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Remote sensing of aquatic vegetation: theory and applications

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Abstract Aquatic vegetation is an important component of wetland and coastal ecosystems, playing a key role in the ecological functions of these environments. Surveys of macrophyte communities are commonly hindered by logistic problems, and remote sensing represents a powerful alternative, allowing comprehensive assessment and monitoring. Also, many vegetation characteristics can be estimated from reflectance measurements, such as species composition, vegetation structure, biomass, and plant physiological parameters. However, proper use of these methods requires an understanding of the physical processes behind the interaction between electromagnetic radiation and vegetation, and remote sensing of aquatic plants have some particular difficulties that have to be properly addressed in order to obtain successful results. The present paper reviews the theoretical background and possible applications of remote sensing techniques to the study of aquatic vegetation.

Keywords Remote sensing · Macrophytes · Aquatic vegetation

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Introduction

Aquatic plants are an important component of wetland and coastal ecosystems, playing a key role in ecological function (Marion and Paillison 2003; Junk 1997). Many macrophyte communities are characterized by high growth rates, rapid biomass accumulation and, in seasonal ecosystems such as wetlands and floodplains, by a tight connection with the flooding pattern of the landscape (Junk 1997). These plants have a large capacity to absorb harmful substances and pollutants, and can be indicators of the eutrophic status of a water body (Onaindia et al. 1996).

Surveys of macrophyte communities are commonly hindered by limited accessibility (Vis et al. 2003). Hence, remote sensing is a valuable tool for assessment of macrophyte stands and associated biophysical and ecological parameters. The use of remotely sensed images allows multitemporal studies and provides comprehensive information from surrounding areas. With the advance of sensor technology and processing techniques, vegetation characteristics such as species composition, leaf area index, biomass, photosynthetically active radiation absorbed and even chemical composition can be determined by analysis of radiometric data (Tilley et al. 2003; Peñuelas et al. 1993).

Aquatic plants and their properties, however, are not as easily detectable as terrestrial vegetation. Proper understanding of the physical interaction between electromagnetic energy and both the vegetation and its environment, as well as careful application of pre-processing steps prior to the analysis of remotely sensed data are requirements for obtaining successful results. Most remote sensing techniques have been employed to assess macrophyte properties: field spectrometry, aerial photography, aerial/orbital multispectral systems, hyperspectral systems, microwave sensors, digital airborne videography and sonar systems. In the present paper, the theoretical background and applications of remote sensing to aquatic plants are examined, in order to provide a comprehensive perspective on its present and future capabilities and needs.

Optical remote sensing

The principles behind aquatic vegetation spectral characteristics are the same as behind its terrestrial counterparts. At the leaf level, presence and concentration of leaf pigments determine the response in the visible region of the spectrum, and leaf morphology and water content are the main factors acting on the infrared wavelengths (Fig. 1).

At the individual level, biophysical factors such as leaf distribution, leaf density and orientation, and overall canopy structure are important. Vertically oriented plants or reduced leaf area offer less available surface to interact with the downwelling radiation, while highly branched canopies and broadleaved plants have a more effective reflective area (Williams et al. 2003). At the community level, plant biomass and density are also important variables. Although the spectral response of aquatic vegetation resembles that of terrestrial vegetation, the submerged or flooded conditions introduce factors that alter its overall spectral characteristics. It is therefore useful to distinguish between submerged and floating or emergent plants, as these factors act differently in each case.

Spectral behavior of submerged vegetation

The green region of the spectrum is considered as the most suitable for sensing submerged macrophytes, followed by the red and red edge regions. Several studies highlight the same narrow spectral regions as optimal for submerged macrophyte discrimination (Table 1). This convergence indicates that common underlying conditions such as pigment concentration and cellular structure are responsible for the main differences among macrophyte species. Also, the green region provides greater light penetration in waters with higher concentrations of suspended and dissolved material (Kirk 1994).

Water strongly absorbs the electromagnetic radiation in the optical spectral region, resulting in significant dampening of the radiometric signal. Because of this, reflectance measurements for submerged species are usually very low, on the order of 10×10^{-2} (Pinnel et al. 2004; Dierssen and Zimmerman 2003; Fyfe 2003; Han and Rundquist 2003; Heege et al. 2003; Paringit et al. 2003; Everitt et al. 1999). In the absence of water (i.e. laboratory conditions), higher reflectance values can be obtained (Paringit et al. 2003; Armstrong 1993). The main challenge of remote sensing of submerged aquatic plants is thus to isolate plant signal from the overall water column interference.

Due to the reduced magnitude of the signal, a careful and adequate correction of atmospheric effects is necessary prior to the analysis of submerged vegetation radiometry derived from airborne and orbital data. This correction is usually obtained through (1) image-based procedures, which employ pixels with known spectral characteristics to correct for atmospheric noise; and (2) model based procedures, which use radiative transfer equations to model atmospheric conditions and the radiation pathway, and then predict the expected surface reflectance for these conditions.

