UNIVERSITY OF TARTU
Faculty of Biology and Geography
Institute of Zoology and Hydrobiology

Ele Vahtmäe

Mapping benthic algal cover in turbid coastal waters with remote sensing technique

M.Sc. Thesis

Supervisor: PhD Tiit Kutser

Tartu 2005

Content

Introduction

Many benthic communities and ecosystems in coastal, estuarine and inland waters possess commercial and ecological value (Werdell & Roesler, 2003). The seashore is a place where specific flora and fauna concentrate, but also where urban developments and tourist facilities are located. It receives all land discharges, including freshwater as well as waste, sewage and erosion products, and it is affected by a number of marine processes such as the action of waves, tides and coastal currents. As a consequents, the shoreline is a highly dynamic border zone, both in its morphological and ecological characteristics (Barale & Folving, 1996).

Sustainable management of coastal environments requires regular collection of accurate information on recognized ecosystem health indicators (Phinn et al. 2004). Benthic algal cover and trends in changes of algal cover are indicators of water state in coastal areas. The objective of monitoring benthic algal cover in coastal areas is to observe short- and long-term changes in species distribution and structure of coastal benthic substrate constituents. Quantitative analysis of coastal marine benthic communities enables adequately estimate coastal marine environmental state, provide better evidence for environmental changes and describe processes that are conditioned by anthropogenic forces.

Mapping benthic algal cover with conventional methods (diving) provides great accuracy and high resolution (Werdell & Roesler 2003) yet is very expensive and is limited by the time and manpower necessary to monitor large bodies of water and long stretches of coastline. Furthermore, in some regions, inclement weather through a portion of the year may prohibit diver observation of seasonal changes (Wittlinger & Zimmerman, 2000). Remote sensing can potentially provide a tool for fast mapping of benthic algal cover provided the algal species are separable from each other based on their optical signatures.

Mapping of substrate cover types and their biophysical properties based on their reflectance properties has been carried out successfully in optically clear, shallow coastal and reef waters (Anstee et al., 2000; Dekker et al., 2001; Kutser et al., 2002; Phinn et al., 2004). In comparison with the reflectance properties of coral reef benthic communities (Hochberg & Atkinson 2000, 2003; Karpouzli et al. 2004; Minghelli-Roman et al. 2002) and seagrass communities (Fyfe 2003; Pasqualini et al. 2004), there is still scant information detailing the reflectance properties of algal communities. However, algal spectral reflectance properties have been published in some of the coral reef benthic community studies (Hochberg & Atkinson, 2000; Kutser et al., 2003). A few published reflectance spectra of various algal types are presented in Maritorena et al. (1994), Anstee et al. (2000), Wittlinger and Zimmerman (2000) and some other publications.

However, those studies were carried out in clear oceanic (Case I) waters. Case I waters were defined by Morel and Prieur (1977) as waters in which phytoplankton is the principal agent responsible for optical properties of the water. Most of suspended matter and coloured dissolved organic matter (CDOM) in such waters are decomposition products of phytoplankton and their concentrations are in correlation with the amount of phytoplankton (usually expressed as concentration of chlorophyll a). Therefore the optical properties of Case I waters can be described with just concentration of chlorophyll a. The Baltic Sea waters are relatively turbid and optically much more sophisticated. Most of CDOM in the Baltic Sea has terrestrial origin and therefore its concentration is not in correlation with the amount of phytoplankton. Most of suspended matter in coastal waters of the Baltic Sea has also terrestrial origin and its concentration is also varying independently from concentration of chlorophyll. Another problem limiting use of remote sensing in mapping of benthic algal cover in the Baltic Sea is absence of information about optical properties of benthic algae in the Baltic Sea. The Baltic Sea is an intracontinental shallow marine environment under strong influence of human activities and terrestrial material. The Baltic Sea waters are often dominated by colour dissolved organic matter (CDOM). Large discharge from rivers, limited exchange with marine waters of the North Sea, and a relatively shallow sea floor significantly influence the optical properties of the Baltic Sea (Darecki & Stramski, 2004).

The objective of this study is to study optical properties of key algal species in the Baltic Sea and to determine how the spectral reflectance of benthic algae is translated into remote sensing reflectance. Mapping algal cover with hyperspectral hand-held, ship-borne or airborne instruments is more cost effective than using divers. Since spectral features that allow differentiating between different benthic substrates are often narrow, hyperspectral instruments are preferable. A hyperspectral scanning system provides the intensity of the radiation received in each of very large number of very narrow bands so that one obtains what is, in fact, a continuous spectrum

(Cracknell, 1999). Our first aim was to study weather or not are green-, brown- and red algae separable from each other, sandy bottom or deep water with hyperspectral remote sensing sensors and to estimate the maximum depths at which the various substrates still have an measurable influence on the remotely sensed reflectance in different coastal water types. Multispectral broad-band satellite sensors provide much larger spatial coverage than airborne remote sensing or remote sensing measurements from boats and could therefore be more cost effective and time saving in mapping benthic algal cover. However, limiting factor of these instruments is the comparatively low spatial and spectral resolution. The second objective of our study is to evaluate the capability of multispectral satellite sensors for mapping the Baltic Sea algal cover.

1. Aquatic remote sensing

Remote sensing is the science of obtaining information about an object, area or phenomenon through the analysis of data acquired by a sensor that is not in contact with the object, area or phenomenon (Lillesand & Kiefer, 1999). The data recorded by a remote sensing sensor is a measure of the electromagnetic radiation or energy reflected by the object and the sun is the most obvious source of radiation (Philipson, 2003).

The radiance flux measured above and below the water surface consists of four separate components (Fig.1): light reaching the sensor after scattering of photons by the atmosphere; light reaching the sensor after specular reflection of direct sunlight at the sea surface; light upwelling from the sea surface after backscattering in water; light reflected off the bottom of a water body (provided the water is sufficiently shallow and the water is sufficiently clear) (Sathyendranath, 2000).

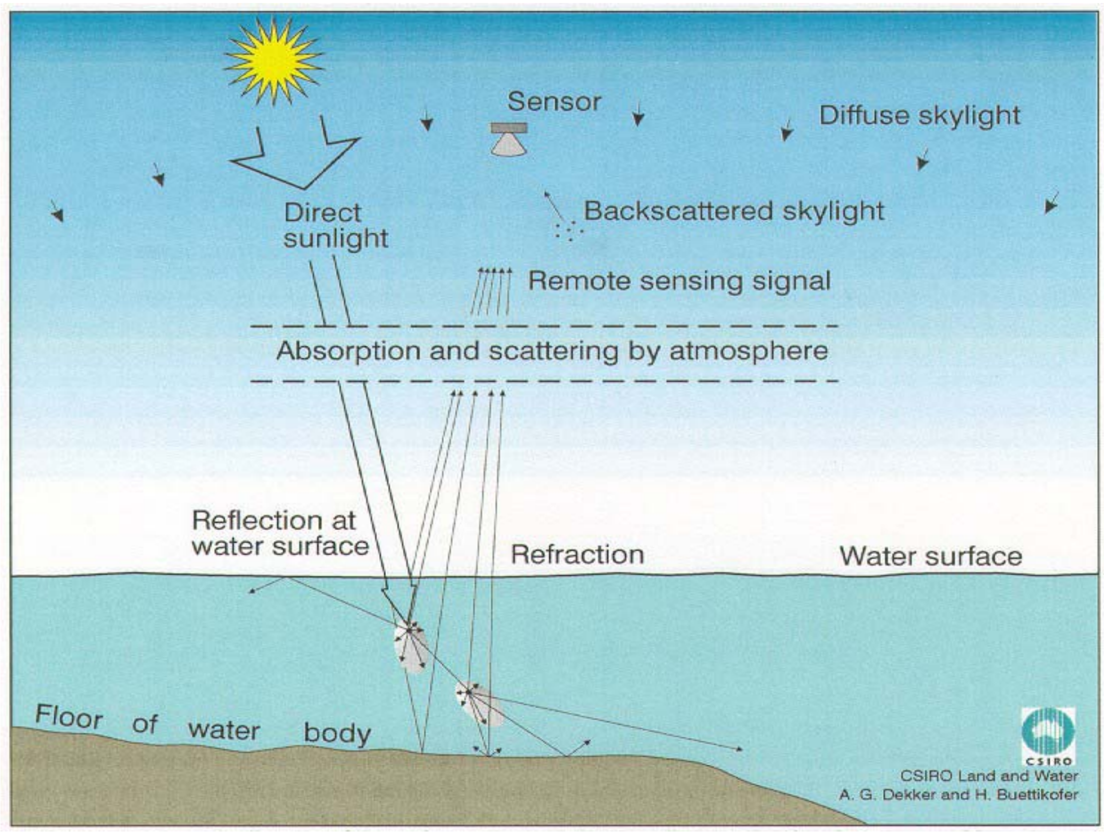


Fig.1. Formation of the signal detectable by remote sensing instruments

Studying the benthic substrate, the interesting part of the signal measured by sensor is not the upwelling radiance emerging from the water through the surface, but a part of it. Only last two of these four light fluxes contain information about the underwater light field and the composition of the aquatic medium, but only the last component gives us information about the type of benthic habitat. Other three components are noise that has to be removed when we are interested in mapping benthic algal cover.

The term ocean colour is used to indicate the visible light spectrum as observed at the sea surface, which is related by the processes of absorption and scattering, to the concentration of water constituents (Gordon & Morel, 1983). Water-leaving signal is influenced by several factors. Optically active substances that influence the optical properties of the water are pure water itself, phytoplankton, coloured dissolved organic matter (CDOM) and particulate matter. The radiance spectrum upwelling from the water body is a direct consequence of the cumulative spectrally selective absorption and scattering that can be attributed to each of these materials (Bukata et al., 1995).

1.1 Remote sensing of shallow water

In shallow, clear waters, where the depth is much less than the potential for light to penetrate, a large fraction of the light may reach the sea floor and be reflected from it. The spectrum of light emanating from the sea surface in shallow waters contains information on the optical properties of the seawater constituents and the benthic substrate (Werdell & Roesler, 2003).

In turbid coastal waters, spectral scattering and absorptsion by phytoplankton, suspended organic and inorganic matter, and dissolved organic substances restrict the light passing to, and reflected from the benthos (Dekker et al., 1992). Thus, the maximum depth of light penetration vary greatly as a function of water clarity. In highly turbid coastal waters, where the amount of water constituents is high and the depth of light penetration is only a metre or even less, the bottom would not be visible and it would not have any influence on reflectance spectrum.

The subsurface light field in shallow water is not only a function of the properties of the water mixture, but also of the depth and properties of the sea floor (Ackleson, 2003). The spectral signature of a bottom cover is heavily dependent upon the water depth as the response signal is decreasing with increasing depth. Previous simulations to investigate the influence of water column depth indicate that much of the useful signal reflected from submersed plant material is rapidly attenuated with increasing depth of the water and bottom reflectance is diminished as it is filtered through the water column (Wittlinger & Zimmermann, 2000). Light penetration is wavelength dependent, being greater in blue wavelengths (400 nm) than in red wavelengths (600 nm) (Mumby et al., 2003). As depth increases, reflectance decreases rapidly in the red and particularly the near-infrared spectral regions due to strong absorption by pure water (Legleiter et al., 2004). Strong absorption by water in the red and the near-infrared implies that substrate characteristics will be subdued as depth increases and substrate mapping can not relay upon that region of the visible spectrum.

Characteristic, which describes from how deep water light photons may come back to waters surface (and can consequently be detected by remote sensing sensors) is depth of penetration (DOP). The depth of penetration is inversely proportional to attenuation coefficient of water (see Eq. 2). Two examples of DOP spectra are shown in Fig. 2.

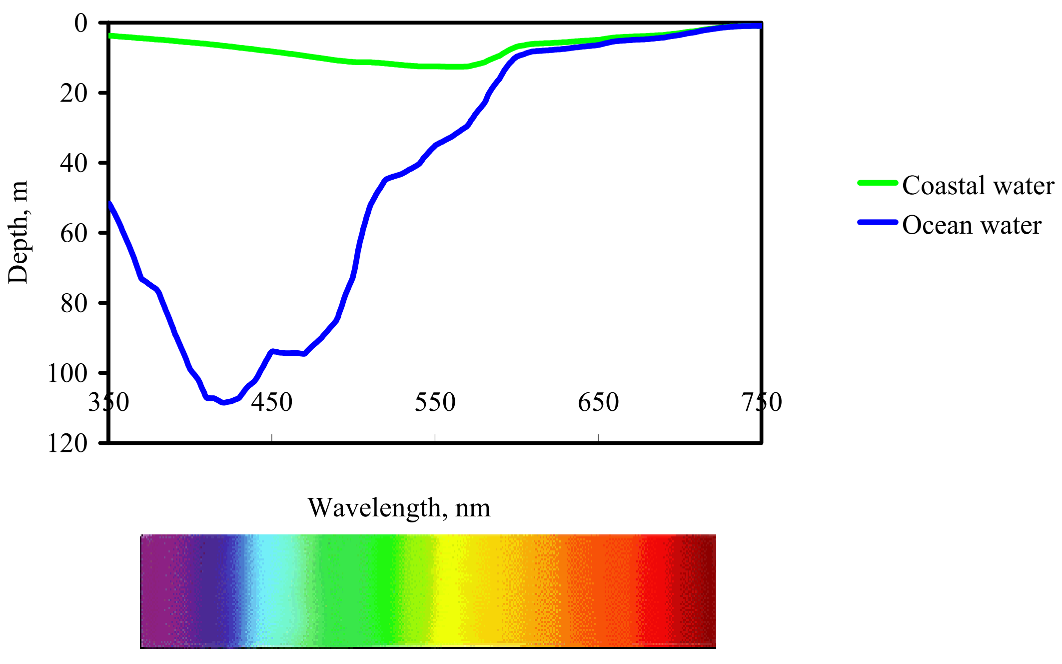


Fig.2. Depth of penetration spectra of coastal water and ocean water

At longer wavelengths the difference between DOP's of turbid coastal and clear oceanic water is small as the dominant factor affecting DOP at these wavelengths is absorption of light by water molecules that is identical in both cases. Smaller DOP at shorter wavelengths in coastal waters is the results of absorbing and scattering properties of phytoplankton as well as light absorption by CDOM.

Altogether, increasing water turbidity and depth increase the relative contribution of the water-reflected photons relative to bottom-reflected photons, decreasing the influence of the bottom reflection on the above-water spectra (Carder et al., 2003).

1.2 Remote sensing sensors for assessment of the coastal zone

A remote sensing sensor has a field-of-view such that at any moment in time, it is viewing a part of Earth's surface and recording how much radiation is being reflected from that part (Philipson, 2003). A remote-sensing instrument is usually located on either an airborne or space-borne platform and light must pass through the water column and atmosphere before being detected by a sensor (Mumby et al., 2004). The number of classes (categories) distinguishable by remote sensing depends on many factors including, the platform (satellite, airborne, towed instrument), type of sensor (spectral, spatial and temporal resolution), atmospheric clarity, surface roughness, water clarity and water depth (Mumby et al., 2003).

The characteristics of a remote sensing sensor are described by its spatial, spectral and radiometric resolution. The spatial resolution of the sensor describes the size of the ground area corresponding to one pixel in the image (Philipson, 2003). A higher spatial resolution will increase the sensors possibility to record spatial detail. There are, however, important disadvantages to using small pixels. The signal-to-noise ratio of measured reflectance is usually low because less light is collected and the high ratio of pixel perimeter to area allows ”nuisance” light, originating from outside the pixel, to exert a relatively large influence on the signal (Mumby et al., 2004).

The spectral resolution describes the ability of a sensor to define wavelength intervals, i.e., the width of the spectral bands in the sensor (Philipson, 2003). Fig. 3 illustrates the difference between a hyperspectral sensor (Hyperion) and a multispectral sensor (ALI, spectral bands almost identical to sensors like Landsat and IKONOS).

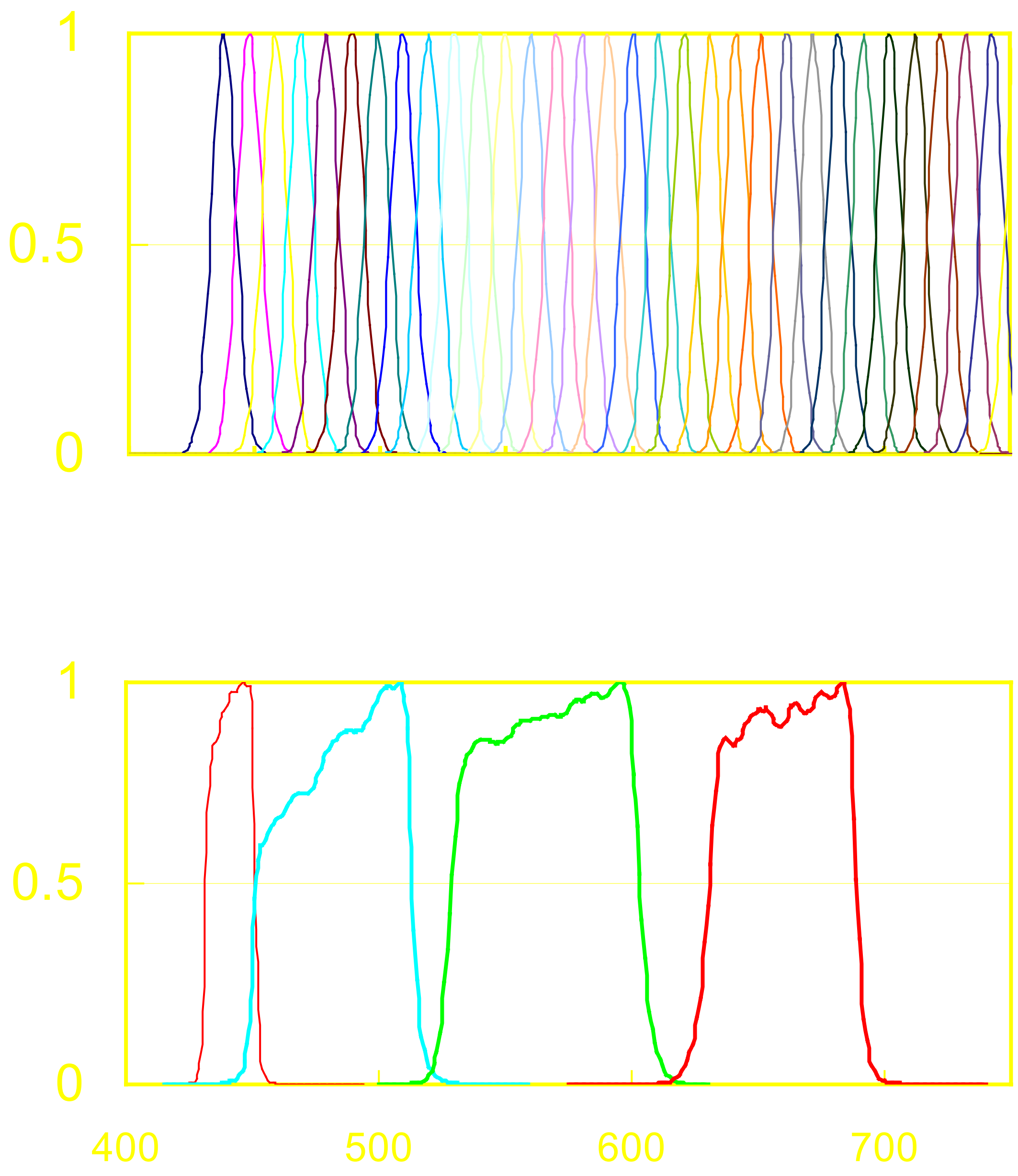


Fig. 3 Spectral response functions of a hyperspectral satellite sensor (Hyperion) and a multispectral satellite sensor (ALI) in visible part of spectrum.

Finally, the radiometric resolution refers to the possible number of greylevels in the image and describes the possibility of the sensor to differentiate between different colours, i.e. its sensitivity (Philipson, 2003).

1.2.1 Multispectral satellites

Traditional satellite-flown multispectral instruments do not generate a reflectance spectrum; they generate a signal in each of a small number of very broad bands (Cracknell, 1999). Most multispectral satellites have only 2-4, quite broad bands in the visible part of the spectrum.

It has been shown that multispectral satellites can be used in some extend for mapping seagrasses (Pasqualini et al., 2005; Andréfouët et al., 2004), coral reefs (Andréfouët et al., 2001; Mumby et al., 1997; Purkis et al., 2002; Kutser et al., 2003), and macroalgae (Andréfouët et al., 2004; Hochberg & Atkinson, 2003). Karpouzli et al. (2004), Malthus & Karpouzli (2003), Call et al. (2003) have studied the ability of multispectral broad-band satellites to discriminate between different benthic communities such as coral reefs, sand, seagrasses, algae etc.

Mapping of benthic algal cover with multispectral satellites largely depends on the characteristics and capabilities of specific satellite sensor. The limitations are caused by sensors poor spatial resolution, limited spectral capabilities and low temporal resolution. ”Conventional” space borne optical sensors (e.g. Landsat 7) are designed for mapping of relatively bright land surfaces. For example Landsat offers spatial resolution of 30 m, poor radiometric resolution (256 measured radiance levels) and limited spectral resolution, thus limiting its use for mapping and monitoring coastal habitats with any reliability (Malthus & Karpouzli, 2003). The inadequate spatial resolution of most satellites (Call et al., 2003) prevents accurate identification of community type. High spatial resolution satellites, such as IKONOS, offer data at high spatial (1-4 m) and radiometric resolution (2048 measured radiance levels) and offer considerable promise for monitoring spatial changes in marine habitats (Malthus & Karpouzli, 2003). Remotely sensed data offering increased spatial resolution offer richer information in the form of variability in spatial diversity (Malthus & Mumby, 2003). IKONOS has enhanced spatial resolution that should minimize the spectral mixing problem, but the limited spectral capacities (three visible waveband) may still be a limitation for vegetation mapping in heterogeneous environments (Andrefouët et al., 2004).

Where distinguishable minima and maxima exist within the water-penetrating spectrum, satellite bands may be too broad to distinguish them (Mumby et al., 1997). Therefore, most satellite sensors lack the sensitivity to discriminate spectra because they have a limited number of water-penetrating bands (Mumby and Edwards, 2002). Mumby et al. (1997) found that using broadband multispectral sensor, algal and seagrass habitats were spectrally and spatially confused with one another, resulting in lower overall accuracies than coral and sand habitats. Malthus & Karpouzli (2003) also demonstrated the limitation of three visible and fairly broad bands alone to classify targets such as seagrass and algal species, which typically were shown to be relatively dark and with only subtle spectral differences. Hochberg & Atkinson (2000) showed that discrimination between coral, algae and sand could be achieved with as few as four narrow, non-contiguous wavebands. However, Hochberg & Atkinson (2003) found that broadband multispectral sensors are not suitable for assessing the global status of reef.

1.2.2 Hyperspectral satellites

A hyperspectral scanning system, or an imaging spectrometer as it is sometimes called, provides the intensity of the radiation received in each of a very large number very narrow bands so that one obtains what is, in effect, a continuous spectrum (Cracknell, 1999). So far such instruments have mostly been flown on aircraft and the cost for airborne surveys is, however, very high.

The first civilian hyperspectral sensor in space, Hyperion, was launched in the end of 2000. Hyperion has 240 10 nm wide spectral bands i.e. it is measuring continuous spectrum is visible and near infrared part of spectrum. It has been shown (Kutser & Jupp, 2002) that Hyperion can be used to map different benthic types in shallow water reef environments. However, Hyperion is a technical demonstration satellite with short lifetime and very limited amount of spatial coverage that can be sensed each day. Therefore, we have to use satellite sensors with considerably purer spectral resolution for mapping benthic algal cover until next generation of hyperspectral sensors in space will be operational.

In addition to a great spectral resolution, airborne hyperspectral remote sensing sensors such as the Compact Airborne Spectrographic Imager (CASI) and the

Airborne Visible Infrared Imager (AVIRIS) usually have a better spatial resolution than satellite sensors. Image data acquired from airborne platforms typically have spatial resolutions of 1-3 m. Such data provide smaller area coverage than that acquired from satellites, thus requiring multiple overlapping flight lines to generate maps of comparable spatial extent. On the other hand, the higher spatial resolution of airborne imagery enables finer habitat discrimination (Mumby et al., 2003).

