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SOFT-BOTTOM NEAR-SHORE ECOSYSTEMS

Satellite-based monitoring of tropical seagrass vegetation: current techniques and future developments

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Abstract Decline of seagrasses has been documented in many parts of the world. Reduction in water clarity, through increased turbidity and increased nutrient concentrations, is considered to be the primary cause of seagrass loss. Recent studies have indicated the need for new methods that will enable early detection of decline in seagrass extent and productivity, over large areas. In this review of current literature on coastal remote sensing, we examine the ability of remote sensing to serve as an information provider for seagrass monitoring. Remote sensing offers the potential to map the extent of seagrass cover and monitor changes in these with high accuracy for shallow waters. The accuracy of mapping seagrasses in deeper waters is unclear. Recent advances in sensor technology and radiometric transfer modelling have resulted in the ability to map suspended sediment, sea surface temperature and below-surface irradiance. It is therefore potentially possible to monitor the factors that cause the decline in seagrass status. When the latest products in remote sensing are linked to seagrass production models, it may serve as an early-warning system for seagrass decline and ultimately allow a better management of these susceptible ecosystems.

Keywords Remote sensing · Seagrass productivity · Early-warning system · Radiative transfer modelling

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Resilience and Restoration of Soft-Bottom Near-Shore Ecosystems

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Introduction

Soft-bottom marine ecosystems, such as seagrass meadows and mangroves, play an important role as nursing grounds and feeding grounds for endemic as well as reef and open ocean marine animals (Sogard et al., 1989; Bell et al., 1992; Hasbún et al., 2000; Hyndes et al., 2003; Cocheret De La Moriniare et al., 2004; Milagros López-Mendilaharsu et al., 2005). As a result, species richness in these systems is relatively high. This high diversity has been named as the main regulator for seagrass-system functioning and is thought to enhance secondary production (Duffy et al., 2003): small grazing fish may remove epiphytes from seagrasses, increasing light availability, resulting in increased seagrass biomass, shoot number, and rates of primary productivity (Heck et al., 2000). With globally declining fish numbers (Myers & Worm, 2003) and severe decreases in populations of several marine herbivores including seaturtles and manatees or dugongs (Jackson et al., 2001), understanding the mechanisms that control their primary resources becomes important.

The present paper provides a review of current remote sensing techniques for mapping seagrass ecosystems. It highlights possible improvements of traditional techniques through the development of radiative transfer theory, and points out how these (empirical and physical-based) techniques can be linked with process-oriented (dynamic) models of seagrass functioning. These can then be used as a basis for early-warning and management systems. The paper starts with an introduction outlining the importance of seagrass ecosystems as well as threats to which these ecosystems are presently exposed. The paper then continuous with an explanation of radiative transfer theory, and how this adds to the understanding of current limits for mapping seagrass meadows and their environment. This provides the theoretical framework required to make better use of data sets from multiple sensors and from new sensor developments (i.e., hyperspectral imagery). By pointing out the link between remote sensing techniques and process-oriented models of seagrass functioning, we show how early-warning and management systems could integrate spatial information and process understanding.

Importance and threats of seagrass ecosystems

Disturbance of seagrass ecosystems

A decline in the cover of seagrasses has been documented in many parts of the world. Green & Short (2003) estimated that in 2000 seagrass meadows globally occupied 177,000 km^2. An initial global decline estimate of 900 km^2 over 10 years, based on documented losses (Short & Wyllie-Echeverria, 1996), was corrected towards a decline of 33.000 km^2 in twenty years corresponding to 15% of the total (Green & Short, 2003). These figures however, are highly uncertain and most likely represent underestimates while seagrass extent and losses remain unknown or inaccurately reported in many parts of the world (Green & Short, 2003).