Image-based methods usually consist of Dark Object Subtraction (DOS) (Chavez 1988), which uses objects with near zero reflectance to

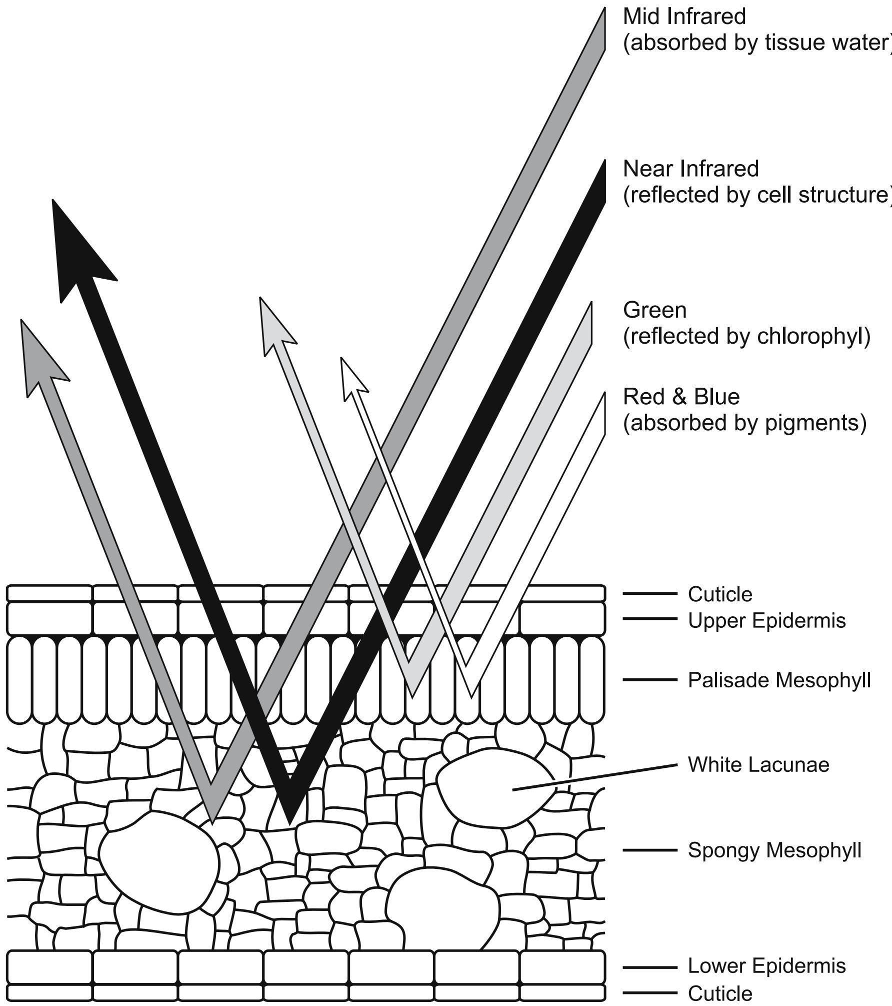

Fig. 1 Leaf-radiation interactions at microscopic level. *Arrow thickness* is proportional to the magnitude of radiation fluxes

estimate and correct for atmospheric haze, or some of its improved versions, which also correct atmospheric transmittance (Chavez 1996). The major drawback associated with this approach is that often the existing dark objects within a scene are in fact the water bodies, and a poor choice of haze values can actually cancel out the water-leaving radiance.

Radiative transfer models are based on parameterization of atmospheric conditions. However, these parameters are seldom available for specific locations, and the model applications thus rely on estimated or average parameters, which can result in erroneous corrections (Song et al. 2001). Common methods include the MODTRAN (Berk et al. 1999), and 6S algorithms (Vermote et al. 1997).

Table 1 Appropriate spectral regions for discriminating submerged macrophyte species, as suggested by different authors

	Wavelength (nm)	Plant species
Williams et al. (2003)	574 / 681	*Vallisneria americana, Myriophyllum spicatum*
Fyfe (2003)	530–580 / 520–530 / 580–600	*Zostera capricorni, Posidonia australis, Halophila ovalis*
Pinnel et al. (2004)	550 / 656	*Chara* spp., *Naja marina, Nitellopsis obtusa, Potamogeton* spp.
Han and Rundquist (2003)	538 / 706	*Ceratophyllum demersum*

Ultimately, the choice of methods should be based on the amount and reliability of available atmospheric data. If available, then model-based procedures are the logical choice. If not, image-based procedures are expected to yield more accurate results and minimize error introduction; refer to Zilioli and Brivio (1997) and Song et al. (2001) for further information.