2. An overview of the Baltic Sea benthic macrovegetation

Benthic macrovegetation of the Baltic Sea is generally dominated by brown-, red- and green algae. Depending on the substrate and depth different species form the dominating communities. Green algae usually occur in the shallowest part of the littoral on hard substrate. Species *Cladophora glomerata* (Fig. 4) is widespread over the Baltic Sea area and could be found in all salinities found in the Baltic. It usually forms monodominant belts on the hard substrate close to the water edge (Söderström, 1963). Brown algae in the Baltic Sea are presented by variety of species with morphological characteristics from ephemeral filamentous species to perennial species with large thalli. Species *Fucus vesiculosus* is the largest macroalgae found in the Baltic Sea. In areas with hard substrate with moderate exposure this species is very important habitat forming function supporting high diversity along rocky shores of Western and NE Baltic. The distribution of this species in the Baltic is limited northwards and eastwards by low salinity (*Fucus* is usually found in salinities higher than 3-4 PSU).

Fig. 4 Brown algae *Fucus vesiculosus* (left) and green algae *Cladophora glomerata* (right)

Unattached *Furcellaria lumbricalis* (Fig.5) is present on limestone or sandy gravel surfaces (Martin & Torn, 2004). It is commercially harvested for galactants in NW Estonian Archipelago, but is also important habitat for fish juveniles. The three algae species studied by us are considered as key species to monitor the effect of eutrophication in the Baltic Sea monitoring program carried out by HELCOM (www.helcom.fi).

Fig.5 Unattached *Furcellaria lumbricalis*

3. Methods

3.1 In situ measurements of benthic reflectance spectra

Reflectance spectra of benthic macroalgae were measured using handheld GER1500 spectroradiometer. Spectral range of the instrument is 300-1100 nm. Spectra are sampled with 1.5 nm intervals and spectral resolution of the GER1500 instrument is 3 nm. Reflectance was calculated as a ratio of radiance from algae to radiance from standard Spectralon panel.

Specimen of most typical green, red and brown algae – *Cladophora glomerata*, *Furcellaria lumbricalis*, and *Fucus vesiculosus* respectively, were collected into water-filled plastic bags. Reflectance measurements of wet algae were carried out on the shore immediately after landing of the boat. Multiple reflectance spectra of each species were measured and an average spectrum of each species was used in following model simulations. Reflectance spectrum of sand used in the model analysis was taken from previous studies (Kutser et al., 2000) as we were not able to carry out underwater reflectance measurements and it is not possible to collect sand samples without changing it's optical properties (due to mixing).

3.2 Bio-optical modelling

If there is no measurable influence of the bottom on the remotely sensed reflectance the water is considered to be optically deep; if there is a measurable reflectance contribution from the substrate in the water column the water is considered to be optically shallow (Dekker et al., 2001).

It has been shown (Maritorena et al., 1994) that diffuse reflectance of optically shallow waters can be calculated using following formula:

$$R(0-,H) = R_\infty + (R_b - R_\infty)\exp(-2KH), \tag{1}$$

where H is water depth, R_b is bottom reflectance, R_∞ is reflectance of optically deep water, and K is diffuse attenuation coefficient of the water. Maritorena et al. (1994)

have also shown that vertical attenuation coefficient for downwelling irradiance, K_d, is a good approximation for K.

Kirk (1984a) has demonstrated with Monte Carlo simulations that the K_d at the midpoint of euphotic zone, z_m, can be expressed as a function of the absorption (a), and scattering (b) coefficients, and the cosine of the incident photons just below the water surface (μ_0) in accordance with

$$K_d(z_m) = \frac{1}{\mu_0}\left[a^2 + (0.473\mu_0 - 0.218ab\right]^{1/2} . \tag{2}$$

Reflectance spectra of the optically deep water were calculated using a semi-empirical model described in detail by Kutser (2004). The model is based on the results of Monte Carlo studies by Gordon et al. (1975) and Kirk (1984b) and is expressed with equation

$$R_\infty(0-,\lambda) = (-0.629\mu_0 + 0.975)\frac{b_b(\lambda)}{a(\lambda)+b_b(\lambda)}, \tag{3}$$

where $a(\lambda)$ is the total absorption coefficient, $b_b(\lambda)$is the total backscattering coefficient, and λ is wavelength. The μ_0 was taken equal to 0.85 according to solar zenith angle in mid-summer at the latitude of the central Baltic Sea.

We assumed that there are three optically active components in the water: phytoplankton, coloured dissolved organic matter (CDOM), and suspended matter. Under these conditions the total spectral absorption coefficient, $a(\lambda)$, is described by:

$$a(\lambda) = a_w(\lambda) + a^*_{Ph}(\lambda)C_{Chl} + a_{CDOM}(\lambda) + a^*_{SM}(\lambda)C_{SM} , \tag{4}$$

where a_w is the absorption coefficient of pure water, $a^*_{Ph}(\lambda)$ is the chlorophyll-specific spectral absorption coefficient of phytoplankton, $a_{CDOM}(\lambda)$ is the spectral absorption coefficient of CDOM, and $a^*_{SM}(\lambda)$ is the specific absorption coefficient of suspended matter. C_{Chl} and C_{SM} are concentrations of chlorophyll-*a* and total suspended matter.

The total spectral backscattering coefficient $b_b(\lambda)$ can be described:

$$b_b(\lambda) = 0.5b_w(\lambda) + b^*_{b,Ph}(\lambda)\,C_{Chl} + b^*_{b,SM}(\lambda)C_{SM}\ , \tag{5}$$

where b_w is the scattering coefficient of pure water and it is assumed that the backscattering probability is 50% in pure water. $b^*_{b,Ph}$ is chlorophyll-specific backscattering coefficient of phytoplankton and $b^*_{b,SM}$ is suspended sediment specific spectral backscattering coefficient of suspended matter.

In our model the values of absorption and scattering coefficients of pure water were taken from Smith and Baker (1981). The absorption by CDOM is expressed as a function of the absorption coefficient of filtered water sample at wavelength 400 nm, $a_{CDOM}(400)$, and slope factor, S, by following formula:

$$a_{CDOM}(\lambda) = a_{CDOM}(400)\exp[-S(\lambda - 400)]. \tag{6}$$

According to estimations by Mäekivi and Arst (1996) S=0.017 gives the best result in case of the Baltic Sea, Estonian and Finnish lakes. Specific absorption coefficient of suspended matter was taken from Kutser (1997), and specific scattering coefficients of suspended matter, as well as backscattering probabilities (backscattering to scattering ratio), were taken from study by Kutser et al. (2001). Absorption and scattering coefficients as well as backscattering probability of a cyanobacterium *Aphanizomenon flos-aquae* (Metsamaa et al. 2005) were used in the modelling as this species is often dominating Baltic Sea waters in July-August period when algal mapping is normally carried out for monitoring purposes.

The modelling was carried out for three distinctly different water types: 1) CDOM-rich waters near a river estuary, 2) coastal waters not directly impacted by high CDOM discharge from rivers, 3) open Baltic waters. Concentrations of optically active substances in these three water types are shown in Table 1. The concentrations were taken from real measurements from a coastal area near CDOM-rich river inflow, a bay with slightly elevated CDOM concentration caused by a creek with moderate CDOM concentrations and from an area near NW Estonian Archipelago tens of kilometres offshore where concentrations of optically active substances resemble the values typical for the open Baltic Sea waters.

Table 1. Concentrations of optically active substances used in model simulations

Water type	C_{Chl}	C_{SM}	$a_{CDOM}(400)$
1	6	6	15
2	10	5	3
3	2	2	1.5
	mg/m^3	mg/l	m^{-1}

3.3 Satellite sensors under investigation

In our study we used four sensors (ALI, IKONOS, Landsat7, MERIS) to evaluate the suitability of multispectral satellites for mapping benthic algal cover in turbid coastal waters. Some technical characteristics of the studied sensors are shown in table 2.

Table 2. Visible bands and signal to noise ratios (SNR) of sensors under investigation

Spectral band	ALI Wavelength (nm)	IKONOS Wavelength (nm)	Landsat 7 Wavelength (nm)	MERIS Wavelength (nm)
1	450-515	450-520	450-520	407.5-417.5
2	525-605	510-600	530-610	437.5-447.5
3	630-690	630-700	630-690	485-495
4				505-515
5				555-565
6				615-625
7				660-670
8				677.5-685
9				703.75-713.75
	SNR 250:1	SNR 100:1	SNR 100:1	SNR 200:1

An European satellite (ENVISAT) with the Medium Resolution Imaging Spectrometer (MERIS) on board was launched in June, 2001. The MERIS sensor is capable of measuring 400 spectral bands with high sensitivity to the conditions in the open ocean, though only 15 bands will be reported to the ground due to constraints in communications (Peterson et al. 2003). Doerffer et al. (1999) gives a good overview of the MERIS instrument focusing on the specifications that make this sensor especially beneficial for the research of coastal areas. MERIS requirements include medium spatial resolution, medium to high temporal resolution and a high number of narrow spectral bands. MERIS full resolution images are with spatial resolution of 300 m for coastal areas and a reduced resolution of 1,2 km over the open ocean. It has nine visible wavebands covering the visible spectral range (410-710 nm).

The Landsat series of instruments have been used for mapping benthic cover since the mid-eighties. They were not designed for water environments, but shallow water benthic habitat are often bright enough to make Landsat sensors suitable for mapping shallow water benthic types (Jupp et al., 1985). ALI is an improved version of the Landsat 7 sensor and a possible precursor of Landsat 8 (Kutser et al. 2003). ALI and Landsat 7 have both three visible wavebands covering the visible spectral range (between 400-700 nm). These instruments offer relatively fine spatial resolution (30 m) compared to ocean colour satellites like MODIS or SeaWiFS. This spatial resolution may not be sufficient for mapping benthic algal cover in areas where spatial heterogeneity of shallow area is very high or mixed communities of algae occur. As was mentioned above, several algal communities in the Baltic Sea form almost monoculture belts. This makes remote sensing of these species easier as there is no need to deal with signal that is mixture of signal from different benthic algae species and 30 m spatial resolution may be adequate in regions where the monospecies belts are wider.

On 24 September 1999, Lockheed Martin's Space Imaging launched the IKONOS satellite for high spatial resolution sensing. IKONOS images provide four spectral bands in the blue, green, red and near-infrared (NIR) parts of the spectrum. Except low tide conditions, only the first three bands are generally useful for habitat mapping as the signal from water is near is band being very quickly absorbed in infra-red band. IKONOS has enhanced spatial resolution (4 m) that should minimize the spectral mixing problem, but the limited spectral capacities (three visible waveband) may still be a limitation for vegetation mapping in heterogeneous environments (Andrefouët et al., 2004). However, the much improved spatial resolution of 4 m is advantageous.

4. Results and discussion

We collected reflectance spectra of sand, green, brown and red algae, measured without an overlying water column. Green algae were represented by a reflectance spectrum of *Cladophora glomerata*, red algae by *Furcellaria lumbricalis*, and brown algae by *Fucus vesiculosus.* Figure 6 shows the spectral reflectance for each bottom type. All substrates have high reflectance in the near-infrared part of the spectrum. Sand has higher reflectance spectra than algae in visible part of spectrum. Green algae reflectance is higher than that of other measured algae. Reflectance values of *Fucus* and *Furcellaria* are very similar. However, there are differences in shape of their reflectance spectra. *Furcellaria* has a double peak near 600 and 650 nm as other red algae which reflectance has been measured in different parts of the World oceans by different authors (see references in the Introduction). *Fucus*, has a maximum in its reflectance spectrum near 600 nm and two "shoulders" near 570 and 650 nm similar to most living corals and many brown algae (see references in the Introduction). Reflectance spectra of green, brown and red algae measured by us are analogical to the reflectance spectra measured in different parts of the world oceans.

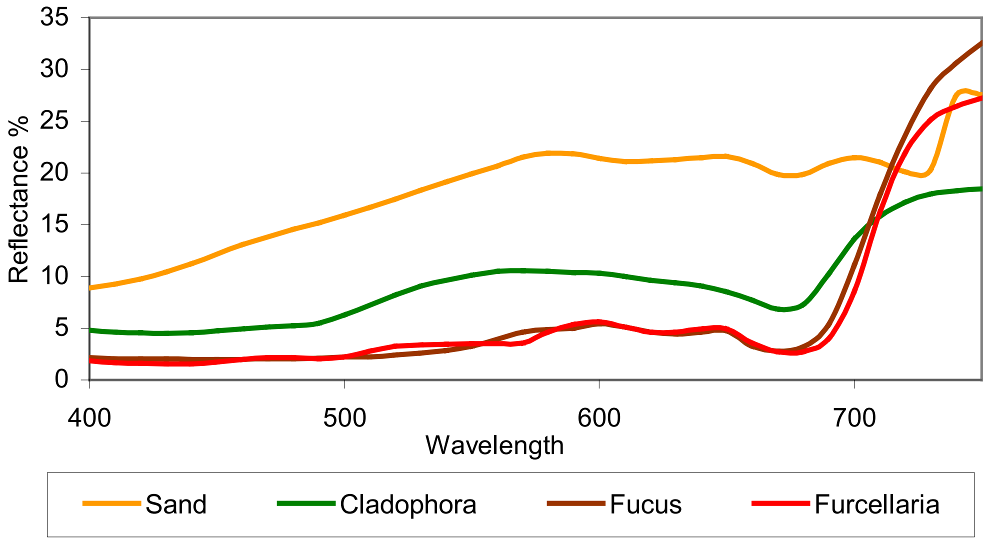


Fig.6 Substrates measured without an overlaying water column

We evaluated water column effects on remotely sensed spectra by simulating bottom-reflected light through different depths of water column for a given concentrations of water column constituents. Figure 7A-7C represents the reflectance

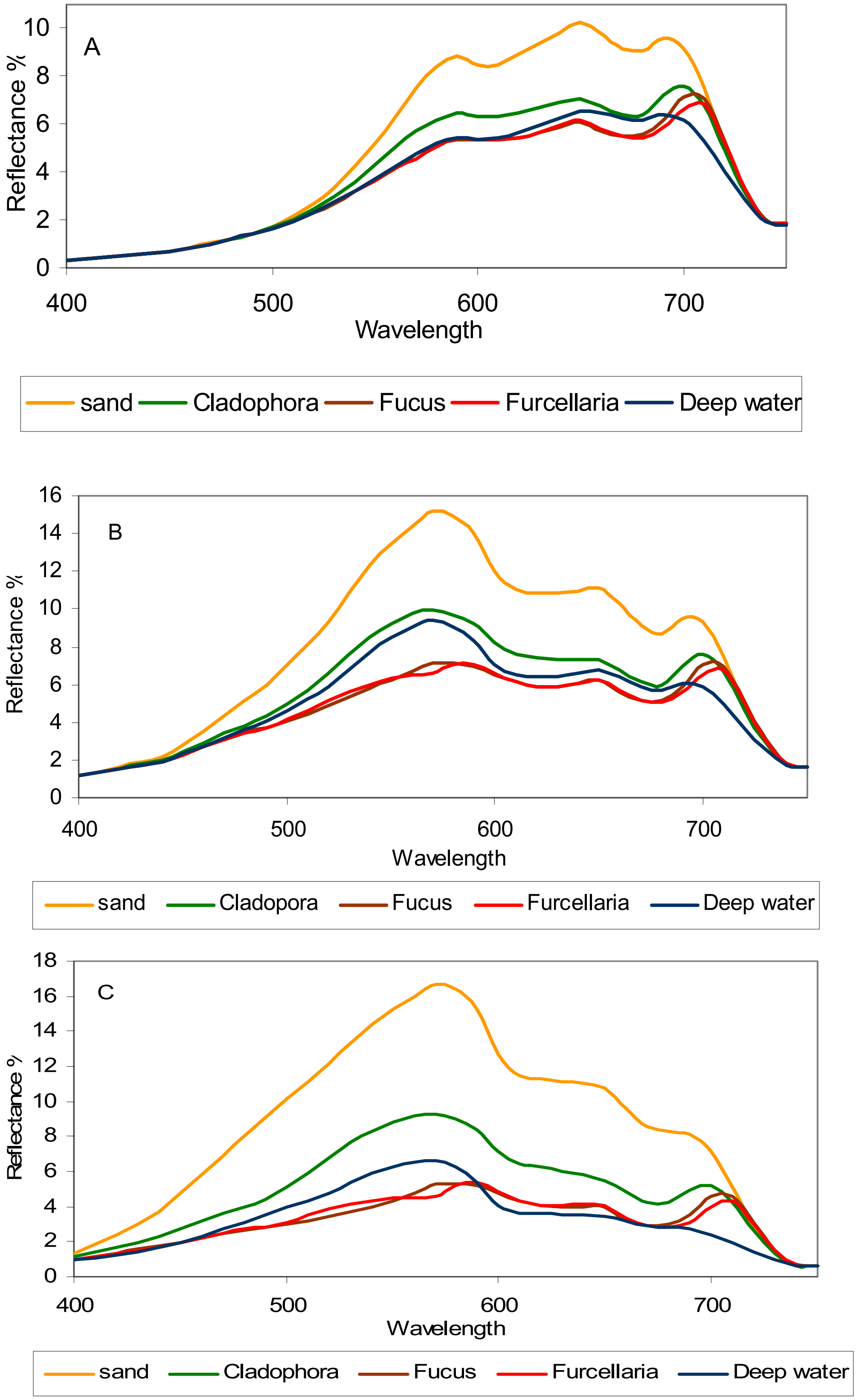


Fig. 7 Just below the water surface reflectance spectra (A) Simulated reflectance spectra of various substrates and deep water at 1 m depth in water type 1. (B) Simulated reflectance spectra of various substrates and deep water at 1 m depth in water type 2. (C) Simulated reflectance spectra of various substrates and deep water at 1 m depth in water type 3.

spectra of various substrates and deep water at 1 m depth in three different water types.

The amount of optically active water constituents is relatively high in the water type 1 (Fig. 7A) (C_{Chl}=6 mg/m^3, C_{SM}=6 mg/l and a_{CDOM}(400)=15 m^{-1}). CDOM absorbs light strongly in the shorter wavelengths and even in 1 m deep water different substrates are not distinguishable in wavelengths shorter than 520 nm. Water itself absorbs light in the red and near-infrared region of the spectrum and thus the reflectance values at the longer wavelengths are dramatically decreased, and become almost identical for all substrates at wavelengths greater than 730 nm. Reflectance values of *Fucus* and *Furcellaria* are lower than that of deep water, but reflectance values of sand and *Cladophora* are higher than that of deep water.

The reflectance values are considerably higher in water type 2 waters (C_{Chl}=10 mg/m^3, C_{SM}=5 mg/l and a_{CDOM}(400)=3 m^{-1}) as seen on Fig. 7B. Concentration of chlorophyll in type 2 waters is typical to bloom values. We used specific absorption and scattering coefficients of a cyanobacterium *Aphanizomenon flos-aquae* in the model. It contains pigment phycocyanin that absorbs light near 630 nm. The phycocyanin absorption is quite strong in case of such high chlorophyll concentrations as is seen in reflectance spectrum of deep water. All studied substrates, except green algae, have also absorption feature in their reflectance spectra near 630 nm. It means that recognising different benthic substrates during cyanobacterial blooms is more complicated than in case of other presence algae that do not contain phycocyanin.

Figure 7C represents the clearest water type (C_{Chl}=2 mg/m^3, C_{SM}=2 mg/l and a_{CDOM}(400)=1.5 m^{-1}). CDOM has significant effect on reflectance spectra even in the open Baltic Sea waters. However, the effect is much smaller than in case of other water types studied by us and CDOM absorption is not masking differences between red and brown algae reflectance at wavelengths 510-600 nm (in 1 m deep water). Relatively large amount of algae are covering coastal substrates around and between island and islets of NW Estonian, Finnish and Swedish archipelago where the waters are similar to water type 3 used in our study. To estimate the maximum depths where the substrates are spectrally separable we used the optical properties of our clearest water type.

4.1 Suitability of hyperspectral sensors for discriminating of benthic algae species

The signal to noise ratio (SNR) specifications currently attainable by airborne remote sensing systems such as AVIRIS and CASI, flown under ideal circumstances, are about 1000:1 (Dekker et al., 2001). About 48% of just below the water surface upwelling irradiance is reflected back into the water column. Thus, the SNR in terms of just below the water surface reflectance, R(0-), has to be 500:1 to be able to detect differences in reflectance spectra by above mentioned instruments. Therefore, we determined the maximum depths at which the various substrates can be spectrally separated from deep water and from each other based on this criterion.

4.1.1 Spectral differences between substrates and deep water

Shallow water reflectance spectra were calculated with 0.5 m increments for each bottom type. Differences between the R(0-) of optically deep water and shallow water reflectance spectra were calculated. We assume that the substrate is separable from deep water if the reflectance difference is higher than the SNR of above mentioned instruments.

Fig. 8A shows the simulated spectral differences between reflectance of sandy bottom and reflectance of our type 3 (open Baltic) deep water. The maximum depth at which sandy bottom can be separated from type 3 deep water is 10 m.

Fig. 8B presents the difference between green algae (*Cladophora glomerata*) reflectance spectra and reflectance of deep water. Green algae are spectrally different from optically deep water, but the difference is not as high as for sand. Differences are largest near 710 nm, but these differences are above the instrument SNR level only in waters shallower than 2.5 m. In shallow water (up to 1.5 m deep) the difference is also high near 600 nm. The differences between green algae and deep water are seen in waters up to 7 m deep near 550-580 nm. However, *Cladophora glomerata* forms monoculture belts near the shore and does usually not grow at depth greater then 3.5 m in Estonian coastal waters. Thus, it is relatively easy to separate *Cladophora* belts from deep water areas as remote sensing could potentially permit

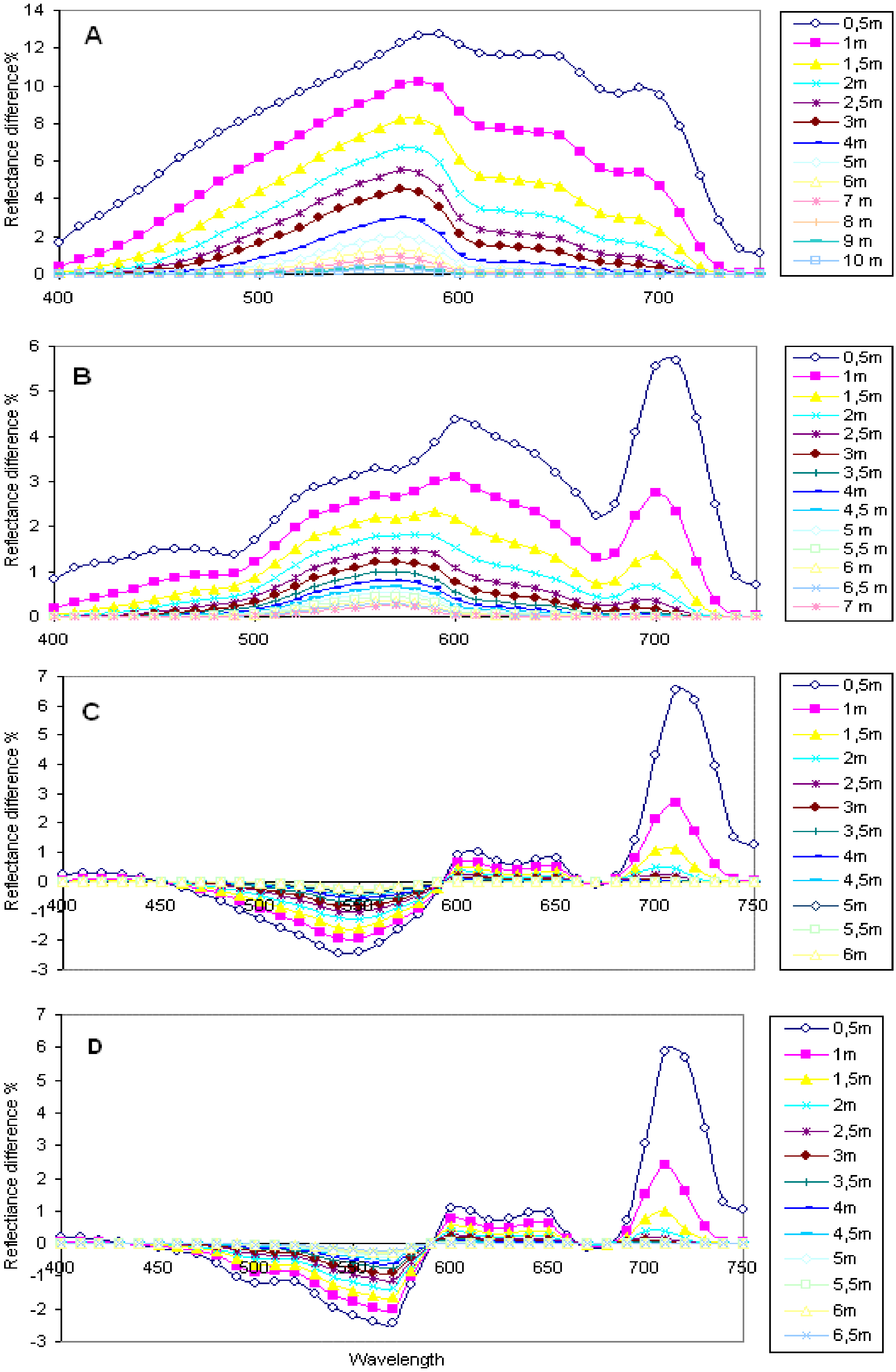


Fig. 8. Spectral differences between simulated reflectance spectra (A) sand and deep water. (B) Green algae (*Cladophora glomerata*) and deep water. (C) Brown algae (*Fucus vesiculosus*) and deep water. (D) Red algae (*Furcellaria lumbricalis*) and deep water. Calculations are made for various water depths indicated in the legend.

detecting *Cladophora* in depths that are greater than the depths where it grows in nature. This concerns areas not affected by high CDOM absorption and suspended matter loads e.g. conditions similar to our water type 3.

