

Quantification of shallow water quality parameters by means of remote sensing

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Abstract: Quantification of quality parameters of inland and near shore waters by means of remote sensing has encountered varying degrees of success in spite of the high variability of the parameters under consideration and limitations of remote sensors themselves. This paper comprehensively evaluates the quantification of four types of water quality parameters: inorganic sediment particles, phytoplankton pigments, coloured dissolved organic material and Secchi disk depth. It concentrates on quantification requirements, as well as the options in selecting the most appropriate sensor data for the purpose. Relevant factors, such as quantification implementation and validation of the quantified results are also extensively discussed. This review reveals that the relationship between *in situ* samples and their corresponding remotely sensed data can be linear or nonlinear, but are nearly always site-specific. The quantification has been attempted from terrestrial satellite data largely for suspended sediments and chlorophyll concentrations. The quantification has been implemented through integration of remotely sensed imagery data, *in situ* water samples and ancillary data in a geographic information system (GIS). The introduction of GIS makes the quantification feasible for more variables at an increasingly higher accuracy. Affected by the number and quality of *in situ* samples, accuracy of quantification has been reported in different ways and varies widely.

Key words: chlorophyll, quantitative remote sensing, remote sensing, shallow estuary, suspended sediment, water quality.

1 Introduction

Water quality refers to the physical, chemical and biological properties of water. It may be degraded by the presence of wastes, nutrients, microorganisms, pesticides, heavy

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metals and sediments. Nutrients in coastal waters have caused a number of environmental problems, such as death of benthic fauna and demersal fish, the occurrence of nuisance algal blooms (Paerl, 1988), and the disappearance of seagrass and mangroves (Silberstein *et al.*, 1986). Suspended sediment directly limits light penetration and reduces primary productivity. Therefore, it is very important to monitor the quality of coastal waters.

Besides being time-consuming and expensive, conventional methods of studying water quality frequently fail to adequately represent heterogenous and patchy areas (Khorram *et al.*, 1991). By comparison, remotely sensed data acquired from an aircraft or a satellite provide a synoptic view not attainable otherwise. This advantage has been widely exploited to monitor and map shallow coastal waters (Bierwirth *et al.*, 1993). The repetitive viewing capability of remote sensing systems has been utilized to study the relationship between suspended sediment and chlorophyll concentrations and the distribution/intrusion patterns of near-shore discharges (Fielder and Laurs, 1990; Walker, 1996). Compared with *in situ* measurements and ecological water quality modelling, remote sensing provides valuable additional information for chlorophyll *a* and Secchi depth measurements (Dekker *et al.*, 1996). Research on estuarine and continental shelf sediment transport dynamics and marine phytoplankton dynamics can benefit tremendously from remote sensing (Johnson and Harriss, 1980). Simultaneously acquired remote sensing data and surface water quality samples may prove useful for studying spatial and seasonal variations in phytoplankton biomass in estuaries and coastal waters (Catts *et al.*, 1985). The integration of remote sensing with *in situ* sample data leads to the creation of dynamic maps of suspended matters and facilitates oceanographic research (Molo *et al.*, 1990). Airborne remote sensing provides a useful means of mapping surface water quality in coastal regions (Rimmer *et al.*, 1987). Satellite remote sensing can serve as a fast and relatively cost-effective tool for early and expeditious assessment of the spatial and temporal variability of lake water quality conditions (Zilioli and Brivio, 1997).

The objective of this paper is to review the potential of remote sensing in mapping, modelling and quantifying quality parameters of shallow waters because their quality is particularly vulnerable to human-induced wastes. The ever-increasing loads of contaminants resulting from increasing anthropogenic activities in the adjacent watershed are accelerating the deterioration of freshwater in lakes, reservoirs and estuaries. It is challenging to remotely sense quality parameters of turbid inland and coastal waters because of the presence of high concentrations of suspended sediments and dissolved organic materials.

Water quality parameters are of a diverse range, and may include pH, microorganisms, nutrients and even minerals. Water quality parameters considered in this paper are primarily in-water constituents (e.g., sediment and chlorophyll). Physical parameters such as temperature, salinity and bathymetry are beyond the scope of the paper, unless they are related to the water constituents focused on in order to limit the paper to a manageable length.

This paper comprises eight sections. After this introduction the spectral properties of near-shore waters are presented, followed by quantification requirements. Section IV deals with the selection of appropriate sensor data for the quantification of a particular water quality parameter. The next section concentrates on water quality parameters that have been successfully quantified. The implementation of quantification is covered

in Section VI. Validation of quantified results is presented in the next section, followed by conclusions.

II Spectral characteristics of shallow waters

Remote sensing of water quality parameters relies on the spectral properties of water-leaving radiance (Hinton, 1991; Stumpf, 1992). It refers to the light re-emerging from water after the incident solar radiation is selectively absorbed and backscattered by in-water constituents. The water-leaving radiance captured by a sensor comprises roughly two components: scattered energy from the atmosphere and radiant energy reflected from the water body. The former is considered noise and has to be effectively removed in accurate remote sensing quantification of water quality parameters. The latter is indicative of inherent optical properties (scattering, absorption and fluorescence) of the water column and in-water constituents (Morel, 1980; Sturm, 1981), even though it is also affected by illumination conditions, water depth and bottom reflectance if the depth is shallow. It is the radiant energy that can be used to study water quality parameters. Thus, how accurately a water quality parameter can be quantified by means of remote sensing relies on how optically active the parameter (e.g. chlorophyll and suspended sediment) is and whether other parameters, if present, interfere with its spectral reflectance. In case of co-existence, not all water constituents contribute to the recorded reflectance equally (Bowers *et al.*, 1998). The infinite combinations of diverse water constituents create a wide variation in the spectral reflectance of shallow waters.

Water-leaving radiant energy over the visible light portion of the spectrum is determined essentially by the colour of water and its turbidity. Colour increases the absorption of light and decreases the remotely sensed signal, whereas turbidity increases the backscatter of light. The intensity of the returned signal varies not only with the type of water quality parameter but also with their concentration level. For instance, spectral reflectance of suspended materials of low concentrations is subject mostly to the absorption characteristics of water, while the absorption characteristics of highly concentrated suspended particles are the most important factors (Moore, 1980). The spectral property of a particular water constituent is especially variable, both temporally and spatially in shallow waters of high river discharge and anthropogenic input.

Short-wavelength radiation in the blue and green regions of the spectrum is commonly used to sense in-water constituents because of its stronger capability of water penetration than longer wavelength radiation. The depth of penetration depends on water clarity. If the radiation is completely adsorbed near the surface, the phenomena detected via remote sensing are thus restricted to the surface of the water body. Fluorescence signal is reduced to 30% if phytoplankton is below 2 m instead of reaching the water surface (Fischer and Kronfeld, 1990).

The spectral behaviour of water parameters varies with the type of constituent. Increases in suspended particulates lead to increases in overall brightness in the narrow band reflectance spectra (Harrington and Repic, 1995). The correlation coefficient between suspended sediment and remotely sensed data peaks in the green/red wavelengths (Novo *et al.*, 1991). Thus, the optimum wavelength for quantifying suspended sediment concentration is 550–650 nm (Novo *et al.*, 1989). Chlorophyll

strongly absorbs radiation at about 450 and 670 nm. A higher chlorophyll concentration reduces reflectance in blue wavelengths but increases it in green wavelengths. With an increase in chlorophyll concentration the position of peak reflectance shifts from about 680 to 715 nm while peak reflectance itself rises (Gitelson, 1992). Both the magnitude and the peak position of reflectance can be used as precise indicators and predictors of phytoplankton concentration.

III Requirements of quantification

Theoretically, it is impossible to extract water quality information from remotely sensed radiance because the boundary condition of the water–atmosphere interface and the characteristics of the atmospheric aerosol are unknown (Sturm, 1981). Thus, feasible approaches to quantifying water quality have to be empirically or semi-empirically based. The empirical relationship may be established through regression analysis. It may also be determined from the known spectral characteristics of the water quality parameter of interest. This is known as the semi-empirical approach.

Quantitative remote sensing of water quality parameters involves transformation of an image into water quality distribution maps based on the empirical and semi-empirical relationship between the parameters and image data (Dekker *et al.*, 1996). Image data can be a single band, a combination of bands, or their ratio. The transformation requires concurrent or near-simultaneous acquisition of both remotely sensed data and *in situ* water quality samples (Molo *et al.*, 1990), and development and validation of empirical or semi-empirical models. The synchronization of *in situ* sample collection with the recording of remotely sensed data effectively ensures that the temporal dynamics of water quality are taken into account, even though logistics make this requirement problematic (Huang and Lulla, 1986). Nonsynchronization would cause the derived models to account for less variance in the dependent water quality variable (Brown and Walsh, 1991). Representative *in situ* samples should be collected over every possible type of water in a highly variable situation. Once acquired, *in situ* samples may be used to spectrally characterize water quality parameters.

