unsupervised and supervised classification, are used and described in this study. In addition we have developed a simplified method to classify a pixel as algae or not algae based on the characteristics in the spectral signature of the algae pixel. This method is called Normalized algae index (NAI). The supervised classification and the NAI are developed to work better. The developed methods are described in chapter 2.4.4. The methods for comparing the satellite image with the air photo inventory are described in chapter 2.5. The working scheme for the image evaluation is shown in fig 2.3.

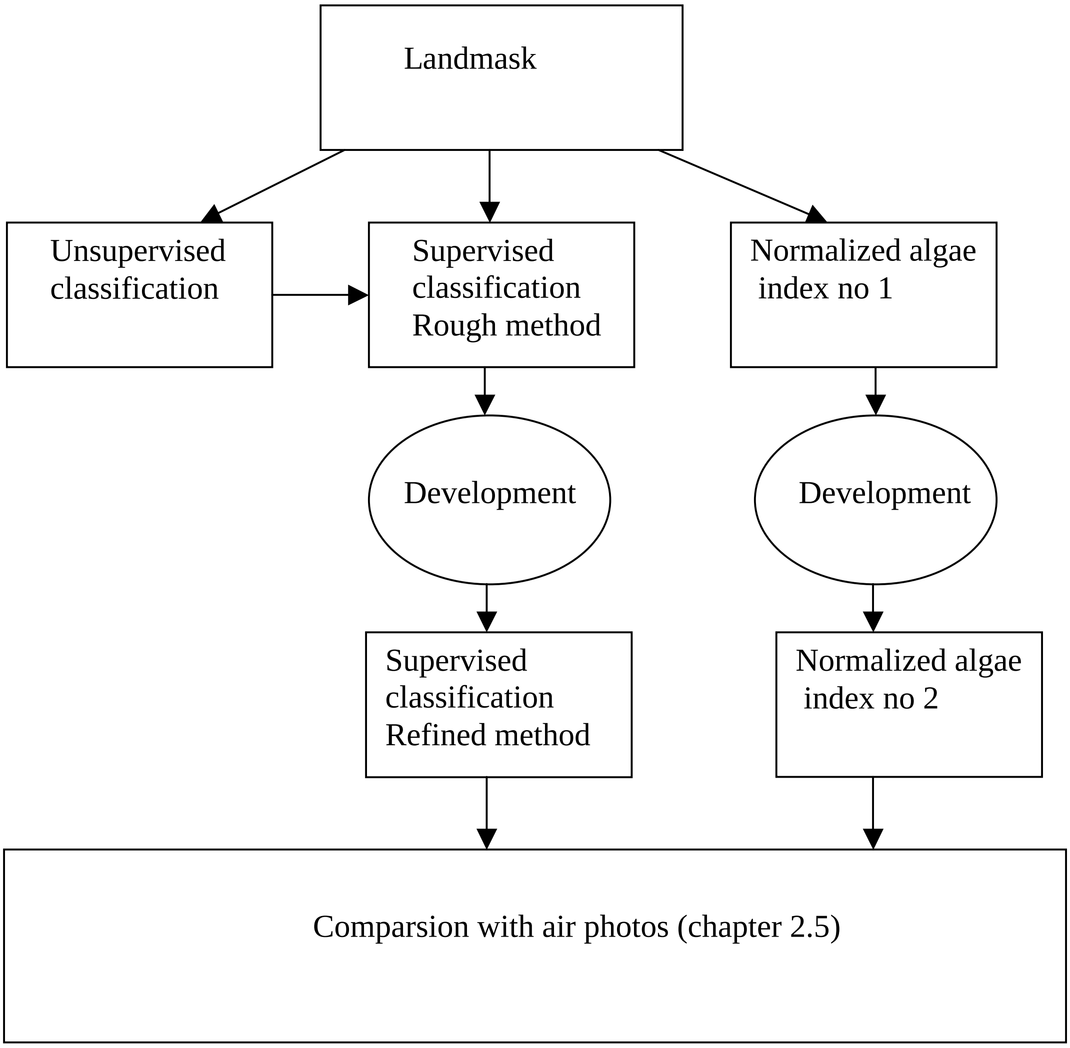

Figure 2.3 Working scheme for the image classification.

The following procedures for image classification were used:

A. Creation of a *landmask.* This
B. *Unsupervised classification*
C. Supervised classification
D. Normalised algae index classification

Step A, creation of a landmask, is rather general, and was performed in the same way before all the different classification methods. The landmask was used to minimize disturbances from land i.e. mixed pixels, see appendix 2. The steps B, C and D are more specific and are described in more detail below.

2.4.1 Unsupervised classification

The unsupervised classification cannot be used as the sole method for a classification but is useful as a tool and complement to other methods, especially for discovering spectral features that is not obvious to the classifier in the initial stage. By using the ISODATA[2]-algorithm with the specifications according to table 2.4 the unsupervised classification was performed automatically.

Table 2.4 Cluster algorithm information

Cluster algorithm	ISODATA- Initialize within eigenvector volume
Number Clusters	40
Convergence (percent)	98.0
Minimum cluster size:	7
Channels used	2,3,4,5,6

2.4.2 Supervised classification

There exist a number of algorithms for classification of satellite data. The most widely used algorithm for supervised classification is the Maximum Likelihood (ML), described in chapter 2.1.2. This classifier is based on interactively selected training areas. The main advantage of ML classification is its solid statistical basis. It is possible to achieve quite good classification results, provided that the classes are homogenous and spectrally well defined and that the training areas have been carefully selected and analysed.

A good training area has two basic requirements: being homogenous and representative. Homogeneity is necessary in order to get a distribution of values that is close to the Gaussian normal distribution, a requirement from the ML classifier. Being representative on the other hand, means that all variations within the class must be covered to get a proper description of the class. In this study the lack of major field measurements makes it difficult to differentiate between what is classified as algae is really algae, sea grass or bottom vegetation in the reality. Such classes are annotated as "vegetation". The procedure of choosing correct and representative training areas is difficult and takes a lot of time. In this study two approaches of choosing training areas have been used: one preliminary rough method and one refined method. In the refined method the training areas were divided into more, and consequently finer, homogenous

[2] Iterative Self-Organising Data Analysis, uses Minimum Distance to mean as method of clustering, ISODATA iterates through the data until specified results are achieved.

training classes. The refined method is describes in the chapter 2.4.4. The rough classification is described below.

Supervised classification – rough method
The training areas for the preliminary rough image were chosen as follows:

1. **Analysis of existing bottom fauna map and depth information**
   A bottom fauna map from Göteborgs and Bohus län from 1983 was carefully studied together with information about the depth. The bays were divided into a certain number of areas, so-called kernels, depending on the type of bottom fauna and depth, see figure 2.4.

2. **Training area selection and classification**
   Calculation of the mean and standard deviation of the kernel areas were carried out for the DN in TM4 and divided into four classes. The kernels that seemed to be rather homogenous were compared with air photos. If they were considered representative they were selected as training areas for the classification. When the classification was carried out all the TM bands but TM1 were used. This combination gave the best Bhattacharrya distances, thus separating the classes the most and seemed to be the best basis for classification. One reason for not using TM1 is that it hits the bottom in shallow waters and would return a bottom signal that could be misinterpreted as algae (Lindell, pers. com.).

3. **Graphical representation and class performance**
   The different classes were displayed in histograms in order to check normality and class performance was calculated.

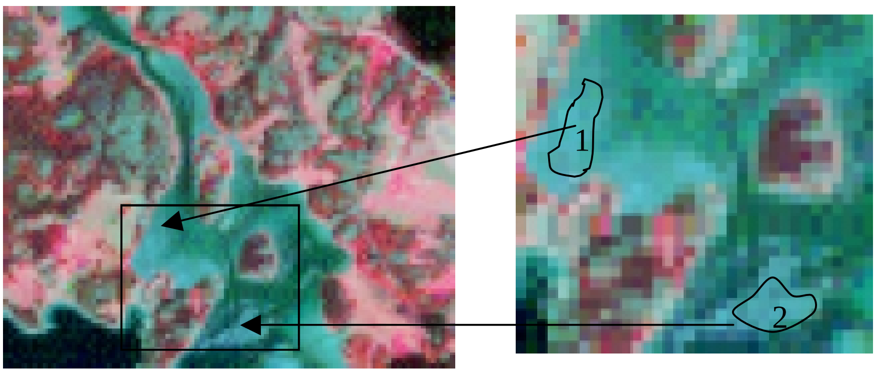

Figure 2.4 Example of how kernel areas can be chosen.

2.4.3 Normalized algae Index

Vegetation has a very particular spectral signature with a bump in the near infrared band due to chlorophyll contents, see figure 2.5. Water has a very low reflectance in the visible part of the spectra and is totally nonexistent in higher wavelengths. The aim of this method is to use these characteristics and via calculation see if a pixel is an algae or a water pixel.

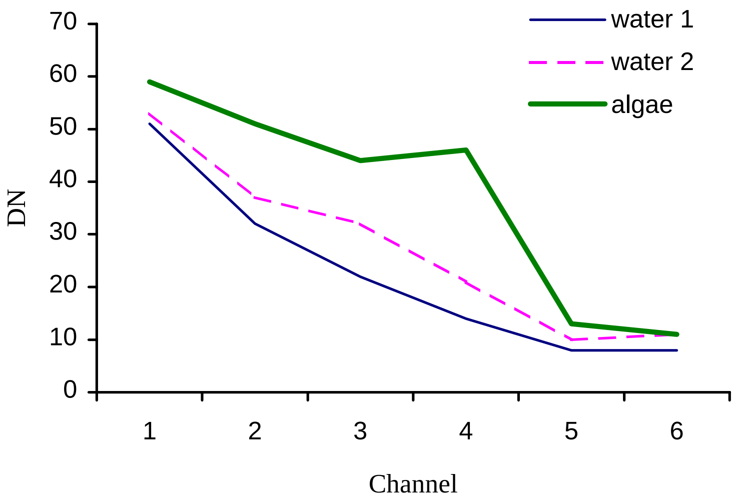

Figure 2.5 The spectral signature from three different pixels.

Normalized algae index 1

This is a very simple method. The theory behind the method is that the ratio between the digital numbers in TM4 and TM3 should be greater than 1 if it is an algae/vegetation pixel and less than 1 if it is a water or other pixel.

$$\left(\frac{TM4}{TM3}\right) < 1 \Rightarrow \text{No vegetation/algae} \qquad (2.2)$$

$$\left(\frac{TM4}{TM3}\right) > 1 \Rightarrow \text{Vegetation/algae} \qquad (2.3)$$

2.4.4 Development of Classification methods

In this chapter the developing of the methods “supervised classification-rough method” and “normalized algae index 1” are described.

Supervised classification – refined method

The intensity of the signal from an algae pixel might be very different. Some of the causes to this effect are:

- If the algae mat is very compact it will give a stronger signal than an algae mat with a loose structure.
- If the water level is low in some parts of a bay the bottom vegetation might give a signal that will be interpreted as algae.
- The mixed pixels between algae-water might be counted as algae.

Problems like this could to a certain extent be avoided when using more and finer classes. The purpose of dividing rough classes into many subclasses was that it later would be possible to merge and combine them in different ways. And it would be possible to choose the combination that mostly corresponds to reality.

To find a more refined grouping of the vegetation, than used for the rough method, the scheme below was used.

1. **Refinement of the classes from the kernels**
   The associated histograms for the kernel training areas were studied in the different TM bands. From the appearance of the histograms finer intervals for the vegetation classes were decided upon, and a refined grouping was obtained.

2. **Graphical representation of spectral response patterns**
   The distributions of training area response patterns were investigated to see if they were normally distributed. Histogram output is very important when a Maximum Likelihood classifier is used since it provides a visual check of the normality of the spectral response patterns.

3. **Separability between the classes**
   The separability between the classes was evaluated by calculation of the Bhattacharrya distance and looking at coincident spectral plots (box plots).

4. **Classification and calculation of class performance**
   Maximum Likelihood classification was carried out. All the weights were chosen to be equal. The classification used all channels but the first.

5. **Merging and combination of classes**
   The method for merging the classes is described in chapter 3.4.1, "assignment of training classes to one of the categories algae or water".

6. **Calculation of algae cover**

Normalized algae index 2

This method is a refinement of normalized algae index 1. When using the NAI no1 described in chapter 2.4.3 one misses algae pixels that do not have a higher DN value in band 4 than in band 3, but still have the "shape" of the spectral signature as the ones that fall into the category for algae pixels in method 1. The digital numbers were explored and evaluated for certain key areas, i.e. areas of known composition. Water always has a tendency to start off at a high DN in TM1 and decline all the way to TM6. This appearance is also conspicuous for water of less depth, often to be found in the inner archiepelago. The pixels considered being algae instead showed a peak value, or sometimes no difference at all between TM3 and TM4. This is illustrated in figure 2.6. The pixels with the spectral signature algae 3 and algae 4 would have fallen into the category "vegetation/algae" if using method 1. But the pixels with the signatures algae 1 and algae 2 would have been classified as water which is not the case. The aim of NAI no 2 is to avoid this problem.