Reduction in water clarity through increased turbidity and nutrient concentrations is considered to be the primary cause of seagrass loss (Short & Wyllie-Echeverria, 1996; Duarte, 2002). Increased sediment loads directly affect seagrass productivity by reducing the light intensity, which drives the photosynthesis in canopy tissue pigments. As in all plant species, at irradiance levels below the light compensation point photosynthesis is lower than respiration (Bazzaz, 1979). The photosynthesis levels strongly increases from irradiance levels below light compensation point, and levels off towards a maximum photosynthetic rate at irradiance levels. Species differ considerably in these parameters that describe their photosynthetic response to light (Bazzaz, 1979; Vermaat et al., 1997). With increasing depth, light intensities decrease, and light is the factor limiting the downward distribution of seagrasses, which is set by the depth where irradiance levels drop below the light compensation point (Hemminga & Duarte, 2000).

The downward boundary where seagrasses can still occur is strongly affected by the presence of dissolved material and suspended matter, which increase absorption and scattering of light. Carruthers & Walker (1999) considered this turbidity-related light stress as a major driver structuring seagrass habitat in tropical Australia. Although slowly settling suspended particles strongly reduce light attenuation within the water column, they may also contribute to nutrient fluxes (Van Duin et al., 2001). Nutrients directly influence seagrass productivity by stimulating growth and increasing foliar nutrient levels (Inversa et al., 2004). Increased nutrient levels may however at the same time have an indirect negative effect when macroalgae and phytoplankton benefit from these nutrients (Deegan et al., 2002) and consequently shade the seagrasses underneath (Gacia et al., 1999). The increased foliar nutrient levels in seagrass and algae may result in increased herbivore pressure (Boyer et al., 2004), but it appears that fish–algal interactions have only limited capacity to buffer the consequences of eutrophication for seagrass growth (Gacia et al., 1999).

Land–water interactions

The role of eutrophication and sedimentation in seagrass loss may differ geographically. Short (2005) remarked that while seagrass loss in the temperate zone comes from increased inputs of nitrogen and phosphorus along more industrialized coasts, in many tropical environments it is primarily caused by sediment discharge into coastal waters, due to watershed deforestation and mangrove clearing. This has been confirmed by Ananda & Herrath (2003) who remarked that increasing population densities and land use intensification resulted in increased erosion throughout the world. Land use change such as the conversion of forest to arable lands may lead to erosion and increased levels of sediment entering the river system. The associated discharge of waste-water and leaching from agro-ecosystems increases riverine nutrient concentrations (Haynes & Michalek-Wagner, 2000; Garnier et al., 2005). These eroded sediments and nutrients eventually end up in the coastal zone. Seagrass systems near river mouths are thus exposed to an increasing influx of sediments and nutrients.

Monitoring requirements

In a synopsis on the status of monitoring techniques and the extent of decline of seagrass ecosystems, Duarte (2002) mentions "*The low power of monitoring techniques implies that most monitoring programmes can only detect a reliable tendency towards seagrass loss when the seagrass meadows monitored have already experienced substantial damage. There is, therefore, an urgent need to design more effective monitoring approaches, capable of detecting losses of 10% or less, as well as to develop early-warning indicators of decline*." He furthermore continues "*Yet, even an optimistic analysis clearly indicates that monitoring efforts cannot possibly encompass but a minimum (< 0.01%) fraction of the world's seagrass extent, although the implementation of seagrass monitoring programmes has increased over the past decades*". This clearly states the importance of developing monitoring techniques which are sensitive enough to map even small alterations in these threatened ecosystems and which provide at the same time a large spatial coverage. As the observed decline is frequently the result of changing water quality, not only the seagrass meadows should be monitored but also the habitat characteristics influencing the seagrass growth conditions (i.e., water clarity, temperature, etc.).

Pertaining to the above stated requirements, remote sensing techniques seem well adopted for providing the necessary information. Satellite sensors offer large spatial coverage with frequent revisit capabilities at low costs. So far, however, the synoptic overview capabilities of aerial photographs or satellite imagery have typically been used to monitor change in seagrass meadow distribution or cover (Kirkman, 1996; Chauvaud et al., 1998; Mumby et al., 1999; Robinson et al., 2001). Yet, remote sensing has a potential to offer more than localizing the distribution of seagrass meadows. Remote sensing may also be used to detect environmental conditions affecting seagrass status, such as the detection of sediment plumes (Burrage et al., 2003; Nezlin et al., 2005). In terrestrial systems remote sensing has been applied to detect concentrations of foliar nitrogen (Lilienthal et al., 2000; Mutanga et al., 2003; Ferwerda et al., 2005; Skidmore et al., 2005) and photosynthesis levels (Zhao et al., 2005) in plants. The potential of using remote sensing for monitoring environmental factors influencing seagrass loss has thus far little been explored.