The regressed relationship between water quality parameters and their reflectance values on remotely sensed imagery can be simple linear, multiple linear or nonlinear, even though simple linear is the most common (Lopez-Garcia and Caselles, 1987; Lathrop and Lillesand, 1989; Lathrop, 1992; Aguirre-Gomez, 2000). Simple linear models are able to shed insightful light on water quality. Linear regression analysis is also effective and robust in inferring turbidity despite possible variation in water constituents and impact of bottom reflectance (Fraser, 1998). Univariate, linear regression analyses of ratioed bands provide the closest correlation to ground-truthed chlorophyll *a* (Dierberg and Carriker, 1994). Regression technique has strong potential for the future application of Indian Remote Sensing (IRS) data in monitoring water quality of inland waters in estuaries (Choubey, 1997).

In multiple linear regression analysis, a water quality parameter is regressed against the reflectance values in a few bands (Johnson *et al.*, 1981; Lathrop and Lillesand, 1986; Shimoda *et al.*, 1986; Rimmer *et al.*, 1987). For instance, water quality parameters were modelled as multiple linear predictors of Landsat MSS bands 4, 5 and 6 in addition to sun elevation (Carpenter and Carpenter, 1983). Local site and situation conditions can

also be accommodated using various multiple regression models (Brown and Walsh, 1991). Multivariate instead of bivariate regression analysis is the default option in developing water quality parameter models from multitemporal remotely sensed data (Carpenter and Carpenter, 1983; Ritchie *et al.*, 1987). Polynomial regression analysis, together with spectral derivative, enables the identification of wavelengths that can be used to characterize pigment compositions of phytoplankton species in an estuary (Bagheri *et al.*, 1999). The incorporation of more spectral information into the modelling improves the accuracy of the established model.

Nevertheless, linear regression models are invalid for inland and shallow coastal waters that have a higher concentration level of water constituents or a higher degree of optical complexity than clear oceanic waters. At a high reflectance the sensor is relatively insensitive to small changes in the water quality parameters, leading to a nonlinear relationship over the large range of water quality conditions (Lathrop and Lillesand, 1989). Nonlinearity has been observed between suspended sediment concentration, turbidity and sensor reflectance (Moore, 1980; Collins and Pattiaratchi, 1984; Harrington *et al.*, 1992; Xia, 1993). This is true even for hyperspectral data (Althuis, 1998). The fit function between suspended sediment concentrations and corrected satellite data is linear between 0.5 and 10 mg l⁻¹ (Froidefond *et al.*, 1993). Similarly, a linear relationship was observed between reflectance and sediment at a low level of concentration, but the relationship became saturated (e.g., asymptotic) at high concentrations (Bowers *et al.*, 1998). Linearity was achieved only after natural logarithmic transformation (Lathrop *et al.*, 1991). An exponential model proves to be more accurate than others in all cases (Harrington *et al.*, 1992).

Apart from empirical and semi-empirical models, there are several strategies to model water quality parameters, including Monte Carlo simulations (Kondratyev *et al.*, 1998), and hydrodynamic and water quality model simulations (Lyon *et al.*, 1988). Through simulations a forecasting system was developed to predict water quality variables (Yang *et al.*, 1999). The National Aeronautical and Space Administration (NASA) standard curve and the spectrum recommended by the World Radiation Center were used to convert remote sensing data into levels of suspended sediment concentration (Schiebe *et al.*, 1992). Recently, neural network analysis has been introduced to model the transfer function between chlorophyll and sediment concentrations and satellite-received radiance with a much higher accuracy than multiple regression analysis (Keiner and Yah, 1998).

Regardless with which method or in what form they are constructed, the empirical and semi-empirical models are site-specific in most cases. For instance, the algorithms between reflectance and water quality derived for Green Bay, Lake Michigan cannot be extrapolated to Yellowstone and Jackson Lakes, Wyoming, despite similarities in the water quality–reflectance relationships (Lathrop, 1992). Correlations between remotely sensed data and turbidity have been found by several authors, but are unique to each body of water (Fraser, 1998). In fact, remote sensing algorithms derived for the open ocean waters are seldom applicable to lakes and inland seas (Kutser *et al.*, 1998). For this reason, mapping of the same water quality parameter in different regions at different times requires development of series of models (Catts *et al.*, 1985; Rimmer *et al.*, 1987; Hinton, 1991). An exception is a case reported by Woodruff *et al.* (1999). They found that the relationship between satellite-derived reflectance and light attenuation in Pamlico Sound estuary, North Carolina is similar to those determined for Delaware Bay and

Mobile Bay. Hence, the developed algorithms may be applicable to coastal bays and estuaries that have similar sediment characteristics.

IV Choice of remote sensors

Successful remote sensing quantification of water quality parameters is affected not only by the type of waters under investigation, but also by the sensor used. Waters fall broadly into two categories, Case 1 and Case 2, depending on their constituents (Morel, 1980). Case 1 waters are generally oceanic. Their optical properties are dominated by phytoplankton and its degraded products. Found exclusively in coastal and inland areas, Case 2 waters form the focus of this paper. Paradoxically, Case 2 waters cannot be satisfactorily studied from ocean observation satellite data such as Coastal Zone Colour Scanner (CZCS) and Sea-viewing Wide-Field-of-View (SeaWiFS) because of their coarse spatial resolution. Instead, the majority of quantification has to rely on meteorological (e.g., Advanced Very High Resolution Radiometer or AVHRR) and Earth resources satellites data such as Landsat, SPOT and IRS, even though they are designed primarily for terrestrial observations.

Of the six CZCS bands, four are designed to detect chlorophyll and yellow substance. CZCS blue and green bands are good at mapping chlorophyll concentrations (Gordon *et al.*, 1980, 1983; Smith and Baker, 1982; Guan *et al.*, 1985). Nevertheless, the absence of infrared bands from the CZCS sensor hampers effective atmospheric correction. This inability leads to inaccurate results in Case 2 waters that are commonly dominated by suspended sediments and biogenic particulates (Doerffer *et al.*, 1999). At a spatial resolution of 825 m, CZCS imagery is more appropriately suited for oceanic waters (Smith and Baker, 1982) at the regional scale such as continental shelf (Tang *et al.*, 1998) than at a local scale.

As an ocean colour monitoring system succeeding CZCS, SeaWiFS is designed to measure water-leaving radiance related to phytoplankton pigments, Coloured Dissolved Organic Material (CDOM) and suspended particulate matter within an uncertainty of 5% in clear waters, and chlorophyll *a* concentrations (0.05–50 mg m⁻³) within 35% (Hooker and Maritorena, 2000). At a spatial resolution of 1.13 km for regional-scale applications, SeaWiFS data are of little use in shallow waters.

Of the five AVHRR bands, band 1 (580–680 nm) is directly applicable to monitoring water quality, while band 2 (725–1100 nm) is used for atmospheric correction. Reflectance on band 1 is robustly correlated with light attenuation under varying water conditions, including changes in sediment optical characteristics (Woodruff *et al.*, 1999). Band 1 reflectance is most sensitive to changes in suspended solids with phytoplankton pigments having a secondary effect and yellow substance hardly any at all (Bowers *et al.*, 1998). This band allows the detection of surface changes in suspended matter concentration on the order of 0.5 mg dm⁻³ (Bradtke and Krezel, 1994), and distinction of concentration variations above 0.5 mg l⁻¹ (Froidefond *et al.*, 1999). AVHRR imagery enables interpretation of water quality parameters and opens up the way in monitoring inland waters (Prangmsma and Roozkrans, 1989). The spatial scale to which AVHRR data has been applied is local, such as estuary (Froidefond *et al.*, 1999) and bay (Lyon *et al.*, 1988; Stumpf *et al.*, 1999). The small number of cases involving shallow waters suggests that AVHRR imagery is appropriate for monitoring water quality parameters

at the mesoscale, owing to its coarse (1.1 km) spatial resolution.

Landsat MSS sensor's four bands cover the green to near infrared (NIR) portion of the spectrum (500–1100 nm). MSS data are able to generate reliable estimates of suspended sediment concentrations between 50 and 250 mg l⁻¹, beyond which underestimation is rather common (Ritchie and Cooper, 1988). MSS red and NIR bands are more appropriate for predicting surface water quality characteristics (Harrington *et al.*, 1992). Band 4 data are closely correlated with depth-integrated Secchi disk depth (SDD) (Garrison and Bryant, 1981). The coefficients of empirical models are high for turbidity, relatively high for suspended solids, but low for chlorophyll *a* concentrations because of the broad MSS bandwidth. MSS-based predictions are very reliable for Secchi estimates and moderately reliable for chlorophyll *a* concentrations (Lillesand *et al.*, 1983).