The algorithm for calculating the NAI no2 is:

- Calculation of the difference between TM 3 and TM4
- Calculate the difference between TM 4 and TM5
- Calculate the absolute ratio between the differences

$$abs\left(\frac{(TM\,5 - TM\,4)}{(TM\,4 - TM\,3)}\right) \tag{2.4}$$

- If the ratio is greater than 1$\Rightarrow$ Vegetation/Algae pixel
- If the ratio is less than 1$\Rightarrow$ Non algae pixel

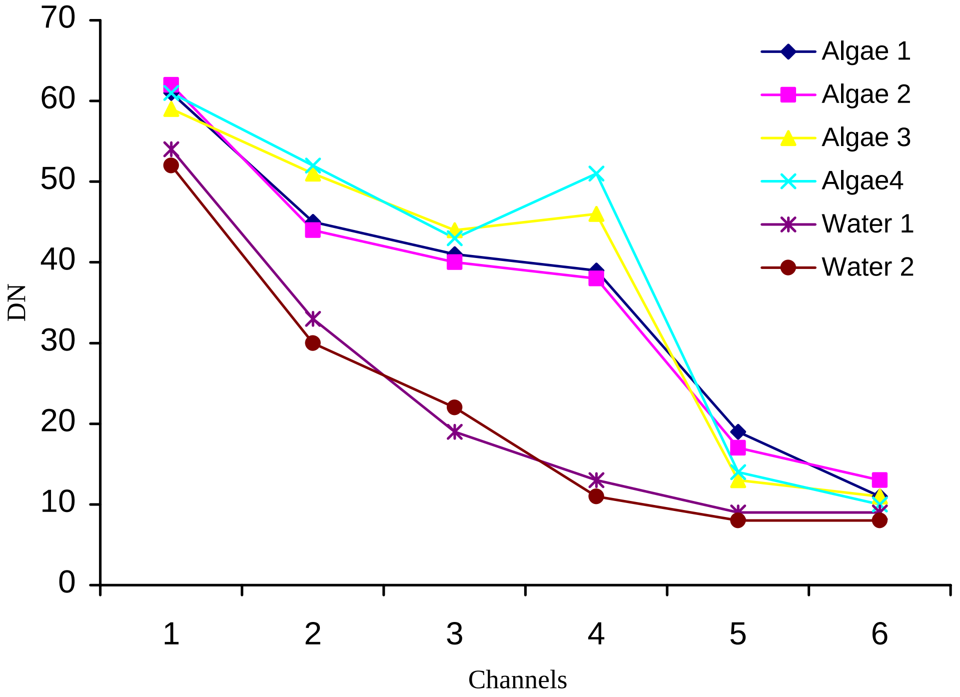

Figure 2.6 Spectral signatures of 4 different algae pixels and 2 different water pixels.

2.5 SATELLITE IMAGE -TO -AIR PHOTO COMPARISON

This approach is based on the assumption that there exists a relationship between the percentages of algae cover estimated from the satellite image to the algae cover from the air photo monitoring. The study is performed in two steps.

1. Delimiting of the feasible bays from open water and generation of an area equivalent to the air photos.
2. Derivation of a valid relationship between the satellite image and the air photo coverage of algae.

2.5.1 Areas of comparison

When dealing with ecosystems it is always tricky to know where to draw the boundary and how to find the best delimitations. After identifying suitable bays corresponding areas were defined on the air photos and the satellite image.

Ecosystem boundaries

One very important issue is where to place the boundary between open water and the bay in order to make it reproducible and to be able to compare the bays. The following criteria were used to define the boundaries in the air photo inventory (Svensson, personal comment).

- The bay should be 0.5-2 ha
- A maximum depth of 1 m when height of tide is normal

The depth information comes from field measurements and experienced guesses by the researchers at Kristineberg Marine Research Station. In this study the same boundaries as in the air photo inventory were used. The bay identification comes from maps from Anders Svensson, see appendix 5.

Bays included in the study

The following selection criteria were applied in this study:

- Bays that are smaller than 0.5 ha, equivalent to 5 pixels were excluded
- The analysis was focused on bays in the inner archipelago

2.5.2 Relationship evaluation

In developing a method for algae detection in the satellite image, there has to be some kind of relationship confirming the degree of algae in the satellite image to that in the aerial photo.

The aim is to establish a correlation between the percentage of algae in the air photo and the percentage of algae in the satellite image.
Two approaches are possible:

1. Regression, see fig 2.7
2. Threshold test, fig 2.8

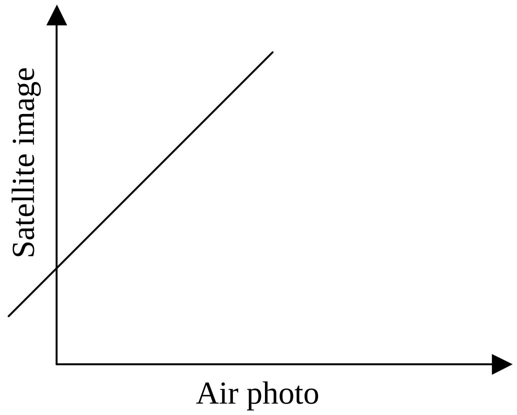

Figure 2.7 Regression test.

The satellite image to air photo comparison uses a traditional least-square regression, where the most extreme values, so called outliers are removed. The ideal case would be establishing a linear relationship between the satellite image and the air photo.

Assuming that there are two certain threshold values, one for the satellite image and one for the air photo, these limits form an upper square in the graph, see figure 2.8. Within this quarter a certain percentage of all the evaluated shallow bays end up. The higher this frequency is the better correlation between the data set and its reference.

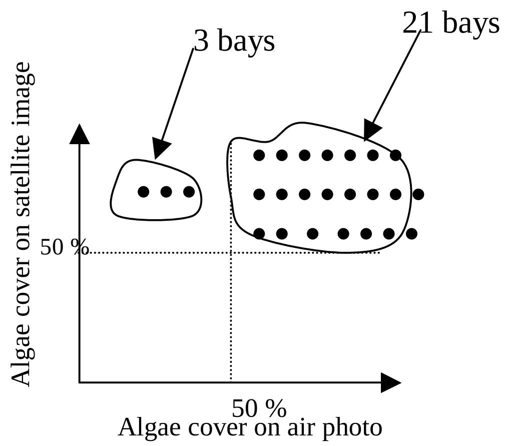

Figure 2.8 Threshold test. Explanation to the figure: Probability that a bay with over 50% algae in the satellite image will have more than 50% on the air photo is 21bays/(21bays+3bays).

The aim of the threshold comparison was to be able to answer the question: "What is the probability that if there is an algae cover of more than X % in the satellite image that this is actually the case i.e. the algae cover in the air photo will also be more than X%?"

2.5.3 Ranking of combinations from the supervised refined classification

The percentages of algae in the bays for all combinations/alternatives from the refined supervised classification were compared with the air photos. The absolute difference from the air photos was calculated:

$$\Delta = \text{abs}(\text{air photo} - \text{alternative X}) \qquad (2.5)$$

The alternatives were ranked according to the differences. The minimum distance was assigned to no. 1 in the ranking list. The largest difference was assigned to no. 15. The number of times each alternative was found in the ranking list at no.1-no.15 was counted. The best alternative was computed.

When choosing the best result it is not certain that it should be the one that occurs most often at ranking no 1. One must also see to how bad that alternative performs. To choose the best alternative each ranking number was multiplied by a weight number. The weights were chosen linearly, see table 2.5.

Table 2.5 Weights for the calculation of the best method

Ranking no.	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
Weight	7	6	5	4	3	2	1	0	-1	-2	-3	-4	-5	-6	-7

2.6 RECTIFICATION

The classified image was composed of land, water and vegetation classes. The fact that no other information such as roads, housing or any other infrastructure were kept made a direct rectification of the image impossible. In stead it had to be done in two steps.

1. The initial satellite had to be rectified against "Gula kartan" see appendix 3.
2. The classified image was then rectified against the rectified satellite image from 1.

All the operations were carried out in ArcView with the extension Image Analysis.

2.7 DATA MERGING AND GIS INTEGRATION

2.7.1 The algae as a GIS-layer

After the classified image was rectified it was possible to display the result together with an ordinary map and to transfer the data into a GIS. Below follows the description of how the algae information in the satellite image was displayed together with features from "Gula kartan" in ArcView.

1. The pixels classified as algae/vegetation were saved as a single polygon theme.
2. Algae polygons that intersected with land were considered as being misjudged and thus removed from the algae theme.
3. The algae layer was displayed together with land, water, islands, roads etc. from the County Administration's GIS database.

2.7.2 GIS as a tool for analysing the data

The extracted algae layer can be used in combination with many of the already existing files in the GIS database file at the County Administration. The method is called overlaying, and is an ordinary method for analysing data in GIS. The principal is that two or more layers that are geocoded are put together geometrically. It is in this way possible to analyse whether objects intersect or not. The aim of this section is to provide a first screening of some of the factors in the local environment influencing the growth of algae in the bays included in the study.

1. Digitising of a polygon theme of the bays included in the air photo survey.
2. Adding attribute fields such as percentage algae cover (from the air photo survey) and bay number.
3. Following themes from the database of the County Administration were added:
   - Watercourses feature theme
   - Watersheds feature theme
   - Land cover feature theme
4. Identifying the watercourses having direct discharge in the bays included in the study.
5. Identifying the watersheds intersecting with the watercourses identified in step 4.
6. Tabulating of land cover area within each watershed identified in step 5.
7. Construction of a R-rank matrix for land cover influencing the growth of algae.

3. RESULTS

Different schemes were followed in order to distinguish the algae from the rest of the environment. In chapter 3.4 the accuracy of the different classification methods for the satellite image is evaluated and chapter 3.6 covers the implementation to a GIS.

3.1 UNSUPERVISED CLASSIFICATION

The classes resulting from unsupervised classification are spectral ones. Because they are based solely on the natural groupings in the image values, the identity of the data will initially not be known. The results from the cluster performance are shown in table 1.1 in appendix 1.

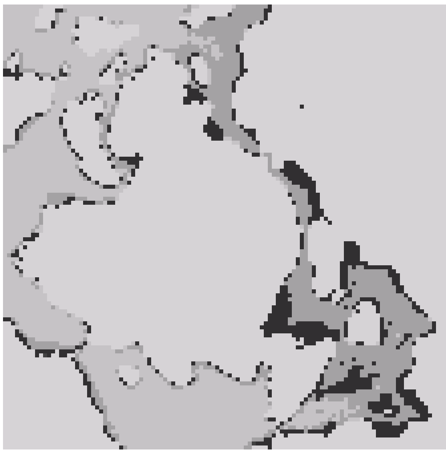

Figure 3.1 The merged outcome from the unsupervised classification. View over Galtöleran. Dark areas are algae and medium and light grey areas are water.

3.2 SUPERVISED CLASSIFICATION

The supervised classification was carried out in two approaches. First a rough method was developed and then followed by a refined method.

3.2.1 Rough image classification

The rough classification was done as a prestudy of the material and to be able to evaluate what kind of result that was possible to attain. The results from the rough image classification are described in this section.

Training area selection

The training areas were chosen according to the scheme described in chapter 2.4.2. The mean and standard deviation of the training areas were calculated from values in TM4. The training areas were then divided into the following four classes, table 3.1.

Table 3.1Classes for training areas in the rough classification.

Class	DN
Water	12-14
Vegetation 1	26-55
Vegetation 2	15-25
Other	>55

Graphical representation of spectral response patterns

The classes generated from the classification behaved as they were expected to do, i.e. they were normally distributed. In figure 3.2 this is shown for vegetation 1 in TM4. All the others had the same appearance.

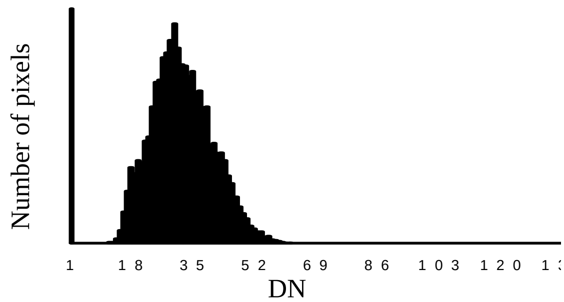

Figure 3.2 Vegetation 1 in TM4.

Classification result

With training areas divided into four classes it resulted in the figure 3.3.