Apart from water, the presence of optically active material (i.e. plankton, sediment, organic molecules) affects the scattering and absorption of radiation (Han and Rundquist 2003; Kirk 1994). In addition, bottom reflectance is a factor to be considered when interpreting the radiometric signal of macrophyte beds in shallow waters.

Ackleson and Klemas (1987) used a single-scattering volume reflectance model to represent the interaction between the three main components of the signal from submerged vegetation (water, bottom, plants). Using this physical representation and a set of pre-determined, representative parameter values, the authors showed that, in shallow depths, the overall reflectance signal is determined mainly by the vegetation density, assuming that bottom reflectance is constant and differs significantly from the vegetation. As depth increased, dominance of reflectance shifted to the water column components. Hence, Ackleson and Klemas (1987) suggested that incorporating depth information into the classification method can reduce the influence of water column variation. Armstrong (1993) accomplished this for Landsat TM visible bands through a linearization procedure developed by Lyzenga (1978), which yields depth invariant bands.

Water column optical models also include bathymetric information as one of the variables used to correct water and bottom effects (Dierssen and Zimmerman 2003; Heege et al. 2003). Paringit et al. (2003) attempted to develop a seagrass canopy model to predict the spectral response of submerged macrophytes in shallow areas. The model considered not only the effects of the water column through radiative transfer modeling, but also viewing and illuminating conditions, leaf and bottom reflectance, leaf area index and the vertical distribution of biomass. With model inversion, plant coverage and abundance were estimated with the use of IKONOS satellite imagery, and compared to field measurements.

Finally, another important source of variation for submerged vegetation reflectance is the presence of epibiont organisms, especially epiphytes, which can cover the plant surface. Fyfe (2003) showed significant differences between the reflectance of cleaned and fouled leaves, in all wavelengths, for different macrophyte species. These effects were more significant between 570 and 590 nm (Fyfe 2003; Williams et al. 2003). The presence of epiphytes can also smooth the spectral curve, reducing the difference in reflectance between wavelengths and masking subtle spectral features (Armstrong 1993).

Spectral behavior of emergent species

With the absence of water attenuation, the average reflectance of emergent macrophytes is usually higher than the observed for submerged plants. Values can range between 0.02 and 0.1 in the visible spectrum (with an usual peak in the green region) and 0.06–0.65 in the near infrared (Tilley et al. 2003; Jakubauskas et al. 2000; Malthus and George 1997; LaCapra et al. 1996; Peñuelas et al. 1993; Best et al. 1981).

The presence of flooding, however, introduces variability in reflectance values due to the mixing of plant and water signals (Malthus and George 1997). This mixing usually results in a decrease in total reflected radiation, especially in the near to mid infrared regions where water absorption is stronger. The intensity of such effect will be determined by vegetation density and canopy structure (Jakubauskas et al. 2000) (Fig. 2), as well as by the nature of the water signal. As noted before, the latter is a function of the amount and nature of suspended materials and depth of the water column, plus substratum composition for shallow depths.

Physiological status of vegetation can be another source of variation in plant spectral signatures. Best et al. (1981) demonstrated that a single species, in different phenological stages, exhibited significant variation in its reflectance. In addition, physiological stress can lead to spectral variability (Tilley et al. 2003; Peñuelas et al. 1997; Bajjouk

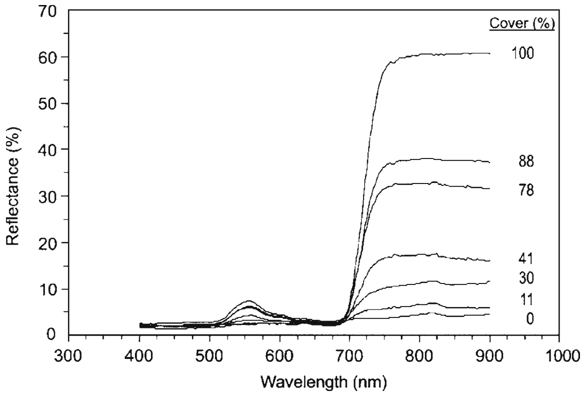

Fig. 2 Effect of plant density in the spectral profile of *Nuphar polysepalum*. On higher densities, the spectral curve is similar to what is expected from a vegetated surface. As it decreases, reflectance values are reduced, especially in the 700–1,000 nm region, and the overall response approaches the one for a water surface (Adapted from Jakubauskas et al. (2000): International Journal of Remote Sensing, Taylor & Francis Ltd, http://www.tandf.co.uk/journals)

et al. 1996; Peñuelas et al. 1993; Best et al. 1981). Stress usually implies alterations on biochemical status and morphological characteristics, which in turn determine the spectral response in the different regions of spectra. Factors such as chlorosis, desiccation or disease can be detected in the spectral signature of plants.