TM imagery has a finer spectral resolution than MSS. The improved resolution substantially increases the accuracy of quantifying SDD, chlorophyll *a* concentrations, and turbidity (Lathrop and Lillesand, 1986). In particular, TM2 is sensitive to chlorophyll *a* levels and SDD while TM3 is highly responsive to variations in turbidity. TM data are of mixed utility in water quality studies. On the positive side, turbidity, SDD and chlorophyll *a* in and around Augusta Bay, Sicily were modelled rather adequately (Khorram *et al.*, 1991). Highly significant empirical models were established for chlorophyll concentration and SDD from atmospherically corrected bands 1 and 3 (Pattiaratchi *et al.*, 1994). On the negative side, airborne TM radiance could not be related directly to chlorophyll *a* concentration, even though the image data exhibited spatial structures related to water quality (Danson *et al.*, 1991). Under ideal circumstances TM can be used to assess chlorophyll *a* and SDD with a limited accuracy for inland waters (Dekker and Peters, 1993).

SPOT data are available in three bands covering green to NIR wavelengths (a shortwave IR band was added to SPOT-4). The green band is least correlated with water quality parameters, whereas the red and NIR bands are more closely correlated (Lathrop and Lillesand, 1989). The last two bands are relatively insensitive to changes in turbidity and total suspended solids of low concentration, but more sensitive at a higher level of concentration. At most, suspended solids and chlorophyll *a* concentrations are derivable from SPOT data (Chacon-Torres *et al.*, 1992). Owing to the coarse spectral resolution (finest 70 nm), caution must be exercised in delineating chlorophyll *a* levels in highly turbid waters. Although SPOT data are significantly correlated with turbidity and chlorophyll *a*, the correlation is so weak that they cannot be used as a practical tool for monitoring water quality (Cairns *et al.*, 1997).

No definite conclusions have emerged from the above discussion regarding the strength, form or even the optimum wavelengths of remote sensing of water quality parameters (Curran and Novo, 1988). The lack of agreement is attributed to the spatial and temporal variability of sediment size, shape, mineralogy, variation in the range of concentration levels of in-water constituents and the presence/absence of co-varying constituents. Even tide height affects the relationship between some water quality parameters and remotely sensed data (Braga *et al.*, 1993). Another reported factor is season. For instance, Dierberg and Carriker (1994) found that chlorophyll *a* is accurately studied during summer when phytoplankton dominates suspended solids composition.

V Water quality parameters quantifiable

Water quality parameters that can be quantified by means of remote sensing fall into three groups: inorganic sediment particulates, phytoplankton pigments and CDOM (Doerffer *et al.*, 1999).

1 Suspended sediment and turbidity

It is relatively easy to remotely sense suspended sediments in a water body because of their strong backscattering of the incident radiation. Suspended solid concentrations have been commonly determined from MSS data (Ritchie *et al.*, 1987; Harrington *et al.*, 1992; Schiebe *et al.*, 1992), TM (Lathrop, 1992), SPOT data (Ouillon *et al.*, 1997), and even colour and colour IR photographs (Khorram, 1981; Gao and O'Leary, 1997b). Photographs are able to reveal subtlety in sediment distribution because of their fine detail, but are subject to artificial radiometry caused by inconsistent photo processing if multiple photographs are involved. The level of suspended sediment concentration that has been quantified varies from 1–30 mg l⁻¹ with background concentrations around 1–3 mg l⁻¹ (Jorgensen and Edelvang, 2000) to over 50 mg l⁻¹ (Ritchie and Schiebe, 1985; Ritchie *et al.*, 1987). The quantification at the lower level is made possible owing to the use of Compact Airborne Spectrographic Imager (CASI) data with a super high radiometric resolution. A much wider concentration level of 0.1–66 mg l⁻¹ was estimated from air-borne spectrometer data at a wavelength of 380 nm (Gitelson *et al.*, 1993).

Since sediments are usually suspended in shallow waters, their quantification is confined to lakes (Ritchie and Cooper, 1988; Harrington *et al.*, 1992), reservoirs (Choubey, 1997), bays (Khorram, 1981; Lathrop *et al.*, 1991), inner harbours (Gao and O'Leary, 1997a,b), and even rivers (Ouillon *et al.*, 1997; Wass *et al.*, 1997). In such a shallow environment, artificial radiometry is minimized by a calm water surface. On the other hand, sediments in shallow waters are vulnerable to re-suspension under turbulent conditions. As with all water quality parameters, the detected suspended sediments are restricted to near-surface waters (Ritchie and Schiebe, 1985). Therefore, remotely sensed levels of suspended sediments tend to be higher than their modelled counterparts because model results are depth-integrated while image signal originates from the surface water (Jorgensen and Edelvang, 2000). The estimation of total suspended solids within a water body requires profiling sediment distribution at representative sites, or making assumptions regarding the vertical distribution. In either case, the use of bathymetry is essential (Gao and O'Leary, 1997b).

Turbidity causes light to be scattered and absorbed instead of transmitted. It is linearly correlated with suspended sediment concentration if water constituent particles are homogenous (Forster *et al.*, 1992). Sediments of differing size but the same concentration reduce turbidity. Hence, it is problematic to estimate suspended sediments from turbidity or *vice versa*. Water turbidity can be correlated with optical density of black and white photographs (Bhargava, 1983). The turbidity of the Tawa Reservoir, India is positively correlated with LISS-I bands 1, 2 and 3 data (Choubey, 1997). Turbidity can also be modelled from MSS data (Carpenter and Carpenter, 1983). Highly significant correlations exist between turbidity and TM reflectance data (Fraser,

1998). Such relationships enable water turbidity along the Swedish coastline to be mapped from Landsat imagery (Lindell *et al.*, 1985).

2 Chlorophyll concentration

Phytoplankton pigments consist mainly of chlorophyll *a*, *b* and *c*, of which chlorophyll *a* is derivable by means of remote sensing. Sun-stimulated natural fluorescence of chlorophyll *a* is a good predictor for phytoplankton, even in waters with varying suspended matter and yellow substance concentrations (Fischer and Kronfeld, 1990). The detection and assessment of chlorophyll *a* concentration and its variations within a water body require narrow bands of imagery (Harrington and Repic, 1995). As an example, the mapping of chlorophyll *a* and phytoplankton requires radiometric data with a spectral resolution finer than 1 nm (Gitelson *et al.*, 1993).

Chlorophyll concentrations have been quantified from a wide variety of images, including MSS and TM. Strong correlations exist between chlorophyll *a* and MSS data (Shimoda *et al.*, 1986). Although chlorophyll *a* concentrations have been modelled from airborne MSS and TM (Catts *et al.*, 1985; Verdin 1985), TM imagery is used more frequently. Commonly used bands are TM1 (Lopez-Garcia and Caselles, 1987; Gracia and Caselles, 1990), TM2 (Lathrop and Lillesand, 1986). Besides, (TM1–TM3)/TM2 is a useful index for estimating chlorophyll concentrations (Mayo *et al.*, 1995). As a matter of fact, ratioed wavelength bands and line height algorithms provide the best correlations to ground-truthed chlorophyll *a* (Dierberg and Carriker, 1994).

The distribution of chlorophyll at a concentration level as low as 3–7 mg m⁻³ was estimated from Landsat TM data in the spectral range 400 to 750 nm (Mayo *et al.*, 1995). A reflectance model based on a spectral vector expression may provide estimates of chlorophyll for concentrations greater than 5 µg l⁻¹ with some calibration in turbid water (Stumpf and Tyler, 1988). Reliable estimates and accurate maps of total chlorophyll concentrations have been derived from high resolution airborne data (Millie *et al.*, 1992), and TM data (Lopez-Garcia and Caselles, 1987). Highly significant, multitemporal predictive algorithms, established from field data collected at the time of the satellite overpass, existed between surface chlorophyll concentration at a range of 0.2–2.7 µg l⁻¹ and atmospherically corrected TM radiance (Pattiaratchi *et al.*, 1994). Phytoplankton chlorophyll *a* at a range of 0.1–350 mg m⁻¹ was estimated from simultaneous measurements of the upwelling and downwelling irradiances (Gitelson *et al.*, 1993). Best results of chlorophyll *a* content were achieved with the use of linear spectral unmixing (Thiemann and Kaufmann, 2000).