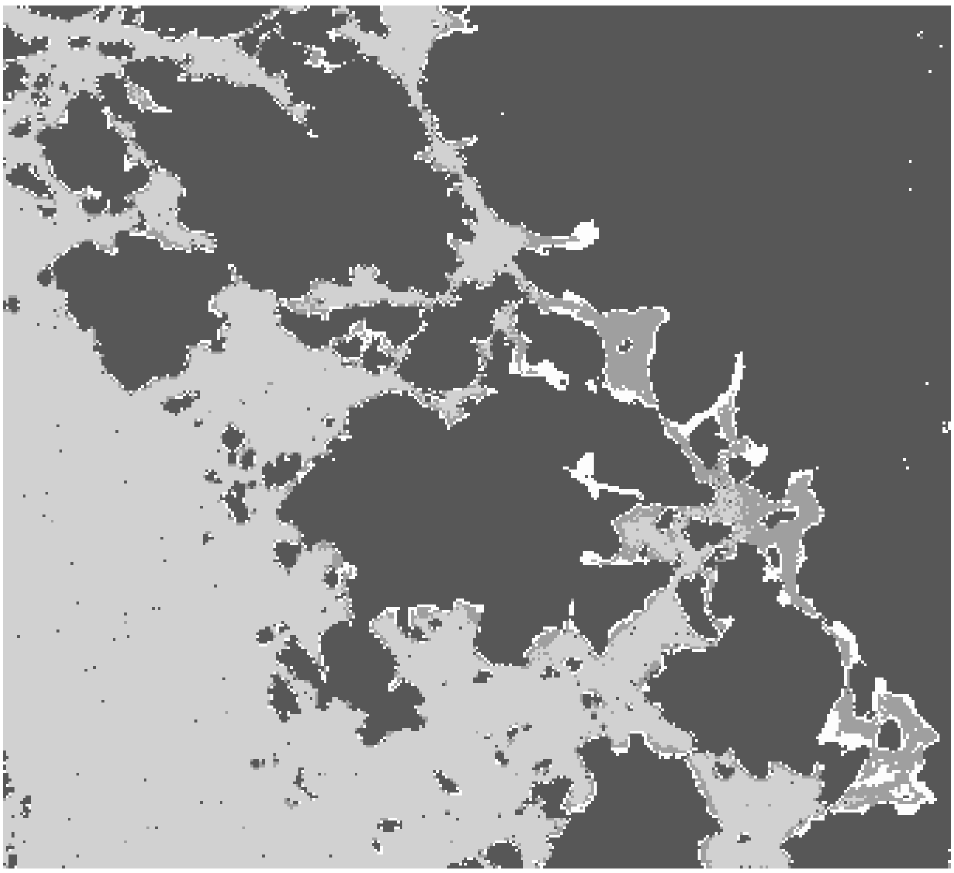

Figure 3.3 Supervised classification, rough method with four different classes. The view is from Råssö and Galtöleran. White areas are algae, grey is water and dark grey is land.

3.2.2 Refined classification

Refinement of the classes from the kernels

Having been classified using the rough method all the classes were then assessed in order to be divided into refined classes. This was done by looking at the spectral histograms for the kernel areas, like in figure 3.4. This resulted in the division in table 3.2.

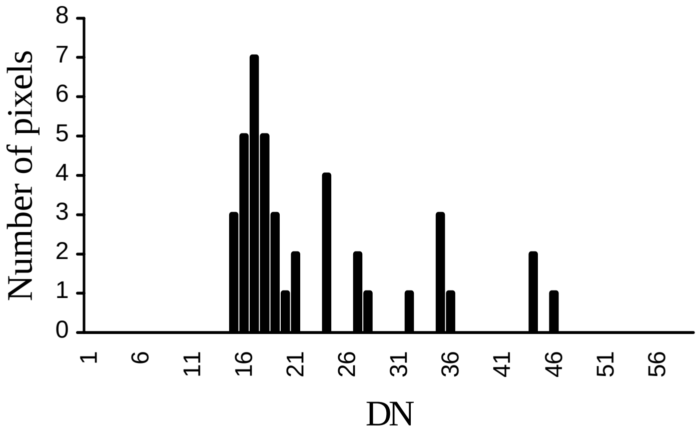

Figure 3.4 Spectral histogram from one of the training areas in the rough method for TM4. This served as a basis for the refined classification.

Table 3.2 Classes for training areas in the refined classification

Class	DN
Nothing (veg 7)	0
Water 1	11-17
Water 2	18-24
Vegetation 1	25-28
Vegetation 2	29-33
Vegetation 3	34-41
Vegetation 4	42-47
Vegetation 5	48-50
Vegetation 6	51-57

Graphical representation of spectral response patterns

The normality for each category of the classes was checked by looking at histograms and checked with the Anderson-Darling test[1]. All the classes showed approximately normal distributions. The Anderson-Darling test is shown in figure 3.5. In the image there are three outliers, but since they only make up 0.3 % of the data set they can be ignored.

[1] The Anderson Darling test is used to test if a sample of data comes from a specific distribution.

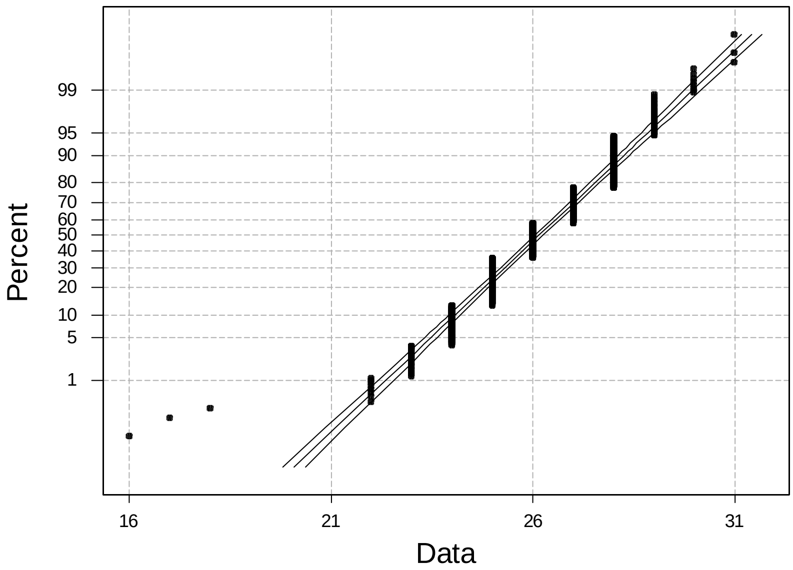

Figure 3.5 Normal Probability Plot for ML Estimates - 95% confidence interval with the Anderson-Darling test. Vegetation 1 in TM4[2].

3.2.3 Separability between classes

The separability between the classes can be visualised in two ways using the Bhattacharraya distance as well as by coincident spectral plots.

The Bhattacharrya method

The band combination giving the highest internal distances between the classes is generated when choosing all bands but TM1 in the classification. The more channels the greater the distance and better result in the classification. Table 3.4 below shows the combinations of the classes and their distances when using all bands but TM1.

Table 3.3 Key to the classes in the Bhattacharrya distance.

Id #	Class	Combination #3
1	Water 1	Water
2	Veg 5	Algae
3	Veg 6	Algae
4	Water 2	Water
5	Veg 1	Algae
6	Veg 4	Algae
7	Veg 3	Water
8	Veg 2	Algae
9	Veg 7	Land

In the supervised classified image Id number 2,3,5,6 and 8 constitute the features that is assumed to be algae, based on comparison with air photos. The group water is made up

[2] To be perfectly normally distributed all the samples should be on the straight line. Between the two outer lines is the 95% confidence interval.

of 1, 4 and 7 and land is class 9. This pattern of the class combinations is almost the same as if one only used TM4.

Table 3.4 Bhattacharrya distance for the different classes[3]. All TM channels except TM1.

Combination of Id#	29	39	69	59	49	89	25	79	19	12	24	13	35	34	28	16	17	38
Distance	9573	550	428	327	157	135	121	112	106	76.9	56.4	45.7	35	32.9	26.8	23.9	19.3	14.5

Combination of Id#	18	46	56	47	15	37	27	57	48	68	23	36	14	26	58	78	45	67
Distance	14.1	12.7	11.7	9.08	8.27	7.59	6.91	6.87	4.98	3.95	2.9	2.6	2.48	2.36	2.35	2.18	1.6	1.05

Coincident spectral plots

Coincident spectral plots can also investigate the separability between classes. This facilitates the comparison between classes.

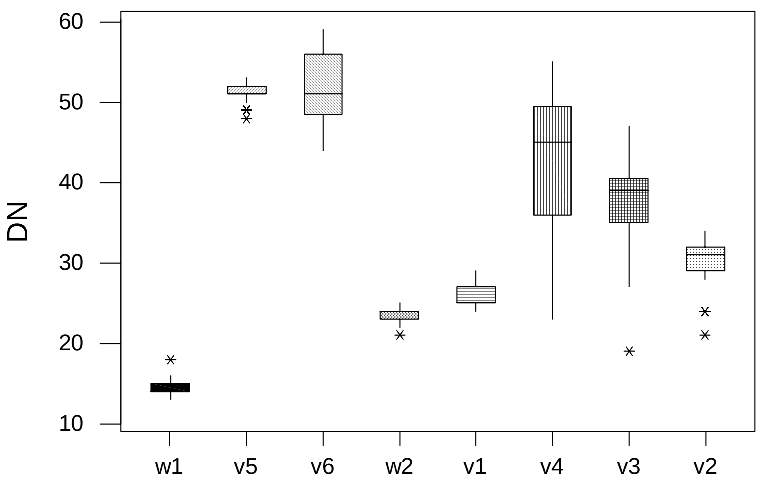

Figure 3.6 Coincident spectral plots[4] for all the classes in TM4.

[3] Values greater than 1 indicate that the classes are separable - but may not be well separated until values of 2 or 3 and larger. Values less than 1 indicate that the classes are not very separable.
[4] The center half of the data, extending from the first to the third quartile, is represented by the box. A line extends from the third quartile to the maximum and another line extends from the first quartile to the minimum.

Classification result

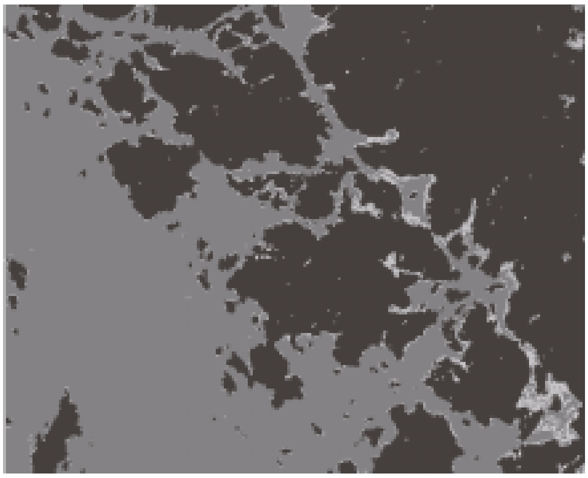

Figure 3.7 Outcome of supervised classification, refined method. The view is from Råssö and Galtöleran. Light areas are algae, grey areas are water and dark areas are land.

3.2.4 Class performance of rough and refined methods

The results from the rough method are displayed in table 3.5 where they can be compared to the results from the refined method. For more details about the results from the refined method, see appendix 1, table 1.3.

Table 3.5 Classification performance from the rough and the refined method

	Overall class performance[5]	Kappa Statistic[6]
Coarse	62.1%	0.1 %
Refined	98.1%	97.2%

3.3 NORMALIZED ALGAE INDEX

The two different methods described in chapter 2 for calculating whether the signal originates from an algae pixel or a water pixel were used to calculate the percentage of algae in each of the bays included in this study. The result is displayed in chapter 3.4, table 3.10, where the result can be compared to the supervised classification.

3.4 SATELLITE IMAGE -TO- AIR PHOTO COMPARISON

In this section the percentage of algae cover for all methods in sections 3.2 and 3.3, in all the bays are compared with the algae cover percentage from the air photo survey. First the best alternative in the refined supervised classification was calculated, described in chapter 3.4.1.

[5] The overall class performance is computed by dividing the total number of correctly classified pixels by the total number of reference pixels.
[6] The kappa statistic is a measure of how well the classifier performs the classifications. A value of 0 suggests that a given classification is no better than a random assignment of pixels.

3.4.1 Assignment of training classes to one of the categories algae or water

The purpose of dividing the water and the vegetation into many subclasses was that it would later be possible to merge them together in different ways in order to choose the combination that gives the best match with the algae cover percentage on the air photos.

Merging of Classes

The classification using the refined method was preformed with 8 different training classes, see table 3.3. Two of these classes were named water (water 1 and water 2) and the other six were named vegetation[7] (veg1-veg6).
Based on the initial satellite image the following assumptions were made:

- Water 1 and water 2 are always assigned to the water class.
- Veg 5 and veg 6 are always assigned to the algae class.

The four vegetation classes, veg 1-veg 4, were combined in 15 different ways, see table 3.6. In alternative 1 all four classes were assigned to the algae class. In alternative 2-5, the vegetation classes were assigned to water one at the time. In alternative 6-11 two of the vegetation classes were put in the water class and in alternative 11-15 three of the vegetation classes were assigned to the water class.