Figure 8C simulates the spectral difference between reflectance of brown algae *Fucus vesiculosus* at different depths and reflectance of deep water. The substrates reflectance signal is lower than reflectance of deep water in the wavelength range 450-590 nm and 660-680 nm. *Fucus* has a relatively low reflectance and differencesbetween algae and deep water reflectance spectra are small, except near 710 nm. However, these differences are above the instrument SNR level only in water shallower than 2.5 m. The next peaks in the spectral difference spectra are near 540 nm, 610 nm and 650 nm. The differences between brown algae and deep water are detectable in waters up to 6 m deep in the wavelength range 540-560 nm in the type 3 waters. Six meters is also the maximum depth where the *Fucus vesiculosus* grows in Estonian coastal waters (Martin & Torn, 2004).

Figure 8D shows the spectral difference between reflectance of red algae *Furcellaria lumbricalis* and reflectance of deep water. The spectral differences between *Furcellaria* and deep water are detectable in waters up to 6.5 m deep in the wavelength range 560-570 nm. Unattached *Furcellaria lumbricalis* may grow at depths down to 10 m deep in Estonian coastal waters (Martin & Torn, 2004).

However, the largest and commercially harvestable community occurs between two biggest Estonian islands Saaremaa and Hiiumaa where it is trapped inside a circular current. Water depths in this area are mainly between 2 m and 8-9 m. Optical water properties in the study area resemble the type 3 water in most of the time, except in case of storms when the amount of suspended matter may be much higher due to resuspension. Thus, most of the commercial stock of *Furcellaria lumbricalis* is in depths where it is potentially detectable by remote sensing sensors.

4.1.2 Spectral differences between algal species in different depths

Difference in spectral reflectance was calculated between all substrates in all water depths by subtracting the reflectance of one substrate from the reflectance of another substrate at the same depth. Examples of spectral differences between two substrates are shown in Fig. 9. Figures 9A-9C show that spectral differences between sandy bottom and all three algal species are relatively high. The difference between sand and green algae reflectance spectra (Fig. 9A) is smaller than differences between sand and red or brown algae reflectance spectra (Fig. 9B, 9C) as *Fucus* and *Furcellaria* are relatively dark substrates compared to sand. The differences between sand and *Cladophora* are detectable in waters up to 10 m deep. The differences between reflectance of sand and reflectance of red or brown algae are detectable in waters up to 11 m in wavelengths near 570 nm.

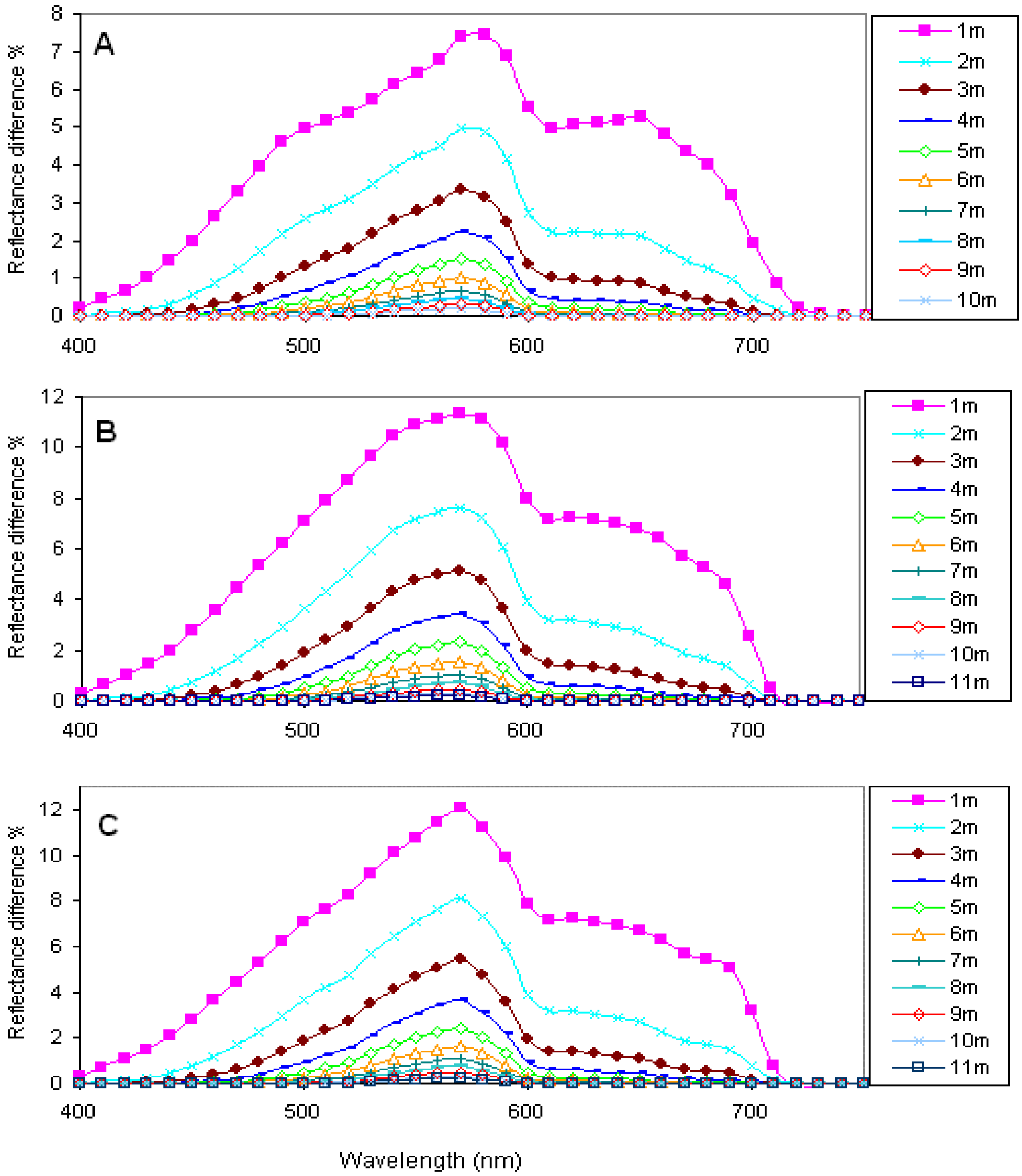


Fig.9. Spectral differences between simulated reflectance spectra (A) Sand and green (*Cladophora glomerata*) algae. (B) Sand and brown algae (*Fucus vesiculosus*). (C) Sand and red algae. Calculations are made for various water depths indicated in the legend.

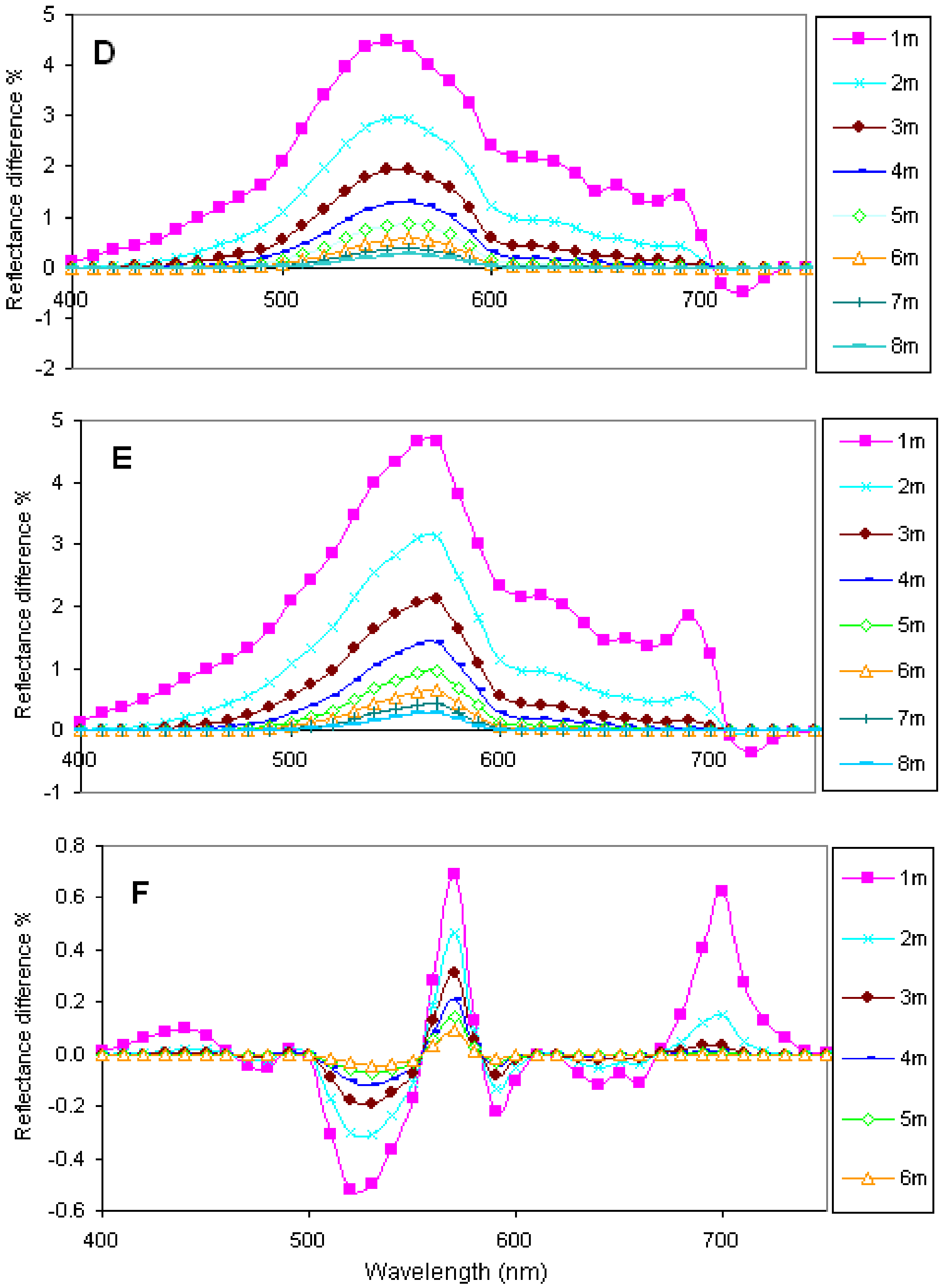


Fig.9. Spectral differences between simulated reflectance spectra (D) Green algae (*Cladophora glomerata*) and brown algae (*Fucus vesiculosus*). (E) Green algae (*Cladophora glomerata*) and red algae (*Furcellaria lumbricalis*). (F) Brown algae (*Fucus vesiculosus*) and red algae (*Furcellaria lumbricalis*). Calculations are made for various water depths indicated in the legend.

Fig. 9D simulates the difference between reflectance of green algae and brown algae; difference is largest at wavelength 550 nm. *Fucus* has higher reflectance than *Cladophora* only in wavelengths greater than 710 nm, but those differences cannot be detectable in waters deeper than 1 m. Our simulations show that the maximum detectable depth at which those species can be separated is 8 m and for that we can use the wavelength range 550-570 nm.

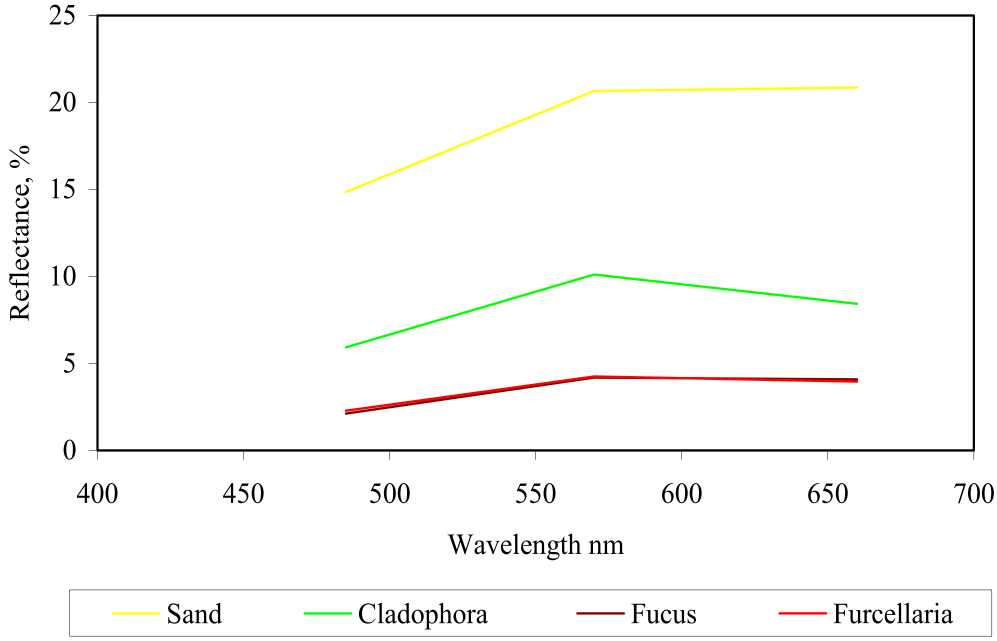
In Fig. 9E the differences between reflectance of *Cladophora* and reflectance of *Furcellaria* are presented. Difference is largest at wavelength 570 nm, and similarly to brown algae, in wavelengths greater than 710 nm red algae have higher reflectance than green algae, but those differences are detectable in waters up to 1 m deep. Some slight differences are detectable between *Cladophora* and *Furcellaria* reflectance spectra till depth 8 m.

Both *Furcellaria* and *Fucus* have relatively low reflectance values. Figure 9F shows the wavelength bands that can be used to separate these two substrates from each other. Considerable differences appear in wavelengths near 520 nm, 570 nm and 700 nm. Difference near 570 nm is the greatest and this wavelength can be used to differentiate brown algae from red algae at depth up to 4 m. Difference near 520 nm can be used to differentiate these two substrate types at depth up to 2,5 m and difference near 700 nm can be used only in waters up to 1,5 m deep.

The depth where the studied bottom types are spectrally separable from each other in CDOM-rich estuaries is small (1-2 m). However, there is usually no bottom vegetation in these areas as the amount of light available for photosynthesis is not sufficient even in so shallow water. Exceptional river plumes with CDOM-rich water can cover larger areas where the vegetation exists, but the remote sensing campaigns can be organised during more favourable situation. It is also not reasonable to carry out benthic mapping by remote sensing in the cases of cyanobacterial blooms as cyanobacteria cause similar effects on reflectance spectra than red and brown algae. Cyanobacteria also form surface scum that is spectrally similar to terrestrial vegetation (Kutser, 2004). The scum is optically opaque and no information about benthic type or water column properties can be obtained when the surface scum occurs. Therefore, it is not reasonable to carry out remote mapping of shallow water benthic habitat during cyanobacterial blooms.

4.2. Suitability of multispectral sensors for discriminating of benthic algae species

Figure 10 illustrates how the sensors under investigation would detect reflectance spectra of studied bottom types without overlaying water column.



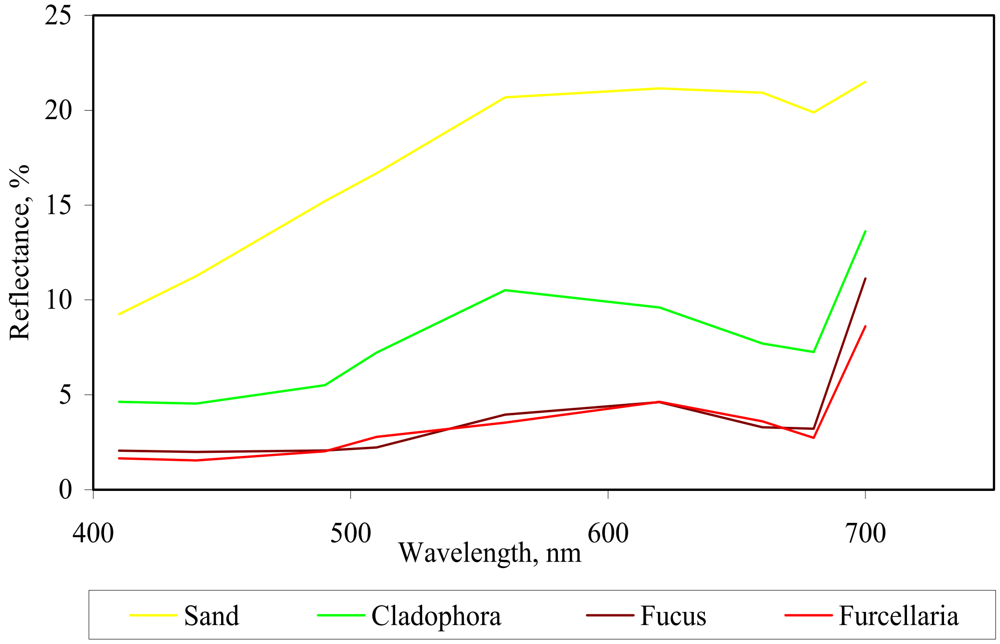


Fig. 10 Reflectance spectra of sand and studied benthic algae species resampled for spectral resolution of multispectral sensors (A) Landsat, ALI, and IKONOS, (B) MERIS.

It is seen in Fig. 10A that the differences between the substrates are mainly in reflectance values rather than in shape if three-band sensors like ALI, Landsat or IKONOS are used. MERIS bands are narrow (10 nm) and are located in spectral regions needed for example to separate brown algae from red algae (see Fig. 10B). However, the effect of water column has to be taken into account before deciding is MERIS suitable for discriminating between the studied substrates.

4.2.1 Simulated ALI, Landsat7 and IKONOS performance for detecting benthic algal cover

Shallow water reflectance spectra were calculated with 0.5 m increments for each bottom type and the expected values in multispectral sensors bands 1, 2 and 3 were derived. Differences between the R(0-) of optically deep water and shallow water reflectance spectra were calculated. The signal to noise ratio (SNR) of Landsat 7 and IKONOS is about 100:1, whereas SNR of ALI is about 250:1. About 48% of just below the water surface upwelling irradiance is reflected back into the water column. Thus, the SNR in terms of just below the water surface reflectance, R(0-), has to be 50:1, for Landsat 7 and IKONOS and 125:1 for ALI to be able to differentiate between two bottom types.

Figure 11A illustrates a case where all three bands can be used in separating sand from deep water in waters up to 3 m deep with ALI and in waters up to 2 m deep with Landsat and IKONOS. The second band near 560 nm can be used in differentiating sand and optically deep water in waters up to 5 m deep with ALI and in waters up to 4 m deep with Landsat and IKONOS. The characteristic spectral reflectance feature of sand is its brightness, and the brightness is so characteristic that even multispectral sensors with their limited spectral responses have no trouble discriminating sand from deep water.

Figure 11B shows the difference between green algal reflectance spectra and reflectance of deep water. The difference between green algae and deep water is becoming undetectable in band 1 in waters deeper than 1 m. Band 3 can be used to separate green alga from deep water in waters no deeper than 1.5 m. Band 2 shows difference between green algae and deep water in waters up to 3 m deep. Landsat 7 and IKONOS are not capable of separating green algae and deep water in the first

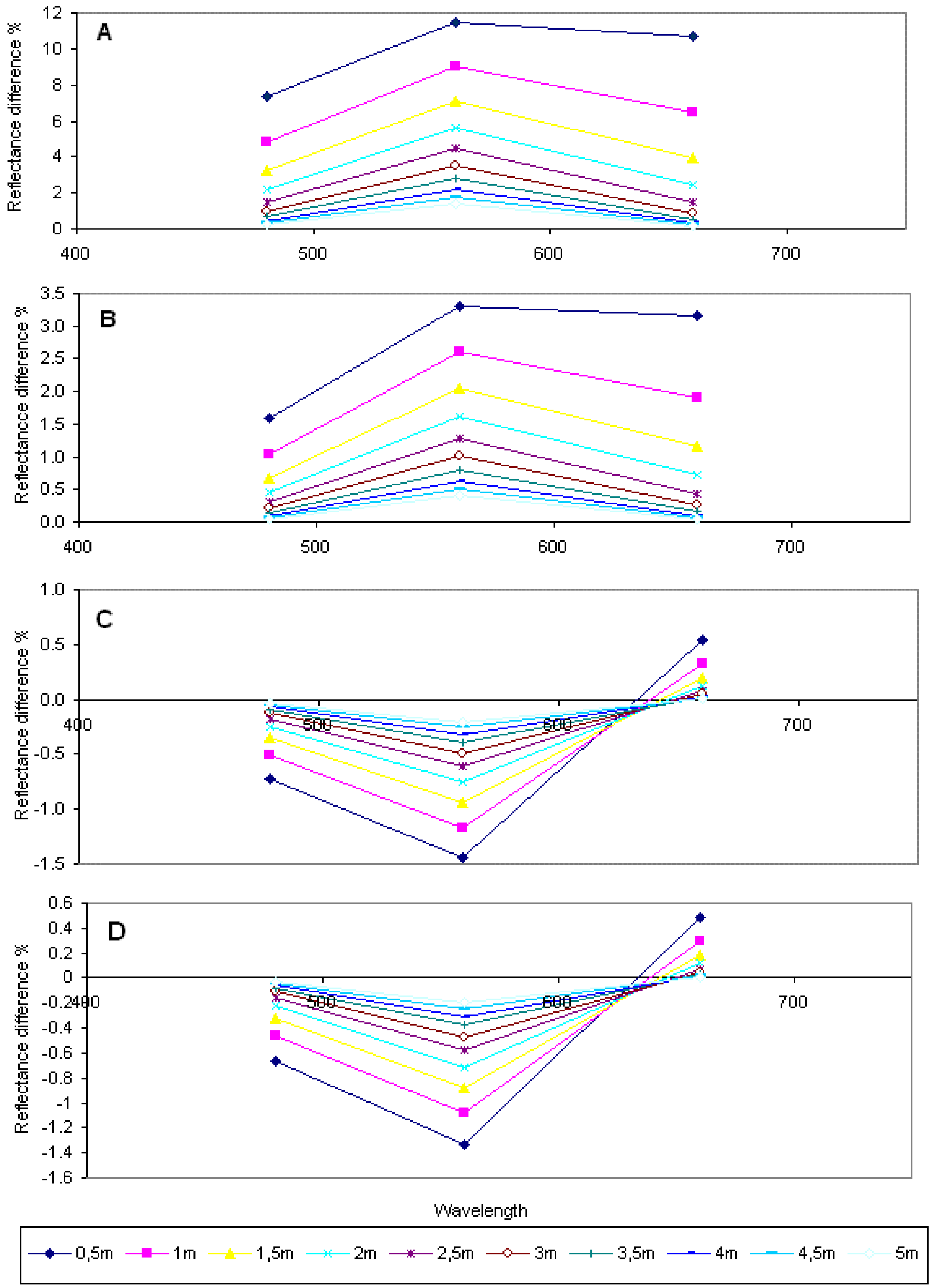


Fig.11 Spectral differences between simulated reflectance spectra (A) sand and deep water. (B) Green algae and deep water. (C) Brown algae and deep water. (D) Red algae and deep water. Calculations are made for various water depths indicated in the legend. Each marker represents the central wavelength of a multispectral sensor band (ALI, Landsat, IKONOS).

band. Band 3 can be used detecting these differences between green algae and deep water if the water is shallower than 0.5 m. Landsat and IKONOS band 2 can be used in waters up to 1.5 m deep.