3 CDOM

CDOM encompasses algae, yellow substance and organic plumes. Algae are simple, variously one-celled organisms containing chlorophyll and other pigments. Remote sensing of algae in inland waters should be based on increased scattering by the cells and not increased absorption by chlorophyll (Quibell, 1992). The upwelling spectral signatures for algae were determined by the reflectance of the particles themselves, and by the absorption by the water surrounding the particles (Quibell, 1991). Concentrations of algae in the photic zone in the very turbid waters off the eastern

Australian coast can be estimated using existing analytical and modelling techniques, provided they can be characterized by *in situ* samples (Jupp *et al.*, 1994). Some algal types and their concentrations are related to CASI data. The relationship can be exploited to detect and monitor algal blooms (Hick *et al.*, 1998). A dense algal bloom at Lake Patzcuaro, Mexico was identified from SPOT images (Chacon-Torres *et al.*, 1992). A thematic map of algae was generated from classification of TM data according to depth and results of water optics modelling (Tassan, 1993). An operational method for algae mapping in the upper layers of lagoon waters from airborne MSS data has been developed by Zibordi *et al.* (1990).

The presence of yellow substance must be carefully considered in inferring water composition from its colour signature (Tassan, 1988) because its absorption affects remote sensing of other water quality parameters, such as chlorophyll-like pigment and total suspended sediment concentrations (Ferrari and Tassan, 1992). The absorption has been measured by a combination of beam transmission and induced fluorescence to a high accuracy (Ferrari and Tassan, 1990). Kowalczyk (1997) calculated the yellow substance absorption coefficient at 400 nm and yellow substance absorption spectrum slope coefficient. Sugihara and Kishino (1988) developed an algorithm for estimating the absorption coefficient from the irradiance reflectance just below the sea surface. Yellow substance concentration is correlated with salinity and chlorophyll concentrations (Warnock *et al.*, 1999). A relationship appears to exist between yellow substance absorbance at 380 nm and yellow substance fluorescence intensity. Predicted yellow substance is more sensitive to a change in detrital material than a change in living phytoplankton in turbid waters (Ferrari *et al.*, 1996). Passive remote sensing is not suitable for investigating waters with a high concentration of yellow substance because extremely strong absorption by water leads to an 'abnormal' shape of the reflectance spectra (Kutser *et al.*, 1998).

4 SDD

SDD is a crude measure of water clarity or transparency. It increases with the decrease in reflected radiance (Choubey, 1998). SDD is significantly correlated to atmospherically corrected satellite radiance (Topliss *et al.*, 1988; Pattiaratchi *et al.*, 1994). SDD is also related to reflectance just below the surface in atmospherically corrected MSS green band, incorporating the ratio of backscattering to total scattering coefficients for suspended particles (Mulhearn, 1995). The relationship is quite accurate for SDD < 16 m. Highly significant models have been developed for SDD from a variety of data, including MSS (Garrison and Bryant, 1981; Verdin, 1985), TM (Lavery *et al.*, 1993; Allee and Johnson, 1999) and even video data (Mausel *et al.*, 1991). SDD is closely correlated with TM data, especially during high tide (Braga *et al.*, 1993). The correlation achieved was as high as -0.83 and -0.91 for the red band (644–656 nm), and 0.93 and 0.84 for the yellow-green/red ratio (543–552 nm) from the original and log transformed data, respectively (Mausel *et al.*, 1991). Highly significant models were developed for SDD that ranged from 4 to 15 m from TM1 and TM3 satellite radiance (Pattiaratchi *et al.*, 1994). The only exception is a study by Lopez-Garcia and Caselles (1987) who reported that SDD did not show significant correlation with any TM bands.

Thanks to the close correlation, SDD can be quantified from reflected radiance

received by the IRS satellite (Choubey, 1998). Once estimated, SDD data may be used to study the relative nutrient and solids loading situations (Lindell *et al.*, 1985).

VI Implementation of quantification

Quantification of water quality parameters requires integration of remotely sensed data and *in situ* water quality samples. For certain parameters, the quantification also needs incorporation of ancillary data. One common type of ancillary data is bathymetry in water quality modelling. The spatial correlation and integration of *in situ* water samples, satellite imagery and bathymetric data with one another are most effectively handled in a GIS. GIS is particularly effective in integrating bathymetric data into the quantification. Both the modelling of water quality and visualization of the modelled results can also be fulfilled in a GIS.

Bathymetric data are usually acquired from navigational charts, and transformed into an array of regular grid cells known as Digital Elevation Models (DEMs). The grid size is kept the same as that of image pixels. A grid DEM has to be co-registered with the remote sensing image layers or referenced to a common coordinate system before it can be integrated with them (Nichol and Gupta, 1990). The incorporation of bathymetric data into water quality studies has facilitated mapping of coastal waters (Nichol and Gupta, 1990; Ruzafa *et al.*, 1996), understanding of transportation of water constituents (Lathrop and Lillesand, 1989), and enhancement of the interpretative capability of water quality maps, in addition to estimation of total suspended sediment within a shallow coastal water body (Gao and O'Leary, 1997b). Bathymetric data have also found applications in transforming airborne MSS imagery into an attenuation coefficient in mapping chlorophyll concentrations (Ruzafa *et al.*, 1996). The relationship between estuarine mixing processes and bathymetry was revealed after bathymetric data were integrated with airborne TM data in a GIS (Ferrier and Anderson, 1996). Overlay of a contour map of bathymetry over a suspended sediment concentration map in a raster GIS shed light on the relationship between the Fox River Plume dispersion and bathymetry in Green Bay, Michigan (Lathrop and Lillesand, 1989). Bathymetric data, together with a SPOT image, were used to map water quality in a raster GIS (Nichol and Gupta, 1990). The reclassification functions were valuable in mapping suspended sediment and chlorophyll concentration in shallow coastal waters.

VII Validation of quantified results

On-spot validation of the quantified results in a post-session is not feasible because of changed water conditions. A common practice is to collect *in situ* samples as sizeable as possible. A portion of them is used to construct the empirical model while the remainder is used as independent checkers to verify the results (Gordon *et al.*, 1983; Khorram, 1985; Lindell *et al.*, 1985; Gracia and Caselles, 1990; Gitelson *et al.*, 1993; Gao and O'Leary, 1997a). The number of *in situ* samples that has been collected in the past is rather small, varying around 21 (Sunar, 1992), 22 (MacFarlane and Robinson, 1984) and 31 (Ramsey *et al.*, 1992). Although a total of 25 samples were collected by Forster *et al.* (1993), only nine were available for chlorophyll *a*, of which two were used for the

verification of the constructed model. Such a small sample size is a consequence of two factors. First, the exorbitant expense associated with the collection means that it is not financially viable to acquire a large sample. Secondly, the constraint of ground truthing within 2–3 hours of image acquisition considerably restricts the availability of field observations (Khorram *et al.*, 1989; Chacon-Torres *et al.*, 1992; Harding *et al.*, 1992). In order to overcome the limitations associated with a small sample size, a frequently adopted alternative is to use all the available samples in constructing the empirical model and to base the validation on its goodness-of-fit (Stumpf and Tyler, 1988; Sunar, 1992; Baranowska, 1993; Lavery *et al.*, 1993; Pattiaratchi *et al.*, 1994). Other strategies for validation include use of regression coefficient (R^2), significance level of the regressed model, normality test of regression residuals, and scatterplots of image and water quality data. For instance, 95% of samples within ± 60 turbidity of the regression line was used as the accuracy indicator (Wass *et al.*, 1997). Multiple correlation coefficients in excess of $R = 0.9$ resulted from regression analysis of site sampled turbidity and chlorophyll *a* parameters to Landsat-TM data (Forster *et al.*, 1993). An R^2 value of 0.9 between reflectance ratios and chlorophyll concentration was used for the same purpose (Olszewski *et al.*, 1999). Similarly, Garrison and Bryant (1981) reported that regression analyses revealed a good correlation between Secchi disk transparencies and Landsat band 4 data ($R^2 = 0.85$). Ground-truthed uncorrected chlorophyll *a* was best correlated with CASI in univariate, linear regression analyses ($R^2 = 0.84\text{--}0.95$) (Dierberg and Carriker, 1994). In the best unbiased prediction of water quality parameters from airborne MSS data, the predictor equations explained 91% of chlorophyll *a* variance, 91% of the total suspended particles variance (Ramsey *et al.*, 1992). Remotely sensed reflectance values agreed well with *in situ* particle densities with an average R^2 of 0.81 for Landsat data and only 0.53 for AVHRR (Carrick *et al.*, 1994).