The introductory paragraph has outlined the ecological importance of seagrass ecosystems as well as causes for the observed decline. It has made clear that remote sensing techniques are required both for direct monitoring of the seagrass meadows and for mapping main environmental factors determining their growth conditions. By mapping seagrass status and environmental conditions influencing seagrass growth, remote sensing provides valuable inputs for ecological simulation models, summarizing and formalizing current knowledge about seagrass functioning. As will be shown later, such models are valuable tools for developing seagrass management and conservation programs.

Current remote sensing techniques

Specific considerations for remote sensing of coastal waters

Because of its translucent nature, water poses some specific remote sensing challenges. From a remote sensing perspective, water bodies can be classified as either case I or case II water bodies. Case I water bodies are generally deep, clear and consequently are non-coastal oceanic water bodies, or in a few very deep lakes. As a direct consequence to their proximity to land masses, waters in the coastal zone (case II waters) are optically complex (Bukata et al., 2001). The optical properties of case II waters are influenced not only by phytoplankton and the substances originating from the phytoplankton's life cycle, but also by other matters independent of phytoplankton (Pozdnyakov et al., 2005). The multiple water constituents, together with the eventually influence of the seafloor, makes the mapping of coastal waters more difficult than to case I waters.

Remote sensing data is acquired through a scattering and absorbing atmosphere, and the presence of atmospheric perturbations requires attention. From this perspective the analysis of case I waters is relatively straightforward, as the atmospheric correction of the recorded signal can be accomplished with high accuracy (Rao et al., 1989; Gordon & Wang, 1994; Tanré et al., 1997). The atmospheric aerosols over case I waters contain mostly marine particulate matter, generally homogenously spatially and chemically. Its optical properties are fairly well established and, hence, can be adequately assessed (Pozdnyakov et al., 2005). On the contrary, due to their proximity to land masses, the aerosols over case II waters reveal a pronounced spatial and compositional heterogeneity. Aerosols over coastal areas originate from a wealth of different sources, often anthropogenic in nature (Pozdnyakov et al., 2005). Consequently, the atmospheric correction over such areas is complicated and the resulting water spectra of lower quality.

Mapping seagrass distribution

Aerial photography has been used for long to map seagrass ecosystems, and maps derived through aerial photo interpretation have typically been used to establish a historic base line in seagrass loss studies. Satellite-borne multi-spectral scanners available since the 1970's offer an alternative to mapping seagrasses. Ferguson & Korfmacher (1997) however, considered the high spatial resolution and the ability to plan the acquisition time a major advantage of aerial photographs over Landsat imagery with a 30 m pixel size.

Since a number of years high spatial resolution multi-spectral (MS) imagery is available for example from SPOT 5 (2.5–10 m) and IKONOS (1 m). Hyperspectral (HS) scanner offers the possibility to record reflected and emitted radiation in many (~100) small spectral bands. The development of high spatial resolution imagery bridges the resolution gap with aerial photography, and makes satellite imagery together with its larger spatial extent and cost efficiency suitable for operational mapping of seagrass cover (Pasqualini et al., 2005). Compared to multi spectral sensors which scan the Earth in 4–8 broad spectral bands, the hyperspectral imagers offer information at many more small spectral wavelengths, located around typical absorption bands. These developments in sensor technology allow production of higher resolution maps of seagrass distribution (Mumby & Edwards, 2002) and better discrimination of seagrasses from other coastal environments and the detection of individual species (Dekker et al., 2005). Mumby & Edwards (2002) for instance compared hyperspectral CASI (5 m ground resolution) and multispectral, IKONOS (1 m), SPOT (20 m) and Landsat imagery (30 m) in their ability to map detailed habitat classes (up to species level) and coarse habitat level (substrate and/or cover) of coastal zones. CASI and IKONOS both were very successful at mapping the area covered by seagrass (85–90% accuracy). However, Landsat data was less accurate, at 59%.