Optically dark marine habitats, such as brown and red algae, are spectrally similar to each other and to deep water when multispectral sensors are used. Figures 11C and 11D show the difference between brown algae and deep water and between red algae and deep water. Landsat 7 and IKONOS are not capable of detecting these differences. ALI is capable of detecting the differences. In both cases bands 1 and 3 are unusable in differentiating algae from deep water, band 2 shows detectable difference in waters up to 1.5 m deep.

Differences in spectral reflectance were calculated between all substrates in various water depths by subtracting the radiance of one substrate from the radiance of another substrate at the same depth. On the basis of the three visible bands available in the multispectral sensors dataset, sand was well differentiated from algal cover. Sand has a higher albedo than any algal substrate in ALI, Landsat7 and IKONOS bands 1, 2 and 3. Submerged feature brightness appears to be strongest attribute for separating substrate type. If there is a high degree of difference in the brightness of substrate types, features can be easily separated (Call et al 2003).

Since the differences between reflectance values of green algae and brown algae and green algae and red algae are small, multispectral satellites are hardly able to discriminate between these algal types.

As brown and red algae have similar spectral reflectance values. Broad-band sensors like ALI, Landsat7 and IKONOS are incapable of discriminating the two substrates from each other.

Cladophora glomerata forms almost monoculture belts near the sore and does not usually grow deeper than 3.5 m in Estonian coastal waters (Martin & Torn, 2004). However, the multispectral sensors under investigation cannot differentiate between deep water and *Cladophora* at such depth. The deepest water where the green algae and water are separable from each other is 3m and in such case only band 2 is capable of detecting the difference.

Six meters is the maximum depth where the *Fucus vesiculosus* grows in belts (Martin & Torn, 2004) in Estonian coastal waters (individual colonies can be found in deeper waters). Multispectral sensor are not capable of mapping *Fucus* belts in

Estonian coastal waters as Landsat and IKONOS cannot separate *Fucus* from deep water and ALI can detect the difference in waters up to 1.5 m deep (using band 2).

Unattached *Furcellaria lumbricalis* grows mainly in depth range 2-9 m in Estonian coastal waters and the commercial stock of this species is at depths between 5-7 m (Martin & Torn, 2004). The multispectral sensors under investigation are not capable of separating *Furcellaria* from optically deep water. However, the *Furcellaria* is floating above sand and ALI can differentiate between sand and *Furcellaria* in waters up to 4 m deep. Thus, ALI can suitable for mapping *Furcellaria* to some extent, but the commercial stock is usually at depth not reachable by ALI or other multispectral sensors under investigation.

4.2.2 Simulated MERIS performance for detecting benthic algal cover

Unattached community of red algae *Furcellaria lumbricalis* occurs between two biggest Estonian islands Saaremaa and Hiiumaa where it is trapped inside a circular current. Spatial scale of the area is suggesting that sensors with more coarse spatial resolution than the multispectral sensors discussed above, can be used to map the extent of *Furcellaria* stock in this region. MERIS full resolution images are with 300 m spatial resolution and spectral resolution of MERIS (9 bands in visible part of spectrum) may be adequate to differentiate between different bottom types. MERIS SNR is 200:1. In just below the water surface reflectance terms it means that the difference between two bottom types has to be 1% to be detectable by MERIS.

Figure 12A shows the simulated spectral differences between reflectance of red algae and reflectance of our water type 3 (open Baltic) deep water. Difference is the greatest in ninth band near 700 nm, but these differences are above the instrument SNR level only in waters shallower than 1 m due to strong absorption of light at these wavelengths by water molecules. The next peak in the spectral difference spectra is in fifth band near 560 nm and these differences are detectable by MERIS in waters shallower than 2.5 m. The differences are detectable also in third and fourth bands in waters not deeper than 0.5 m.

Figure 12B shows that the difference between sand and red algae is relatively high as *Furcellaria* is considerably darker substrate compared to sand. The difference

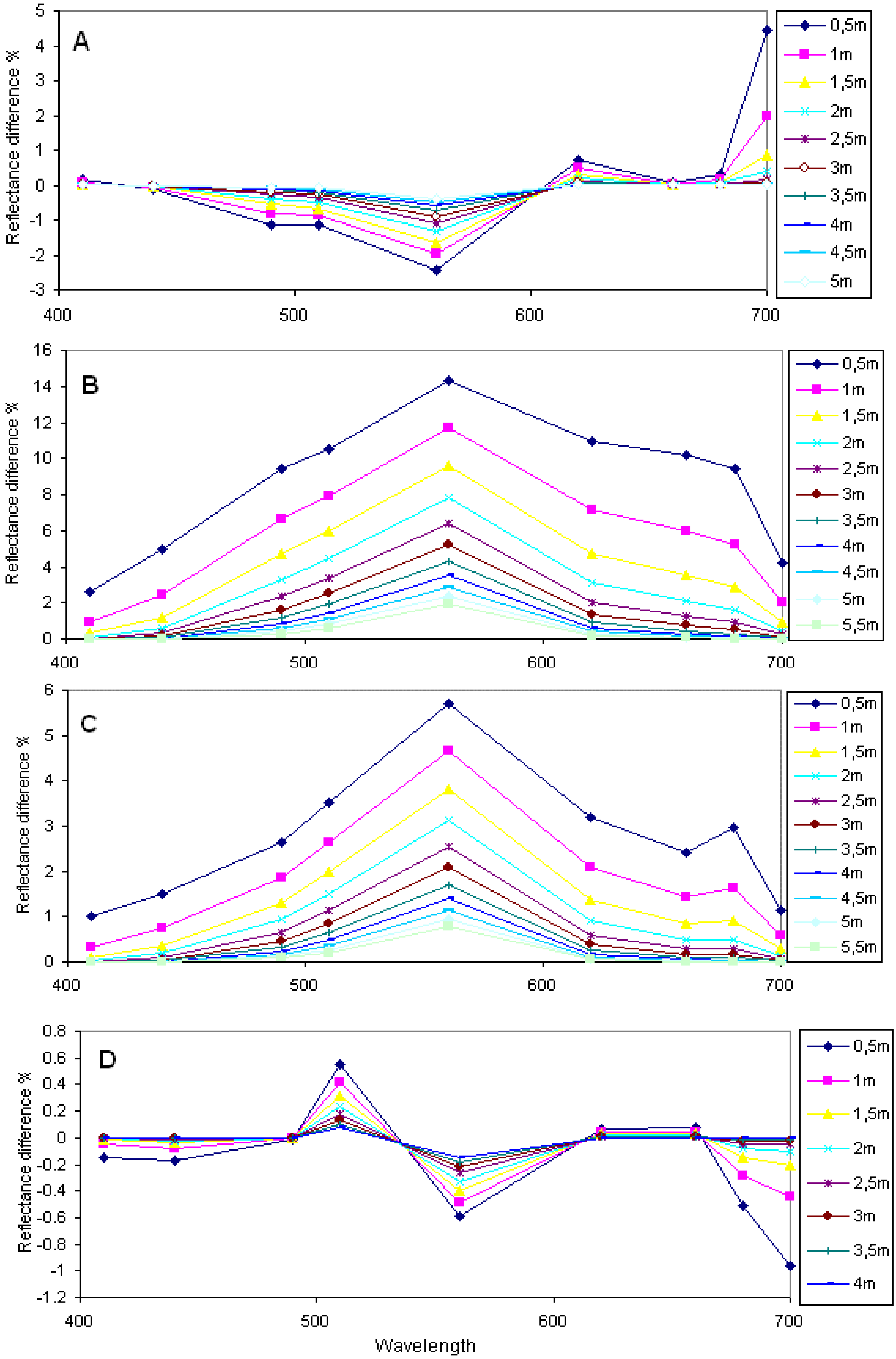


Fig.12 Spectral differences between simulated reflectance spectra (A) Red algae and deep water. (B) Sand and red algae. (C) Green algae and red algae. (D) Red algae and brown algae. Calculations are made for various water depths indicated in the legend. Each marker represents the central wavelength of MERIS.

is greatest in fifth band near 560 nm and this difference is detectable at least in waters up to 5.5 m.

In Fig. 12C the difference between reflectance of *Cladophora* and reflectance of *Furcellaria* are presented. The difference is higher in fifth band near 560 nm, but these differences are above the instrument SNR level in waters up to 4.5 m deep. Compared to previous figure the difference is smaller between red algae and green algae reflectance since the reflectance of green algae is not as high as the reflectance of sand.

Figure 12D represents the difference between reflectance of *Furcellaria* and *Fucus.* There are spectral differences between the two substrates in MERIS bands. However, SNR of the instrument does not allow detecting the small differences between red and brown algae.

The depth where MERIS can separate *Furcellaria* from deep water is about 2.5 m. As mentioned above the unattached *Furcellaria* is floating usually above sandy bottom. Sand and *Furcellaria* are optically separable from each other by MERIS sensor in waters up to 6 m deep. It means that part of the commercial stock of *Furcellaria lumbricalis* may be mapped by MERIS in ideal circumstances.

Modelling carried out with inherent optical properties of water types 1 and 2 suggest that multispectral sensors are not suitable for mapping benthic algal cover in CDOM-rich coastal waters or during cyanobacterial blooms. The spectral differences between benthic algae are relatively small in band 1 and absorption by CDOM masks even those small differences. Differences between benthic algae and other bottom types are largest in band 3. However, water molecules themselves absorb light very strongly at those wavelengths. It means that practically the only band where some differences can be detected is band 2. Consequently, the differences between bottom types come out as differences in intensity of signal in band 2. One band is not enough to be able to map different bottom types.

The situation is better in waters which optical properties resemble the open Baltic Sea waters as was described above. However, in many cases the separation between two bottom types comes also to detecting differences in band 2 signal intensity. This may be enough for mapping benthic habitat if a single image is used and a lot of in situ data is available as then it becomes possible to classify the image into as many classes as statistically meaningful and to name each class based on ground truth results. Andrefouët et al. (2003) have tried to use a consistent classification system to map coral reef bottom types with IKONOS. This trial had only limited success, obviously due to the same reason that many substrates are spectrally identical for multispectral sensors and variable illumination and atmospheric conditions cause misclassification if multiple images are used. Thus, mapping of benthic algal cover in turbid waters may be possible to greater extent than our modelling results suggest if a single image from a location where lot of ground truth data is available is used.

Summary

The objective of this Master thesis was to study is it possible to map benthic algal cover in turbid coastal environments by means of remote sensing. We studied optical properties of three algal species, *Cladophora glomerata*, *Furcellaria lumbricalis*, *Fucus vesiculosus,* selected by HELCOM as key indicator species for eutrophication in the Baltic Sea and used a bio-optical model to estimate are these algae separable from each other, sandy bottom or deep water with different remote sensing instruments and in how deep water can it be done.

Our modelling results indicate that the reflectance spectra of *Cladophora glomerata* (green algae), *Furcellaria lumbricalis* (red algae), and *Fucus vesiculosus* (brown algae) differ from each other and from sand and deep water reflectance spectra. The differences are detectable by remote sensing instruments, which spectral resolution is at least as good as spectral resolution of our model (10 nm) and SNR is better than 1000:1 (airborne and ship board instruments). In that case the maximum depths where the algae occur (at least in Estonian coastal waters) are smaller than the depth where such remote sensing instruments could potentially detect the spectral differences between the studied substrates.

Cladophora and *Fucus* form almost monospecies belts, which are often located at different depths. This is making mapping of those species easier by remote sensing instruments as the spectral differences of those species are detectable and there is usually no need to deal with mixed bottoms. Unattached *Furcellaria* is mainly located in an area with clay and sandy bottom with no attached bottom vegetation. Thus, the commercially available *Furcellaria* stock is relatively easy to map by (airborne) remote sensing instruments in calm and sunny weather conditions as it has to be spectrally separable only from sandy bottom and water in the area is usually shallower than the maximum depth where *Furcellaria* and sand are separable.

Hyperspectral data can at present be collected mainly by airborne instruments (excluding experimental Hyperion satellite sensor). Therefore we evaluated the capability of currently available multispectral satellite sensors for mapping Baltic Sea algal cover. The modelling results indicate that to some extent it is possible to map *Cladophora glomerata*, *Furcellaria lumbricalis*, *Fucus vesiculosus* with multispectral satellite sensors such as ALI Landsat 7 and IKONOS, in turbid waters which optical

properties resemble those of the open Baltic Sea. However, the depths where the algae can be detected are shallower than the maximum depths where the algae grow.

In waters deeper than just a few meters the differences between the studied bottom types are seen only in band 2 of the multispectral sensors under investigation. It means that multispectral sensors are capable of detecting difference in brightness only in one band which is insufficient for recognition of different bottom types in waters where no or few in situ data is available as intensity of signal in band 2 may vary due to different illumination, water column or atmospheric conditions not only due to change in benthic algae cover.

Configuration of MERIS spectral bands does allow mapping red, green and brow algae provided the algal belts of *Fucus* and *Cladophora* are wider than MERIS spatial resolution. Commercial stock of *Furcellaria lumbricalis* in Estonian North-West Archipelago covers area where MERIS 300 m spatial resolution is potentially adequate. However, SNR of the sensor does not allow mapping of *Furcellaria* down to maximum depths where it occurs.

Kokkuvõte

Käesoleva magistritöö “Põhjataimestiku kaardistamine häguses rannikumeres kaugseire meetodil” põhieesmärgiks oli uurida kas Läänemere vetes on võimalik kaardistada põhjataimestikku kaugseire meetoditega, millised liigid on potentsiaalselt eristavad, kui sügavas vees on see võimalik ning milliseid kaugseire sensoreid oleks vaja kasutada. Selleks uurisime HELCOM’i poolt Läänemere eutrofeerumise indikaatoriteks valitud vetikaliikide *Cladophora glomerata* (rohevetikas), *Fucus vesiculosus* (pruunvetikas) ja *Furcellaria lumbricalis* (punavetikas) optilisi omadusi ning kasutasime bio-optilist mudelit ja erinevate kaugseire sensorite tehnilisi parameetreid hindamaks kas ja kui sügavas vees on need vetikaliigid üksteisest ning liivapõhjast ja sügavast veest eristatavad optiliselt erinevates rannavetes.

Modelleerimise tulemused näitavad, et C*ladophora glomerata*, *Furcellaria lumbricalise* ja *Fucus vesiculosuse* heleduskoefitsiendi spektrid erinevad üksteisest, liivast ning sügava vee heleduskoefitsiendi spektritest. Kaugseire sensorid, mille spektraalne lahutatavus on vähemalt sama hea nagu meie mudelil (10 nm) ning signaali ja müra suhe vähemalt 1000:1 (praegused lennuvahenditel paiknevad sensorid), suudavad neid põhjatüüpe üksteisest eristada. Seejuures on maksimaalne sügavus, kus see eristamine on võimalik, sügavamal kui nende vetikate esinemissügavus Eesti rannavetes.

Cladophora ja *Fucus* moodustavad monodominantseid vetikavööndeid, mis asustavad sageli erinevaid sügavusi. See muudab eelpool nimetatud liikide kaardistamise kaugseire meetoditega lihtsamaks, kuna kaugseire sensorid on võimelised avastama nende liikide spektraalseid erinevusi ning harilikult ei ole vajadust tegeleda segakooslusega põhjadega. Kinnitumata *Furcellaria* asustab peamiselt saviseid ja liivaseid põhjasid, kus ei ole kinnitunud põhjataimestikku. Seega on rahuliku ja päikesepaistelise ilmaga hüperspektraalsete (pidevspektrit mõõtvate) kaugseire instrumentidega suhteliselt lihtne majanduslikult kasutatavaid *Furcellaria* varusid kaardistada, kuna *Furcellaria* peab olema spektraalselt eristatav ainult liivapõhjast ning Saaremaa ja Hiiumaa vahelisel alal on vesi tavaliselt madalam maksimaalsest sügavusest, kus *Furcellaria* ja liiv on teineteisest optiliselt eristatavad.

Käesoleval ajal kasutatavad hüperspektraalsed sensorid (peale eksperimentaalse Hyperioni, mille eluiga on lõppemas) võimaldavad koguda informatsiooni vaid lennuvahendite või laevade pardalt ning see on pindalaühiku kohta suhteliselt kallis. Seetõttu hindasime saadaolevate multispektraalsete satelliitide võimet kaardistada Läänemere põhjataimestikku. Modelleerimistulemustele toetudes võib öelda, et Läänemere tingimustes on multispektraalsete riistadega (nagu ALI, Landsat 7 ja IKONOS) mingil määral võimalik kaardistada rohevetikaid *Cladophora glomerata*, punavetikaid *Furcellaria lumbricalis* ja pruunvetikaid *Fucus vesiculosus*. Sellegipoolest on sügavus, milleni multispektraasled riistad on võimelised vetikaid eristama madalam, kui maksimaalne sügavus, kus need vetikad Eesti rannikuvetes kasvavad. Multispektraalsete sensorite puuduseks on ka see, et juba paari meetri sügavuses vees on erinevused põhjatüüpide vahel mõõdetavad kui heleduse muutused ühes spektrikanalis. Sellest jääb aga väheks, et ära tunda erinevaid põhjatüüpe vetes, mille kohta puuduvad in situ andmed või ei ole neid piisavalt, sest ühes spektrikanali abil ei ole võimalik öelda kas muutus signaalis on tingitud muutustest valgustatuses, veesamba- või atmosfääri optilistest omadustest või erinevast põhjatüübist.

MERISE spektrikanalite konfiguratsioon võimaldab kaardistada puna-, rohe- ja pruunvetikaid juhul kui *Fucuse* ja *Cladophora* vetikavööndid on laiemad kui MERISE ruumiline lahutusvõime (300 m). *Furcellaria lumbricalise* töönduslikult kasutatavad varud Lääne-Eesti saarestikus hõlmavad maa-ala, kus MERISE ruumiline lahutusvõime võiks olla küllaldane. Sellegi poolest ei võimalda sensori signaali-müra suhe *Furcellariat* kaardistada tema esinemise maksimaalse sügavuseni.

Acknoledgement

Author scholarship was funded from the Estonian Science Foundation grant 6051 and the study in general was funded from research grant 0712699s05 from Estonian Ministry of Education and Research.

The author of this thesis is very thankful to her supervisor PhD Tiit Kutser for his great support throughout the *studium*. PhD Georg Martin is acknowledged for his valuable comments on the manuscript.

References

Ackleson, S. G. (2003) Light in shallow waters: A brief recearch review. *Limnology and Oceanography*, 48, 323-328.

Andrefouët, S., Muller-Karger, F. E., Hochberg, E. J., Hu, C., Carder, K. L. (2001). Change detection in shallow coral reef environments using Landsat 7 ETM+ data. *Remote Sensing of Environment*, 78, 150-162.

Andréfouët, S., Kramer, P., Torres-Pulliza, D., Joyce, K. E., Hochberg, E. J., Garza-Perez, R., Mumby, P. J., Riegl, B., Yamano, H., White, W. H., Zubia, M., Brock, J. C., Phinn, S. R., Naseer, A., Hatcher, B. G., Muller-Karger, F. E. (2003). Multi-site evaluation of IKONOS data for classification of tropical coral reef environments. *Remote Sensing of Environment*, 88, 128-143.

Andrefouët, S., Zubia, M., Payri, C. (2004). Mapping and biomass estimation of the invasive brown algae *Turbinaria ornata* (Turner) J. Agardh and *Sargassum mangarevense* (Grunow) Setchell on heterogeneous Tahitian coral reefs using 4-meter resolution IKONOS satellite data. *Coral Reefs*, 23, 26-38.

Anstee, J., Dekker, A., Byrne, G., Daniel, P., Held, A., Miller, J. (2000). Use of hyperspectral imaging for benthic species mapping in South Australian coastal waters. 10th Australasian Remote Sensing and Photogrammetry Conference, Adelaide, 1051-1061.,

Barale, V., Folving, S. (1996). Remote sensing of coastal interactions in the Mediterranean region. *Ocean & Coastal Management*, 30, 217-233.

Bukata, R. P., Jerome, J. H., Kondratyev, K. Y., Pozdnyakov. (1995). Optical Properties and Remote Sensing of Inland and Coastal Waters. CRC Press, Ontario.

Call, K. A., Hardy, J. T., Wallin, D. O. (2003). Coral reef habitat discrimination using multivariate spectral analysis and satellite remote sensing. *International Journal of Remote Sensing*, 13, 2627-2639.

Carder, K. L., Liu, C., Lee, Z., English, D. C., Patten, J., Chen, F. R., Ivey, J. E. (2003) Illumination and turbidity effects on observing faceted bottom elements with uniform Lambertian albedos. *Limnology and Oceanography*, 48, 355-363.

Cracknell, A. P. (1999). Remote sensing tehniques in estuaries and coastal zones – an update. *International Journal of Remote Sensing*, 3, 485-496.

Darecki, M., Stramski, D. (2004). An evaluation of MODIS and SeaWiFS bio-optical algorithms in the Baltic Sea. *Remote Sensing of Environment*, 89, 326-350.

Dekker, A. G., Malthus, T. J. Goddijn, L. M. (1992). Monitoring cyanobacteria in eutrophic waters using airborne imaging spectroscopy and multispectral remote sensing system. Proc. 6th Australasian Remote Sensing Conf., Wellington, 1, 204-214.

Dekker, A.G., Brando, V.E., Anstee, J.M., Pinnel, N., Kutser, T., Hoogenboom, E.J., Peters, S., Pasterkamp, R., Vos, R., Olbert, C., Malthus, T.J.M. (2001) Imaging spectrometry of water. In: *Imaging Spectrometry: Basic principles and Prospective Applications* (Eds. F. D van der Meer, S. M. De Jong), Kluwer Academic Publishers, Drodrecht.

Doerffer, R., SØrensen, K., Aiken, J. (1999) MERIS potential for coastal zone applications. *International Journal of Remote Sensing,* 9, 1809-1818.

Foster, M. S., Schiel, D. R. (1985). The ecology of giant kelp forests in California: a community profile. U.S. Fish Wildl. Serv. Biol. Rep. 85(7.2):152.

Fyfe, S. K. (2003). Spatial and temporal variation in spectral reflectance: Are seagrass species spectrally distinct? *Limnology and Oceanography,* 48, 464-479.

Gordon, H. R., Brown, O. B. and Jacobs, M. M. (1975). Computed relationships between the inherent and apparent optical properties of a flat, homogenous ocean. *Applied Optics*, 14, 417-427.

Gordon, H. R., Morel, A. (1983). Remote assessment of ocean colour for interpretation of satellite visible imagery: a rewiev. Lecture Notes on Coastal and Estuarine Studies, Vol. 4, Springer-Verlag, New York, Berlin, Heidelberg, and Tokyo.

Hochberg, E. J., Atkinson, M. J. (2000). Spectral discrimination of coral reef benthic communities. *Coral Reefs,* 19, 164-171.

Hochberg, E. J., Atkinson, M. J. (2003). Capabilities of remote sensors to classify coral, algae, and sand as pure and mixed spectra. *Remote Sensing of Environment*, 85, 174-189.