Because of the wide range of reflectance values, the spectral signature of emergent aquatic vegetation often overlaps the signals from terrestrial vegetation, water and occasionally soil. This variability can lead to poor results from simple automated classification procedures and hinder visual interpretation (Silva 2004; Ozesmi and Bauer 2002; Best et al. 1981). In such cases, the use of alternative image classification algorithms such as decision tree (Baker et al. 2006) or neural network classifiers (Filippi and Jensen 2006) may help.

Optical remote sensing applications to aquatic vegetation studies

Aerial photography was the first remote sensing method to be employed for studying and mapping plant stands, and early studies date back to the 1960s and 1970s (Austin and Adams 1978; Benton and Newman 1976; Edwards and Brown 1960). Although most airphoto analyses rely on visual interpretation, plant species can be often discriminated due to its high spatial resolution (Moore et al. 2003; Schulz et al. 2003). Digitization of aerial photography may allow the application of computer aided classification algorithms (Valta-Hullkonen et al. 2003; Marshall and Lee 1994). Aerial photography, however, often lacks the capacity to record in multiple spectral bands, a hindrance especially significant for submerged vegetation.

Digital multispectral airborne systems can provide high spatial resolution coupled with an increased number of spectral bands. Its spectral refinement can support more accurate quantitative analysis and classification of data (Malthus and George 1997). Nevertheless, as data acquisition from these sensors can be more expensive than the acquisition of aerial photography, the latter remain as a common data source when information at high spatial resolution (meter to sub-meter range) is required (Maheu-Giroux and de Blois 2005).

Another alternative to airphoto surveying is the use of videographic systems, which employ a digital video camera instead of photographic sensors. These devices can attain fine spatial resolutions (sub-meter), and by using filters and multiple cameras, acquire simultaneous images in different spectral bands. Videography has been employed with success to map both emergent and submerged vegetation (Sprenkle et al. 2004; Hess et al. 2002; Everitt et al. 1999).

In recent years, numerous studies employing hyperspectral imaging sensors have been performed (Pinnel et al. 2004; Dierssen and Zimmerman 2003; Thomson et al. 2003; Williams et al. 2003; Anstee 2001; Alberotanza 1999; Thomson et al. 1998; Bajjouk et al. 1996; Lacapra et al. 1996; Zacharias et al. 1992). These sensors offer good spatial resolution (about 1–4 m) and the capacity of recording full spectra for each pixel. Such richness of data is of special interest to the study of submerged vegetation, since the overall signal is low and an acceptable degree of discrimination can be only obtained by the examination of subtle spectral characteristics.

Specific features in the reflectance curves can often be related to physiological and biophysical parameters, allowing the indirect estimation of these. The application of hyperspectral imagery is one of the most promising uses of remote sensing to the study of aquatic vegetation. Specifications of some of the more widely used hyperspectral sensors are listed in Table 2.

Satellite systems have also been successfully applied to the study of aquatic vegetation. Although the spatial resolution of these systems is, in most cases, incapable of discriminating aquatic vegetation at the species level (Jensen et al. 1993), satellite imagery is useful for mapping macrophytes communities. Landsat MSS and TM images have been employed for mapping submerged (Zhang 1998; Armstrong 1993; Ackleson and Klemas 1987) and emergent vegetation. Images with spatial resolutions higher than Landsat have also been applied to both vegetation types, e.g., SPOT data (Pasqualini et al. 2005; Jensen et al. 1995, 1993, 1986) and IKONOS images, with 1m resolution (Sawaya et al. 2003). Coarser resolution data have been proved useful as well, e.g. the Indian IRS-LISS I, with ground resolution of 72.5 m (Pal and Mohanty 2002; Chopra et al. 2001), and MODIS images (250 and 500 m resolution) have been shown to be able to map macrophyte occurrence after the use of spatial resolution enhancement techniques (Silva 2004).

The usual application of remote sensing imagery is to produce cover maps for aquatic plants, in general or for different populations or communities. Considering both airborne and orbital imaging sensors, accuracies ranging between 70 and 96% can be achieved (Pasqualini et al. 2005; Sawaya et al. 2003; Valta-Hullkonen et al. 2003; Anstee 2001; Everitt et al. 1999; Malthus and George 1997; Bajjouk et al. 1996). High overall accuracy can be obtained with the correct choice and application of mapping techniques. Another inherent advantage of satellite imagery is the regular temporal acquisition, allowing utilization of time series to analyze seasonal patterns (Silva 2004; Jensen et al. 1993) or landscape changes (Moore et al. 2003; Jensen et al. 1995). Instruments such as the Landsat series provide almost 30 years of imagery, which is a valuable and unparalleled source of temporal data.