The numerical accuracy of quantification is not routinely reported in the literature. When it is mentioned, the accuracy is rather vague in some cases. For instance, the accuracy of water turbidity measurements was sufficient to meet certain monitoring requirements (McKim *et al.*, 1984). Significant relationships established between chlorophyll *a* and TM data led to modelled chlorophyll results consistent with the available general knowledge (Baban, 1993). Maracci and Ooms (1988) merely mentioned that analytical results of chlorophyll determination were in good agreement with optical *in situ* data. Suspended matter concentrations in a plume mapped from CASI data were in reasonable agreement with two-dimensional hydrodynamic modelled results (Jorgensen and Edolvang, 2000). Garcia and Robinson (1991) found that the accuracy of determining chlorophyll *a* concentration was lower in the Bristol Channel off the south Gower coastline than elsewhere.

Among reported numerical accuracy levels, there is a wide variation. An accuracy of 20–60% was achieved in estimating chlorophyll concentration and the absorption of light by yellow substance (Olszewski *et al.*, 1999). The estimation error of chlorophyll concentration from atmospherically corrected TM data was smaller than 0.85 mg m^{-3} (Mayo *et al.*, 1995). A discrepancy of $\pm 25\%$ existed between the estimated total suspended solids and water transparency over the calibration data range (Lathrop *et al.*, 1991). Water quality parameters could be predicted within approximately $\pm 10\%$ for the mean over most of their range (5% due to sampling error alone) (Lathrop and Lillesand, 1989). Remotely sensed estimates of suspended sediment concentration were $\pm 18\%$ to $\pm 48\%$ within those derived from *in situ* turbidity record, depending on location (Wass

et al., 1997). A deviation of less than 10% was achieved in modelling sediment concentrations using a neural network, much lower than 25% achieved with regression analysis (Keiner and Yah, 1998). The sum of chlorophyll *a* and pheophytin was retrieved from remotely sensed data at a discrepancy of 23% from *in situ* measurements for concentration of 2 mg m^{-3} and at 10–12% for concentrations exceeding 12 mg m^{-3} (Hoogenboom *et al.*, 1998). Interpretation techniques developed to process the spectra of upwelling radiation from water in the visible spectrum make it possible to retrieve chlorophyll *a* concentration with a standard error of less than 2.6 mg l^{-1} , and dissolved organic matter concentration less than 0.5 C l^{-1} (Gitelson and Kondratyev, 1991). Gordon *et al.* (1985) concluded that under typical atmospheric conditions phytoplankton pigment concentration (the sum of the concentrations of chlorophyll *a* and pheophytin *a*) can be extracted from CZCS satellite imagery to within about $\pm 30\%$ over concentration ranges from 0 to 5 mg m^{-3} for Morel Case 1 water. Naturally, this accuracy would drop for Case 2 water because of a higher degree of spatial variability.

No uniform accuracy is achieved in quantifying water quality parameters for several reasons. They include the concentration levels of the parameter (Hoogenboom *et al.*, 1998), its spatial and temporal variability, the type of remotely sensed data used, the closeness of the regressed models and the quality of assessment data (Catts *et al.*, 1985; Rimmer *et al.*, 1987; Khorram *et al.*, 1989; Cipollini *et al.*, 1993). *In situ* data used in the assessment showed substantial variability and were poorly correlated with their image data even at short distances (Van Raaphorst *et al.*, 1998).

VIII Conclusions

This review has revealed that a diverse range of water quality parameters has been quantified from various sensors. These parameters include suspended sediment, chlorophyll *a* concentrations, CDOM (i.e., algae, yellow substance and organic blooms) and SDD. So far, suspended sediment and chlorophyll *a* concentration have received the most attention because ocean colour remote sensing provides a convenient method for determining them from upwelling radiance. The quantification has been carried out with both space-borne and airborne data. Ocean observation satellites such as CZCS and SeaWiFS are of little utility in monitoring quality of shallow waters because of their coarse spatial resolution. Such meteorologic satellite data as AVHRR have shown some success at the semoscale. Existing Earth resources satellite data have generated mixed outcomes in the quantification. It is difficult for them to result in accurate maps of water quality parameters in relatively clear waters because of low image spectral variations. The quantification has to rely on airborne remote sensing.

The aforementioned water quality parameters have been quantified based on linear and nonlinear empirical models that are established from *in situ* samples collected concurrently with the recording of remotely sensed data. Atmospherically corrected satellite data are indispensable in the establishment of highly significant, predictive models (Lavery *et al.*, 1993). Apart from the closeness of the models, the accuracy of quantification is also affected by the spatial variability of the parameter in consideration and its concentration levels. Thus, the achieved accuracy of quantification varies considerably. Specific to a geographic area for which it is constructed, the model is

applied to the entire remote sensing image. Their integration with GIS creates a new environment in which more water quality parameters are quantified ever more accurately.

References

- Aguirre-Gomez, R.** 2000: Detection of total suspended sediments in the North Sea using AVHRR and ship data. *International Journal of Remote Sensing* 21, 1583–96.
- Allee, R.J. and Johnson, J.E.** 1999: Use of satellite imagery to estimate surface chlorophyll *a* and Secchi disc depth of Bull Shoals Reservoir, Arkansas, USA. *International Journal of Remote Sensing* 20, 1057–72.
- Althuis, Ij.A.** 1998: Suspended particulate matter detection in the North Sea by hyper spectral airborne remote sensing. *Aquatic Ecology* 32, 93–98.
- Baban, S.M.J.** 1993: Detecting water quality parameters in the Norfolk Broads, U.K., using Landsat imagery. *International Journal of Remote Sensing* 14, 1247–67.
- Bagheri, S., Zetlin, C. and Dios, R.** 1999: Estimation of optical properties of nearshore water. *International Journal of Remote Sensing* 20, 3393–97.
- Baranowska, T.** 1993: The estimation of water quality and trophic state in lakes with application of multitemporal Landsat-MSS and -TM images. In Winkler, P., editor, *Remote sensing for monitoring the changing environment*. Proceedings of the 12th EARSeL Symposium, Hungary, 8–12 September 1992. Rotterdam: Balkema, 189–94.
- Bhargava, D.S.** 1983: Very low altitude remote sensing of the water quality of rivers. *Photogrammetric Engineering and Remote Sensing* 49, 805–809.
- Bierwirth, P.N., Lee, T.J. and Burne, R.V.** 1993: Shallow sea-floor reflectance and water depth derived by unmixing multispectral imagery. *Photogrammetric Engineering and Remote Sensing* 59, 331–38.
- Bowers, D.G., Boudjelas, S. and Harker, G.E.L.** 1998: The distribution of fine suspended sediments in the surface waters of the Irish Sea and its relation to tidal stirring. *International Journal of Remote Sensing* 19, 2789–805.
- Bradtke, K. and Krezel, A.** 1994: The inhomogeneity of vertical distributions of suspended matter in the sea – consequences for remote sensing. *Oceanologia* 36, 47–79.
- Braga, C.Z.F., Setzer, A.W. and De Lacerda, L.D.** 1993: Water quality assessment with simultaneous Landsat 5 TM data at Guanabara Bay, Rio de Janeiro, Brazil. *Remote Sensing of Environment* 45, 95–106.
- Brown, D.G. and Walsh, S.J.** 1991: Compatibility of nonsynchronous in situ water quality data and remotely sensed spectral information for assessing lake turbidity levels in complex and inaccessible terrain. *Geocarto International* 6, 5–11.
- Cairns, S.H., Dickson, K.L. and Atkinson, S.F.** 1997: An examination of measuring selected water quality trophic indicators with SPOT satellite HRV data. *Photogrammetric Engineering and Remote Sensing* 63, 263–65.
- Carpenter D.J. and Carpenter, S.M.** 1983: Modelling inland water quality using Landsat data. *Remote Sensing of Environment* 13, 345–52.
- Carrick, H.J., Worth, D. and Marshall, M.L.** 1994: The influence of water circulation on chlorophyll–turbidity relationships in Lake Okeechobee as determined by remote sensing. *Journal of Plankton Research* 16(9), 1117–35.
- Catts, G.P., Khorram, S., Cloern, J.E., Knight, A.W. and DeGloria, S.D.** 1985: Remote sensing of tidal chlorophyll-*a* variations in estuaries. *International Journal of Remote Sensing* 11, 1685–706.
- Chacon-Torres, A., Ross, L.G., Beveridge, M.C.M. and Watson, A.I.** 1992: The application of SPOT multispectral imagery for the assessment of water quality in Lake Patzcuaro, Mexico. *International Journal of Remote Sensing* 13, 587–603.
- Choubey, V.K.** 1997: Monitoring turbidity with IRS-1A data. *Hydrological Processes* 11, 1907–15.
- 1998: Laboratory experiment, field and remotely sensed data analysis for the assessment of suspended solids concentration and secchi depth of the reservoir surface water. *International Journal of Remote Sensing* 19, 3349–60.
- Cipollini, P., Corsini, G. and Ferretti, E.** 1993: Multitemporal water quality analysis along the Ligurian Coast. In *Better understanding of Earth environment. Proceedings of the IGARSS 93*