Jupp, D. L. B., Mayo, K. K., Kuchler, D. A., Classen, D. V. R., Kenchington, R. A., Guerin, P. R. (1985). Remote sensing for planning and managing the Great Barrier Reef of Australia. Photogrammetria 40: 21-42.

Karpouzli, E., Malthus, T. J., Place, C. J. (2004). Hyperspectral discrimination of coral reef benthic communities in western Caribbean. *Coral Reefs*, 23, 141-151.

Kirk, J.T.O. (1984). Dependence of relationship between inherent and apparent optical properties of water on solar altitude. *Limnology and Oceanography*, 29, 350-356.

Kutser, T. (1997) Estimation of water quality in turbid inland and coastal waters by passive optical remote sensing. *Dissertationes Geophysicales Universitas Tartuensis*, 8, Tartu University Press.

Kutser, T., Skirving, W., Parslow, J., Done, T., Clementson, L., Wakeford, M., Miller, I. (2000). Hyperspectral detection of coral reef health**.** *Proceedings of 10th Australasian Remote Sensing Conference*, Adelaide, CD-ROM**.**

Kutser, T., Herlevi, A. Kallio, K. and Arst, H. (2001). A hyperspectral model for interpretation of passive optical remote sensing data from turbid lakes. *The Science of the Total Environment*, 268, 47-58.

Kutser, T., Jupp, D. L. B. (2002). Mapping coral reef benthic habitat with a hyperspectral space borne sensor. Proc Ocean Optics XVI, Santa Fe, CD-ROM.

Kutser, T., Dekker, A. G., Skirving, W. (2003). Modeling spectral discrimination of Great Barrier Reef benthic communities by remote sesing instruments. *Limnology and Oceanography*, 48, 497-510.

Kutser, T. (2004) Quantitative detection of chlorophyll in cyanobacterial blooms by satellite remote sensing. *Limnology and Oceanography,* 49, 2179-2189.

Legleiter, C. J., Roberts, D. A., Marcus, W. A., Fonstad, M. A. (2004) Passive optical remote sensing of river channel morphology and in-stream habitat: Physical basis and feasibility. *Remote Sensing of Environment*, 93, 493-510.

Lillesand, T., Kiefer, R. (1999). Remote Sensing and Image Interpretation. 4th Edition, John Wiley & Sons Inc., ISBN 0-417-25515-7.

Malthus, T. J., Karpouzli, E. (2003). Integrating field and high spatial resolution satellite-based methods for monitoring shallow submersed aquatic habitats in the Sound of Eriskay, Scotland, UK.

Malthus, T. J., Mumby, P. J. (2003) Remote sensing of the coastal zone: an overview and priorities for future research. *International Journal of Remote Sensing*, 13, 2805-2815.

Maritorena, S., Morel, A., and Gentili B. (1994) Diffuse reflectance of oceanic shallow waters: Influence of water depth and bottom albedo. *Limnology and Oceanography*, 37, 1689-1703.

Martin, G., Torn, K. (2004). Classification and description of phytobenthic communities in the waters of the West-Estonian Archipelago Sea. *Hydrobiology*, 514, 151-162.

Metsamaa, L., Kutser, T., Strömbeck, N. (2005). Recognising cyanobacterial blooms based on their optical signature. Harmful Algae (submitted).

Minghelli-Roman, A., Chisholm, J. R. M., Marchioretti, M., Jaubert, J. M. (2002). Discrimination of coral reflectance spectra in the Red Sea. *Coral Reefs*, 21, 307-314.

Morel, A., Prieur, L. (1977). Analysis of variations in ocean colour. *Limnology and Oceanography*, 22, 709-722.

Mumby, P. J., Edwards, A. J. (2002). Mapping marine environments with IKONOS imagery: enhanced spatial resolution can deliver greater thematic accuracy. *Remote Sensing of Environment*, 82, 248-257.

Mumby, P. J., Green, E. P., Edwards, A. J., Clark, C. D. (1997). Coral reef habitat-mapping: how much detail can remote sensing provide? *Marine Biology*, 130, 193-202.

Mumby, P. J., Skirving, W., Strong, A. E., Hardy, J. T., LeDrew, E. F., Hochberg, E. J., Stumpf, R. P., David, L. T. (2003). Remote sensing of coral reefs and their physical environment. *Marine Pollution Bulletin*, 48, 219-228.

Mumby, P. J., Hedley, J. D., Chisholm, J. R. M., Clark, C. D., Ripley, H., Jaubert, J. (2004). The cover of living and dead corals from airborn remote sensing. *Coral Reefs*, 23, 171-183.

Mäekivi, S., Arst, H. (1996) Estimation of the concentration of yellow substance in natural waters by beam attenuation coefficient spectra. Proceedings of Estonian Academy of Science, Ecology, 6, 108-123.

Pasqualini, V., Pergent-Martini, C., Pergent, G., Agreil, M., Skoufas, G., Sourbes, L., Tsirika, A. (2005). Use of SPOT 5 for mapping seagrasses: An application to *Posidonia oceanica. Remote Sensing of Environment*, 94, 39-45.

Peterson, D. L., Brass, J. A., Smith, W. H., Langford, G., Wegener, S., Dunagan, S., Hammer, P., Snook, K. (2003). Platform options of free-flying satellites, UAVs or the International Space Station for remote sensing assessment of the littoral zone. *International Journal of Remote Sensing*, 13, 2785-2804.

Philipson, P. (2003). Environmental Applications of Aquatic Remote Sensing. Acta Universitatis Upsaliensis, Uppsala.

Phinn, S.R., Dekker, A.G., Brando, V.E., & Roelfsema, C.M. (2005) Mapping water quality and substrate cover in optically complex coastal and reef waters: an integrated approach. *Marine Pollution Bulletin,* 51, 459-469.

Purkis, S., Kenter, J. A. M., Oikonomou, E. K., Robinson, I. S. (2002). High-resolution ground verification, cluster analysis and optical model of reef substrate coverage on LandsatTM imagery (Red Sea, Egypt). *International Journal of Remote Sensing*, 8, 1677-1698.

Sathyendranath, S. (2000). Remote Sensing of Ocean Colour in Coastal and Other Optically Complex Waters. Reports of the International Ocean-Colour Coordinating Group 3.

Smith, R.C., Baker, K.S. (1981). Optical properties of the clearest natural waters (200-800 nm). *Appl. Optics*, 20, 177-184.

Söderström, J. (1963). Studies in Cladophora. Botanica gothenburgensia, 1, 1-147.

Werdell, P. J., Roesler, C. S. (2003). Remote assessment of benthic substrate composition in shallow waters using multispectral reflectance. *Limnology and Oceanography*, 48, 557-567.

Wittlinger, S. K., Zimmerman, R. C. (2000). Hyperspectral remote sensing of subtidal macroalgal assemblages in optically shallow waters. Proc. Ocean Optics XV. CD-ROM.

Appendexes

Appendex I - Vahtmäe, E., Kutser, T., Martin, G. (2005). Feasibility of hyperspectral remote sensing for mapping benthic algal cover in turbid coastal waters – a Baltic Sea case study. *Remote Sensing of Environment* (Submitted).

Appendex II – Kutser, T., Vahtmäe, E., Martin, G. Suitability of multispectral satellites for mapping benthic algal cover in turbid coastal waters. *Marine Ecology Progress Series* (Submitted).

Appendex I

Feasibility of hyperspectral remote sensing for mapping benthic algal cover in turbid coastal waters – a Baltic Sea case study

Ele Vahtmäe, Tiit Kutser, Georg Martin

Estonian Marine Institute, University of Tartu, Mäealuse 10a, Tallinn 12618, Estonia,

E-mail: Tiit.Kutser@sea.ee

Abstract

Quantitative analysis of coastal marine benthic communities enables adequately estimate coastal marine environmental state, provide better evidence for environmental changes and describe processes that are conditioned by anthropogenic forces. Remote sensing could provide a tool for mapping bottom vegetation if the substrates are spectrally resolvable. We measured reflectance spectra of green- (*Cladophora glomerata*), red- (*Furcellaria lumbricalis*), and brown algae (*Fucus vesiculosus*) and used a bio-optical model in attempt to estimate are these algae separable from each other and sandy bottom or deep water in such turbid waters like the Baltic Sea. The simulation was carried out for three different water types: 1) CDOM-rich coastal water, 2) coastal waters not directly impacted by high CDOM discharge from rivers but with high concentration of cyanobacteria, 3) open Baltic waters. Our modelling results indicate that the reflectance spectra of *Cladophora glomerata*, *Furcellaria lumbricalis*, *Fucus vesiculosus* differ from each other and from sand and deep water reflectance spectra. The differences are detectable by remote sensing instruments which spectral resolution is at least as good as spectral resolution of our model (10 nm) and SNR is better than 1000:1. In that case the maximum depths where the algae usually occur in nature are smaller than the depth

where such remote sensing instruments could potentially detect the spectral differences between the studied substrates.

1. Introduction

Sustainable management of coastal environments requires regular collection of accurate information on recognized ecosystem health indicators (Phinn et al., 2005). Benthic algal cover and trends in changes of algal cover are indicators of water state in coastal areas. The objective of monitoring benthic algal cover in coastal areas is to observe short- and long-term changes in species distribution and structure of coastal benthic substrate constituents. Quantitative analysis of coastal marine benthic communities enables adequately estimate coastal marine environmental state, provide better evidence for environmental changes and describe processes that are conditioned by anthropogenic forces.

Benthic macrovegetation of the Baltic Sea is generally dominated by brown-, red- and green algae. Distribution of phytobenthic communities is determined by substrate availability, depth and light climate on local scale and salinity on the Baltic Sea scale (Kautsky, 1988; Martin, 2000). Green algae usually occur in the shallowest part of the littoral on hard substrate. Species *Cladophora glomerata* is wide spread over the Baltic Sea area and could be found in full salinity range found in the Baltic. It usually forms monodominant belts on the hard substrate close to the water edge (Söderström, 1963) Brown algae in the Baltic Sea are presented by variety of species with morphological characteristics from ephemeral filamentous species to perennial species with large thalli. Species *Fucus vesiculosus* is the largest macroalgae found in the Baltic Sea. In areas with hard substrate with moderate exposure this species is very important as habitat forming element of coastal ecosystem, supporting high biodiversity along rocky shores of Western and NE Baltic. The distribution of this species in the Baltic is limited northwards and eastwards by low salinity (*Fucus* is usually found in salinities higher than 3-4 PSU). Unattached form of *Furcellaria lumbricalis* could be found in the waters of West Estonian Archipelago on sandy gravel surfaces (Martin & Torn, 2004). It is commercially harvested for galactants there, but is also important habitat for fish juveniles. The tree algae species studied by us are considered as key species to monitor the effect of eutrophication in the Baltic Sea monitoring program carried out by HELCOM (www.helcom.fi).

Mapping benthic algal cover with conventional methods (diving) provides great accuracy and high resolution (Werdell & Roesler, 2003) yet is very expensive and is limited by the time and manpower necessary to monitor large bodies of water and long stretches of coastline. Remote sensing can potentially provide a tool for fast mapping of benthic algal cover provided the algal species are separable from each other based on their optical signatures.

Mapping of substrate cover types and their biophysical properties has been carried out successfully in optically clear, shallow coastal and reef waters (Anstee et al., 2000; Dekker et al., 2001; Kutser & Jupp, 2002; Phinn et al., 2005). In comparison with the reflectance properties of coral reef benthic communities (Hochberg & Atkinson, 2000, 2003; Karpouzli et al., 2004; Minghelli-Roman et al., 2002) and seagrass communities (Fyfe, 2003; Pasqualini et al., 2004), there is still scant information detailing the reflectance properties of algal communities. However, algal spectral reflectance properties have been published in some of the coral reef benthic community studies (Hochberg & Atkinson, 2000; Kutser et al., 2003). A few published reflectance spectra of various algal types are presented in Maritorena et al. (1994), Anstee et al., (2000), Wittlinger & Zimmerman (2000) and some other publications.

Remote sensing techniques have been successfully applied for operational mapping of the biophysical properties of clear waters, but turbid waters continue to represent a challenge to remote sensing techniques (Phinn et al., 2005). The Baltic Sea waters are relatively turbid and there is no information about optical properties of benthic algae in the Baltic Sea. The Baltic Sea is an intracontinental shallow marine environment under strong influence of human activities and terrestrial material. The Baltic Sea waters are often dominated by coloured dissolved organic matter (CDOM). Large discharge from rivers, limited exchange with marine waters of the North Sea, and a relatively shallow sea floor significantly influence the optical properties of the Baltic Sea (Darecki & Stramski, 2004).

The objective of this study is to determine how the spectral reflectance of benthic algae is translated into remote sensing reflectance. In shallow water, where the depth is much less than the potential for light to penetrate, a large fraction of the subsurface light reaches the ocean floor, where portions of the light energy are absorbed, reflected back into the overlying water column or re-emitted as fluorescence (Ackleson, 2003). In coastal waters, spectral scattering and absorption by phytoplankton, suspended organic and inorganic matter, and dissolved organic substances restrict the light passing to, and reflected from, the benthos (Dekker et al., 1992). Previous simulations to investigate the influence of water column depth indicate that much of the useful signal reflected from submersed plant material is rapidly attenuated with increasing depth of the water and bottom reflectance is diminished as it is filtered through the water column (Wittlinger & Zimmermann, 2000).

Increasing water turbidity and depth increase the relative contribution of the water-reflected photons relative to bottom-reflected photons, decreasing the influence of the bottom reflection on the above-water spectra (Carder et al., 2003). Our aim was to study weather or not are green-, brown-, and red algae separable from each other, sandy bottom or deep water and to estimate the maximum depths at which the various substrates still have an measurable influence on the remotely sensed reflectance in different coastal water types.

2. Methods

2.1 In situ measurements of benthic reflectance spectra

Reflectance spectra of benthic macroalgae were measured using handheld GER1500 spectroradiometer. Spectral range of the instrument is 300-1100 nm. Spectra are sampled with 1.5 nm intervals and spectral resolution of the GER1500 instrument is 3 nm. Reflectance was calculated as a ratio of radiance from algae to radiance from standard Spectralon panel.

Specimen of most typical green, brown and red algae – C*ladophora glomerata*, *Fucus vesiculosus,* and *Furcellaria lumbricalis* respectively, were collected into water-filled plastic bags. Reflectance measurements of wet algae were carried out on the shore immediately after landing of the boat. Multiple reflectance spectra of each species were measured and an average spectrum of each species was used in following model simulations. Reflectance spectrum of sand used in the model analysis was taken from previous studies (Kutser et al., 2000) as we were not able to carry out underwater reflectance measurements and it is not possible to collect sand samples without changing it's optical properties (due to mixing).

2.2 Bio-optical modelling

It has been shown (Maritorena et al., 1994) that the diffuse reflectance of shallow waters can be calculated using following formula:

$$R(0-,H) = R_\infty + (R_b - R_\infty)\exp(-2KH), \tag{1}$$

where H is water depth, R_b is bottom reflectance, R_∞ is reflectance of optically deep water, and K is diffuse attenuation coefficient of the water. Maritorena et al. (1994) have also shown that vertical attenuation coefficient for downwelling irradiance, K_d, is a good approximation for K.

Kirk (1984) has demonstrated with Monte Carlo simulations that the K_d at the midpoint of euphotic zone, z_m, can be expressed as a function of the absorption (a), and scattering (b) coefficients, and the cosine of the incident photons just below the surface (μ_0) in accordance with

$$K_d(z_m) = \frac{1}{\mu_0}\left[a^2 + (0.473\mu_0 - 0.218ab\right]^{1/2} . \tag{2}$$

Reflectance spectra of the optically deep water were calculated using a semi-empirical model described in detail by Kutser (2004). The model is based on the results of Monte Carlo studies by Gordon et al. (1975) and Kirk (1984) and is expressed with equation

$$R_\infty(0-,\lambda) = (-0.629\mu_0 + 0.975)\frac{b_b(\lambda)}{a(\lambda) + b_b(\lambda)}, \tag{3}$$

where $a(\lambda)$ is the total absorption coefficient, $b_b(\lambda)$is the total backscattering coefficient, and λ is wavelength. The μ_0 was taken equal to 0.85 according to solar zenith angle in mid-summer at the latitude of the central Baltic Sea.

We assumed that there are three optically active components in the water: phytoplankton, CDOM, and suspended matter. Under these conditions the total spectral absorption coefficient, $a(\lambda)$, is described by:

$$a(\lambda) = a_w(\lambda) + a^*_{Ph}(\lambda)C_{Chl} + a_{CDOM}(\lambda) + a^*_{SM}(\lambda)C_{SM}, \quad (4)$$

where a_w is the absorption coefficient of pure water, $a^*_{Ph}(\lambda)$ is the chlorophyll-specific spectral absorption coefficient of phytoplankton, $a_{CDOM}(\lambda)$ is the spectral absorption coefficient of CDOM, and $a^*_{SM}(\lambda)$ is the specific absorption coefficient of suspended matter. C_{Chl} and C_{SM} are concentrations of chlorophyll-*a* and total suspended matter.

The total spectral backscattering coefficient $b_b(\lambda)$ can be described:

$$b_b(\lambda) = 0.5b_w(\lambda) + b^*_{b,Ph}(\lambda)C_{Chl} + b^*_{b,SM}(\lambda)C_{SM}, \quad (5)$$

where b_w is the scattering coefficient of pure water and it is assumed that the backscattering probability is 50% in pure water. $b^*_{b,Ph}$ is chlorophyll-specific backscattering coefficient of phytoplankton and $b^*_{b,SM}$ is suspended sediment specific spectral backscattering coefficient of suspended matter.

In our model the values of absorption and scattering coefficients of pure water were taken from Smith & Baker (1981). The absorption by CDOM is expressed as a function of the absorption coefficient of filtered water sample at wavelength 400 nm, $a_{CDOM}(400)$, and slope factor, S, by following formula:

$$a_{CDOM}(\lambda) = a_{CDOM}(400)\exp[-S(\lambda - 400)]. \quad (6)$$

According to estimations by Mäekivi and Arst (1996) S=0.017 gives the best result in case of the Baltic Sea, Estonian and Finnish lakes. Specific absorption coefficient of suspended matter was taken from Kutser (1997), and specific scattering coefficients of suspended matter, as well as backscattering probabilities (backscattering to scattering ratio), were taken from study by Kutser et al. (2001). Absorption and scattering coefficients as well as backscattering probability of a cyanobacterium *Aphanizomenon flos-aquae* (Metsamaa et al., 2005) were used in the modelling as this species is often dominating Baltic Sea waters in July-August period when algal mapping is normally carried out for monitoring purposes.

The modelling was carried out for three distinctly different water types: 1) CDOM-rich waters near a river estuary, 2) coastal waters not directly impacted by high CDOM discharge from rivers but with high concentration of cyanobacteria, 3) open Baltic waters. Concentrations of optically active substances in these three water types are shown in Table 1. The concentrations were taken from real measurements from a coastal area near CDOM-rich river inflow, a bay with slightly elevated CDOM concentration caused by a creak with moderate CDOM concentrations, and from an area near NW Estonian Archipelago tens of kilometres offshore where concentrations of optically active substances resemble the values typical for the open Baltic Sea waters.

3. Results and discussions

We collected reflectance spectra of sand, green, brown and reg algae, measured without an overlying water column. Green algae were represented by a reflectance spectrum of *Cladophora glomerata*, red algae by free floating form of *Furcellaria lumbricalis*, and brown algae by *Fucus vesiculosus.* Figure 1A shows the spectral reflectance for each bottom type. All substrates have high reflectance in the near-infrared part of the spectrum. Sand has higher reflectance spectra than algae in visible part of spectrum. Green algae reflectance is higher than that of other measured algae. Reflectance values of *Fucus* and *Furcellaria* are very similar. However, there are differences in shape of their reflectance spectra. *Furcellaria* has a double peak near 600 and 650 nm as other red algae which reflectance has been measured in different parts of the World oceans by different authors (see references in the Introduction). *Fucus*, has a maximum in its reflectance spectrum near 600 nm and two “shoulders” near 570 and 650 nm similar to most living corals and many brown algae (see references in the Introduction). Reflectance spectra of green, brown and red algae measured by us are analogical to the reflectance spectra measured in different parts of the world oceans.

We evaluated water column effects on remotely sensed spectra by simulating bottom-reflected light through different depths of water column for a given concentrations of water column constituents. Figure 1B-1D represents the reflectance spectra of various substrates and deep water at 1 m depth in three different water types.

The amount of optically active water constituents is relatively high in the water type 1 (C_{Chl}=6 mg/m^3, C_{SM}=6 mg/l and $a_{CDOM}(400)$=15 m^{-1}). CDOM absorbs light strongly in the shorter wavelengths and even in 1 m deep water different substrates are not distinguishable in wavelengths shorter than 520 nm. Water itself absorbs light in the red and near-infrared region of the spectrum and thus the reflectance values at the longer wavelengths are dramatically decreased, and become almost identical for all substrates at wavelengths greater than 730 nm. Reflectance values of *Fucus* and *Furcellaria* are lower than that of deep water, but reflectance values of sand and *Gladophora* are higher than that of deep water.

The reflectance values are considerably higher in water type 2 waters (C_{Chl}=10 mg/m^3, C_{SM}=5 mg/l and $a_{CDOM}(400)$=3 m^{-1}) as seen on Fig. 1C. Concentration of chlorophyll in type 2 waters is typical to bloom values. We used specific absorption and scattering coefficients of a cyanobacterium *Aphanisomenon flos-aquae* in the model. It contains pigment phycocyanin that absorbs light near 630 nm. The phycocyanin absorption is quite strong in case of such high chlorophyll concentrations as is seen in reflectance spectrum of deep water. All studied substrates, except green algae, have also absorption feature in their reflectance spectra near 630 nm. It means that recognising different benthic substrates during cyanobacterial blooms is more complicated than in case of other algae that do not contain phycocyanin.

Figure 1D represents the clearest water type (C_{Chl}=2 mg/m^3, C_{SM}=2 mg/l and $a_{CDOM}(400)$=1.5 m^{-1}). CDOM has significant effect on reflectance spectra even in the open Baltic Sea waters. However, the effect is much smaller than in case of other water types studied by us and CDOM absorption is not masking differences between red and brown algae reflectance at wavelengths 510-600 nm (in 1 m deep water). Relatively large amount of algae are covering coastal substrates around and between island and islets of NW Estonian, Finnish and Swedish archipelago where the waters are similar to water type 3 used in our study.

The signal to noise ratio (SNR) specifications currently attainable by airborne remote sensing systems such as AVIRIS and CASI, flown under ideal circumstances, are about 1000:1 (Dekker et al., 2001). About 48% of just below the water surface upwelling irradiance is reflected back into the water column. Thus, the SNR in terms of just below the water surface reflectance, R(0-), has to be 500:1 to be able to detect differences in reflectance spectra by above mentioned instruments. Therefore, we determined the maximum depths at which the various substrates can be spectrally separated from deep water and from each other based on this criterion. To estimate the maximum depths where the substrates are spectrally separable we used the optical properties of our clearest water type.

3.1 Spectral differences between substrates and deep water.

Shallow water reflectance spectra were calculated with 0.5 m increments for each bottom type. Differences between the R(0-) of optically deep water and shallow water reflectance spectra were calculated. We assume that the substrate is separable from deep water if the reflectance difference is higher than the SNR of above mentioned instruments.

Fig. 2A shows the simulated spectral differences between reflectance of sandy bottom and reflectance of our type 3 (open Baltic) deep water. The maximum depth at which sandy bottom can be separated from type 3 deep water is 10 m.

Fig. 2B presents the difference between green algae (*Cladophora glomerata*) reflectance spectra and reflectance of deep water. Green algae are spectrally different from optically deep water, but the difference is not as high as for sand. Differences are largest near 710 nm, but these differences are above the instrument SNR level only in waters shallower than 2,5 m. In shallow water (up to 1,5 m deep) the difference is also high near 600 nm. The differences between green algae and deep water are seen in waters up to 7 m deep near 550-580 nm. However, *Cladophora glomerata* forms monoculture belts near the shore and does usually not grow at depth greater then 3.5 m in Estonian coastal waters. Thus, it is relatively easy to separate *Cladophora* belts from deep water areas as remote sensing could potentially permit detecting

Cladophora in depths that are greater than the depths where it grows in nature. This concerns areas not affected by high CDOM absorption and suspended matter loads e.g. conditions similar to our water type 3.