Table 3.6 The combinations of the training classes into one of the categories W (water) or A (algae)

Alternative	W1	W2	V1	V2	V3	V4	V5	V6
1	W	W	A	A	A	A	A	A
2	W	W	A	A	A	W	A	A
3	W	W	A	A	W	A	A	A
4	W	W	W	A	A	A	A	A
5	W	W	A	W	A	A	A	A
6	W	W	A	A	W	W	A	A
7	W	W	A	W	A	W	A	A
8	W	W	A	W	W	A	A	A
9	W	W	W	A	A	W	A	A
10	W	W	W	A	W	A	A	A
11	W	W	W	W	A	A	A	A
12	W	W	A	W	W	W	A	A
13	W	W	W	A	W	W	A	A
14	W	W	W	W	A	W	A	A
15	W	W	W	W	W	A	A	A

[7] Vegetation could be anything that gives a stronger signal than water such as macrophytes or sometimes a response signal from shallow water.

3.4.2 Refined method - comparison between alternatives

Among the different alternatives there were two that showed the best correspondence when compared to the air photos. Alternative 3 gave the best overall result. But this was not the alternative showing best correspondence the most number of times. That was alternative 1. It correlates best with the aerial photos, eight times while this only occurs twice for alt. 3 cf. table 3.7. But on the other hand alternative 1 also shows very low relationship with the air photos in very many cases, disguising the good outcomes.

Table 3.7 The ranking matrix between the alternatives

Ranking no.	Alt 1	Alt 2	**Alt 3**	Alt 4	Alt 5	Alt 6	Alt 7	Alt 8	Alt 9	Alt 10	Alt 11	Alt 12	Alt 13	Alt 14	Alt 15
1	8	3	**2**	1	2	1	0	2	3	0	2	1	1	0	0
2	2	2	**2**	5	5	0	3	0	0	1	0	3	0	1	2
3	0	5	**3**	4	3	2	4	2	1	0	0	0	0	1	1
4	1	0	**5**	4	3	0	0	1	5	1	3	0	0	2	1
5	1	3	**4**	4	1	6	1	3	1	0	1	0	0	1	0
6	1	1	**0**	1	1	3	5	4	0	0	6	0	3	0	1
7	0	2	**6**	2	1	2	1	5	2	3	1	0	0	1	0
8	1	0	**1**	0	0	1	5	2	3	4	2	2	1	3	1
9	2	4	**1**	1	1	3	1	2	2	5	4	0	0	0	0
10	0	0	**1**	0	2	1	3	0	6	2	2	3	0	4	2
11	0	1	**0**	0	1	5	3	0	1	7	2	3	0	1	2
12	1	1	**0**	2	2	0	0	3	2	2	0	4	4	3	2
13	2	3	**0**	0	1	2	0	2	0	1	3	4	4	4	0
14	2	1	**0**	0	3	0	0	0	0	0	0	3	5	4	8
15	5	0	**1**	2	0	0	0	0	0	0	0	3	8	1	6

The number of times each alternative is found in the ranking list at no.1-no.15 in table 3.7 was counted. When multiplying the number of times at each rang number with the weights from table 2.5 the absolute ranking list in table 3.8 is obtained. Alternative 3 is thus the best.

Table 3.8 Ranking of alternatives when weights are used.

Ranking	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
Alternative	3	4	2	5	7	8	9	1	6	11	10	14	12	15	13

3.4.3 Comparison between the different methods

All the different classification methods used in this study were correlated to the results from the air photo survey. In the table below all results are put together. The supervised rough classification is represented by two different combinations differing in what is allocated to be algae and not. These are called A and B. Also the supervised refined classification is represented by two different alternatives, diverging in what is considered to be algae or not. C represents alternative 3 and D represents alternative 1. The normalised algae index (NAI) is also epitomized by two alternatives, one being more elaborate than the other. They are called E (NAI no. 2) and F (NAI no. 1), NB the reversed order of these two in table 3.9 as well as in the figure 3.8.

Table 3.9 Comparsion between air photo and satellite percentages of algae for the different methods

Air photo No.	Air Photo %	Supervised Coarse Veg1 A	Supervised Coarse Veg1+Veg2 B	Supervised Refined Alt 3 C	Supervised Refined Alt 1 D	NAI no. 2 E	NAI no. 1 F
416	35.2	26	78	29.7	37.8	42.6	0.0
418	89	31	85	53.8	61.5	53.8	35.7
419	65	23	31	40.9	54.5	36.4	22.7
424	63	70	90	31.3	46.9	80.0	25.0
425	68	30	85	50.0	65.0	62.5	20.8
426	57	30	89	41.9	62.8	72.1	23.3
428	76	45	59	57.1	89.3	85.7	67.9
430	33.9	99	100	59.5	100.0	98.6	48.6
431	76.7	70	93	57.6	96.6	98.3	78.0
432	96.2	72	78	59.6	98.2	96.3	41.3
439	34	72	97	64.8	100.0	100.0	29.7
440	82	48	100	44.1	62.1	93.8	27.6
441	79	23	93	42.1	55.0	79.4	15.8
442	62	76	96	56.0	100.0	94.0	14.0
443	66	60	97	75.7	100.0	98.6	35.7
444	35	26	91	48.8	66.1	97.8	12.1
446	43.6	33	99	44.6	70.7	82.5	24.4
449	34.1	23	97	51.3	76.9	94.9	19.5
450	63.7	47	100	53.3	83.3	94.3	11.7
455	52.2	31	65	44.0	60.0	64.0	20.0
462	70.6	43	66	58.5	82.9	85.4	68.3
467	56	25	79	18.9	29.7	31.6	14.3
468	13.6	48	88	37.0	65.2	65.2	21.6
470	58	9	52	28.6	51.4	40.0	62.5
471	39	67	87	40.0	80.0	69.2	18.8
473	32	41	65	38.6	75.0	61.4	37.6

Evaluating the differences between the air photos and the satellite image and plotting them gave the following result.

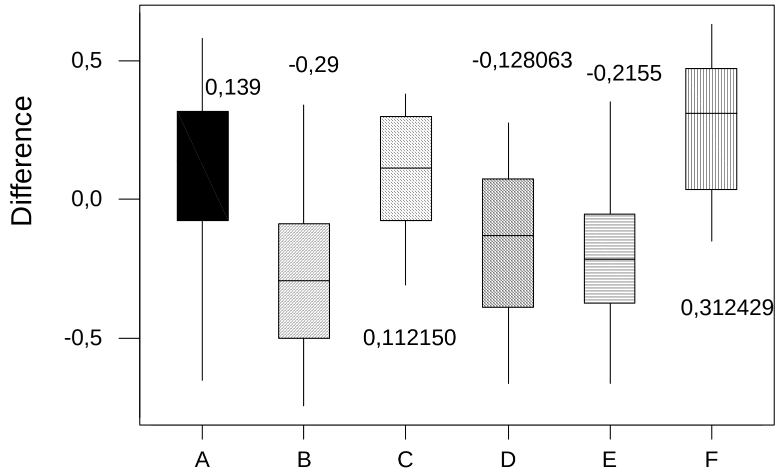

Figure 3.8 Box plot[8] over the differences in the air photos and satellite image for the different methods. The median values are written in the figure. Key to the figure is found in table 3.10.

The box plot, figure 3.8 is built on the differences between the percentage in the air photo material and the percentage from the different methods. The box plot shows if the method is over or under estimated. The best correspondence to the air photos is alt no. 3. It has the smallest range and the difference is closest to zero.

3.4.4 Relationship evaluation

In total 26 bays have been investigated. First a regression was performed to evaluate the correspondence between the algae coverage in the air photos compared to that in the satellite image. Secondly a threshold evaluation was performed. This evalution answers the question “what is the probability if there is an algae cover of more than X % in the satellite image that this is actually the case, i.e. the algae cover in the air photo will also be more than X %.

Regression evaluation

None of the methods in table 3.9 showed any significant signs of regression when compared to the air photos. The method that showed the best performance, although not that good in the box plot, was alternative 3, the refined classification. The regression for this method is illustrated in 3.9.

[8] The center half of the data, extending from the first to the third quartile, is represented by the box. A line extends from the third quartile to the maximum and another line extends from the first quartile to the minimum.

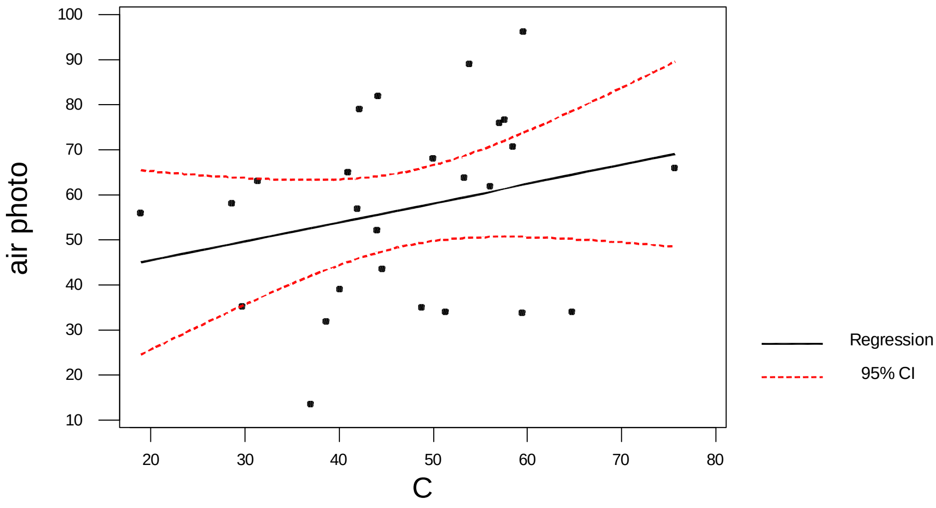

Figure 3.9 Regression between the air photo survey and the refined image classification, method C in table 3.10 R-Sq = 6,8 %

Threshold evaluation

The percentages in the cells in table 3.10 and 3.11 show how the percentage algae cover in the satellite image relates to the coverage in the air photos for all the studied bays. The tables show the refined classification and normalized algae index, NAI. There is a good match between the air photos and satellite image up to 50 %. The tables are best demonstrated with an example. If the satellite image shows for example algae cover of 50 % or more, then one can find out for how many of the bays in the air photo this also is valid. In table 3.10 this would correspond to 64 % of the bays from the air photo that showed an algae cover of 50 % or more.

Table 3.10 Normalized algae index. Relation between the air photo and satellite image. A stands for air photos and S for satellite image.

A \ S	10	20	30	40	50	60	70	80	90
10	1.00	1.00	1.00	0.92	0.85	0.81	0.62	0.54	0.38
20	0.96	0.96	0.96	0.96	0.95	0.95	1.00	1.00	1.00
30	0.96	0.96	0.96	0.96	0.95	0.95	1.00	1.00	1.00
40	0.69	0.69	0.69	0.67	0.68	0.67	0.75	0.71	0.60
50	0.65	0.65	0.65	0.63	0.64	0.62	0.69	0.64	0.60
60	0.50	0.50	0.50	0.50	0.55	0.52	0.63	0.64	0.60
70	0.27	0.27	0.27	0.29	0.32	0.29	0.38	0.36	0.30
80	0.12	0.12	0.12	0.13	0.14	0.10	0.13	0.14	0.20
90	0.04	0.04	0.04	0.04	0.05	0.05	0.06	0.07	0.10

Table 3.11 Refined classification. Relation between the air photo and satellite image. A stands for air photos and S for satellite image.

A \ S	10	20	30	40	50	60	70
10	1.00	1.00	1.00	1.00	1.00	1.00	1.00
20	0.96	0.96	0.96	1.00	1.00	1.00	1.00
30	0.96	0.96	0.96	1.00	1.00	1.00	1.00
40	0.69	0.68	0.70	0.75	0.75	0.50	1.00
50	0.65	0.64	0.65	0.70	0.75	0.50	1.00
60	0.50	0.52	0.57	0.60	0.75	0.50	1.00
70	0.27	0.28	0.30	0.35	0.42	0.00	0.00
80	0.12	0.12	0.13	0.15	0.17	0.00	0.00
90	0.04	0.04	0.04	0.05	0.08	0.00	0.00

3.5 RECTIFYING-RESULT

1. Image-to-map rectification: The study area in the Landsat image was rectified against Gula kartan. The RMS for this rectification was 0.63.

2. Image-to-image rectification: The classified image was rectified against the coast line and corners of the rectified Landsat image from 1. The RMS of this rectification was 1.3.

3.6 DATA MERGING AND GIS INTEGRATION

3.6.1 The algae as a GIS layer

The rectified classified image was displayed in ArcView and the algae cover was separated and saved as a single layer.