Dekker et al. (2005) used Landsat TM data to detect changes in seagrass communities in a coastal lagoon (< 2m), and were able to determine shifts in species composition. It is important to note however, that this study was performed in a shallow lagoon with most seagrass occurring in very shallow water (< 0.5m). Discrimination of individual seagrass species or of seagrasses from other coastal bottom classes becomes more difficult with increased depth, because the proportion of reflectance reaching the remote sensing device, which can be attributed to the seagrass canopy, will diminish with depth.

Under favourable measurement conditions (i.e., clear water), seagrass meadows have been mapped at greater depths. For example, Pasqualini et al. (2005) mapped *Poseidonia oceanica* at depths from 0 to 20 m with 73% to 96% accuracy. In general, however, the discrimination of seagrasses from other bottom types and/or the identification of habitat classes becomes more difficult with increased depth. Duarte (1991) reported that the depth limit of seagrasses occurs at light intensities of 11% of that just below the sea surface. Assuming similar attenuation for the upwelling radiance would imply that only 1% or less of the incident light will be reflected by the canopy or other bottom types and captured by the remote sensing device. As a consequence, confusion of seagrasses with other bottom types increases with increasing water depth as their contribution to the total radiation flux received by the scanner diminishes. At the same time, with increasing water depth, the (negative) effects of any increase of turbidity on seagrass growth become more pronounced, and a slight decrease in light attenuation may reduce light intensity below the light compensation point. Hence, at those water depths where seagrass decline becomes relevant to monitor, remote sensing techniques become less accurate. It raises the question how appropriate current remote sensing techniques are for monitoring seagrass decline. So far this problem received little attention in the remote sensing community. Dedicated studies are required to evaluate the influence of optical water depth on the accuracy of remotely sensed sea bottom type classifications.

Mapping sediment concentrations and light climate

It has been recognised since long that remote sensing can be used to monitor the distribution of sediment plumes in coastal environments (e.g., Harrington et al., 1992; Ruhl et al., 2001; Hu et al., 2004). Water quality assessment of ocean and inland waters using satellite data has been carried out since the first remote sensing satellite Landsat-MSS became operational (Thiemann & Kaufmann, 2002). Today, there are many satellites which have high enough resolution for use in water quality monitoring studies.

Photons travelling through water are subjected to interactions with the water molecules and the encountered organic and inorganic colour producing agents (CPA), coexisting within the water column (Bukata et al., 2001). This leads to essential alterations of the spectral composition of the upwelling radiative flux which is perceived (by the human eye) as colour. The various existing water colours show that the backscattered flux contains information about the optical properties and composition of the water column. Hence, satellite sensors that measure the reflected flux at multiple wavelengths are, in principle, able to observe in-water parameters and associated processes (Kester et al., 1996; Dey & Singh, 2003; Pozdnyakov et al., 2005). Although broad-band Landsat-TM, SPOT HVR, or Linear Imaging Self-Scanning Sensor (LISS-III) satellite data can not be analysed for retrieval of specific absorption characteristics due to the broad bandwidths, they offer the advantage of large area coverage and multi-temporal use. In addition, the Landsat series of satellites provides the longest continuous dataset of high-spatial-resolution imagery of Earth, with data available back to 1972.

The general approach for mapping water constituents by remote sensing is based on the use of spectral bands ranging from blue to near infrared, as only shortwave radiation penetrates appreciably into the water column (Brivio et al., 2001). To explore the relationship between the spectral signature of a water body and the water's biophysical parameters, both linear and non-linear models have been developed (Zhang et al., 2002; Darecki et al., 2003; Kishino et al., 2005). For mid-oceanic (case I) waters, regression models are even processed operationally (Esaias et al., 1998; Carder et al., 2004).