Figure 2C illustrates the spectral difference between reflectance of brown algae *Fucus vesiculosus* at different depths and reflectance of deep water. The substrates reflectance signal is lower than reflectance of deep water in the wavelength range 450-590 nm and 660-680 nm. *Fucus* has a relatively low reflectance and differences between algae and deep water reflectance spectra are small, except near 710 nm. However, these differences are above the instrument SNR level only in water shallower than 2,5 m. The next peaks in the spectral difference spectra are near 540 nm, 610 nm and 650 nm. The differences between brown algae and deep water are detectable in waters up to 6 m deep in the wavelength range 540-560 nm in the type 3 waters. Six meters is also the maximum depth where the *Fucus vesiculosus* grows in belts (Martin & Torn, 2004) in Estonian coastal waters (individual colonies can be found in deeper waters).

Figure 2D shows the spectral difference between reflectance of red algae *Furcellaria lumbricalis* and reflectance of deep water. The spectral differences between *Furcellaria* and deep water are detectable in waters up to 6.5 m deep in the wavelength range 560-570 nm. Unattached *Furcellaria lumbricalis* may grow at depths down to 10 m deep in Estonian coastal waters (Martin & Torn, 2004). However, the largest and commercially harvestable community occurs between two biggest Estonian islands Saaremaa and Hiiumaa where it is trapped inside a circular current. Water depths in this area are mainly between 2 m and 8-9 m and the commercial stock of *Furcellaria* is mainly in depths of 5-7 m. Optical water properties in the study area resemble the type 3 water in most of the time, except in case of storms when the amount of suspended matter may be much higher due to resuspension. Thus, most of the commercial stock of *Furcellaria lumbricalis* is in depths where it is potentially detectable by remote sensing sensors.

3.2 Spectral differences between algal species in different depths.

Difference in spectral reflectance were calculated between all substrates in all water depths by subtracting the reflectance of one substrate from the reflectance of another substrate at the same depth. Examples of spectral differences between two substrates are shown in Fig. 3. Figures 3A-3C show that spectral differences between sandy bottom and all three algal species are relatively high. The difference between sand and green algae reflectance spectra (Fig. 3A) is smaller than differences between sand and red or brown algae reflectance spectra (Fig. 3B, 3C) as *Fucus* and *Furcellaria* are relatively dark substrates compared to sand. The differences between sand and *Cladophora* are detectable in waters up to 10 m deep. The differences between reflectance of sand and reflectance of red or brown algae are detectable in waters up to 11 m in wavelengths near 570 nm.

Fig. 3D simulates the difference between reflectance of green algae and brown algae; difference is largest at wavelength 550 nm. *Fucus* has higher reflectance than *Cladophora* only in wavelengths greater than 710 nm, but those differences cannot be detectable in waters deeper than 1 m. Our simulations show that the maximum detectable depth at which those species can be separated is 8 m and for that we can use the wavelength range 550-570 nm.

In Fig. 3E the differences between reflectance of *Cladophora* and reflectance of *Furcellaria* are presented. Difference is largest at wavelength 570 nm, and similarly to brown algae, in wavelengths greater than 710 nm red algae have higher reflectance than green algae, but those differences are detectable in waters up to 1 m deep. Some slight differences are detectable between *Cladophora* and *Furcellaria* reflectance spectra till depth 8 m.

Both *Furcellaria* and *Fucus* have relatively low reflectance values. Figure 3F shows the wavelength bands that can be used to separate these two substrates from each other. Considerable differences appear in wavelengths near 520 nm, 570 nm and 700 nm. Difference near 570 nm is the greatest and this wavelength can be used to differentiate brown algae from red algae at depth up to 4 m. Difference near 520 nm can be used to differentiate these two substrate types at depth up to 2,5 m and difference near 700 nm can be used only in waters up to 1,5 m deep.

The depth where the studied bottom types are spectrally separable from each other in CDOM-rich estuaries is small (1-2 m). However, there is usually no bottom vegetation in these areas as the amount of light available for photosynthesis is not sufficient even in so shallow water. Exceptional river plumes with CDOM-rich water can cover larger areas where the vegetation exists, but the remote sensing campaigns can be organised during more favourable situation. It is also not reasonable to carry out benthic mapping by remote sensing in the cases of cyanobacterial blooms as cyanobacteria cause similar effects on reflectance spectra than red and brown algae. Cyanobacteria also form surface scum that is spectrally similar to terrestrial vegetation (Kutser, 2004). The scum is optically opaque and no information about benthic type or water column properties can be obtained when the surface scum occurs. Therefore, it is not reasonable to carry out remote mapping of shallow water benthic habitat during cyanobacterial blooms.

4. Conclusions

Our modelling result indicate that the reflectance spectra of *Cladophora glomerata*, *Furcellaria lumbricalis*, *Fucus vesiculosus* differ from each other and from sand and deep water reflectance spectra. The differences are detectable by remote sensing instruments which spectral resolution is at least as good as spectral resolution of our model (10 nm) and SNR is better than 1000:1. In that case the maximum depths where the algae occur (at least in Estonian coastal waters) is smaller than the depth where such remote sensing instruments could potentially detect the spectral differences between the studied substrates.

Cladophora and *Fucus* form almost monospecies belts which are often located at different depths. This is making mapping of those species easier by remote sensing instruments as the spectral differences of those species are detectable and there is usually no need to deal with mixed bottoms. Unattached *Furcellaria* is mainly located in an area with clay and sandy bottom with no attached bottom vegetation. Thus, the commercially available *Furcellaria* stock is relatively easy to map by (airborne) remote sensing instruments in calm and sunny weather conditions as it has to be spectrally separable only from sandy bottom and water in the area is usually shallower than the maximum depth where *Furcellaria* and sand are separable.

5. References

Ackleson, S. G. (2003). Light in shallow waters: A brief recearch review. *Limnology and Oceanography*, 48, 323-328.

Anstee, J., Dekker, A., Byrne, G., Daniel, P., Held, A., & Miller, J. (2000). Use of hyperspectral imaging for benthic species mapping in South Australian coastal waters. 10th Australasian Remote Sensing and Photogrammetry Conference, Adelaide, 1051-1061.

Carder, K. L., Liu, C., Lee, Z., English, D. C., Patten, J., Chen, F. R., & Ivey, J. E. (2003). Illumination and turbidity effects on observing faceted bottom elements with uniform Lambertian albedos. *Limnology and Oceanography*, 48, 355-363

Darecki, M., & Stramski, D. (2004). An evaluation of MODIS and SeaWiFS bio-optical algorithms in the Baltic Sea. *Remote Sensing of Environment*, 89, 326-350.

Dekker, A.G., Malthus T.J., & Goddijn L.M. (1992). Monitoring cyanobacteria in eutrophic waters using airborne imaging spectroscopy and multispectral remote sensing systems. Proc. 6th Australasian Remote Sensing Conf., Wellington, 1: 204-214.

Dekker, A.G., Brando, V.E., Anstee, J.M., Pinnel, N., Kutser, T., Hoogenboom, E.J., Peters, S., Pasterkamp, R., Vos, R., Olbert, C., & Malthus, T.J.M. (2001). Imaging spectrometry of water. In: *Imaging Spectrometry: Basic Principles and Prospective Applications* (Eds. F.D van der Meer, S.M. de Jong), Kluwer Academic Publishers, Dordrecht.

Fyfe, S. K. (2003). Spatial and temporal variation in spectral reflectance: Are seagrass species spectrally distinct? *Limnology and Oceanography,* 48, 464-479.

Gordon, H.R., Brown, O.B. & Jacobs, M.M. (1975). Computed relationships between the inherent and apparent optical properties of a flat, homogenous ocean. *Applied Optics*, 14, 417-427.

Hochberg, E. J., & Atkinson, M. J. (2000). Spectral discrimination of coral reef benthic communities. *Coral Reefs,* 19, 164-171.

Hochberg, E. J., & Atkinson, M. J. (2003). Capabilities of remote sensors to classify coral, algae, and sand as pure and mixed spectra. *Remote Sensing of Environment*, 85, 174-189.

Karpouzli, E., Malthus, T. J., & Place, C. J. (2004). Hyperspectral discrimination of coral reef benthic communities in the westrn Caribbean. *Coral Reefs,* 23, 141-151.

Kautsky, H. (1988) Factors structuring phytobenthic communities in the Baltic Sea. Akademitryck, Edsbruk: 1-30.

Kirk, J.T.O. (1984). Dependence of relationship between inherent and apparent optical properties of water on solar altitude. *Limnology and Oceanography*, 29, 350-356.

Kutser, T. (1997). Estimation of water quality in turbid inland and coastal waters by passive optical remote sensing. *Dissertationes Geophysicales Universitas Tartuensis*, 8, Tartu University Press.

Kutser, T., Skirving, W., Parslow, J., Done, T., Clementson, L., Wakeford, M., & Miller, I. (2000). Hyperspectral detection of coral reef health**.** *Proceedings of 10th Australasian Remote Sensing Conference*, Adelaide, CD-ROM**.**

Kutser, T., Herlevi, A. Kallio, K. & Arst, H. (2001). A hyperspectral model for interpretation of passive optical remote sensing data from turbid lakes. *The Science of the Total Environment*, 268, 47-58.

Kutser T., & Jupp, D.L.B (2002). Mapping coral reef benthic habitat with a hyperspectral space borne sensor. Proceedings of Ocean Optics XVI, Santa Fe, CD-ROM

Kutser, T., Dekker, A.G., & Skirving,W. (2003). Modeling spectral discrimination of Great Barrier Reef benthic communities by remote sensing instruments. *Limnology and Oceanography,* 48, 497-510.

Kutser, T. (2004). Quantitative detection of chlorophyll in cyanobacterial blooms by satellite remote sensing. *Limnology and Oceanography,* 49, 2179-2189.

Maritorena, S., Morel, A., & Gentili B. (1994). Diffuse reflectance of oceanic shallow waters: Influence of water depth and bottom albedo. *Limnology and Oceanography*, 37, 1689-1703.

Martin, G. (2000) Phtobenthic communities of the Gulf of Riga and the inner sea of the West-Estonian Archipelago. *Dissertationes Biologicae Universitas Tartuensis*, 64, Tartu University Press.

Martin, G., & Torn, K. (2004) Classifdication and description of phytobenthic communities in the waters of the West-Estonian Archipelago Sea. *Hydrobiologia*, 514, 151-162.

Minghelli-Roman, A., Chisholm J.R.M., Marchioretti M., & Jaubert J.M. (2002) Discrimination of coral reflectance spectra in the Red Sea. *Coral Reefs*, 21, 307-314.

Metsamaa, L., Kutser, T., & Strömbeck, N., (2005). Recognising cyanobacterial blooms based on their optical signature. *Harmful Algae* (submitted).

Mäekivi, S., & Arst, H. (1996). Estimation of the concentration of yellow substance in natural waters by beam attenuation coefficient spectra. Proceedings of Estonian Academy of Science, Ecology, 6, 108-123.

Pasqualini, V., Pergent-Martini, C., Fernandez, C., & Pergent G. (1997) The use of airborne remote sensing for benthic cartography: advantages and reliability. *International Journal of Remote Sensing*, 18, 1167-1177.

Phinn, S.R., Dekker, A.G., Brando, V.E., & Roelfsema, C.M. (2005) Mapping water quality and substrate cover in optically complex coastal and reef waters: an integrated approach. *Marine Pollution Bulletin,* 51, 459-469.

Smith, R.C., &K.S. Baker. 1981. Optical properties of the clearest natural waters (200-800 nm). *Applied Optics*, 20, 177-184.

Söderström J., (1963). studies in Cladophora. *Botanica gothenburgensia*, 1:1-147.

Werdell, P. J., & Roesler, C.S. (2003). Remote assessment of benthic substrate composition in shallow waters using multispectral reflectance. *Limnology and Oceanography*, 48, 557-567.

Wittlinger, S.K., & R.C. Zimmerman. 2000. Hyperspectral remote sensing of subtidal macroalgal assemblages in optically shallow waters. Proc. Ocean Optics XV, Monaco, CD-ROM.

Captions to figures and tables

Table 1. Concentrations of optically active substances used in model simulations

Fig. 1. Just below the water surface reflectance spectra (A) Substrates measured without an overlaying water column. (B) Simulated reflectance spectra of various substrates and deep water at 1 m depth in water type 1. (C) Simulated reflectance spectra of various substrates and deep water at 1 m depth in water type 2. (D) Simulated reflectance spectra of various substrates and deep water at 1 m depth in water type 3.

Fig.2. Spectral differences between simulated reflectance spectra (A) sand and deep water. (B) Green algae (*Gladophora glomerata*) and deep water. (C) Brown algae (*Fucus vesiculosus*) and deep water. (D) Red algae (*Furcellaria lumbricalis*) and deep water. Calculations are made for various water depths indicated in the legend.

Fig.3. Spectral differences between simulated reflectance spectra (A) Sand and green (*Gladophora glomerata*) algae. (B) Sand and brown algae (*Fucus vesiculosus)*. (C) Sand and red algae. (D) Green algae (*Gladophora glomerata*) and brown algae (*Fucus vesiculosus)*. (E) Green algae (*Gladophora glomerata*) and red algae (*Furcellaria lumbricalis)*. (F) Brown algae (*Fucus vesiculosus*) and red algae (*Furcellaria lumbricalis)*. Calculations are made for various water depths indicated in the legend.

Table 1.

Water type	C_{Chl}	C_{SM}	$a_{CDOM}(400)$
1	6	6	15
2	10	5	3
3	2	2	1.5
	mg/m^3	mg/l	m^{-1}

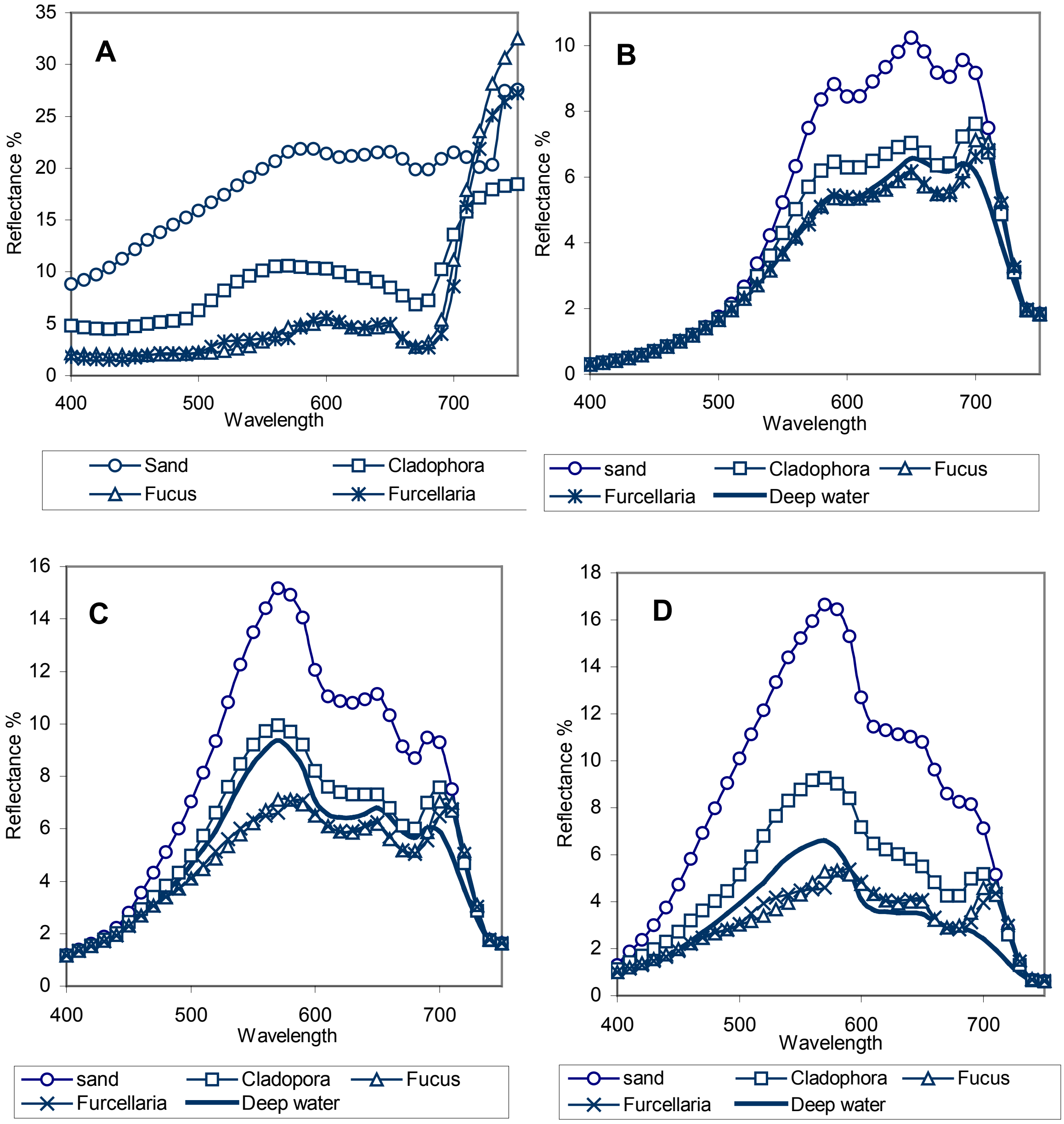

A
Reflectance %
Wavelength
Sand
Cladophora
Fucus
Furcellaria
B
Reflectance %
Wavelength
sand
Cladophora
Fucus
Furcellaria
Deep water
C
Reflectance %
Wavelength
sand
Cladopora
Fucus
Furcellaria
Deep water
D
Reflectance %
Wavelength
sand
Cladophora
Fucus
Furcellaria
Deep water

Fig. 1

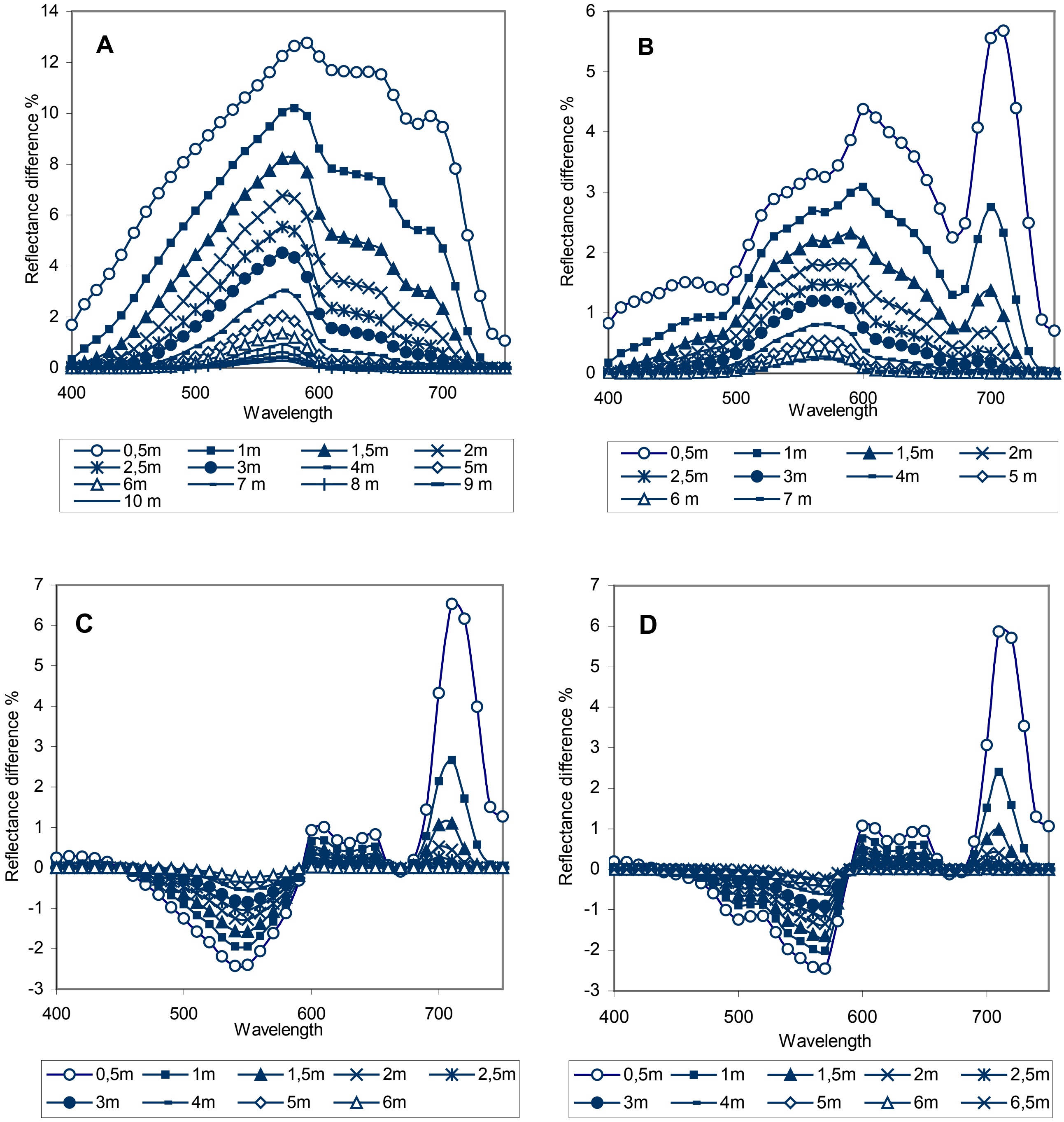

A
Reflectance difference %
Wavelength
0,5m
1m
1,5m
2m
2,5m
3m
4m
5m
6m
7 m
8 m
9 m
10 m
B
Reflectance difference %
Wavelength
0,5m
1m
1,5m
2m
2,5m
3m
4m
5 m
6 m
7 m
C
Reflectance difference %
Wavelength
0,5m
1m
1,5m
2m
2,5m
3m
4m
5m
6m
D
Reflectance difference %
Wavelength
0,5m
1m
1,5m
2m
2,5m
3m
4m
5m
6m
6,5m