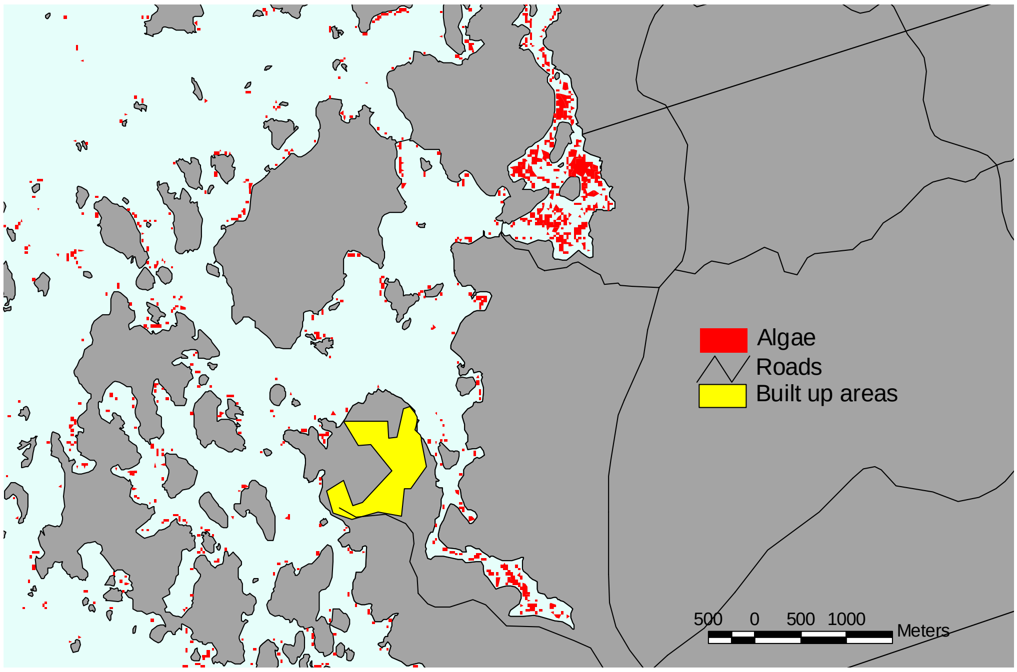

Figure 3.10 Algae cover displayed in ArcView.

3.6.2 GIS as a tool for analysing the data

Here GIS has been used to show some of many possibilities of analysing the data acquired from satellite images[9]. In this section the results from a study of land cover analysis within each watershed is shown. The relation between algae cover and land cover within the bay's watershed is analysed.

The result from step 1-6 described in section 2.7.2 is a map, which is partly displayed in figure 3.11 here below. The tabulating of land cover within each watershed, step 6, is shown in appendix 4, table 1. The regression between arable land and the percentage of algae cover in shown in figure 3.12. Table 3.12 gives an r-rank matrix based on linear correlation coefficients for the percentage of algae cover versus different land cover types within respective watershed.

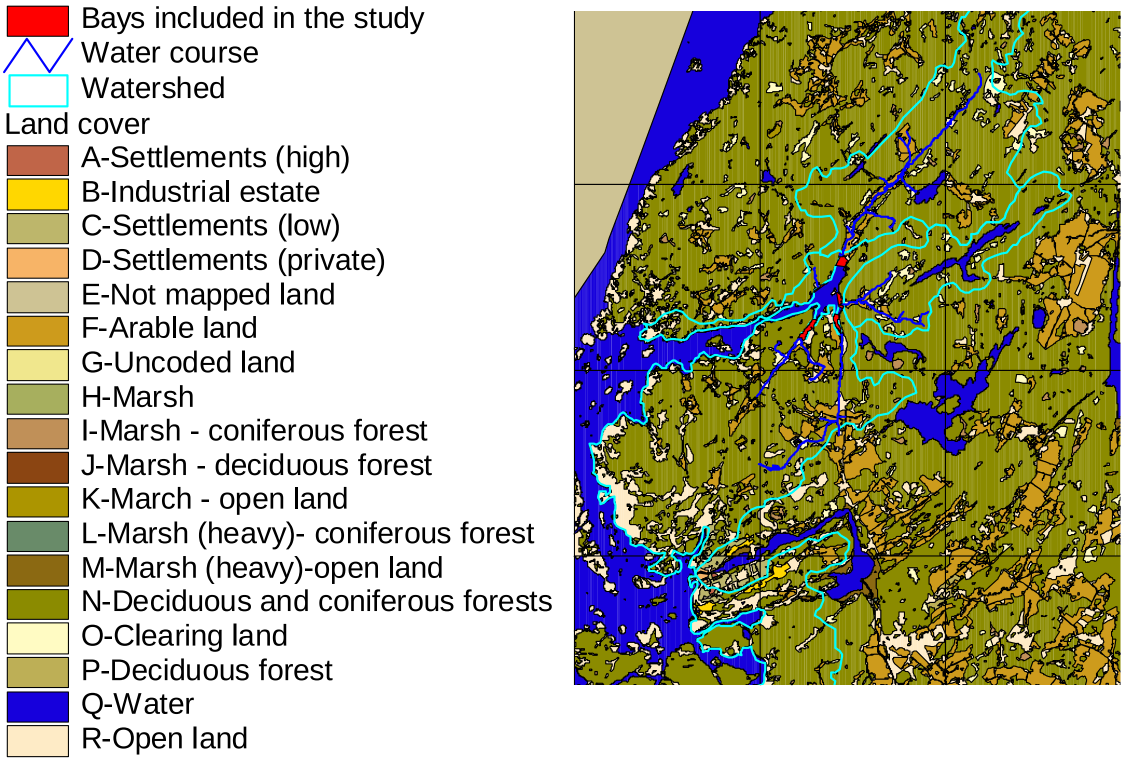

Figure 3.11 The watersheds and watercourses connected to the bays included in the study in Dynekilen. In appendix 6 there is a Swedish key to the land covers.

[9] Here the percentages from the air photo survey has been used so the results from the analysis will be more accurate.

Table 3.12 An r-rank table for the percentage of algae versus the percentage different land cover types within respective watershed.

Land cover	**r-value**
Arable land (F)	0.69
Marsh-coniferous forest (I)	0.43
Marsh-open land (K)	0.43
Deciduous and coniferous forest (N)	0.32
Clearing land (O)	0.30
Industrial estate (B)	0.14
Settlements (low) (C)	0.12
Marsh (heavy)-open land (M)	0.00
Open land (R)	0.00

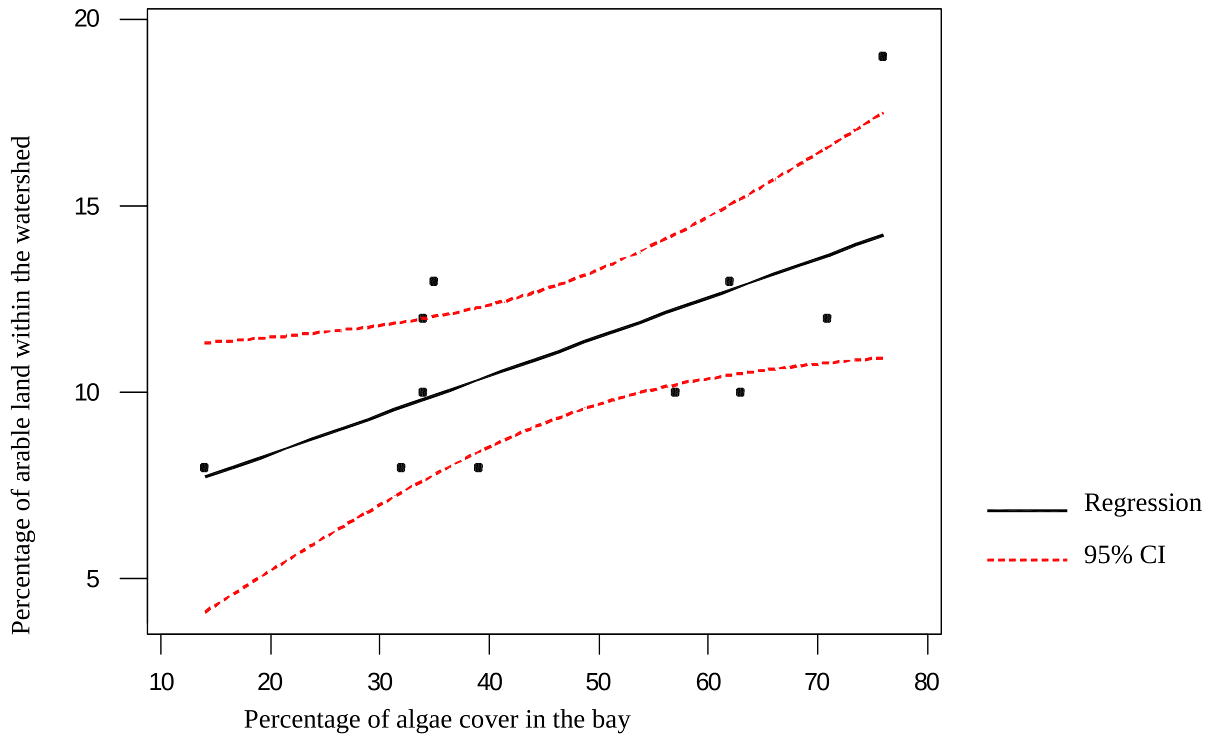

Figure 3.12 Regression between the percentage of arable land within the watershed connected to the bay and the percentage of algae in the same bays. R=0.69.

4 DISCUSSION

4.1 CLASSIFICATION

4.1.1 Supervised classification

When looking at the result from the classification one has to bear in mind that this only describes the class performance of the training areas, i.e. well defined training areas result in a well-classified image.

The *overall class performance* was considerable better for the refined method than the rough indicating the importance of choosing small, quite narrow training areas and giving the choice of merging them together afterwards.

4.1.2 Normalized algae index

The supervised classification showed better correspondence to the air photos than the normalized algae index although the difference in outcome between this method and the supervised refined method is not that great. Since no training areas are needed it is a less time consuming approach. This method should also be less subjective than the supervised classification and would be more valuable to the County Administration. An advantage of this method, compared to the supervised classification, is that it would be possible to automatize without making any atmospheric corrections[1]. This is because the procedure only requires band ratio calculations for each pixel and the ratio would be approximately the same even if the absolute values differ from time to time.

4.2 SATELLITE IMAGE COMPARED TO AIR PHOTOS

All the different methods in this thesis have been made for estimating the algae cover in bays with shallow water. The estimated algae cover in each bay has then been compared with the algae cover from the air photo survey. The results from the satellite-to air photo comparison are used to estimate the accuracy of the methods described in this thesis. The air photo monitoring is here considered to be the absolute truth, which of course is not the case. There are many potential sources of error in the estimation of algae cover in the air photo survey; these potential errors are described in chapter 4.3.4.

4.2.1 The Different methods

The best method was from the refined supervised classification. This should come as no surprise. The refined method is just as the name implies, a refined and thorough method. According to Pihl (1998), there may be errors up to 10 to 15 per cent when measuring the coverage in the air photos, which means the deviation from the air photo percentage may be considered to fall within the range of error.

[1] This could be corrections of the signal due to disturbances in the atmosphere, described more in section 4.3.

4.2.2 Threshold matrix

The number of bays included is 26. It is a small selection but there had to be a lucid set to work with. Only 7 of the 26 bays have a coverage of more than 70 % in the air photo. This must be taken into account since it results in a smaller selection and making evaluations less significant. This means that the percentages in the upper left corner in tables 3.10 and 3.11, i.e. the lower percentages are more accurate because of the bigger selection. The higher percentage results in fewer included bays.

4.3 SOURCES OF ERROR

There are different kinds of errors effecting the interpretation and evaluation of the image.

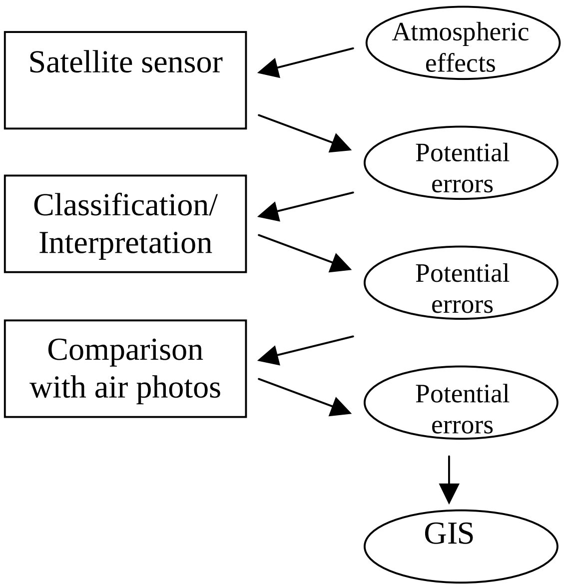

Figure 4.1 Potential errors affecting the analysis.

4.3.1 Atmospheric errors

Compensation for atmospheric effects is of importance when working with satellite data from different time frames and when one wants to automize the classification. In this study no atmospheric correction was done since only satellite data from one time is dealt with. Neither the supervised nor the normalized algae index method requires atmospheric correction in this study. But if one wants to classify an image from another time, the supervised classification has to be made again as thoroughly as this time. One cannot use the groupings of TM4 for the new image. The normalized algae index on the other hand is possible to automatize with out atmospheric correction.

4.3.2 Limitations in the sensor system

Coherent noise

The coherent noise is mostly a problem in TM1 but the other bands are also affected and the fine intervals made in the refined classification method may be too narrow to be absolute.