- Symposium*. 18–21 August 1993, Tokyo. Piscataway NJ: IEEE (IEEE cat no. 93ch3294-6), 700–702.
- Collins, M.B. and Pattiaratchi, C.B.** 1984: Identification of suspended sediment in coastal waters using airborne TM data. *International Journal of Remote Sensing* 5, 635–57.
- Curran, P.J. and Novo, E.M.M.** 1988: The relationship between suspended sediment concentration and remotely sensed spectral radiance: a review. *Journal of Coastal Research* 4, 351–68.
- Danson, F.M., Heathwaite, A.L. and Trudgill, S.T.** 1991: Multi-temporal monitoring of lake water quality. In Hunt, J.J., editor, *Physical measurements and signatures in remote sensing*. Proceedings 5th International Colloquium, Courchevel. Noordwijk: European Space Agency. Special Publication 319, vol. 1, 169–72.
- Dekker, A.G. and Peters, S.W.M.** 1993: The use of the Thematic Mapper for the analysis of eutrophic lakes: a case study in the Netherlands. *International Journal of Remote Sensing* 14, 799–821.
- Dekker, A.G., Zamurovic-Nenad, Z., Hoogenboom, H.J. and Peters, S.W.M.** 1996: Remote sensing, ecological water quality modelling and in situ measurements: a case study in shallow lakes. *Journal des Sciences Hydrologiques* 41, 531–47.
- Dierberg, F.E. and Carriker, N.E.** 1994: Field testing two instruments for remotely sensing water quality in the Tennessee Valley. *Environmental Science and Technology* 28, 16–25.
- Doerffer, R., Sorensen, K. and Aiken, J.** 1999: MERIS potential for coastal zone applications. *International Journal of Remote Sensing* 20, 1809–18.
- Ferrari, G.M. and Tassan, S.** 1990: Measurement of yellow substance absorption and evaluation of its influence on the remote sensing of water quality. In Konecny, G., editor, *Proceedings of the Tenth EARSeL Symposium: new European systems, sensors and applications*. Boulogne-Billancourt: EARSeL, 244–50.
- 1992: Evaluation of the influence of yellow substance absorption on the remote sensing of water quality in the Gulf of Naples: a case study. *International Journal of Remote Sensing* 13, 2177–89.
- Ferrari, G.M., Hoepffner, N. and Mingazzini, M.** 1996: Optical properties of the water in a deltaic environment: prospective tool to analyze satellite data in turbid waters. *Remote Sensing of Environment* 58, 69–80.
- Ferrier, G. and Anderson, J.M.** 1996: The application of remote sensing data in the study of effluent dispersal in the Tay Estuary, Scotland. *International Journal of Remote Sensing* 17, 3541–66.
- Fieldler, P.C. and Laurs, R.M.** 1990: Variability of the Columbia River plume observed in visible and infrared satellite imagery. *International Journal of Remote Sensing* 11, 999–1010.
- Fischer, J. and Kronfeld, U.** 1990: Sun-stimulated chlorophyll fluorescence 1: influence of oceanic properties. *International Journal of Remote Sensing* 11(12), 2125–47.
- Forster, B.C., Sha, X. and Xu, B.** 1993. Remote sensing of sea water quality parameters using Landsat-TM. *International Journal of Remote Sensing* 14, 2759–71.
- Forster, I.D.L., Millington, R. and Grew, R.G.** 1992: The impact of particle size controls on stream turbidity measurements: some implications for suspended sediment yield estimation. In Bogen, J., Walling, D.E. and Day, T.J., editors, *Erosion and sediment transport monitoring programmes in river basins*. Proceedings of the Oslo Symposium, August 1992. IAHS Publication No. 210, 51–62.
- Fraser, R.N.** 1998: Multispectral remote sensing of turbidity among Nebraska Sand Hills lakes. *International Journal of Remote Sensing* 19, 3011–16.
- Froidefond, J.M., Castaing, P., Jouanneau, J.M., Prud'homme, R. and Dinet, A.** 1993: Method for the quantification of suspended sediments from AVHRR NOAA-11 satellite data. *International Journal of Remote Sensing* 14, 885–94.
- Froidefond, J.M., Castaing, P. and Prud'homme, R.** 1999: Monitoring suspended particulate matter fluxes and patterns with the AVHRR/NOAA-11 satellite: Application to the Bay of Biscay. *Deep Sea Research Part II: Topical Studies in Oceanography* 46, 2029–55.
- Gao, J. and O'Leary, S.M.** 1997a: Quantification of SSC from airborne remotely sensed data: the role of spatial resolution. *Photogrammetric Engineering and Remote Sensing* 63, 267–71.
- 1997b: Estimation of suspended solids from aerial photographs in a GIS. *International Journal of Remote Sensing* 18, 2073–85.
- Garcia, C.A.E. and Robinson, I.S.** 1991: Chlorophyll *a* mapping using airborne Thematic Mapper in the Bristol Channel (South Gower coastline). *International Journal of Remote Sensing* 12, 2073–86.
- Garrison, V. and Bryant, N.** 1981: Lake classifica-

- tion in Vermont. In *Proceedings of the 2nd Eastern Regional Remote Sensing Applications Conference*. Danvers, MA, March 1981 (US NASA, Goddard Space Flight Center, Greenbelt, MD, NASA CP 2198), 345–51.
- Gitelson, A.** 1992: The peak near 700 nm on radiance spectra of algae and water: relationships of its magnitude and position with chlorophyll concentration. *International Journal of Remote Sensing* 13, 3367–73.
- Gitelson, A.A. and Kondratyev, K.Y.** 1991: Optical models of mesotrophic and eutrophic water bodies. *International Journal of Remote Sensing* 12, 373–85.
- Gitelson, A., Garbuzov, G., Szilagy, F., Mittenzwey, K.H., Karnieli, A. and Kaiser, A.** 1993: Quantitative remote sensing methods for real time monitoring of inland waters quality. *International Journal of Remote Sensing* 14, 1269–95.
- Gordon, H.R., Clark, D.K., Mueller, J.L. and Hovis, W.A.** 1980: Phytoplankton pigments from the Nimbus-7 Coastal Zone Color Scanner: comparison with surface measurements. *Science* 210, 63–66.
- Gordon, H.R., Clark, D.K., Brown, J.W., Brown, O.B., Evans, R.H. and Broenkow, W.W.** 1983: Phytoplankton pigment concentrations in the Middle Atlantic Bight: comparison of ship determinations and CZCS estimates. *Applied Optics* 22, 20–36.
- Gordon, H.R., Austin, R.W., Clark, D.K., Hovis, W.A., and Yentsch, C.S.** 1985: Ocean color measurements. In Saltzman, B., editor, *Satellite oceanic remote sensing*. *Advances in Geophysics* 27, 297–333.
- Gracia, M.J.L. and Caselles, V.** 1990: A multitemporal study of chlorophyll-*a* concentration in the Albufera lagoon of Valencia, Spain, using Thematic Mapper data. *International Journal of Remote Sensing* 11, 301–11.
- Guan, F., Pelaez, J. and Stewart, H.** 1985: The atmospheric correction and measurement of chlorophyll concentration using the Coastal Zone Color Scanner. *Limnology and Oceanography* 30, 273–85.
- Harding, L.W. Jr., Itsweire, E.C. and Esaias, W.E.** 1992: Determination of phytoplankton chlorophyll concentrations in the Chesapeake Bay with aircraft remote sensing. *Remote Sensing of Environment* 40, 79–100.
- Harrington, J. and Repic, R.L.** 1995: Hyperspectral and video remote sensing of Oklahoma lakes. *Papers and Proceedings of Applied Geography Conferences*, State University of New York at Binghamton 18, 79–85.
- Harrington, J.A. Jr., Schiebe, F.R. and Nix, J.F.** 1992: Remote sensing of Lake Chicot, Arkansas: monitoring suspended sediments, turbidity, and secchi depth with Landsat MSS data. *Remote Sensing of Environment* 39, 15–27.
- Hick, P., Jernakoff, P. and Hosja, W.** 1998: Algal bloom research using airborne remotely sensed data: Comparison of high spectral resolution and broad bandwidth CASI data with field measurements in the Swan River in Western Australia. *Geocarto International* 13, 19–28.
- Hinton, J.C.** 1991: Application of eigenvector analysis to remote sensing of coastal water quality. *International Journal of Remote Sensing* 12, 1441–60.
- Hoogenboom, H.J., Dekker, A.G. and Althuisi, Ij.A.** 1998: Simulation of AVIRIS sensitivity for detecting chlorophyll over coastal and inland waters. *Remote Sensing of Environment* 65, 333–40.
- Hooker, S.B. and Maritorena, S.** 2000: An evaluation of oceanographic radiometers and deployment methodologies. *Journal of Atmospheric and Oceanic Technology* 17, 811–30.
- Huang, K. and Lulla, K.** 1986: Modelling water quality using Thematic Mapper data: Case of Lake Michigan. *Geocarto International* 2, 3–16.
- Johnson, R.W. and Harriss, R.C.** 1980: Remote sensing for water quality and biological measurements in coastal waters. *Photogrammetric Engineering and Remote Sensing* 46, 77–85.
- Johnson, R.W., Bahn, G.S. and Thomas, J.P.** 1981: Synoptic thermal and oceanographic parameter distributions in the New York Bight apex. *Photogrammetric Engineering and Remote Sensing* 47, 1593–98.
- Jorgensen, P.V. and Edrelvang, K.** 2000: CASI data utilized for mapping suspended matter concentrations in sediment plumes and verification of 2-D hydrodynamic modelling. *International Journal of Remote Sensing* 21, 2247–58.
- Jupp, D.L.B., Kirk, J.T.O. and Harris, G.P.** 1994: Detection, identification and mapping of cyanobacteria using remote sensing to measure the optical quality of turbid inland waters. *Australian Journal of Marine and Freshwater Research* 45, 801–28.
- Keiner, L.E. and Yah, X.H.** 1998: A neural network model for estimating sea surface chlorophyll and sediments from thematic mapper imagery. *Remote Sensing of Environment* 66, 153–65.