In the case of mid-oceanic (case I) waters, simple algorithms are effective due to the optical simplicity of such waters (Pozdnyakov et al., 2005). Case I waters are generally only loaded with phytoplankton and accompanying and co-varying products of their life cycle as well as some microscopic organisms (e.g., flagellates, bacteria, viruses) which are also native to off-shore waters. Due to the optical simplicity of these waters, relatively close relationships can be established between the spectral signature and the concentration of phytoplankton (or chlorophyll). As already pointed out, the analysis of case I waters is also relatively straightforward as the atmospheric correction of the recorded signal can be accomplished with high accuracy.

The task of analysing coastal (case II) waters is much more complicated. Bilge et al. (2003) performed a linear regression analysis between Landsat TM bands 1–4 and suspended sediments, chlorophyll a, and transmitted light intensity depth, which resulted in regression sum of squares ranging between 0.8 and 0.95. However, this study was performed only once, and did not test the predictive capabilities of the models. Nezlin et al. (2005) used Sea-viewing Wide Field-of-view Sensor (SeaWiFS) imagery to assess the factors influencing the extent of sediment plumes. They found that the primary factors regulating the relationship between rainstorms and sediment plumes were watershed land-use characteristics, size, and elevation. Burrage et al. (2003) used a prototype Scanning Low Frequency Microwave Radiometer (SLFMR) to describe the structure and extent of a river plume. The SLFMR was found to have sufficient precision (1 psu) and accuracy (3 psu) to provide a useful description of plumes emanating from estuaries of moderate discharge levels. The main disadvantage of these regression techniques is that the models remain empirical and are highly site specific.

The analysis of case II waters is also more complicated compared to the analysis of case I waters, as coastal waters may contain large amounts of inorganic/terrigenous particulate matter in suspension and dissolved organic matter, which seldom, if ever, covary (Bukata et al., 2001). The contents of these additional CPAs are often abundant enough to compete with phytoplankton in influencing the resulting optical properties of case II waters (Pozdnyakov et al., 2005). Hence, when remotely observing case II waters, it is impossible to retrieve the concentration of a single component without also inferring simultaneously the content of the other major water constituents (Pozdnyakov et al., 2005).

Non-perfect atmospheric correction of coastal imagery inevitably leads to large uncertainties in the retrieved water constituents, as the water leaving radiance (the "useful" signal) is very low compared to the (perturbing) atmospheric "fingerprint" (Mélin & Zibordi, 2005). As a consequence, models developed for case II waters often have a strong local and seasonal character. A generalization of regional algorithms to larger scales and/or different seasons generally fails (Kutser et al., 2001; Mélin & Zibordi, 2005)

Mapping foliage composition

Remote sensing is particularly suitable for mapping continuous variables, such as the chemical composition of vegetation foliage. For mapping the chemical composition of vegetation, absorption bands must be detected that are often spectrally narrow. Hence, for this kind of application, hyperspectral (HS) remote sensing is best suited. Over the past decades, HS remote sensing (imaging spectroscopy) has developed from a laboratory-based technique, used to measure the chemical composition of standardized, dried and ground samples (Marten et al., 1985), to an experimental technique used to measure vegetation characteristics from airplanes and satellites (Secker et al., 2001; Williams & Hunt, 2002; Underwood et al., 2003; Schmidtlein & Sassin, 2004).

Nutrient detection, and in particularly nitrogen detection, is often done using a combination of bands which are sensitive to chlorophyll concentration. The strong relationship between foliar nitrogen and chlorophyll (Baret & Fourty, 1997; Zhao et al., 2005) makes this a valid approximation. One important step towards linking the chemical concentration of vegetation to remotely sensed data is the selection of meaningful wavelengths to include in the model. Curran (1989) generated an overview of wavebands related to a wide range of chemical components in fresh vegetation, and the related chemical bonds. More recently, Soukupova et al. (2002) did the same, specifically for condensed tannins and lignin. In a recent study, Mutanga & Skidmore (2004) showed that it is possible to map variation in nitrogen content in savannah vegetation by using a neural network to relate grass nitrogen concentrations to hyperspectral HyMap imagery.