Remote sensing can be employed as a tool for estimating biophysical measures. Plant biomass can be estimated by means of spectral data, mainly through the use of regression analysis, with bands or band combinations (ratios, indexes) as predictor variables. It is important to note that with increases in biomass, the relationship between the spectral signal and the actual biomass approaches an asymptote (Peñuelas et al. 1993).

Zhang (1998), using the first and second principal components of a PCA transformed TM image, estimated the biomass of submerged stands in the Honghu Lake (China), obtaining a coefficient of determination of $R^2 = 0.85$. Also, submerged vegetation biomass has been estimated by Armstrong (1993), using depth normalized TM images and obtaining an overall $R^2 = 0.79$. This high degree of agreement, considering the radiometric (8 bit), spectral (few, broad bands) and spatial (30 m) limitations of such images, suggests that even better results could be acquired with the use of systems with more resolving power. Other biophysical

Table 2 Some of the most widely used hyperspectral sensors currently in operation

Sensor	Number of bands	Spectral interval (excl. thermal)	Bandwidth	Spatial resolution	Platform	Manufacturer
MIVIS	102	430–2,500 nm	8–20 nm	Variable	Airborne	Daedalus Enterprises
CASI-2	19–288	400–1,050 nm	1.9 nm	Variable	Airborne	ITRES research
PHILLS	128	380–1,000 nm	0.5–3 nm	Variable	Airborne	Naval Research Laboratory, US
HyMap	100–200	450–2,500 nm	10–20 nm	Variable	Airborne	Integrated Spectronics
AVIRIS	224	400–2,500 nm	10 nm	Variable	Airborne	Jet Propulsion Lab
Hyperion	220	400–2,500 nm	10 nm	30 m	NASA EO-1	TRW Inc.

indexes can also be estimated through the use of remote sensing, such as percentage cover (Heege et al. 2003; Pinnel et al. 2004) and Leaf Area Index (Dierssen and Zimmerman 2003). These measures represent important ecological variables, and are often employed as inputs to ecosystem models. Physiological characteristics can also be inferred from the spectral response of macrophytes, due to alterations in optically active substances. Examples are chlorophyll concentration (Peñuelas et al. 1993), photosynthetic efficiency (Peñuelas et al. 1997, 1993), chemical composition (LaCapra et al. 1996) and environmental pressures (Tilley et al. 2003).

Synthetic aperture radar (SAR) systems

The use of SAR data have been long acknowledged as a valuable tool for studying wetlands. In the microwave range, differences in the signal recorded from dry and flooded vegetation allow the mapping of flooding extent (Costa 2004; Hess et al. 1995). In addition, numerous studies have shown that SAR images can be utilized to study aquatic vegetation (Costa 2005; Kasischke et al. 2003; Moreau and Le Toan 2003; Costa et al. 2002; Novo et al. 2002; Noernberg et al. 1999; Le Toan et al. 1997; Pope et al. 1997; Kasischke and Borgeau-Chavez 1997; Hess et al. 1995).

Synthetic Aperture Radar data offers information about canopy biophysical characteristics and dielectric properties (a proxy for water content), instead of biochemical and morphological features. The longer microwave wavelengths penetrate into the canopy, resulting in a "volumetric" signal. Coupled with its active source of energy, image acquisition can be performed regardless of weather conditions or time of day. Such capability is valuable as wetland environments frequently occur in cloudy locations. However, as radar wavelengths do not penetrate into water, these systems can only be applied to emergent macrophytes.

Radar systems operate in specific regions of the electromagnetic spectrum, and radar bands are usually coded by a single letter. The most common bands used are X (3 cm wavelength), C (5.6 cm), S (10 cm), L (23 cm) and P (75 cm). Longer wavelengths tend to have deeper canopy penetration and less sensitivity to smaller biophysical variations. In addition to wavelength, every radar system has defined polarizations for sending and receiving the radiation pulse, either vertically (V) or horizontally (H). Same-polarization systems are usually referred as HH and VV systems, and cross-polarization systems as HV or VH. Different polarizations, as well as ratios or differences in polarizations can highlight specific characteristics for some types of targets (Lewis and Henderson 1998).

Many of the current applications of SAR systems are derived from satellite-borne sensors, such as the Japanese Earth Resources Satellite 1 (JERS-1), the Canadian Radarsat 1, and the European systems Earth Resources 1 and 2 (ERS-1 and ERS-2) and Envisat ASAR. Important research has been also generated by data collected from the SIR-C/X-SAR instrument flown on a space shuttle in 1994, and applications of airborne SAR systems are also significant (Table 3).

To understand the radiometric responses in SAR data, it is necessary to realize that radar sensors are side-looking systems, meaning that the electromagnetic pulse hits the surface in a sub-nadir angle. For this reason, it is expected that, for smooth plain surfaces, most of the radiation is reflected specularly and does not return to the sensor. With increasing surface roughness and addition of volume components, such as vegetation, the backscattered radiation increases (Lewis and Henderson 1998).