Spatial resolution

In this study the problems with mixed pixels are along the shore-water border and along the border algae-water. The spatial resolution of Landsat 7 is 30 m. So between the coastline and at least 30 m out in the water there will be an area that is not possible to classify correctly.

As a result of the uncertainty in the classification theses border zones have to be ignored. This is accomplished when using the landmask. But still it is of great importance to know the morphology along the coastline, i.e. whether the bay is shallow and over grown with reeds or other vegetation, or whether it is sheer rock falling into the sea. The influence further out from the shore is then different. If the coast is bare rock, the influence from the rock can be ignored, when being one pixel from the land, and outlying pixels can be considered as water, but if the trees go all the way down to the sea and then a zone of wetlands or reeds takes over, further diffuse and mixed pixels appear, i.e. there is a second mixed pixel zone of vegetation in the water and algae. With a moving water level confusion may also appear due to clay beds that were hidden below the water during high-tide come into day during low-tide, resulting in signals different from both water and vegetation. This complex problem occurs especially when comparing two images of the same area but from different times.

The Landsat 7 scene used here has a spatial resolution of 30 x 30 m. It renders detection of object of less extension impossible. Another problem within this field is that the occurrence of algae may well have a larger extent than 30 x 30 meter but with a very loose structure. The loose structure does not generate a strong enough signal for the sensor to be able to detect the algae and hence no algae are mapped. It can also be the other way around, i.e. the loose structure, say 50% of the pixel, does generate a signal that will be interpreted as an algae signal and thus the coverage will be counted as 100% of the pixel. This problem is illustrated in figure 4.2 and 4.3.

Figure 4.2 Estimate of algae cover according to the air photo survey.

Figure 4.3 Potential pixel spread over a bay.

In the air photo survey, figure 4.2, the algae cover has been estimated to 63 %. Two possible estimates of algae cover according to the remote sensing methods are described here:

1. **Underestimation of percentage of algae cover**
   All the pixels around the shore have been filtered away with the landmask in figure 4.3. The pixel (row no 2 and column no 3) will probably be classified as an algae pixel. The rest of the pixels may not generate a signal strong enough to be classified as algae. This results in an algae cover of 20% (one algae pixel and five water pixels).

2. **Overestimation of the percentage of algae cover**
   The pixels that have not been filtered away with that landmask, in figure 4.3, and have some algae within its borders will be interpreted as algae pixels. The pixel (row no 3, column no1) will be interpreted as a water pixel. This results in an algae cover of 80%.

The actual estimates of algae cover in this bay, no 424, by the methods described in this thesis are listed in table 3.9, chapter 3.4.

4.3.3 Difficulties in the classification - Physical obstacles

The classification divides the satellite image into different classes, all coming down to how the training areas have been chosen. Ambiguity in the image makes the interpretation more difficult when dealing with classifications in aquatic environments than one would encounter on land.

Training areas

The result of the classification depends totally on how the training areas were chosen. The large amount of subjectivity is both the strength and drawback of the method. In these waters there are other types of vegetation. This study is too superficial to be able to distinguish the spectral differences between the filamentous algae and other sorts of marine vegetation. This problem appears mostly in the really shallow water where Zostera reach the surface and is also classified as vegetation/algae. To be sure to make a complete separation between the two an initial survey with more air photos of bays with both Zostera and Filamentous algae would have been needed. An example of the problem can be seen in figure 4.4 and 4.5.

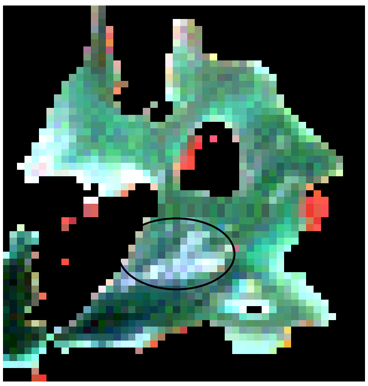

Figure 4.4 Landsat 7 over Galtöleran.

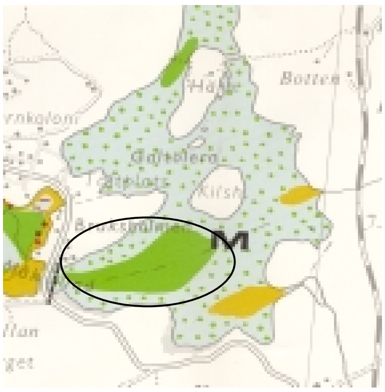

Figure 4.5 Bottomfauna map, Naturvårdsenheten,1983.

The enclosed part in figure 4.4 probably is algae floating on the water (Svensson, pers. com.). But when looking at an old bottom fauna inventory by Naturvårdsstyrelsen, it can be seen that Zostera was growing here in 1983, figure 4.5. There are no air photos that can confirm the hypothesis that this is Zostera instead of algae. One hypothesis is that it is both Zostera and filamentous algae since these two often grow together and that filamentous algae often are “caught” by Zostera (Sköld, pers. com.).

Shallow water

Light with short wavelengths (blue) penetrates water better than longer wavelengths. This has the effect that TM1 hits the bottom of the sea and is therefore not recommendable to use. In the classification this channel was omitted. But for the bands with longer wavelengths there should not be a problem when water depths are deeper than 10 cm (Lindell pers.com.). But problems can still arise since there may be tidal effects such as a moving water level and occurrences of areas partly in clay and partly under water.

4.3.4 Comparison with air photos

Date of acquisition

The satellite image acquisition and the air photo survey did not take place on the same day. This may cause a problem because the algae are floating and move quite easily and may have drifted “out of or into” the mapped area, making the results, i.e. the percentages, difficult to compare. Other effects from different dates of acquisition, or even different times of the day, are tidal effects. The three bays in focus are rather small and any tidal effects in the satellite scene among them would be synchronized and there should not be any differences in reflected signals due to different water stands.

Areas of comparison

The delimitation of the shallow bays is probably the main source of error. The algae percentages depend totally on how the shallow bays have been defined. In the air photo survey the bay boundaries were chosen such that the depth should be less than 1 m when height of tide is normal. There are no depth measurements made for the bays and the delimitation made from Kristineberg is to a great extent carried out from previous experiences. When the percentage of algae cover was calculated in the satellite image we tried to draw the bay limitations as closely as possible to the air photo delimitation, see appendix 5. Uncertainty in this step can make it hard to really compare the percentage between bays.

The aerial photos received from Kristineberg Marine Research Station have been considered to be absolute and true, otherwise there would not be anything to compare with. The photos are taken with a normal camera, handheld in the airplane resulting in different oblique angles each time. Even though the same person has done the calculation of the algae cover there are still uncertainties in the figures that have been used to compare the algae covers from this study. As stated before it is also known that there is a variation of 10 to 15 per cent among the air photos resulting in even greater uncertainty in the percentages in the satellite images.

4.4 DATA MERGING AND GIS INTEGRATION

4.4.1 Geometric correction

The geometric correction of the image was made after classification since we in the beginning did not have access to software that could perform a rectification. This caused some problems since it is more difficult to rectify the classified image. There were no features left such as roads or other kinds of easily identifiable infrastructures. We solved this by first rectifying the Landsat image and then rectify the classified image to the rectified Landsat image. The rectification was carried out using ArcView Image Analysis. There are no rectification possibilities in MultiSpec. When rectifying twice we got two RMS errors which result in more uncertainty in the location of an algae pixel. The RMS equals to 1 means that the rectified pixel is within a pixel's distance of the desired location. The problem with two RMS is illustrated in figure 4.6.

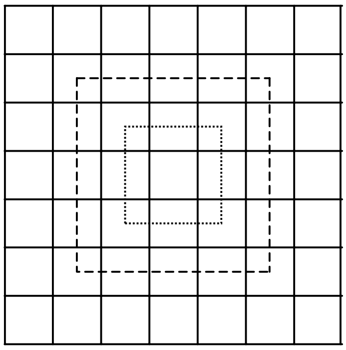

Figure 4.6 Illustration of RMS error.

In our case we had the two RMS errors of 0.63 and 1.3, meaning the true position of the pixel could be within a radius of 1.93 (~2) pixels from that pixel's border. This means that the maximum dislocation of the pixel in the middle could be somewhere between the two dotted lines. This is an area of 25 pixels with the centre pixel included. With a resolution of 30 m this is an area of 22500 m^2 i.e. 2.25 ha. This could be the size of a bay. This source of error only effects the position of the algae pixel when transferring it to a map in GIS. The algae cover percentage in each bay was calculated before the rectifying step and is thus not affected. This problem with two RMS errors is easily overcome if rectifying takes place before classification or if one from the beginning uses an already rectified image.

4.4.2 The algae cover as a GIS-layer

When overlaying the algae as a GIS-layer on an ordinary map there are problems with the uncertainty of the exact position of the algae pixels. This uncertainty in position originates from the rectifying and RMS errors discussed above.

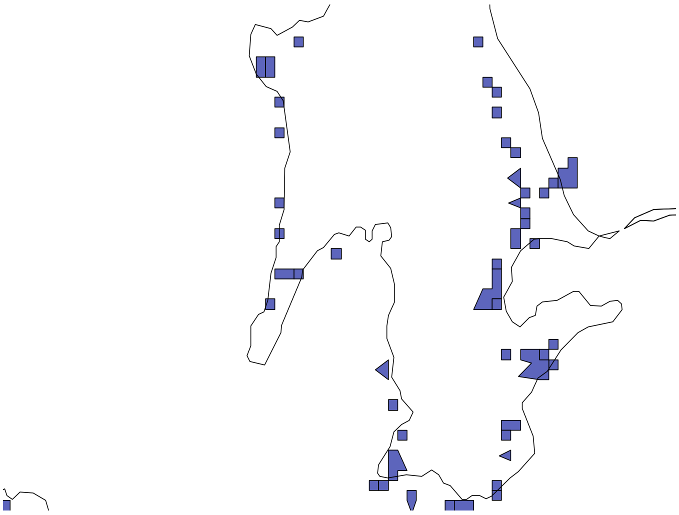

Figure 4.7 The position of algae

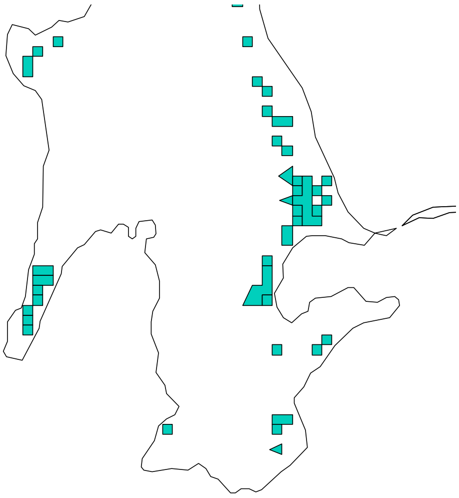

Figure 4.8 The position of algae when pixels overlapping land are removed.

With the aim that the algae cover should only represent areas having algae and not exact position or the amount of algae cover we chose to remove pixels intersecting with land, see figure 4.7 and 4.8. This has to be kept in mind when looking at the algae cover theme.

4.4.3 GIS as a tool for analysing the data

There is an enormous amount of possibilities of analysing data in GIS. In this study we wanted to show one approach. The analysis was based on the theory that the growth of algae in a bay depends on the type of landscape the watercourses flow through before reaching the bay. Since the data acquired from the satellite contains very many uncertainties we chose to analyse the algae cover-land cover relation using the algae cover data from the air photo survey. It was done just for displaying one of many applications of GIS. Things that have been neglected in the analysis are:

- Diffuse effluents
- The length of the water course
- Discharge from watersheds nearby

And of course the algae growth depends on many other factors such as exposure to the adjacent sea, bottom characteristics or direct discharges from plants etc.

Analyse of algae cover-land cover relation

First of all has to be emphasised that there are not enough data to say too much about the results. In the example the correlation between algae cover and arable land had a high r-value. This only indicates that there might exist some relations but further analysis is needed. In figure 3.12 “Regression between the percentage of arable land within the watershed connected to the bay”, outliers could be explained by factors such as the bay might be very closed towards the adjacent sea compared to the other bays, thus giving a higher algae cover than expected. There exists a model predicting the growth of algae based on factors like this (Sköld pers. com.). This model could be interesting to connect with a GIS-system. But this was out of the scope of this master thesis.

4.5 EVALUATION OF THE SOFTWARE USED.

4.5.1 MultiSpec

The strength of MultiSpec is primarily that it is a freeware. Many of the functions needed are still under development and we often faced that we had to do our own procedures to go around a problem that in a more commercial program would be easier to perform. With other words it is time consuming. But one should not be too harsh; even though some functions are lacking one can perform many operations, one simply has to carry them out in several steps. The office environment is user-friendly. Further more there are no such things as support or even a user group to consult. Luckily we have been in contact with one of MultiSpec's originators Professor Larry Biehl, Purdue University. Mr Biehl has been to a great help and the work would have taken much more time with out his support.