The mentioned studies have looked at terrestrial applications. To our knowledge, no studies have been published that look at the foliar chemical composition of seagrasses using hyperspectral data. Only for oceanic waters, the (medium resolution) MODIS chlorophyll products deliver highly accurate maps of chlorophyll a concentration (phytoplankton) (Carder et al., 2004).

Mapping water temperature

In seagrass ecosystems, water temperature is an important habitat characteristic. The (skin) temperature of a water body can be remotely mapped as the emitted radiation of a water surface increase with temperature, as formalized in Planck's law.

Nowadays, several datasets are available which can be used to derive water temperature (e.g., SeaWiff, AVHRR). With the launch of the MODIS (Moderate Resolution Imaging Spectrometer) sensor on board of the NASA Terra/Aqua satellites, calibrated ocean temperature images are available with a worldwide coverage, and an accuracy of up to 0.2 degrees Kelvin (Esaias et al., 1998). Although the pixel size of this sensor is large (1 km^2), this is probably the best ocean surface temperature data set available.

Radiative transfer modelling

To overcome the reliance on statistical methods, radiative transfer models (also called bio-optical models) have been developed. Through the application of sound physical modelling, it is no longer essential to take water samples synchronously with the sensor overflight for calibrating the regression models (Dekker et al., 2001b). This makes the physical approach much more flexible. For example, using bio-optical models, spectral measurements from different sensors (with different band settings, different bandwidths and/or recorded under various view/illumination angles) can be pooled together for model inversion. This greatly reduces the confidence intervals of the final data products (Maritorena & Siegel, 2005). Moreover, several water constituents can be retrieved simultaneously (Bukata et al., 2001). From radiative transfer theory, limits of current empirical regression approaches can also be better understood. Probably, the full information content of hyperspectral imagery can be best analysed using bio-optical models as these models can be inverted even with highly redundant input data.

Most existing bio-optical models are very similar and are based on the theoretical framework first developed by Gordon et al. (1975). In case of optically deep waters (i.e., waterbodies where no light reaches the seafloor), the subsurface reflectance just underneath the water surface, R_∞^- at wavelength λ, can according to (Dekker et al., 2001a) be expressed as:

$$R_\infty^-(\lambda) = (0.975 - 0.629\mu_0)\frac{b_b(\lambda)}{a(\lambda) + b_b(\lambda)} \quad (1)$$

where μ_0 is the cosine of the solar zenith angle under the water surface (i.e., by taking the refraction at the air-water surface into account). The spectral absorption, a(λ), (m^{-1}) and backscattering coefficients, $b_b(\lambda)a$, (m^{-1}) represent inherent optical properties of the water body. They are closely related to the concentrations of optically active water constituents and the optical properties of the materials themselves. For example, the total absorption coefficient of a water column, $a(\lambda)$, can be further developed into four additive coefficients which describe the absorption of water (a_W), yellow substances (a_Y), detrital material (a_D) and phytoplankton (a_{PH}):

$$a(\lambda) = a_W(\lambda) + a_Y(\lambda) + a_D(\lambda) + a_{PH}(\lambda) \quad (2)$$

Similarly, the total backscattering coefficient, $b_b(\lambda)$, can be related to two separate components: water (b_{bW}) and particles of all kind (b_{bP}):

$$b_b(\lambda) = b_{bW}(\lambda) + b_{bP}(\lambda) \quad (3)$$

The spectral absorption and backscattering coefficients of pure water, $a_W(\lambda)$, and $b_{bW}(\lambda)$, can be found in many textbooks (Pope & Fry, 1997). The remaining non-water coefficients can be modelled as a function of the chlorophyll a concentration (C_{CHL}), gthe concentration of yellow substances (C_Y), the concentration of suspended particulate organic matter (C_{SPOM}), the concentration of particulate matter (C_P), and wavelength (λ in nm):

$$a_{PH}(\lambda) = \theta^a_{PH(\lambda)} \cdot C_{CHL}^{-\theta^b_{PH(\lambda)}} \cdot C_{CHL} \text{(Bricaud et al., 1995)} \quad (4.1)$$