The overall radar signal from aquatic vegetation is composed primarily of the volumetric backscatter from the canopy elements, the surface backscatter from the ground surface, and the double-bounce interaction from radiation that is forward scattered from the surface but bounces off the canopy elements and returns to the sensor (Fig. 3).

The geometry of the canopy, moisture content and the presence of strongly vertically or horizontally oriented features may affect the resulting signal at some wavelength and polarization combinations. For instance, dense, tall (1.5 m or more), vertically-oriented wetland herbaceous plants show double-bounce in L band (HH and VV), and even C-HH at low incidence angles

Table 3 Past, current and planned spaceborne radar systems (expected launch date in parenthesis)

Sensor	Bands	Polarization	Incid. angle(°)	Spat. ses. (m)	Swath width (km)	Orbit cycle (days)	Agency
ERS-1[a]	C	VV	23	28	100	35	European Space Agency (ESA)
JERS-1[a]	L	HH	38	18	74	44	National Space Development Agency of Japan (NASDA) - currently JAXA
SIR-C/X-SAR[a]	L, C, X	Full Pol. (L,C) VV (X)	15–50	10–26	15–60	–	Jet Propulsion Lab, USA
ERS-2	C	VV	23	28	100	35	European Space Agency (ESA)
Radarsat-1	C	HH	10–59	10–100	50–500	24	Radarsat International
Envisat ASAR	C	HH, VV, HV, VH	15–45	30–1,000	60–405	35	European Space Agency (ESA)
Radarsat-2 (2007)	C	Full Pol.	10–60	3–100	10–500	24	Radarsat International
Alos PALSAR	L	Full Pol.	8–60	10–100	20–350	46	Japan Aerospace Exploration Agency (JAXA)
MAPSAR (2010)	L	HH, VV, HV, VH	20–45	3–20	20–55	7	Brazilian National Institute for Space Research (INPE)/ German Aerospace Center (DLR)

[a] Currently deactivated

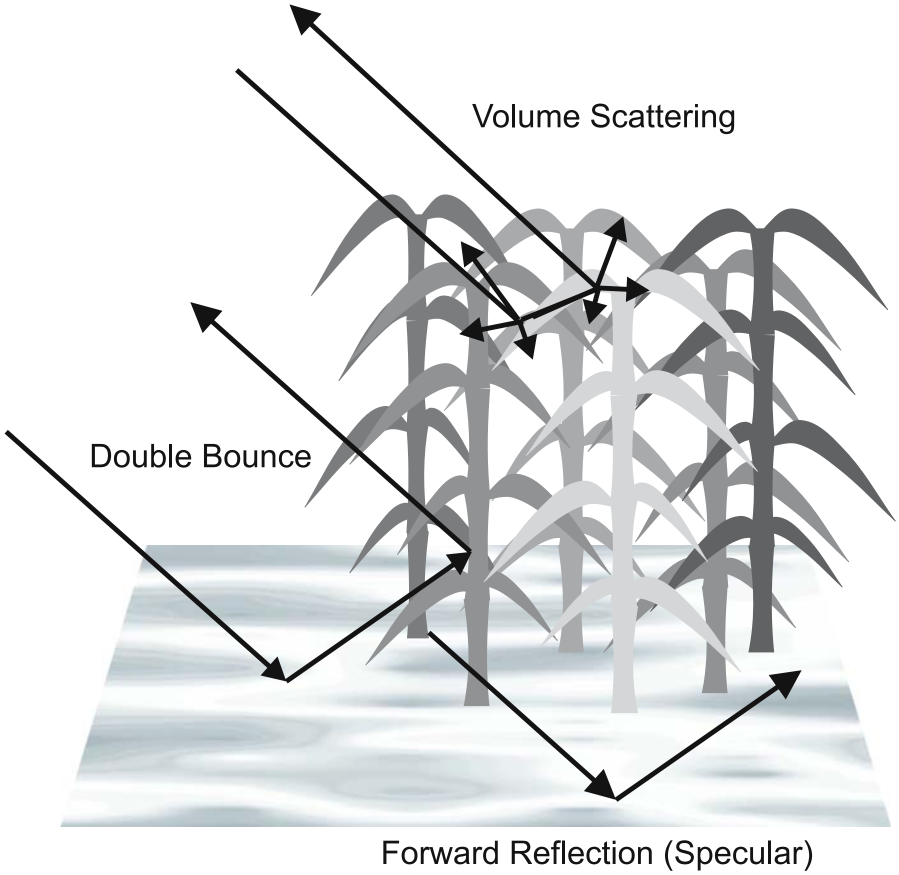

Fig. 3 Schematic representation of the scattering mechanisms at C and L bands for aquatic vegetation (Adapted from Costa 2004)

(Costa et al. 2002; Pope et al. 1997). Double-bounces are caused by the interaction of the radiation with the stem/trunk, followed by a change in direction towards the surface (water) and a strong bounce back towards the radar antenna (dihedral corner reflector behavior). The inverse is also possible.