4.5.2 ArcView

ArcView together with the two extensions Spatial Analyst and Image Analysis is a very powerful tool. When data is saved in GIS-format many different users can work with GIS and get access to the same information. This means that the information can be used in an abundance of different applications. Analysing the data is easily carried out and reproduced.

5 CONCLUSION

The objective of this master thesis was to investigate and evaluate if satellite remote sensing is a feasible method for detection of filamentous algae in shallow bays. The answer is that with a Landsat 7 satellite image it is possible to see where there might be vegetation on the water surface. However it is not possible to quantify the algae cover very well. Algae in the middle of the bays are mapped more accurately than algae along the shores. If the algae cover in a bay is calculated to be more than 50% the probability that this is true is:

- 64% for the normalised algae index 2 method (see table 3.10)
- 75% for the refined supervised classification, alternative 3 (see table 3.11)

ACCURACY

We have used 26 bays but this is a very small basis for drawing conclusions and would need to be increased in a future implementation. The method using the normalized algae index 2 seems to be a very good method, in theory, but showed poorer performance than the supervised classification after comparison to the air photos. Comparing the two methods between them selves the spectral normalized algae index 2 includes more coverage and has a tendency to overestimate.

TIME

To chose and refine training areas is a time consuming process. If time is a constraint this is a bottleneck in the supervised classification method. Once having defined a normalized algae index this method is straightforward and could easily be automized to classify images in the future very fast.

COSTS

The acquired Landsat image has a reasonable price, but with the too low resolution it is no idea using it for this purpose. The software, MultiSpec is indeed free and has many useful functions, but not all and cannot be used on its own. The County Administration in Västra Götaland already has access to ArcView, but not to the extensions Spatial Analyst and Image Analysis. These two extensions are necessary for the image analysis. The choice of satellite image and appropriate software needs to be evaluated together with the length of a future project.

DATA ACCESSIBILITY DURING MONITORING PERIODS

Irrespective of which satellite image used a big constraint is the fact the weather has to be fairly good. Clouds between the sensor and the ground render all image processing impossible. The Landsat 7 satellite passes the study area every 14 days.

SUBJECTIVITY

As stated in section 4.4.3, the result of the classification depends totally on how the training areas are chosen and it is a large amount of subjectivity involved in the supervised classification. The result depends partly upon how well the analyst knows the study area. The method using the normalized algae index, on the other hand, does not involve any subjectivity at all, and can be made by any person having a slight grasp on how the method works.

FUTURE OF THE METHOD

With Landsat7 ETM+ images

We believe that remote sensing with a Landsat 7 image is a good way of obtaining information of where algae exist but not to what extent. Remote sensing of filamentous algae might be a good supplement to an air photo monitoring. Today one chose by random a minor part of all the bays to photograph each flight. The satellite image might point out where to concentrate the air photos. There are 742 bays to be investigated; this would take many days to cover with an air photo monitoring, while a satellite image covers the same area instantly.

With high resolution satellites

Satellite images with higher resolution, such as IKONOS, would have the same or almost the same accuracy as an air photo and would cover all the bays in no time. Satellite remote sensing with high-resolution imagery would be a perfect way of monitoring the growth of filamentous algae.

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PERSONAL COMMENTS

Tommy Lindell, Centre for Image Analysis, Uppsala University.
Mattias Sköld, The County Administration of Västra Götaland.
Anders Svensson, Kristineberg Marine Research Station.
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LINKS

http://www.o.lst.se/projekt/eulife-algae/indexeng.htm. Homepage of EU-life algae project
http://www.esri.com
http://www.purdue.edu
http://dynamo.ecn.purdue.edu/~biehl/MultiSpec. MultiSpec download

APPENDIX 1

1.1 UNSUPERVISED CLASSIFICATION-CLUSTER PERFORMANCE

Although the algorithm was requested to divide the image into 40 clusters the number was reduced to 11.

Table 1.1 Final cluster class statistics, channel means

Cluster	Pixels	Channel Means				
		2	3	4	5	6
1	211	52.0	43.5	26.0	35.6	29.2
2	257	31.4	21.9	14.8	26.3	12.9
3	2859	37.3	29.9	25.0	40.6	30.4
4	2614	42.6	35.3	22.1	13.5	11.8
5	11193	34.8	27.0	25.6	20.3	15.4
6	332946	30.5	21.2	12.7	9.0	8.6
7	23610	34.7	26.2	41.4	21.3	13.6
8	61735	31.7	23.4	24.1	13.0	10.2
9	8089	41.8	35.9	39.6	28.4	20.6
10	6115	44.4	38.9	37.0	14.6	12.1
11	472322	0.0	0.0	0.0	0.0	0.0

Table 1.2 Final cluster statistics, standard deviations

Cluster	Channel Standard Deviations				
	2	3	4	5	6
1	6.3	9.7	5.3	5.7	5.4
2	1.5	1.7	2.0	7.7	4.8
3	3.5	4.6	5.6	7.1	6.4
4	3.5	4.0	3.7	4.5	3.6
5	2.4	2.8	4.8	3.9	3.4
6	1.2	1.5	1.1	1.0	1.3
7	2.2	2.6	7.7	4.3	2.4
8	2.4	2.5	3.7	2.0	1.5
9	4.0	5.0	5.5	4.3	4.0
10	4.3	5.3	6.8	3.8	2.8
11	0.0	0.0	0.0	0.0	0.0

APPENDIX 1

1.2 SUPERVISED CLASSIFICATION-CLASS PERFORMANC

Table 1.3. Training class performance

Def.	Class	Accuracy (%)	Samples	Water1	Veg5	Veg6	Water2	Veg1	Veg4	Veg3	Veg2	Veg7
Water1	1	99.0	192	190	0	0	1	0	0	0	1	0
Veg5	2	100.0	8	0	8	0	0	0	0	0	0	0
Veg6	3	100.0	9	0	0	9	0	0	0	0	0	0
Water2	4	95.4	65	0	0	0	62	3	0	0	0	0
Veg1	5	93.3	15	0	0	0	1	14	0	0	0	0
Veg4	6	93.3	15	0	0	1	0	0	14	0	0	0
Veg3	7	83.8	37	0	0	0	0	0	4	31	2	0
Veg2	8	100.0	12	0	0	0	0	0	0	0	12	0
Veg7	9	100.0	349	0	0	0	0	0	0	0	0	349
	TOTAL		702	190	8	10	64	17	18	31	15	349
	Reliability Accuracy (%)*			100.0	100.0	90.0	96.9	82.4	77.8	100.0	80.0	100.0

- Qverall class performance (689 / 702) = 98.1%
- Kappa Statistic (X100) = 97.2%.
- Kappa Variance = 0.000057.
- The *average likelihood probability* is 71.7%.

The column “accuracy” shows how well the pixels in a certain training field were classified into the class it really belongs to.

APPENDIX 2

CRIB 2.1 CREATION OF A LANDMASK IN MULTISPEC

1. Chose cluster under Processor
2. Use the algorithm ISODATA and 4 clusters. Normally it should work with only two clusters but because we have clouds in our image the classifier will confuse them with the water.
3. Classification threshold is set to 100 this forces every pixel into one of the four categories. Write classification results to disk file.
4. Open your classification image.clu
5. The classified image does not contain class numbers of 1,2,3 but ascii values for 1,2,3 etc. Run a histogram on the classification file to see that the data values are something like:
   - 32 for thresholded (ascii character blanc)
   - 49 for cluster 1 (ascii character 1)
   - 50 for cluster 2 (ascii character 2)
   - 51 for cluster 3 (ascii character 3)

   If you look in your image.clu you will se what ascci caracter cluster 49-51 stands for.

CRIB 2.2 HOW TO SEPARATE LAND FROM WATER IN A CLASSIFIED IMAGE.GIS IN MULTISPEC

1. Choose reformat under processor. Then mark Recode thematic image. Remember to always work on a copy of the image when using recode, since changes the values of the input file.
2. Set data to 0 in image.clu, the mask you made in fich 1, when data is >= 50 in mandag.clu. If cluster 50 equals land this makes all the pixels exept for the land pixels to change into 0.
3. Reopen image.gis. (nya noga)

APPENDIX 2

CRIB 2.3 HOW TO SEPARATE LAND FROM WATER IN IMAGE.LAN

This procedure is a little bit more complicated than in fiche 2 because The Process Recode thematic image in not possible to use directly on .lan images.

1. Open a .lan image
2. Convert each channel of the Landsat image to a separate file. (Processor-Reformat- chanells subset ..)
3. Load each channel into MultiSpec and treat as a Thematic Image. (File-Open image-open image as Thematic)
4. For each channel, use Reformat-Recode thematic Image. Select the mask file generated in fich 1. It is an image.clu. (Remember that this file contains ascii numbers so if land is displayed as nr 1 this is 49 in the mask file)
5. Load the revised individual images into MultiSpec treating them as multispectral linking them together
6. Use reformat – Change image file format processor to create a new image file whith all of thew channels in a single . lan fil.

CRIB 2.4 HOW MAKE HISTOGRAM OVER THE CLASSES

Since the histogram function is not developped for the PC version this is a littelbit omständlig method.

1. Convert each channel of the Landsat image to a separate file. (Processor-Reformat-chanells subset ..)
2. Load each channel into MultiSpec and treat as a Thematic Image. (File-Open image-open image as Thematic
3. For each channel, use Reformat-Recode thematic Image. Select you classified image.gis as a maskfile. Your claseses is numberd from 1 to X . Background values are 0. Mask away everything exept the class that you want to histogram.
4. Reopen each channel as a multispectral one.
5. Chose Historgam image under Processor. Check the option List histogram.
6. Copy the results exept the 0’s and past them into for example Exel.
7. Make plots for all the channels .

APPENDIX 2

CRIB 2.5 UNSUPERVISED CLASSIFICATION IN MULTISPEC

1. With the window of the image.lan active choose Cluster under Processor.
2. Chose ISODATA .
3. Open image.clu

CRIB 2.6 HOW TO OPEN A FAST FORMAT SATELLITE IMAGE IN MULTISPEC

1. Open image under File. Chose the header file ex. L71197019_01919990824_HRF.FST.
2. Mark the area that you want to work with
3. Chose Reformat under Prosessor.
4. Check Change image file format
5. Chose header file Erdas 74 .
6. Save your image as .lan

CRIB 2.7 SUPERVISED CLASSIFICATION IN MULTISPEC

1. Selection of training fields

Figure 2.2 Selection of training fields

- With the false-color image open choose statistics under the processor menu.
- Check the box ”polygon enter” and select a training field that seems to be a consistent land covers. Close the polygon by doubbelkilcking.
- Then choose add to list.
- Name the class Algae for example.
- Select more training fields in the same category by marking Algae in the pull down menu.

APPENDIX 2

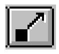
- Select new training field class by marking ”new” in the pull down menu. Name it Water
- Define a big training sample encompassing the entire image and call this class other.

2. Classifying the image

- Choose Classify from the processor menu
- Check the box “Write classification results to disk file”
- Open the image that you have just saved. Image.gis

APPENDIX 3

CRIB 3.1 RECTIFICATIONS

In order to be able to rectify an image in ArcView the extension *Image Analysis*[1] is required. With this extension one gets the *align tool*. 

1. The image that is going to be rectified is opened as *Image Analysis Data source*. The reference image is opened as *feature theme*.
2. Making sure that the image that is going to be rectified is active one clicks on the *align tool*. The two different scenes are then shown at the same time in the view but in different scales.
3. The Ground Control Points, GPC are identified i.e. distinct features that are easily identified in both images. By starting in the unrectified image one draws a line to the reference image, combining the two images.
4. After a four alignments the RMS (root mean square) error is reported and it is possible to remove bad ones and replace with better chosen.
5. When the RMS is satisfactory the new image is saved as .img and the control points are saved in a point theme.
6. The new image is *convert*ed *to shapefile.*

NB It is very important that the .trl is accompanying the image that is going to be rectified. Otherwise there is information missing.

Further reading see ArcView Image Analysis Tutorial Chapter 2.

[1] All words written in italics are syntax from ArcView.

APPENDIX 3

CRIB 3.2 CALCULATION OF LAND COVER ARE WITHIN A WATERSHED

Aim. To find total area of different land cover features (polygon) within a watershed (polygon).

The information about the watersheds was in vector format. This was also the case for the files with land cover information. In this study the areas of interest were not all the watersheds but a few selected. This gave rise to a problem when combing these two.

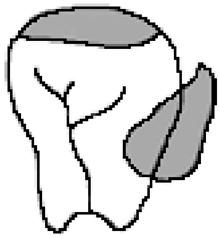


Figure 1 Watershed
with two types of land

The grey areas in figure 1 are two different land covers in the watershed. The top one is totally within the watershed and there is no problem to intersect the land cover theme with the watershed. The land cover to the right has features inside and outside the selected watershed. If one is only interested in finding the area, perimeter etc of the land cover within the watershed it is no longer possible to simply intersect the two themes. This should have given an over estimation of that type of land cover within the watershed.

The size of different land covers in separate watersheds was wanted. Since it was only the statistics that was looked for, an easy command could be used.