$$a_Y(\lambda) = \theta^a_Y \cdot C_Y \cdot e^{-\theta^b_Y(\lambda-400)} \text{(e.g., Kutser et al., 2001)} \quad (4.2)$$

$$a_{SPOM}(\lambda) = \theta^a_{SPOM} \cdot C_{SPOM} \cdot e^{-\theta^b_{SPOM}(\lambda-400)} \text{ (e.g., Pierson \& Strombeck, 2001)} \quad (4.3)$$

$$b_{bP}(\lambda) = \theta^a_P \cdot C_P \cdot \left(\frac{\lambda}{443}\right)^{-\theta^b_P} \quad (4.4)$$

(e.g., Maritorena & Siegel, 2005)

In the case of optically shallow waters where light reaches the seafloor, the spectral reflectance of the bottom (sediment plus vegetation), $R_B(\lambda)$, and the water depth, z, have to be taken into account in order to calculate the shallow water reflectance (Dekker et al., 2001a):

$$R^-_{SW}(\lambda) = R_B(\lambda) \cdot e^{-2K(\lambda)z} + R^-_\infty(\lambda) \cdot \left(1 - e^{-2K(\lambda)\cdot z}\right) \quad (5)$$

$$\text{with}: K(\lambda) = \frac{a(\lambda)}{\mu_0} \cdot \left(1 + \frac{b_b(\lambda)}{a(\lambda)}\right) \text{(Gordon et al., 1975)} \quad (6)$$

Prospects of radiative transfer models

Equations 1–6 provide the theoretical framework for analyzing (hyperspectral) remote sensing data of shallow coastal waters. To make use of the theoretical framework, one has to distinguish between parameters representing (unknown) concentrations of the various water constituents (C_{CHL}, C_P, C_{SPOM}), and parameters that define the spectral shape of absorption and backscattering coefficients (in vector θ). The latter parameters have to be calibrated using an appropriate (in situ) data set, but can be assumed to be stable. To calibrate the unknown parameters, it is necessary to acquire an in situ data set with simultaneous measurements of the subsurface reflectance, $R^-_\infty(\lambda)$, as well as the concentrations of the optically active water constituents. Using such an in situ data set, model parameters can be calibrated/parameterized by (iteratively) minimizing the residual error between the measured $R^-_\infty(\lambda)$ and the $R^-_\infty(\lambda)$ simulated according to Eq. 1, with measured concentrations as inputs. Only if this so called forward modelling yields acceptable accuracies, the inverse problem should be tackled. Inverse modelling consists the estimation of concentrations of optically active substances on the basis of measured reflectance spectra and known model parameters.

Modelling seagrass productivity

The previous sections pointed out what kind of input (and accuracy) can be expected from various remote sensing products. Not only is it possible to map the area covered by seagrass, and changes therein, but remote sensing may also help to measure the factors that determine seagrass productivity. Hence, creating spatial seagrass production models becomes within reach.

Based on the well studied ecophysiology of seagrasses, dynamic production models formalize the productivity of seagrasses as a function of the canopy status (i.e., amount of photosynthetically active tissue, nutrient status), the light intensity reaching the canopy, the nutrient and CO_2 concentration, and the temperature and salinity of the surrounding waters (Hemminga & Duarte, 2000). The process-driven spatial models would require similar input data as the non-spatial models, but then expressed spatially, e.g., information on the water temperature, sediment load, light climate and vegetation status.

Based on existing knowledge on minimum requirements for light levels and temperature, threshold levels for growth of different species may be determined. When linked to remotely sensed images and sediment and/or irradiance models, early-warning systems may be developed that flags regions where growth conditions degrade, before the seagrass beds itself display changes in cover or density.