The characteristics from both the plants and the sensor are needed to explain double-bounce interaction. The combination of a long wavelength (L band), horizontal polarization (HH), and steep incidence angle allows higher penetration of the radiation through the canopy. At L band plant leaves are quasi-transparent; hence the radiation interacts mostly with the stem and the underlying water. For the same configuration of radiation/target, but with VV polarization, the interaction is mostly with the upper canopy (Ulaby et al. 1986). Double-bounce mechanisms are enhanced for radiation at lower incidence angles (i.e. closer to nadir) when compared with higher incidence angles (Hess et al. 1990; Ford and Casey 1988). At lower angles, the pathway of the incident wave through the canopy is minimal; therefore, the radiation is less attenuated by the canopy.

For less dense herbaceous plants in flooded wetlands, backscattering values are not as high as those observed for high density stands, due to the increase in the forward scattering of water patches (Pope et al. 1997). For herbaceous plants (varying densities), at either C-VV or cross-polarized and low incidence angles, double-bounces were not observed, but signals related to canopy volume-scattering (Pope et al. 1997; Kasischke and Borgeau-Chavez 1997; Hess et al. 1995) were observed.

Volume-scattering mechanisms are characterized by the interaction of the radiation within the vegetation canopy, i.e. leaves and stems. The radiation is scattered by the elements in all directions within the volume, and the resulting backscattering towards the antenna is not as strong as it is for double-bounce mechanisms (Ulaby et al. 1982).

The backscatter from aquatic vegetation stands usually has low values, in all wavelengths and polarizations. The low return is caused mainly by forward scattering from the water surface and the attenuation of the signal from the canopy. Some controversy exists about the factors affecting aquatic vegetation signal in different configurations and about which is the most appropriate configuration to remotely sense macrophytes. Costa et al. (2002) showed that a combination of L and C band signal was sensitive to stand height and biomass, while C band alone responded only to the latter, and presented a lower signal saturation value. Rosenthal et al. (1985), however, suggested that C band should be more sensitive to plant height than biomass. For a more comprehensive discussion of the microwave radiometric behavior of aquatic vegetation, the reader is suggested to refer to Kasischke et al. (2003); Costa et al. (2002); Noernberg et al. (1999); Pope et al. (1997); Kasishcke and Borgeau-Chavez (1997).

Overall, the total backscattering from wetland herbaceous plants is dependent on the interaction of the microwave energy with both the canopy and the canopy-ground. Not only plant characteristics, such as density, distribution, orientation, leaf shape, dielectric constant, height and components of the canopy, but also the sensor parameters (polarization, incidence angle and wavelength) play an important role in determining the amount of radiation backscattered toward the radar antenna. Due to this multitude of factors, visual interpretation usually requires more training and familiarity with radar imagery than optical data.

One of the main hindrances of spaceborne radar systems is that most have a single band/polarization configuration, reducing the data available for an accurate identification of macrophyte stands (Hess et al. 2003). This limitation can be overcome with the combination of different satellite imagery (Costa et al. 2002) or the use of textural and contextual measures (Simard et al. 2000, 2002; Noernberg et al. 1999). Also, the use of multitemporal, multi-incidence angle or multi-polarization data could offer some improvement in overall discrimination (Proisy et al. 2000; Hess et al. 1995). The new generation of full polarimetric sensors, for example, does not suffer from this limitation (Table 3). Multiple bands and/or polarization are also more commonly found among airborne SAR systems.

For macrophyte mapping, accuracies ranging from 65 to 97% can be achieved (Costa 2004; Hess et al. 2003, 1995; Novo et al. 2002), and species can be differentiated in some degree, such as grasslike versus broadleaved (Noernberg et al. 1999). Another promising application for radar remote sensing is biomass estimation. Studies show relationships between stand biomass and radar backscatter ranging from R^2 = 0.59 to 0.78 (Moreau and Le Toan 2003; Costa et al. 2002; Novo et al. 2002). Saturation values range from 470 g m^{-2} to 2000 g m^{-2} of above water biomass, depending on community characteristics (Moreau and Le Toan 2003; Costa et al. 2002).

To overcome the issue of signal saturation, radar interferometry has also been used as an alternative to backscatter signal analysis. Interferometry is a technique where two radar images taken at different locations are used to map ground elevation (topography). Each pixel at the radar scenes contains not only amplitude but also the phase information, corresponding to the distance between platform and a given place at the Earth's surface. The phase differences between these two images are used to derive precise information on surface height (Lu et al. 2007). Vegetation height can be also determined by interferometry, and later on be used as a proxy for biomass determination (Simard et al. 2006; Dutra et al. 2007; Santos et al. 2004).