- Khorram, S.** 1981: Water quality mapping from Landsat digital data. *International Journal of Remote Sensing* 2, 145–53.
- 1985: Development of water quality models applicable through the entire San Francisco bay and delta. *Photogrammetric Engineering and Remote Sensing* 51, 53–62.
- Khorram, S., Cheshire, H., Geraci, A. and Rosa, G.L.** 1989: Water quality mapping of Augusta Bay, Italy from Landsat TM data. In *Proceedings of IGARSS 89 Symposium, remote sensing, an economic tool for the nineties*, 10–14 July 1989. Vancouver: IGARSS, 335–38.
- 1991: Water quality mapping of Augusta Bay, Italy from Landsat TM data. *International Journal of Remote Sensing* 12, 803–808.
- Kondratyev, K.Y., Pozdnyakov, D.V. and Petterson, L.H.** 1998: Water quality remote sensing in the visible spectrum. *International Journal of Remote Sensing* 19, 957–79.
- Kowalczyk, P.** 1997: Seasonal variability of the yellow substance absorption in the euphotic zone in the case II waters (Baltic Sea). In Cecchi, G., Engman, E.T. and Zilioti, E.I., editors, *Earth surface sensing*. Proceedings SPIE Conference, London, 22–25 September 1997. Bellingham WA: SPIE, 435–43.
- Kutser, T., Arst, H., Maekivi, S. and Kallaste, K.** 1998: Estimation of the water quality of the Baltic Sea and lakes in Estonia and Finland by passive optical remote sensing measurements on board vessel. *Lakes and Reservoirs: Research and Management* 3, 53–66.
- Lathrop, R.G., Jr.** 1992: Landsat Thematic Mapper monitoring of turbid inland water quality. *Photogrammetric Engineering and Remote Sensing* 58, 465–70.
- Lathrop, R.G., Jr. and Lillesand, T.M.** 1986: Use of Thematic Mapper data to assess water quality in Green Bay and central Lake Michigan. *Photogrammetric Engineering and Remote Sensing* 52, 671–80.
- 1989: Monitoring water quality and river plume transport in Green Bay, Lake Michigan with SPOT-1 imagery. *Photogrammetric Engineering and Remote Sensing* 55, 349–54.
- Lathrop, R.G., Jr., Lillesand, T.M. and Yandell, B.S.** 1991: Testing the utility of simple multirate Thematic Mapper calibration algorithms for monitoring turbid inland waters. *International Journal of Remote Sensing* 12, 2045–63.
- Lavery, P., Pattiaratchi, C., Wyllie, A. and Hick, P.** 1993: Water quality monitoring in estuarine waters using the Landsat Thematic Mapper. *Remote Sensing of Environment* 46, 268–80.
- Lillesand, T.M., Johnson, W.L., Deuell, R.L., Lindstrom, O.M. and Meisner, D.E.** 1983: Use of Landsat data to predict the trophic state of Minnesota Lakes. *Photogrammetric Engineering and Remote Sensing* 49, 219–29.
- Lindell, T., Steinvall, O., Jonsson, M. and Claesson, Th.** 1985: Mapping of coastal-water turbidity using Landsat imagery. *International Journal of Remote Sensing* 6, 629–42.
- Lopez-Garcia, M.J. and Caselles, V.** 1987: Use of Thematic Mapper data to assess water quality in Albufera Lagoon of Valencia (Spain). In *Advances in digital image processing*. Proceedings 13th Annual Conference of the Remote Sensing Society, Nottingham. Nottingham: Remote Sensing Society, 510–19.
- Lyon, J.G., Bedford, K.W., Yen, C.J, Lee, D.H. and Mark, D.J.** 1988: Determination of suspended sediment concentrations from multiple day Landsat and AVHRR Data. *Remote Sensing of Environment* 25, 107–15.
- MacFarlane, N. and Robinson, I.S.** 1984: Atmospheric correction of Landsat MSS data for a multirate suspended sediment algorithm. *International Journal of Remote Sensing* 5, 561–76.
- Maracci, G. and Ooms, M.** 1988. Optical properties of seawater bodies: measurements with an underwater radiometer and a high-resolution spectroradiometer. In Guyenne, T.D. and Hunt, J.J., editors, *Remote sensing*. Proceedings IGARSS 88 symposium, Edinburgh, 1988., Vol. 3 (European Space Agency, ESTEC, Noordwijk; ESA SP-284), 1379–80.
- Mausel, P.W., Karaska, M.A., Mao, C.Y., Escobar, D.E. and Everitt, J.H.** 1991: Insights into secchi transparency through computer analysis of aerial multispectral video data. *International Journal of Remote Sensing* 12, 2485–92.
- Mayo, M., Gitelson, A., Yacobi, Y.Z. and Ben Avraham, Z.** 1995: Chlorophyll distribution in Lake Kinneret determined from Landsat Thematic Mapper data. *International Journal of Remote Sensing* 16, 175–82.
- McKim, H.L., Merry, C.J. and Layman R.W.** 1984: Water quality monitoring using an airborne spectroradiometer. *Photogrammetric Engineering and Remote Sensing* 50, 353–60.
- Millie, D.F., Baker, M.C., Tucker, C.S., Vinyard, B.T. and Dionigi, C.P.** 1992: High resolution airborne remote sensing of bloom forming phytoplankton. *Journal of Phycology* 28, 281–90.
- Molo, V.D., Piccazzo, M., Ramella, A., Giusto,**