Fig. 2

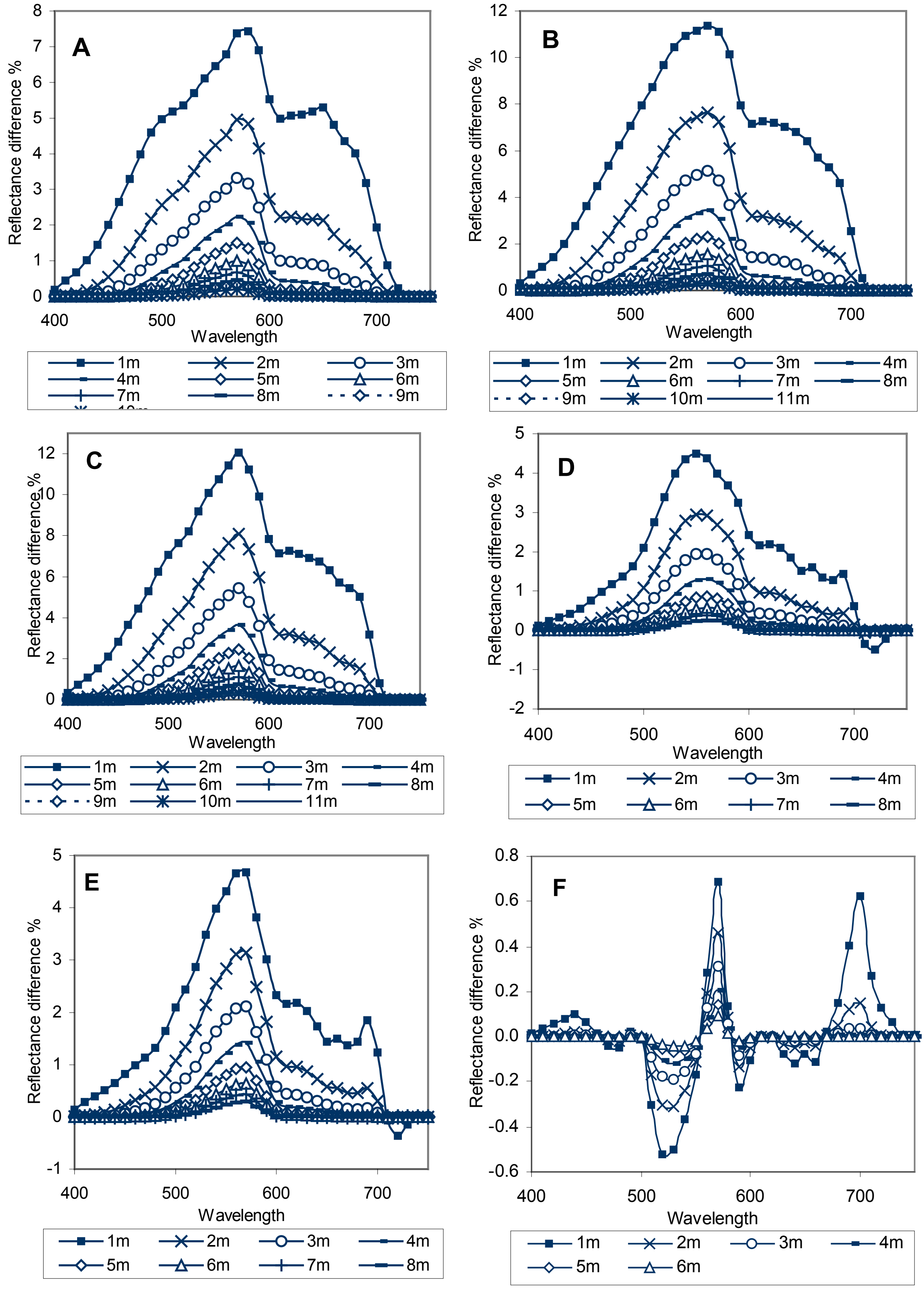

A
B
C
D
E
F
Reflectance difference %
Wavelength
1m
2m
3m
4m
5m
6m
7m
8m
9m
10m
11m

Fig. 3

Appendex II

Suitability of multispectral satellites for mapping benthic algal cover in turbid coastal waters

Tiit Kutser, Ele Vahtmäe, Georg Martin

Estonian Marine Institute, University of Tartu, Mäealuse 10a, Tallinn 12618, Estonia,
E-mail: Tiit.Kutser@sea.ee

Running head: Mapping algal cover with multispectral satellites
Keywords: remote sensing, benthic algae, coastal waters, multispectral

Abstract

The objective of monitoring benthic algal cover in is to observe short- and long-term changes in species distribution and structure of coastal benthic substrate constituents. Mapping benthic algal cover with conventional methods (diving) provides great accuracy and high resolution yet is very expensive and is limited by the time and manpower necessary. We measured reflectance spectra of three indicator species for the Baltic Sea: green- (*Cladophora glomerata*), red- (*Furcellaria lumbricalis*), and brown algae (*Fucus vesiculosus*) and used a bio-optical model in attempt to estimate are these algae separable from each other and sandy bottom or deep water. Our modelling results indicate that to some extent it is possible to map the studied species with multispectral satellite sensors in turbid waters. However, the depths where the algae can be detected are shallower than the maximum depths where the algae grow. In waters deeper than just a few meters the differences between the studied bottom types are seen only in band 2 of the multispectral sensors under investigation. It means that multispectral sensors are capable of detecting difference in brightness only in one band which is insufficient for recognition of different bottom types in waters where no or few in situ data is available. Configuration of MERIS spectral bands does allow mapping red, green and brow algae provided the algal belts are wider than MERIS spatial resolution. Commercial stock of *Furcellaria lumbricalis* in Estonian North-West Archipelago covers area where MERIS 300 m spatial resolution is adequate. However, SNR of the sensor does not allow mapping of *Furcellaria* down to maximum depths where it occurs.

1. Introduction

Benthic algal cover and trends in changes of algal cover are indicators of water state in coastal areas. There is need for regular collection of accurate information on recognized ecosystem health indicators for sustainable management of coastal environments. The objective of monitoring benthic algal cover in coastal areas is to observe short- and long-term changes in species distribution and structure of coastal benthic substrate constituents. Quantitative analysis of coastal marine benthic communities enables adequately estimate coastal marine environmental state, provide better evidence for environmental changes and describe processes that are conditioned by anthropogenic forces.

Mapping benthic algal cover with conventional methods (diving) provides great accuracy and high resolution (Werdell and Roesler 2003) yet is very expensive and is limited by the time and manpower necessary to monitor large bodies of water and long stretches of coastline. Remote sensing can potentially provide a tool for fast mapping of benthic algal cover provided the algal species are separable from each other based on their optical signatures.

Spectral features that allow differentiating between different benthic substrates are often narrow (Kutser et al 2000, 2003, Dekker et al 2001;,Fyfe 2003). Therefore, hyperspectral instruments are preferable for mapping benthic habitat. In our previous study (Vahtmäe et al 2005) we concluded that it is feasible to map benthic algal cover with hyperspectral remote sensing instruments in turbid coastal waters like the Baltic Sea, as the depths where red-, green- and brown algae are spectrally separable from each other or sand and deep water is mainly deeper than the depth where these algae types are growing.

The first hyperspectral sensor in space, Hyperion, has been used for mapping shallow water benthic habitat (Kutser and Jupp 2002). However, Hyperion was designed as technical demonstration instrument with short lifetime. Hyperion has already collected data during much longer period than was originally planned and this mission is close to ending. Airborne instruments can also provide spectral and spatial resolution needed. However, cost of the image data per study area is too high to allow using of hyperspectral airborne imagery in benthic habitat mapping in large coastal areas. Therefore, it would be more cost effective to use satellite sensors in mapping of benthic algal cover provided the satellite sensors are capable of differentiation between different benthic types.

In the Baltic Sea benthic macroalgae are often growing in almost monoculture belts. This makes their mapping by remote sensing easier. However, spatial resolution of ocean colour sensors (SeaWiFS, MODIS) is too coarse compared with spatial dimensions of the algal belts. Therefore, satellites with finer spectral resolution (IKONOS, Landsat, ALI) have to be used. However, such satellite sensors lack the sensitivity to discriminate spectra because they have a limited number of water-penetrating bands (Mumby and Edwards 2002). Mumby et al (1997) found that using broadband multispectral sensor, algal and seagrass habitats were spectrally and spatially confused with one another, resulting in lower overall accuracies than coral and sand habitats. Hochberg and Atkinson (2000) showed that discrimination between coral, algae and sand can be achieved with as few as four narrow, noncontiguous wavebands. However Hochberg and Atkinson (2003) found that broadband multispectral sensors are not suitable for assessing the global status of reefs.

In the absence of better sensors multispectral satellites have been used to some extent for mapping seagrasses (Pasqualini et al 2005, Andrefouet et al 2004), coral reefs (Jupp et al 1985, Andrefouet et al 2001, Mumby et al 1997, Call et al 2003, Karpouzli et al 2004, Purkis et al 2002, Kutser et al 2003), and macroalgae (Andrefouet et al 2004, Hochberg and Atkinson 2003). However, those studies were carried out in clear oceanic (Case I) waters. The Baltic Sea waters are typical Case II waters where concentrations of phytoplankton, suspended matter and coloured dissolved organic matter (CDOM) do not co-vary. The dominating optically active substance in the Baltic Sea is CDOM, except in case of intensive algal blooms when phytoplankton is the dominating optically active substance in water. In the Baltic Sea chlorophyll concentrations are between 1 and 4 mg/m^3 during winter and summer minimum, but the concentration increases to 30-40 mg/m^3 during spring bloom and reaches values of hundreds of mg/m^3 during cyanobacterial blooms in summer Kutser 2004). The objective of our study was to evaluate the capability of multispectral satellite sensors for mapping algal cover in such turbid coastal environments like the Baltic Sea.

2. Methods

2.1 In situ measurements of benthic reflectance spectra

Reflectance spectra of benthic macroalgae were measured using handheld GER1500 spectroradiometer. Spectral range of the instrument is 300-1100 nm. Spectra are sampled with 1.5 nm intervals and spectral resolution of the GER1500 instrument is 3 nm. Reflectance was calculated as a ratio of radiance from algae to radiance from standard Spectralon panel.

Tree algae species in the Baltic Sea are considered by HELCOM (www.helcom.fi) as key species to monitor the effect of eutrophication. These are *Cladophora glomerata* (green algae), *Furcellaria lumbricalis* (red algae), and *Fucus vesiculosus* (brown algae). Therefore we decided to emphasize our study on these species. Samples of the algae were collected into water-filled plastic bags. Reflectance measurements of wet algae were carried out on the shore immediately after landing of the boat. Multiple reflectance spectra of each species were measured and an average spectrum of each species was used in following model simulations. Reflectance spectrum of sand used in the model analysis was taken from literature (Kutser et al 2000) as we were not able to carry out underwater reflectance measurements and it is not possible to collect sand samples without mixing it.

2.2 Bio-optical modelling

It has been shown (Maritorena et al 1994) that diffuse reflectance of shallow waters can be calculated using following formula:

$$R(0-,H) = R_\infty + (R_b - R_\infty)\exp(-2KH), \qquad (1)$$

where H is water depth, R_b is bottom reflectance, R_∞ is reflectance of optically deep water, and K is diffuse attenuation coefficient of the water. Maritorena et al (1994) have also shown that vertical attenuation coefficient for downwelling irradiance, K_d, is a good approximation for K.

Kirk (1984) has demonstrated with Monte Carlo simulations that the K_d at the midpoint of euphotic zone, z_m, can be expressed as a function of the absorption (a), and scattering (b) coefficients, and the cosine of the incident photons just below the surface (μ_0) in accordance with

$$K_d(z_m) = \frac{1}{\mu_0}\left[a^2 + (0.473\mu_0 - 0.218ab\right]^{1/2} . \qquad (2)$$

Reflectance spectra of the optically deep water were calculated using a semi-empirical model described in detail by Kutser (2004). The model is based on the results of Monte Carlo studies by Gordon et al. (1975) and Kirk (1984) and is expressed with equation

$$R_{\infty}(0-,\lambda) = (-0.629\mu_0 + 0.975)\frac{b_b(\lambda)}{a(\lambda) + b_b(\lambda)}, \tag{3}$$

where $a(\lambda)$ is the total absorption coefficient, $b_b(\lambda)$is the total backscattering coefficient, and λ is wavelength. The μ_0 was taken equal to 0.85 according to solar zenith angle in mid-summer at the latitude of the central Baltic Sea.

We assumed that there are three optically active components in the water: phytoplankton, coloured dissolved organic matter, and suspended matter. Under these conditions the total spectral absorption coefficient, $a(\lambda)$, is described by:

$$a(\lambda) = a_w(\lambda) + a^*_{Ph}(\lambda)C_{Chl} + a_{CDOM}(\lambda) + a^*_{SM}(\lambda)C_{SM}, \tag{4}$$

where a_w is the absorption coefficient of pure water, $a^*_{Ph}(\lambda)$ is the chlorophyll-specific spectral absorption coefficient of phytoplankton, $a_{CDOM}(\lambda)$ is the spectral absorption coefficient of CDOM, and $a^*_{SM}(\lambda)$ is the specific absorption coefficient of suspended matter. C_{Chl} and C_{SM} are concentrations of chlorophyll-*a* and total suspended matter.

The total spectral backscattering coefficient $b_b(\lambda)$ can be described:

$$b_b(\lambda) = 0.5b_w(\lambda) + b^*_{b,Ph}(\lambda)C_{Chl} + b^*_{b,SM}(\lambda)C_{SM}, \tag{5}$$

where b_w is the scattering coefficient of pure water and it is assumed that the backscattering probability is 50% in pure water. $b^*_{b,Ph}$ is chlorophyll-specific backscattering coefficient of phytoplankton and $b^*_{b,SM}$ is suspended sediment specific spectral backscattering coefficient of suspended matter.

In our model the values of absorption and scattering coefficients of pure water were taken from Smith and Baker (1981). The absorption by CDOM is expressed as a function of the absorption coefficient of filtered water sample at wavelength 400 nm, $a_{CDOM}(400)$, and slope factor, S, by following formula:

$$a_{CDOM}(\lambda) = a_{CDOM}(400)\exp[-S(\lambda - 400)]. \tag{6}$$

According to estimations by Mäekivi and Arst (1996) S=0.017 gives the best result in case of the Baltic Sea, Estonian and Finnish lakes. Specific absorption coefficient of suspended matter was taken from Kutser (1997), and specific scattering coefficients of suspended matter, as well as backscattering probabilities (backscattering to scattering ratio), were taken from study by Kutser et al. (2001). Absorption, scattering and backscattering coefficients of a cyanobacterium *Aphanizomenon flos-aquae* (Metsamaa et al 2005) were used in the modelling as this species is often dominating Baltic Sea waters in July-August period when algal mapping is normally carried out.

The modelling was carried out for three distinctly different water types: 1) CDOM-rich waters near a river estuary, 2) coastal waters not directly impacted by high CDOM discharge from rivers, 3) open Baltic waters. Concentrations of optically active substances in these three water types are shown in Table 1. The concentrations were taken from real measurements from a coastal area near CDOM-rich river inflow, a bay with slightly elevated CDOM concentration caused by a creak with moderate CDOM concentrations and from an area near islands tens of kilometres offshore where concentrations of optically active substances resemble the values typical for the open Baltic Sea waters.

2.3 Satellite sensors under investigation

Monitoring of changes in benthic algal cover by remote sensing requires availability of time series of imagery. Thus, it is difficult to relay on experimental satellites like EO1 (Hyperion and ALI). On the other hand spatial extent and optical properties of the benthic substrates require high spatial and spectral resolution of satellite sensors. Landsat series sensors have been operating for decades. They were not designed for water environments, but shallow water benthic habitat are often bright enough to make Landsat sensors suitable for mapping shallow water benthic types (Jupp et al 1985). Sensors with almost identical spectral bands but better spatial (IKONOS, 4 m) or radiometric (ALI, a prototype of next generation Landsat, 30 m) resolution are available at present. Therefore we choose those sensors for our study. The area covered with freely floating *Furcellaria lumbricalis* between Islands

Saaremaa and Hiiumaa (Estonian North-west Archipelago) is large enough allowing use of sensors with coarse spatial resolution. Therefore we tried to estimate is it possible to use MERIS full resolution imagery to detect this red algae on sand background. MERIS has nine visible wavebands covering the visible spectral range (410-710 nm), but its spatial resolution is limited by 300 m. Some technical characteristics of the sensors used are given in Table 2.

3. Results and discussions

We evaluated water column effects on remotely sensed reflectance spectra by simulating bottom-reflected light through different depths of water column for a given concentrations of water column constituents for three different waters types. As our aim was to estimate maximum depths where the substrates can potentially be separated from each other using satellite sensors we concentrate our discussion mainly on the clearest water type which resembles optical properties of the open Baltic Sea.

Figure 1 shows the spectral reflectance for each bottom type. All substrates have high reflectance in the near-infrared part of the spectrum. Sand has higher reflectance spectra than algae in visible part of spectrum. Green algae reflectance is higher than that of other measured algae. Reflectance values of *Fucus* and *Furcellaria* are very similar. However, there are differences in shape of their reflectance spectra. *Furcellaria* has a double peak near 600 and 650 nm as other red algae which reflectance has been measured in different parts of the World oceans by different authors (see references in the Introduction). *Fucus*, has a maximum in its reflectance spectrum near 600 nm and two “shoulders” near 570 and 650 nm similar to most living corals and many brown algae (see references in the Introduction). Reflectance spectra of green, brown and red algae measured by us are analogical to the reflectance spectra measured in different parts of the world oceans.

Figure 2 illustrates how the sensors under investigation would detect reflectance spectra of studied bottom types without overlaying water column. It is seen in Fig. 2A that the difference between the substrates are mainly in reflectance values rather than in shape if three-band sensors like ALI, Landsat or IKONOS are used. MERIS bands are narrow (10 nm) and are located in spectral regions needed for example to separate brown algae from red algae (see Fig. 2B). However, the effect of water column has to be taken into account before deciding is MERIS suitable for discriminating between the studied substrates.

3.1 Simulated ALI, Landsat7 and IKONOS performance for detecting benthic algal cover

Shallow water reflectance spectra were calculated with 0.5 m increments for each bottom type and the expected values in multispectral sensors bands 1, 2 and 3 were derived. Differences between the R(0-) of optically deep water and shallow water reflectance spectra were calculated. The signal to noise ratio (SNR) of Landsat 7 and IKONOS is about 100:1, whereas SNR of ALI is about 250:1. About 48% of just below the water surface upwelling irradiance is reflected back into the water column. Thus, the SNR in terms of just below the water surface reflectance, R(0-), has to be 50:1, for Landsat 7 and IKONOS and 125:1 for ALI to be able to differentiate between two bottom types.

Figure 3A illustrates a case where all three bands can be used in separating sand from deep water in waters up to 3 m deep with ALI and in waters up to 2 m deep with Landsat and IKONOS. The second band near 560 nm can be used in differentiating sand and optically deep water in waters up to 5 m deep with ALI and in waters up to 4 m deep with Landsat and IKONOS. The characteristic spectral reflectance feature of sand is its brightness, and the brightness is so characteristic that even multispectral sensors with their limited spectral responses have no trouble discriminating sand from deep water.

Figure 3B shows the difference between green algal reflectance spectra and reflectance of deep water. The difference between green algae and deep water is becoming undetectable in band 1 in waters deeper than 1 m. Band 3 can be used to separate green alga from deep water in waters no deeper than 1.5 m. Band 2 shows difference between green algae and deep water in waters up to 3 m deep. Landsat 7 and IKONOS are not capable of separating green algae and deep water in the first band. Band 3 can be used detecting these differences between green algae and deep water if the water is shallower than 0.5 m. Landsat and IKONOS band 2 can be used in waters up to 1.5 m deep.

Optically dark marine habitats, such as brown and red algae, are spectrally similar to each other and to deep water when multispectral sensors are used. Figures 3C and 3D show the difference between brown algae and deep water and between red algae and deep water. Landsat 7 and IKONOS are not capable of detecting these differences. ALI is capable of detecting the differences. In both cases bands 1 and 3 are unusable in differentiating algae from deep water, band 2 shows detectable difference in waters up to 1.5 m deep.

Differences in spectral reflectance were calculated between all substrates in various water depths by subtracting the radiance of one substrate from the radiance of another substrate at the same depth. On the basis of the three visible bands available in the multispectral sensors dataset, sand was well differentiated from algal cover. Sand has a higher albedo than any algal substrate in ALI, Landsat7 and IKONOS bands 1, 2 and 3. Submerged feature brightness appears to be strongest attribute for separating substrate type. If there is a high degree of difference in the brightness of substrate types, features can be easily separated (Call et al 2003).

Since the differences between reflectance values of green algae and brown algae and green algae and red algae are small, multispectral satellites are hardly able to discriminate between these algal types.

As brown and red algae have similar spectral reflectance values. Broad-band sensors like ALI, Landsat7 and IKONOS are incapable of discriminating the two substrates from each other.

3.2 Simulated MERIS performance for detecting benthic algal cover

Unattached community of red algae *Furcellaria lumbricalis* occurs between two biggest Estonian islands Saaremaa and Hiiumaa where it is trapped inside a circular current. Spatial scale of the area is suggesting that sensors with more coarse spatial resolution than the multispectral sensors discussed above, can be used to map the extent of *Furcellaria* stock in this region. MERIS full resolution images are with 300 m spatial resolution and spectral resolution of MERIS (9 bands in visible part of spectrum) may be adequate to differentiate between different bottom types. MERIS SNR is 200:1. In just below the water surface reflectance terms it means that the difference between two bottom types has to be 1% to be detectable by MERIS.

Figure 4A shows the simulated spectral differences between reflectance of red algae and reflectance of our water type 3 (open Baltic) deep water. Difference is the greatest in ninth band near 700 nm, but these differences are above the instrument SNR level only in waters shallower than 1 m due to strong absorption of light at these wavelengths by water molecules.. The next peak in the spectral difference spectra is in fifth band near 560 nm and these differences are detectable by MERIS in waters shallower than 2.5 m. The differences are detectable also in third and fourth bands in waters not deeper than 0.5 m.

Figure 4B shows that the difference between sand and red algae is relatively high as *Furcellaria* is considerably darker substrate compared to sand. The difference is greatest in fifth band near 560 nm and this difference is detectable at least in waters up to 5.5 m.

In Fig. 4C the difference between reflectance of *Cladophora* and reflectance of *Furcellaria* are presented. The difference is higher in fifth band near 560 nm, but these differences are above the instrument SNR level in waters up to 4.5 m deep. Compared to previous figure the difference is smaller between red algae and green algae reflectance since the reflectance of green algae is not as high as the reflectance of sand.

Figure 4D represents the difference between reflectance of *Furcellaria* and *Fucus.* There are spectral differences between the two substrates in MERIS bands. However, SNR of the instrument does not allow detecting the small differences between red and brown algae.

Gladophora glomerata forms almost monoculture belts near the sore and does not usually grow deeper than 3.5 m in Estonian coastal waters (Martin and Torn 2004). However, the multispectral sensors under investigation cannot differentiate between deep water and *Gladophora* at such depth. The deepest water where the green algae and water are separable from each other is 3m and in such case only band 2 is capable of detecting the difference.

Six meters is the maximum depth where the *Fucus vesiculosus* grows in belts (Martin and Torn 2004) in Estonian coastal waters (individual colonies can be found in deeper waters). Multispectral sensor are not capable of mapping *Fucus* belts in Estonian coastal waters as Landsat and IKONOS cannot separate *Fucus* from deep water and ALI can detect the difference in waters up to 1.5 m deep (using band 2).

Unattached *Furcellaria lumbricalis* grows mainly in depth range 2-9 m in Estonian coastal waters and the commercial stock of this species is at depths between 5-7 m (Martin and Torn 2004). The multispectral sensors under investigation are not capable of separating *Furcellaria* from optically deep water. However, the *Furcellaria* is floating above sand and ALI can differentiate between sand and *Furcellaria* in waters up to 4 m deep. Thus, ALI can suitable for mapping *Furcellaria* to some extent, but the commercial stock is usually at depth not reachable by ALI or other multispectral sensors under investigation.

The depth where MERIS can separate *Furcellaria* from deep water is about 2.5 m. As mentioned above the unattached *Furcellaria* is floating usually above sandy bottom. Sand and *Furcellaria* are optically separable from each other by MERIS sensor in waters up to 6 m deep. It means that part of the commercial stock of *Furcellaria lumbricalis* may be mapped by MERIS in ideal circumstances.

Modelling carried out with inherent optical properties of water types 1 and 2 suggest that multispectral sensors are not suitable for mapping benthic algal cover in CDOM-rich coastal waters or during cyanobacterial blooms. The spectral differences between benthic algae are relatively small in band 1 and absorption by CDOM masks even those small differences. Differences between benthic algae and other bottom types are largest in band 3. However, water molecules themselves absorb light very strongly at those wavelengths. It means that practically the only band where some differences can be detected is band 2. Consequently, the differences between bottom types come out as differences in intensity of signal in band 2. One band is not enough to be able to map different bottom types.

The situation is better in waters which optical properties resemble the open Baltic Sea waters as was described above. However, in many cases the separation between two bottom types comes also to detecting differences in band 2 signal intensity. This may be enough for mapping benthic habitat if a single image is used and a lot of in situ data is available as then it becomes possible to classify the image into as many classes as statistically meaningful and to name each class based on ground truth results. Andrefouët et al. (2003) have tried to use a consistent classification system to map coral reef bottom types with IKONOS. This trial had only limited success, obviously due to the same reason that many substrates are spectrally identical for multispectral sensors and variable illumination and atmospheric conditions cause misclassification if multiple images are used. Thus, mapping of benthic algal cover in turbid waters may be possible to greater extent than our modelling results suggest if a single image from a location where lot of ground truth data is available is used.