A somewhat less developed application of radar is the merging of both optical and radar data by image fusion techniques. Since the information content in each one differs, there is low redundancy when joining these sources, permittin better mapping and discriminative results. At usual land cover mapping, accuracies can be increased by as much as 10% by optical-radar fusion (Haack and Bechdol 2000). For aquatic macrophytes, the fusion between Radarsat-1 and Landsat TM allowed species-level discrimination of macrophyte stands (Graciani and Novo 2003).

Other remote sensing systems

Optical and radar remote sensing together comprise the vast majority of systems and applications. However, other methods can also provide valuable information about macrophyte communities. For submerged vegetation mapping, successful results have been obtained by the use of side-scan (Pasqualini et al. 2005) and multibeam sonar systems (Komatsu et al. 2003). Multibeam systems offer the advantage of generating three-dimensional information, including vertical height distribution, and allowing visualization of the community structure.

Recently, airborne LiDAR(Light Detection and Ranging) systems have been applied with success to the study of aquatic vegetation. These sensors employ a high-frequency laser pulse, using differences between the return time of each beam to derive height and terrain information and produce 3-D datasets. The accuracy of LiDAR systems is usually very high, attaining meter to sub-meter spatial resolution and less than 0.5m vertical accuracy (Brennan and Webster 2006; Rosso et al. 2006; Hopkinson et al. 2005). These systems were initially utilized for the generation of digital terrain models, but vegetation mapping and estimation of biophysical parameters have been successful (Kotchenova et al. 2004; Maltamo et al. 2004; Patenaude et al. 2004; Popescu et al. 2002).

As with other optical systems, a major factor affecting the LiDAR response is water absorption. As most LiDAR systems operate in the infrared region, saturated soils and free water surfaces will dampen the returning signal. The resulting reduction on the number of returns from the substratum then affects the proper determination of canopy heights (Hopkinson et al. 2005). On the other hand, signal penetration in the canopy may generate the same problem; if canopy is sparse or too vertically oriented, lesser returns are expected from the top elements, thus underestimating height. Hopkinson et al. (2005) studied both aquatic and terrestrial grasses, and found that these factors combined resulted in a mean difference of 53% between LiDAR estimations and ground measured height, against only 33% for terrestrial plants. In tidal systems, differences in tide levels both during and between flights must be acknowledged, as it introduces significant measurement errors (Brennan and Webster 2006).

The overall precision of the system in use is a factor that must be considered, as vegetation heights shorter than the minimum measurable return difference cannot be properly determined (Hopkinson et al. 2006). For the same reason, proper calibration and validation of LiDAR heights from ground truth is paramount. Nonetheless, differences in the signal from vegetated and non-vegetated areas can still be useful for thematic classification, as shown by Rosso et al. (2006) for *Spartina* spp.

Wang and Philpot (2007) applied bathymetric LiDAR to map submerged vegetation. Again, the effect of the water column on the LiDAR signal is the main source of interference to be dealt with. For bathymetric systems, green wavelengths are used instead of infrared, as they offer the best trade off between water absorption and scattering due to suspended material (Wang and Philpot 2007).

Conclusions

The use of remote sensing for studying aquatic vegetation is well established. From the earlier mapping applications, employing analog aerial photography and visual interpretation, to the use of modern digital high resolution systems and complex automated classification algorithms, there are many opportunities and advantages in applying remote sensing techniques to obtain a synoptic view of macrophyte communities and its properties. Plant cover and distribution, biomass and other biophysical and physiological parameters can be estimated from field spectral data, or by images. This information can then be used for environmental assessment and modeling, and for better understanding of the ecological dynamics of aquatic plant communities.

Among the new developments of remote sensing science, the use of hyperspectral imagery appears to be a very promising tool for studying aquatic vegetation in the present and near future. Many airborne hyperspectral systems are available nowadays (AVIRIS, CASI, HyMap), and orbital hyperspectral sensors are becoming available, such as NASA Hyperion. The coupling of spatial data with rich spectral information allow better treatment of the main problems associated with the usual multispectral systems, and provide more detailed and sensitive information. Medium resolution sensors, such as MODIS, MERIS and SPOT-Vegetation can provide useful information for regional and global scale studies. Although SAR orbital sensors were restrained to only a few bands and polarizations, new multi-polarized and full polarimetric systems are currently available (Envisat ASAR, ALOS Palsar) or expected to become operational in the upcoming years (Radarsat-2, MAPSAR). This type of information, especially if combined with optical data, can supply a good set of data for the study of emergent macrophytes. Remote sensing is a powerful tool to be considered when studying large scale phenomena in aquatic vegetation communities, and is capable of delivering information unmatched by any other surveying techniques.

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