1. The vector theme with the land covers is transformed into a grid, by using *Convert to Grid*.
2. Under *Analysis* one finds the function *Tabulate Areas.* Here one can combine the newly created raster file with the original vector file.

APPENDIX 3

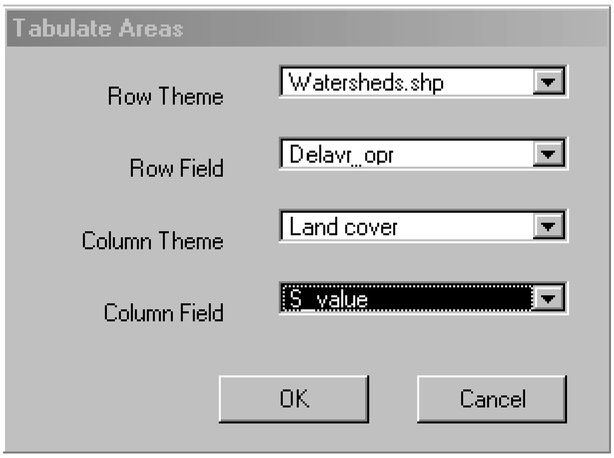


Figure 2. Tabulate areas

These inputs result in a table with the different watersheds in the rows and the area of the different land cover types in the columns. Analysing the data can easily be carried out in for example Excel.

APPENDIX 4

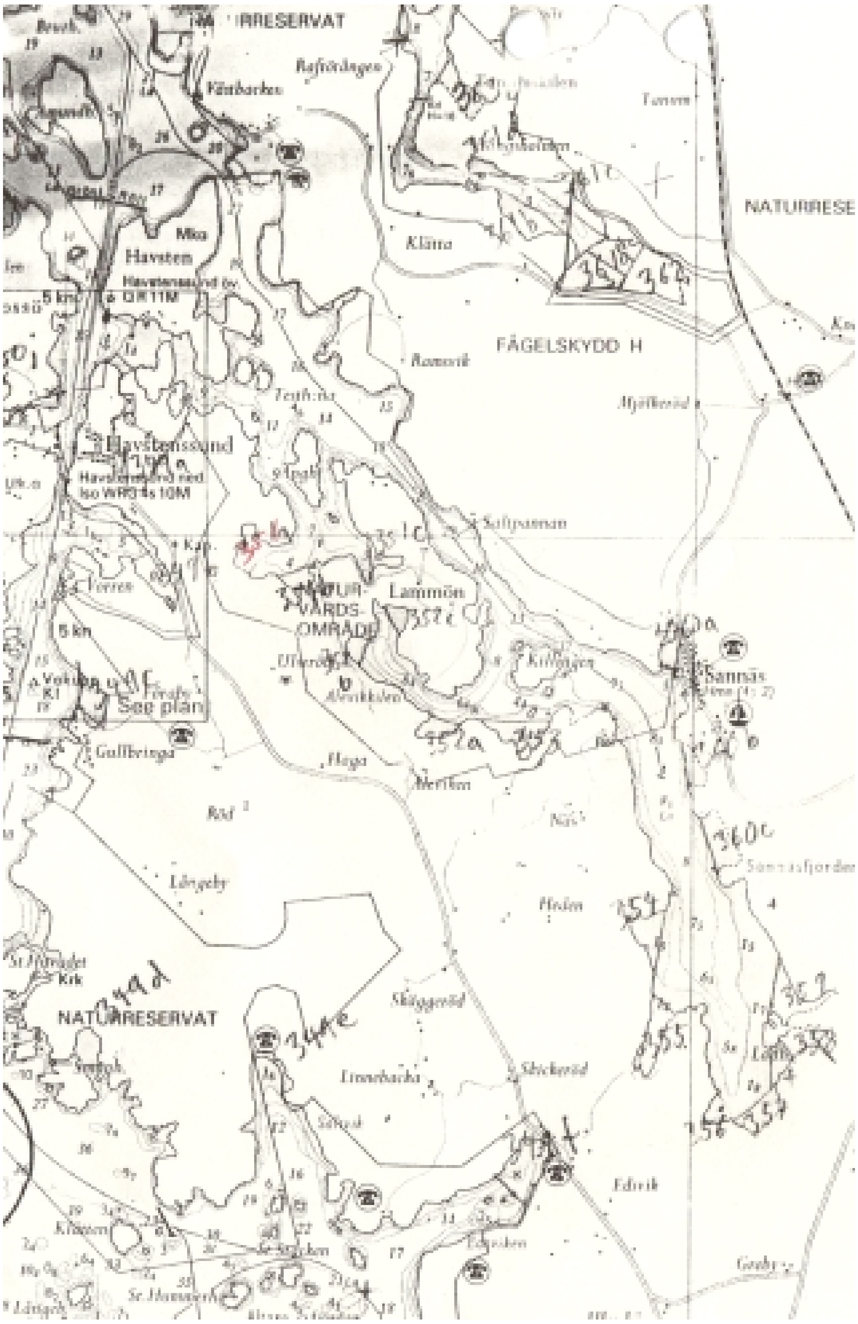
Table 4.1 Area (m^2) of a certain land cover within each watershed. See figure 3.11 in Results for the key to the landcovers

Watershed nr	Bay nr	Algae cover (%)	R	N	F	K	I
724	470	14	1462258	15859875	1630980	0	112481
767	469a	39	6355198	20809056	2418350	281203	56241
767	468	32	6355198	20809056	2418350	281203	56241
782	439b	71	6580161	18728150	3768126	112481	224963
782	413	34	6580161	18728150	3768126	112481	224963
798	379	79	1687221	8211141	899851	112481	56241
1580	360a	63	6467680	19571761	3093238	168722	506166
1580	360c	57	6467680	19571761	3093238	168722	506166
1580	362	34	6467680	19571761	3093238	168722	506166
1581	376	62	4499255	24127257	4780459	337444	731129
1587	359	76	10067084	22721239	8042419	674888	618648
1590	354	35	25983200	10629491	6017754	393685	168722

Watershed nr	O	M	C	B
724	1181055	0	0	0
767	281203	0	337444	0
767	281203	0	337444	0
782	56241	224963	393685	224963
782	56241	224963	393685	224963
798	56241	0	0	0
1580	449926	0	0	0
1580	449926	0	0	0
1580	449926	0	0	0
1581	1124814	0	0	0
1587	956092	0	0	0
1590	224963	281203	0	0

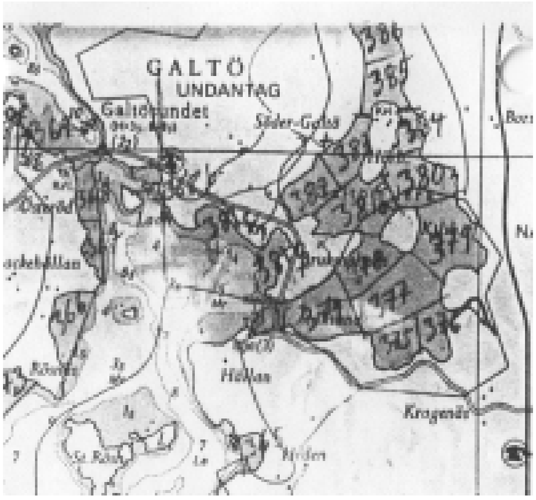
APPENDIX 5

5.1 BAY BOUNARIES IN TANUMSKILEN AND SANNÄSFJORDEN

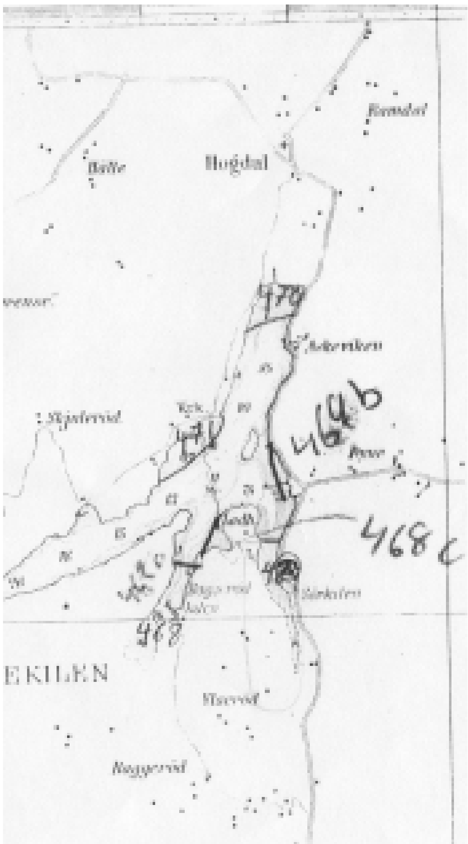


APPENDIX 5

5.2 BAY BOUNARIES IN GALTÖLERAN



5.3 BAY BOUNDARIES IN DYNEKILEN



APPENDIX 6

Water course	Vattendrag
Watershed	Avrinningsområde
A-Settlements (high)	Hög bebyggelse
B-Industrial estate	Industriområde
C-Settlements (low)	Låg bebyggelse
D-Settlements (private)	Sluten bebyggelse
E-Not mapped land	Ospecificerad yta
F-Arable land	Åker
G-Uncoded land	Oklassificerad
H-Marsh	Sankmark
I-Marsh Coniferous forest	Sankmark normal – barrskog
J-Marsh Deciduous forest	Sankmark normal – lövskog
K-Marsh Open land	Sankmark normal – annan öppen mark
L-Marsh (heavy) Coniferous forest	Sankmark svår - barrskog
M-Marsh (heavy) Open land	Sankmark svår – annan öppen mark
N-Deciduous and Coniferous forests	Barr- och lövskog
O-Clearing land	Hygge
P-Deciduous forest	Lövskog
Q-Water	Vattenyta
R-Open land	Annan öppen mark

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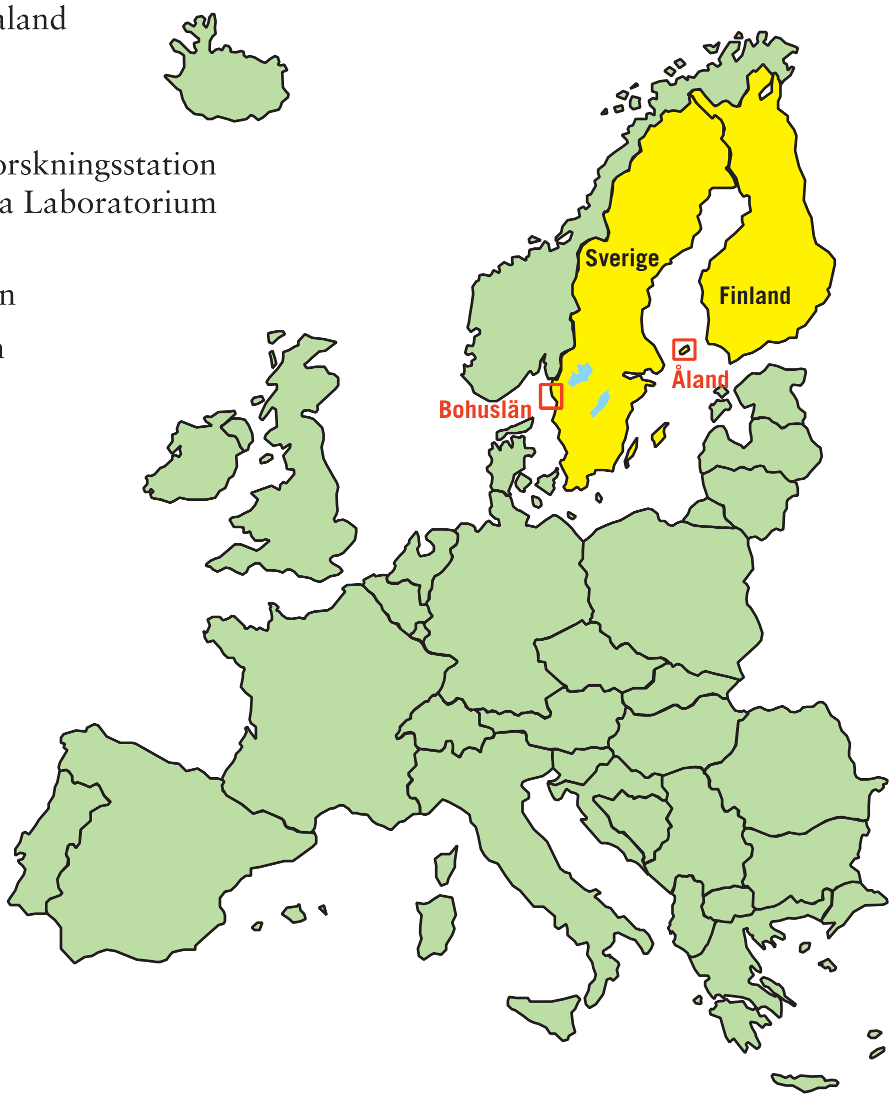
Västra Götalandsregionen

Strömstads Kommun

Fiskeriverket

Vägverket



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