4. Conclusions

Our modelling results indicate that to some extent it is possible to map *Cladophora glomerata*, *Furcellaria lumbricalis*, *Fucus vesiculosus* with multispectral satellite sensors in turbid waters which optical properties resemble those of the open Baltic Sea. However, the depths where the algae can be detected are shallower than the maximum depths where the algae grow.

In waters deeper than just a few meters the differences between the studied bottom types are seen only in band 2 of the multispectral sensors under investigation. It means that multispectral sensors are capable of detecting difference in brightness only in one band which is insufficient for recognition of different bottom types in waters where no or few in situ data is available. Comparing maps obtained from multiple images of multispectral sensors is also questionable as intensity of signal in band 2 may vary due to different illumination, water column or atmospheric conditions not due to change in benthic algae cover.

Configuration of MERIS spectral bands does allow mapping red, green and brow algae provided the algal belts of *Fucus* and *Cladophora* are wider than MERIS spatial resolution. Commercial stock of *Furcellaria lumbricalis* in Estonian Nort-West Archipelago covers area where MERIS 300 m spatial resolution is adequate. However, SNR of the sensor does not allow mapping of *Furcellaria* down to maximum depths where it occurs.

References

Andrefouët S, Muller-Karger FE, Hochberg EJ, Hu C, Carder K L (2001). Change detection in shallow coral reef environments using Landsat 7 ETM+ data. Remote Sens Environ 78: 150-162

Andréfouët S, Kramer P, Torres-Pulliza D, Joyce KE, Hochberg EJ, Garza-Perez R, Mumby PJ, Riegl B, Yamano H, White WH, Zubia M, Brock JC, Phinn SR, Naseer A, Hatcher BG, Muller-Karger FE (2003) Multi-site evaluation of IKONOS data for classification of tropical coral reef environments, Remote Sens Environ 88: 128-143

Andrefouët S, Zubia M, Payri C (2004). Mapping and biomass estimation of the invasive brown algae *Turbinaria ornata* (Turner) J. Agardh and *Sargassum mangarevense* (Grunow) Setchell on heterogeneous Tahitian coral reefs using 4-meter resolution IKONOS satellite data. Coral Reefs 23: 26-38

Call KA, Hardy JT, Wallin DO (2003). Coral reef habitat discrimination using multivariate spectral analysis and satellite remote sensing. Int J Remote Sens 13: 2627-2639

Dekker AG, Brando VE, Anstee JM, Pinnel N, Kutser T, Hoogenboom EJ, Peters S, Pasterkamp R, Vos R, Olbert C, Malthus TJM (2001). Imaging spectrometry of water. In: FD van der Meer, SM de Jong (eds.) Imaging Spectrometry: Basic Principles and Prospective Applications. Kluwer Academic Publishers, Dordrecht.

Fyfe SK (2003). Spatial and temporal variation in spectral reflectance: Are seagrass species spectrally distinct? Limnol. Oceanogr 48: 464-479

Gordon HR, Brown OB, Jacobs MM (1975) Computed relationships between the inherent and apparent optical properties of a flat, homogenous ocean. Appl Optics 14: 417-427

Hochberg EJ, Atkinson MJ (2000). Spectral discrimination of coral reef benthic communities. Coral Reefs*:* 19: 164-171

Hochberg EJ, Atkinson MJ (2003). Capabilities of remote sensors to classify coral, algae, and sand as pure and mixed spectra. Remote Sens Environ 85: 174-189

Jupp DLB, Mayo KK, Kuchler DA, Classen DVR, Kenchington RA, Guerin PR (1985) Remote sensing for planning and managing the Great Barrier Reef of Australia. Photogrammetria 40: 21-42

Karpouzli E, Malthus TJ, Place CJ (2004). Hyperspectral discrimination of coral reef benthic communities in western Caribbean. Coral Reefs 23: 141-151

Kirk JTO (1984) Dependence of relationship between inherent and apparent optical properties of water on solar altitude. Limnol Oceanogr 29: 350-356

Kutser T. (1997) Estimation of water quality in turbid inland and coastal waters by passive optical remote sensing. Dissertationes Geophysicales Universitas Tartuensis, 8, Tartu University Press.

Kutser T, Skirving W, Parslow J, Done T, Clementson L, Wakeford M, Miller I (2000) Hyperspectral detection of coral reef health**.** Proc 10th Australasian Remote Sens Conf, Adelaide, CD-ROM**.**

Kutser T, Herlevi A, Kallio K, Arst H (2001) A hyperspectral model for interpretation of passive optical remote sensing data from turbid lakes. *The Science of the Total Environ* 268: 47-58

Kutser T, Jupp DLB (2002). Mapping coral reef benthic habitat with a hyperspectral space borne sensor. Proc Ocean Optics XVI, Santa Fe, CD-ROM

Kutser T, Dekker AG, Skirving W (2003). Modeling spectral discrimination of Great Barrier Reef benthic communities by remote sesing instruments. Limnol Oceanogr 48: 497-510

Kutser T (2004) Quantitative detection of chlorophyll in cyanobacterial blooms by satellite remote sensing. Limnol Oceanogr 49: 2179-2189

Maritorena S, Morel A, Gentili B (1994) Diffuse reflectance of oceanic shallow waters: Influence of water depth and bottom albedo. Limnol Oceanogr 37: 1689-1703

Martin G, Torn K. (2004) Classifdication and description of phytobenthic communities in the waters of the West-Estonian Archipelago Sea. Hydrobiol 514: 151-162

Mäekivi S, Arst H (1996) Estimation of the concentration of yellow substance in natural waters by beam attenuation coefficient spectra. Proc Estonian Acad Sci, Ecol 6: 108-123

Metsamaa L, Kutser T, Strömbeck N, (2005). Recognising cyanobacterial blooms based on their optical signature. Harmful Algae (submitted).

Mumby PJ, Green EP, Edwards AJ, Clark CD (1997). Coral reef habitat-mapping: how much detail can remote sensing provide? Marine Biol 130: 193-202

Mumby PJ, Edwards AJ (2002). Mapping marine environments with IKONOS imagery: enhanced spatial resolution can deliver greater thematic accuracy. Remote Sens Environ 82: 248-257

Pasqualini V, Pergent-Martini C, Pergent G, Agreil M, Skoufas G, Sourbes L, Tsirika A (2005). Use of SPOT 5 for mapping seagrasses: An application to *Posidonia oceanica.* Remote Sens Environ 94: 39-45

Purkis S, Kenter JAM, Oikonomou EK, Robinson IS (2002). High-resolution ground verification, cluster analysis and optical model of reef substrate coverage on LandsatTM imagery (Red Sea, Egypt). Int J Remote Sens 8: 1677-1698

Smith RC and Baker KS (1981) Optical properties of the clearest natural waters (200-800 nm). Appl. Optics 20: 177-184

Vahtmäe E, Kutser T, Martin G (2005) Feasibility of hyperspectral remote sensing for mapping benthic algal cover in turbid coastal waters – a Baltic Sea case study. Rem Sens Environ (submitted).

Werdell PJ, Roesler CS (2003). Remote assessment of benthic substrate composition in shallow waters using multispectral reflectance. Limnol Oceanogr 48: 557-567

Captions to figures

Fig.1. Reflectance spectra of sand and studied benthic algae species measured with GER1500 spectrophotometer.

Fig. 2. Reflectance spectra of sand and studied benthic algae species resampled for spectral resolution of multispectral sensors (A) Landsat, ALI, and IKONOS, (B) MERIS.

Fig.3. Spectral differences between simulated reflectance spectra (A) sand and deep water. (B) Green algae and deep water. (C) Brown algae and deep water. (D) Red algae and deep water. Calculations are made for various water depths indicated in the legend. Each marker represents the central wavelength of a multispectral sensor band (ALI, Landsat, IKONOS).

Fig.4 Spectral differences between simulated reflectance spectra (A) Red algae and deep water. (B) Sand and red algae. (C) Green algae and red algae. (D) Red algae and brown algae. Calculations are made for various water depths indicated in the legend. Each marker represents the central wavelength of MERIS.

Table 1. Concentrations of optically active substances used in model simulations

Water type	C_{Chl}	C_{SM}	$a_{CDOM}(400)$
1	6	6	15
2	10	5	3
3	2	2	1.5
	mg/m^3	mg/l	m^{-1}

Table 2. Visible bands and signal to noise (SNR) factors of sensors under investigation

Spectral band	ALI Wavelength (nm)	IKONOS Wavelength (nm)	Landsat 7 Wavelength (nm)	MERIS Wavelength (nm)
1	450-515	450-520	450-520	407.5-417.5
2	525-605	510-600	530-610	437.5-447.5
3	630-690	630-700	630-690	485-495
4				505-515
5				555-565
6				615-625
7				660-670
8				677.5-685
9				703.75-713.75
	SNR	SNR	SNR	SNR
	250:1	100:1	100:1	200:1

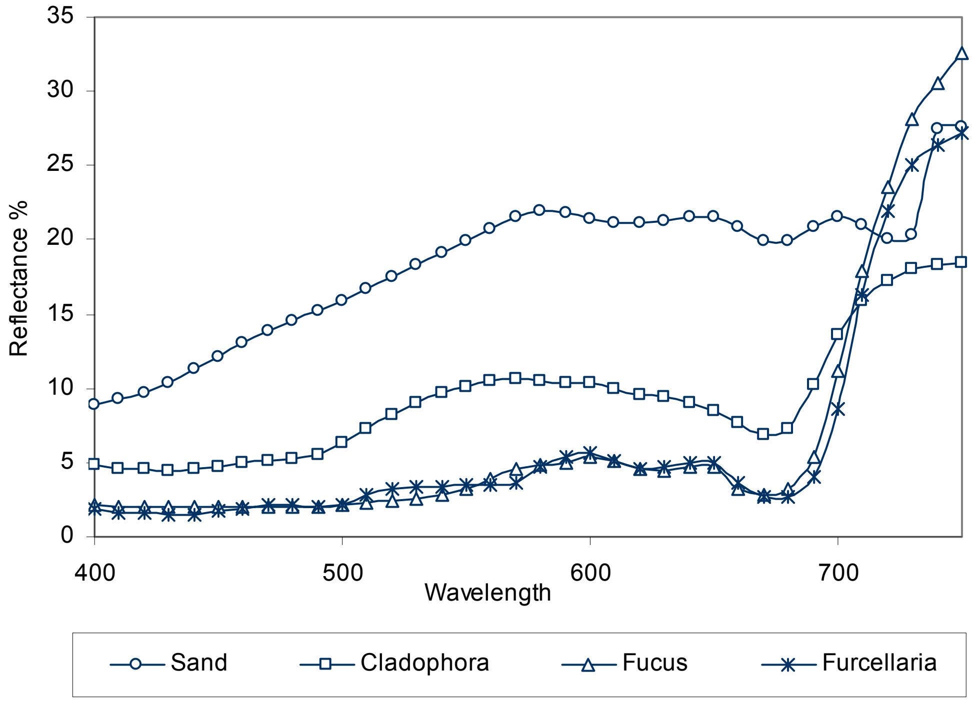
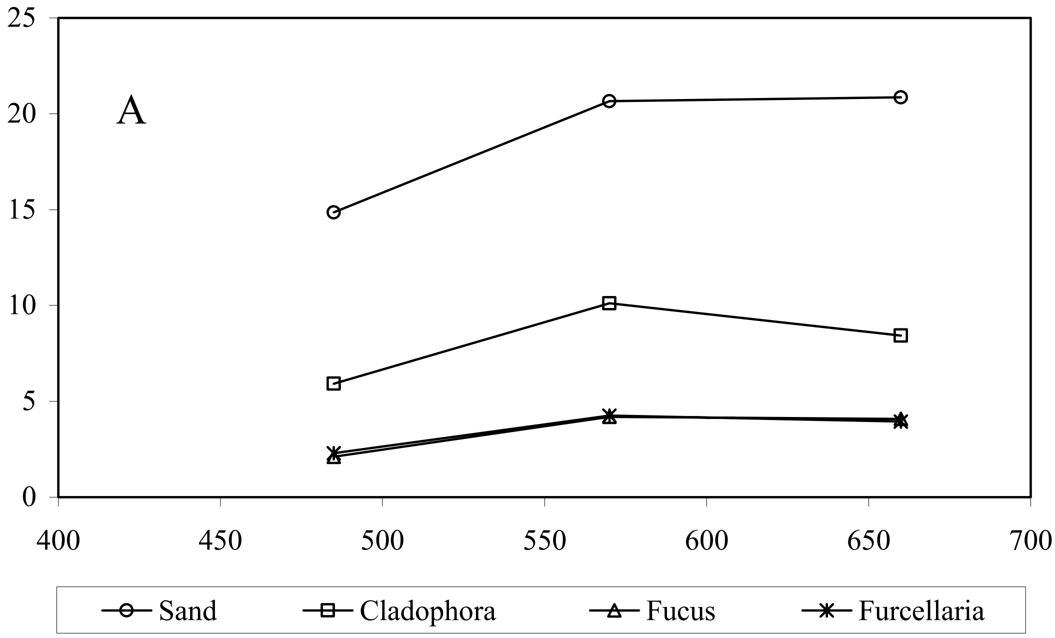

35
30
25
20
15
10
5
0
Reflectance %
400
500
600
700
Wavelength
Sand
Cladophora
Fucus
Furcellaria

Fig. 1


25
20
15
10
5
0
A
400
450
500
550
600
650
700
Sand
Cladophora
Fucus
Furcellaria

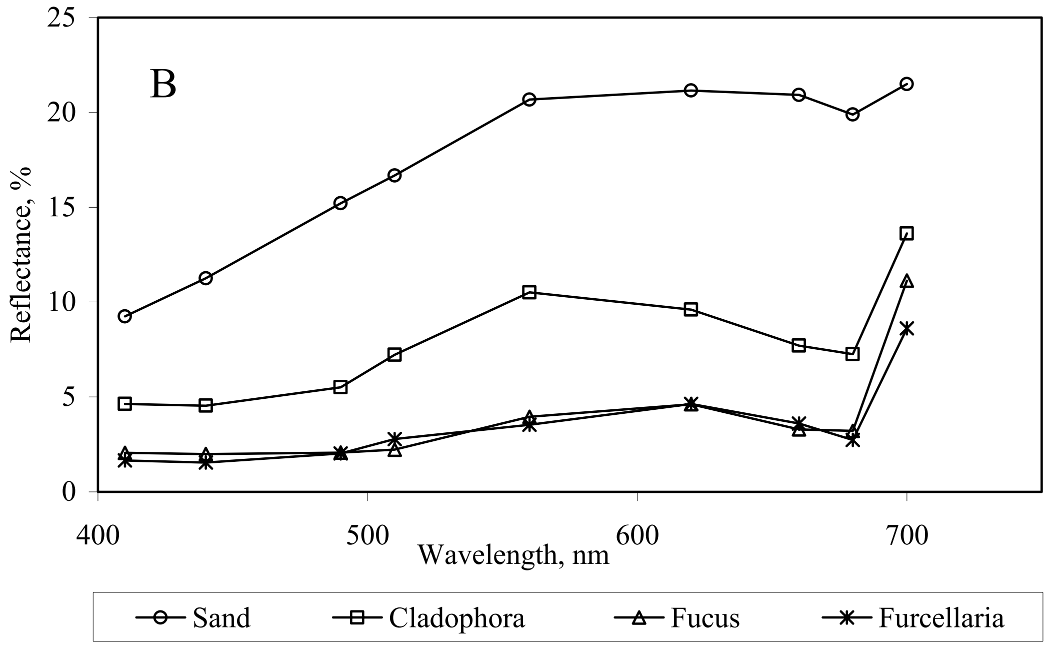

25
20
15
10
5
0
B
Reflectance, %
400
500
600
700
Wavelength, nm
Sand
Cladophora
Fucus
Furcellaria

Fig. 2

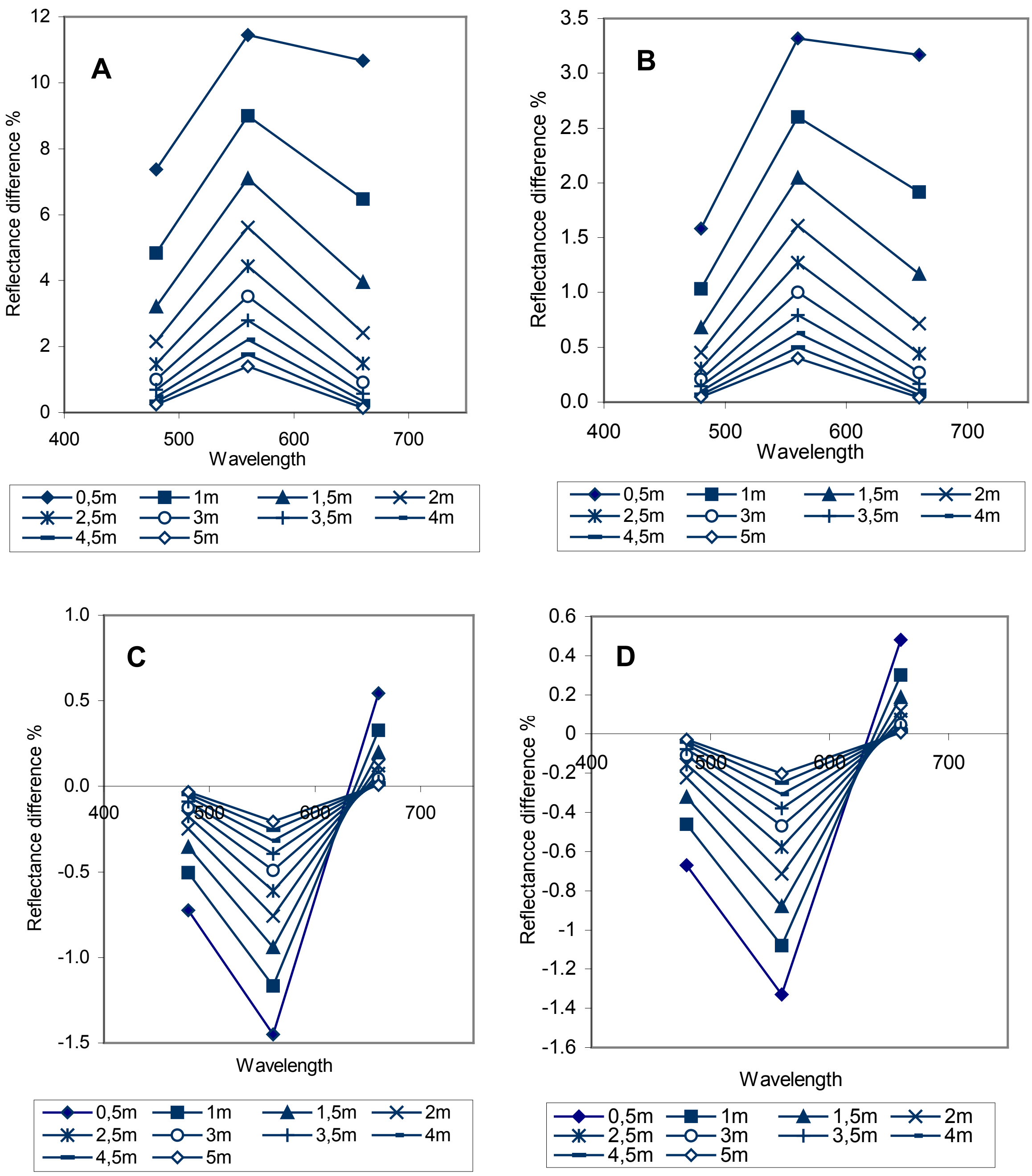

A
B
C
D
Reflectance difference %
Reflectancce difference %
Wavelength
0,5m
1m
1,5m
2m
2,5m
3m
3,5m
4m
4,5m
5m

Fig. 3

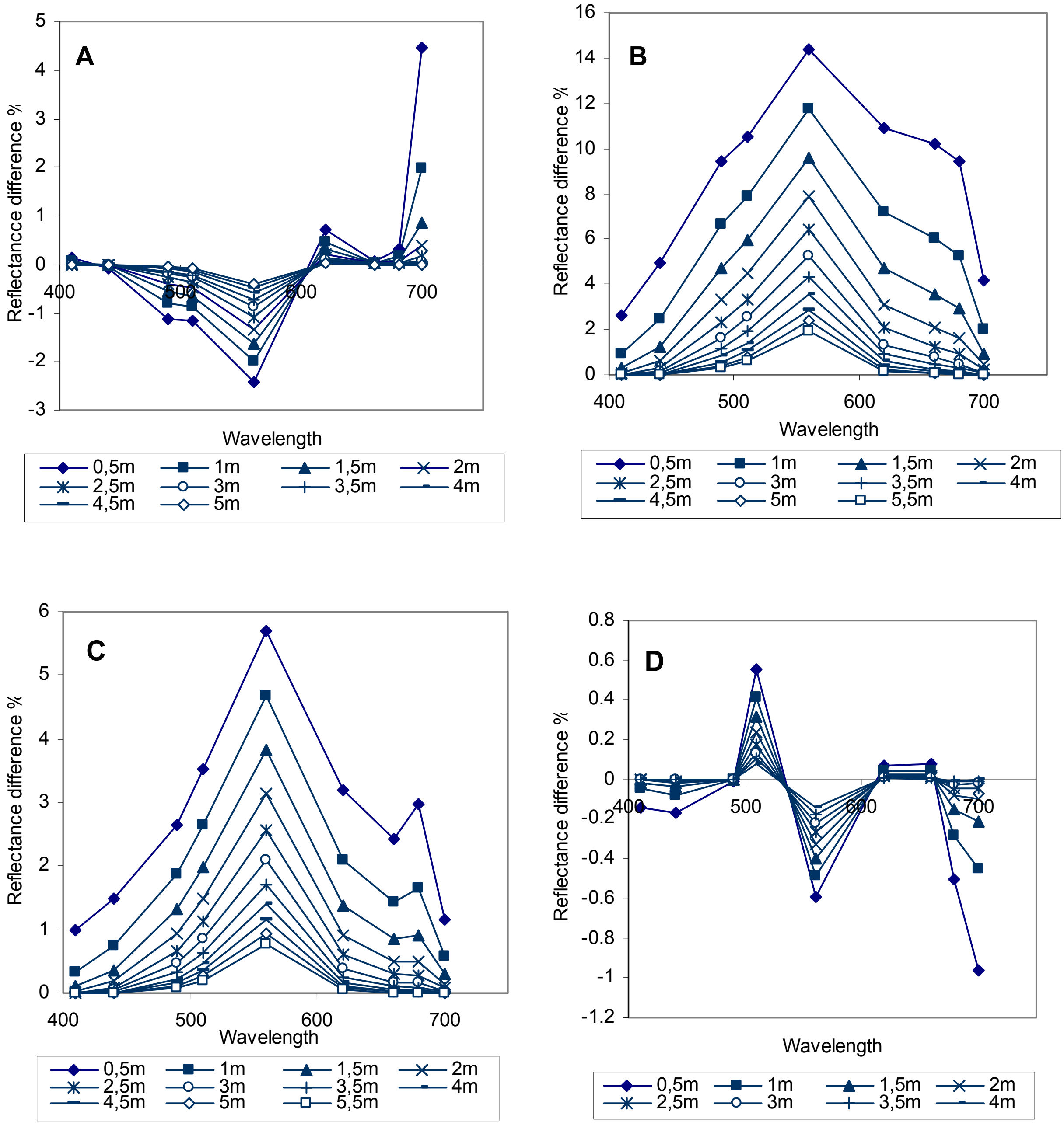

A
Reflectance difference %
Wavelength
400
500
600
700
0,5m
1m
1,5m
2m
2,5m
3m
3,5m
4m
4,5m
5m
B
Reflectance difference %
Wavelength
0,5m
1m
1,5m
2m
2,5m
3m
3,5m
4m
4,5m
5m
5,5m
C
Reflectance difference %
Wavelength
0,5m
1m
1,5m
2m
2,5m
3m
3,5m
4m
4,5m
5m
5,5m
D
Reflectance difference %
Wavelength
0,5m
1m
1,5m
2m
2,5m
3m
3,5m
4m

Fig. 4