Existing dynamic productions models differ in complexity. Some account for direct environmental effects on seagrass production, while others also include indirect effects such as shading by increased growth of algae following increased nutrient loads. A two-flow bio-optical model (Zimmerman, 2003) allowed the simulation of light climate over and in the seagrass canopy. Modelling predictions of downwelling spectral irradiance distributions were within 15% of field measurements. Thus, it provides a fairly robust tool for investigating the photosynthetic performance of seagrass canopies as a function of water quality, depth distribution, canopy architecture, and leaf orientation.

A combined growth model for drift-algae, ephiphytes and ryzome-algae by Biber et al. (2004) made it clear that currently data on recruitment and mortality rates in seagrasses are lacking, especially for tropical waters. However, through model calibration and parameterisation they were able to approximate them. Hydrodynamic transport of unattached biomass was important in simulating drift dynamics accurately in this model. It was found to be a very important process in describing the temporal change in biomass at locations with different intensities of tidal flow. In order to make their model current, some further development was needed. This includes investigating the formulation of the epiphyte substrate-dependent mortality function, determining the importance of grazing losses, and linking the algal model to a pre-existing seagrass model.

Plus et al. (2003) used a model, originally designed for *graminae* productivity modelling, to determine seagrass productivity, while taking into account the effect of canopy shading effects on irradiance levels. This model, linked to field-data on nutrient availability, precipitation, irradiance, and temperature resulted in highly accurate prediction of above-ground biomass and shoot density of *Z. noltii* beds in the Thau lagoon over the course of 2 years. The model probably underestimates the seagrass rhizome and root biomass. Although seagrass production models result in good predictions of production over time (e.g., see Plus et al., 2003), to our knowledge, none of these models have been used spatially. However, with the increasingly accurate remote sensing products, attempts to do this become more realistic.

Discussion

Seagrass beds form continuous grazing areas for herbivores, and changes in growth, health, and cover should be seen in this continuous perspective. Although sediment loads may reduce canopy irradiance levels at one location, and sedimentation may inhibit growth and reduce seagrass biomass at some points, increased nutrient fluxes may results in increased growth and vigour of seagrass on other locations. To understand the dynamics of seagrass communities it is therefore crucial to monitor growth and health status spatially over extensive areas.

Remote sensing can play an important role in monitoring of seagrass status. One of the drawbacks for using remote sensing imagery is the costs involved in purchasing the images, and perhaps specialist software and hardware. Purchasing imagery, acquisition of hardware and software all add to the cost of a project. However, when taken into account the time saved on field work, calibration and rectification compared to standard field-based observation, it is often less expensive than performing a ground-survey based study (Mumby et al., 1999).

Clearly, advances are being made in mapping seagrass cover using remotely sensed information. However, it is important to realize the influence of landscape fragmentation and image resolution on classification accuracy, especially when monitoring cover change. Classification accuracy is strongly affected by the spatial resolution of the imagery used, as well as the amount of fragmentation of the landscape to be classified (Jones et al., 2006). Doubling the pixel size when classifying highly fragmented landscapes may result in a classification shift in more than 30% of the pixels. Comparing classifications based on images of different resolution can therefore result in major errors between actual and remotely sensed cover changes (Jones et al., 2006).

Not only is it possible to map the area covered by seagrass, and changes therein using remote sensing, but remote sensing may also help to measure the factors that determine seagrass productivity. Radiative transfer models can be used to model the underwater light climate (photosynthetically active radiation) at the depth of plant growth, and secchi-disk depth of total suspended matter (Thiemann & Kaufmann, 2002). Recent satellite products deliver accurate measure of sea-surface temperature. The mapping of seagrass cover and eventually foliage composition seems possible. With these advanced remote sensing products, creating spatial seagrass production models becomes within reach. These models would require similar input data as the non-spatial models, but then expressed spatially, e.g., information on the water temperature, sediment load, light climate and vegetation cover. By continuously updating the remotely sensed input data, the temporal variability of growth conditions can be taken into account.

Based on existing knowledge of seagrass productivity (formalized in production models), as well as minimum requirements for light levels and temperature, threshold levels for growth of different species may be determined. When linked to remotely sensed images and sediment and/or irradiance models, early-warning systems may be developed that flags regions where growth conditions degrade, before the seagrass beds itself display changes in cover or density.

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