- D.D.** and **Vernazza, G.** 1989: Monitoring of coastal water quality through integration between 'in situ' measurements and remote sensing data. In Hallikainen, M., editor, *Proceedings of the Ninth EARSeL Symposium*, Espoo, 27 June–1 July 1989. Luxembourg: Commission of the European Communities, Directorate General for Science Research and Development, 86–91.
- Moore, G.K.** 1980: Satellite remote sensing of water turbidity. *Hydrological Sciences Bulletin* 25, 407–21.
- Morel, A.Y.** 1980: In-water and remote measurement of ocean colour. *Boundary Layer Meteorology* 18, 177–201.
- Mulhearn, P.J.** 1995: Landsat reflectivities versus Secchi disc depths. *International Journal of Remote Sensing* 16, 257–68.
- Nichol, J.E.** and **Gupta, A.** 1990: Remote sensing of sediment plumes in South-East Asia: a case study of Singapore. In *Proceedings of the Twenty-third International Symposium on Remote Sensing of Environment*, 18–25 April 1990, Bangkok, Thailand. Ann Arbor MI: Environmental Research Institute of Michigan, Vol. 1, 385–93.
- Novo, E.M.M., Hansom, J.D.** and **Curran, P.J.** 1989: The effect of viewing geometry and wavelength on the relationship between reflectance and suspended sediment concentration. *International Journal of Remote Sensing* 10, 1357–72.
- Novo, E.M.M., Steffen, C.A.** and **Braga, Z.E.** 1991: Results of a laboratory experiment relating spectral reflectance to total suspended solids. *Remote Sensing of Environment* 36, 67–72.
- Olszewski, J., Kowalczyk, P.** and **Darecki, M.** 1999: In-water remote sensing algorithms for the detection of chlorophyll and yellow substances in the Pomeranian Bay. *Oceanologia* 41, 461–74.
- Ouillon, S., Forget, P., Froidefond, J.M.** and **Naudin, J.J.** 1997: Estimating suspended matter concentrations from SPOT data and from field measurements in the Rhone River plume. *Marine Technology Society Journal* 31, 15–20.
- Paerl, H.W.** 1988: Nuisance phytoplankton blooms in coastal, estuarine and inland waters. *Limnology and Oceanography* 33, 823–47.
- Pattiaratchi, C., Lavery, P., Wyllie, A.** and **Hick, P.** 1994: Estimates of water quality in coastal waters using multirate Landsat Thematic Mapper data. *International Journal of Remote Sensing* 15, 1571–84.
- Prangma, G.J.** and **Rooskrans, J.N.** 1989: Using NOAA AVHRR imagery in assessing water quality parameters. *International Journal of Remote Sensing* 10, 811–18.
- Quibell, G.** 1991: The effect of suspended sediment on reflectance from freshwater algae. *International Journal of Remote Sensing* 12, 177–82.
- 1992: Estimating chlorophyll concentrations using upwelling radiance from different freshwater algal genera. *International Journal of Remote Sensing* 13, 2611–21.
- Ramsey, E.W., III, Jensen, J.R., Mackey, H.** and **Gladden, J.** 1992: Remote sensing of water quality in active to inactive cooling water reservoirs. *International Journal of Remote Sensing* 13, 3465–88.
- Rimmer, J.C., Collins, M.B.** and **Pattiaratchi, C.** 1987: Mapping of coastal water quality in coastal waters using airborne Thematic Mapper data. *International Journal of Remote Sensing* 8, 85–102.
- Ritchie, J.C.** and **Cooper, C.M.** 1988: Comparison of measured suspended sediment concentrations with suspended sediment concentrations estimated from Landsat MSS data. *International Journal of Remote Sensing* 9, 379–87.
- Ritchie, J.C.** and **Schiebe, F.R.** 1985: Monitoring suspended sediments with remote sensing techniques. In *Hydrologic Applications of Space Technology*. Proceedings Workshop, Cocoa Beach, FL, 1985. IAHS Publication, 160, 233–43.
- Ritchie, J.C., Cooper, C.M.** and **Jiang, Y.** 1987: Using Landsat multispectral scanner data to estimate suspended sediments in Moon Lake, Mississippi. *Remote Sensing of Environment* 23, 65–81.
- Ruzafa, P.A., Gilabert, J., Bellan, A., Moreno, V.** and **Gutierrez, J.M.** 1996: New approach to chlorophyll *a* determination in shallow coastal waters by remote sensing. *Scientia Marina* 60 (suppl. 1), 19–27.
- Schiebe, F.R., Harrington, J.A., Jr.** and **Ritchie, J.C.** 1992: Remote sensing of suspended sediments, the Lake Chicot, Arkansas project. *International Journal of Remote Sensing* 13, 1487–509.
- Shimoda, H., Etaya, M., Sakata, T., Goda, L.** and **Stelczer, K.** 1986: Water quality monitoring of Lake Balaton using Landsat MSS data. In *Remote sensing for resources development and envi-*

- ronmental management. Proceedings 7th ISPRS Commission VII symposium, Enschede, 1986, Rotterdam: Balkema, 2, 765–70.
- Silberstein, K., Chiffings, A.W. and McComb, A.W.** 1986: The loss of seagrass in Cockburn Sound III: The effects of epiphytes on productivity of *Posidonia australis* Hook. *Aquatic Botany* 24, 355–71.
- Smith, R.C. and Baker, K.S.** 1982: Oceanic chlorophyll concentrations as determined by satellite (Nimbus-7 Coastal Zone Color Scanner). *Marine Biology* 66, 269–79.
- Stumpf, R.P.** 1992: Remote sensing of water clarity and suspended sediment in coastal waters. In *Proceedings of SPIE, The International Society for Optical Engineering*, Vol. 1930, Part 1, Bellingham, WA, USA, 293–305.
- Stumpf, R.P. and Tyler, M.A.** 1988: Satellite detection of bloom and pigment distribution in estuaries. *Remote Sensing of Environment* 24, 385–404.
- Stumpf, R.P., Frayer, M.L., Durako, M.J. and Brock, J.C.** 1999: Variations in water clarity and bottom albedo in Florida Bay from 1985 to 1997. *Estuaries* 22, 431–44.
- Sturm, B.** 1981: The atmospheric correction of remotely sensed data and the quantitative determination of suspended matter in marine water surface layers. In Cracknell, A.P., editor, *Remote sensing in meteorology, oceanography, and hydrology*. Chichester: Ellis Horwood, 163–97.
- Sugihara, S. and Kishino, M.** 1988: An algorithm for estimating the water quality parameters from irradiance just below the sea surface. *Journal of Geophysical Research* 93, 10857–62.
- Sunar, F.** 1992: Water-quality assessment in the Izmit Bay using Landsat-TM image data. *Photogrammetric Journal of Finland* 13, 79–86.
- Tang, D.L., Ni, I.H., Muller-Karger, F.E. and Liu, Z.J.** 1998: Analysis of annual and spatial patterns of CZCS derived pigment concentration on the continental shelf of China. *Continental Shelf Research* 18, 1493–515.
- Tassan, S.** 1988: The effect of dissolved 'yellow substance' on the quantitative retrieval of chlorophyll and total suspended sediment concentrations from remote measurements of water colour. *International Journal of Remote Sensing* 9, 787–97.
- 1993: An improved in-water algorithm for the determination of chlorophyll and suspended sediment concentration from Thematic Mapper data in coastal waters. *International Journal of Remote Sensing* 14, 1221–29.
- Thiemann, S. and Kaufmann, H.** 2000: Determination of chlorophyll content and trophic state of lakes using field spectrometer and IRS-C satellite data in the Mecklenburg Lake District, Germany. *Remote Sensing of Environment* 73, 227–35.
- Topliss, B.J., Payzant, L. and Hurley, P.C.F.** 1988: Monitoring offshore water quality from space. In Guyenne, T.D. and Hunt, J.J., editors, *Remote Sensing*. Proceedings IGARSS '88 Symposium, Edinburgh, 1988. Noordwijk: European Space Agency, Special Publication 284, Vol. 3, 1399–402.
- Van Raaphorst, W., Philippart, C.J.M., Smit, J.P.C., Dijkstra, F.J. and Malschaert, J.F.P.** 1998: Distribution of suspended particulate matter in the North Sea as inferred from NOAA/AVHRR reflectance images and in situ observations. *Journal of Sea Research* 39, 197–215.
- Verdin, J.P.** 1985: Monitoring water quality conditions in a large western reservoir with Landsat imagery (USA). *Photogrammetric Engineering and Remote Sensing* 51, 343–53.
- Walker, N.D.** 1996: Satellite assessment of Mississippi River plume variability: causes and predictability. *Remote Sensing of Environment* 58, 21–35.
- Warnock, R.E., Gieskes, W.W.C. and Van Laar, S.** 1999: Regional and seasonal differences in light absorption by yellow substance in the Southern Bight of the North Sea. *Journal of Sea Research* 42, 169–78.
- Wass, P.D., Marks, S.D., Finch, J.W., Leeks, G.J.L. and Ingram, J.K.** 1997: Monitoring and preliminary interpretation of in river turbidity and remote sensed imagery for suspended sediment transport studies in the Humber catchment. *Science of the Total Environment* 194–195, 263–83.
- Woodruff, D.L., Stumpf, R.P., Scope, J.A. and Paerl, H.W.** 1999: Remote estimation of water clarity in optically complex estuarine waters. *Remote Sensing of Environment* 68, 41–52.
- Xia, L.** 1993: A united model for quantitative remote sensing of suspended sediment concentration. *International Journal of Remote Sensing* 14, 2665–76.
- Yang, M.D., Merry, C.J. and Sykes, R.M.** 1999: Integration of water quality modeling, remote sensing, and GIS. *Journal of the American Water Resources Association* 35, 253–63.

Zibordi, G., Parmiggiani, F. and Alberotanza, L. 1990: Application of aircraft multispectral scanner data to algae mapping over the Venice Lagoon. *Remote Sensing of Environment* 34, 49–54.

Zilioli, E. and Brivio, P.A. 1997: The satellite derived optical information for the comparative assessment of lacustrine water quality. *Science of the Total Environment* 196, 229–45.