Multiplatform optical monitoring of eutrophication in temporally
and spatially variable lakes

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Received 20 November 2001; received in revised form 13 March 2003; accepted 15 March 2003

Abstract

Representative spatial patterns of eutrophication variables cannot be produced using traditional in situ sampling techniques. Spatial heterogeneity complicates the study of seasonal and long-term trends and the evaluation of water management policies. Remote sensing, however, with its broad view has the potential to deliver the relevant information. This paper will address the added value of synoptic eutrophication maps to the standard monitoring program of two large, spatially and temporally variable lakes in the Netherlands, Lakes IJssel and Marken. Remote sensing images were obtained from SeaWiFS; and combined with hyperspectral reflectance data from the airborne EPS-a sensor and the shipboard PR-650 spectroradiometer. The PR-650 data were used in selecting the most appropriate algorithms for SeaWiFS and EPS-a. A special algorithm for case II waters with high chlorophyll content was applied to SeaWiFS data to obtain chlorophyll concentrations. Synoptic maps of suspended matter were retrieved using inversion of a model for irradiance reflectance. For the airborne sensor inversion of reflectance was used for both suspended matter and chlorophyll. Satellite and airborne sensors clearly are complementary to each other. Comparison of satellite data with the airborne data and the (scarcely available) in situ data reveal underlying problems with: (i) validation of remote sensing images; and (ii) comparing data at different spatial and temporal scales. In our study, we found a reasonable agreement between different data sources at seasonal time scales, but at shorter time scales the differences can be (much) larger. In situ data suffer from poor reproducibility, related to the natural variability at small spatial scales (patchiness), combined with a significant temporal variability. The standard in situ monitoring program in Lakes IJssel and Marken lacks both the necessary spatial coverage as well as an appropriate sampling frequency. This indicates that for reliable monitoring, a synoptic data set, sampled at a high frequency is required. Remote sensing can partially fulfil this demand but still lacks the demanded frequency, mainly due to regular cloud cover. The answer may be in a multiplatform monitoring approach, as used in our study (combining in situ data with shipboard, airborne and satellite optical data) and in combining monitoring data with models. Satellite
remote sensing is most powerful in determining properties that are inherent to the whole lake system, like the overall mean chlorophyll-a concentration. Computational models may meet the demand for a sufficiently high sampling frequency by deterministic interpolation of the data in time.

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**Keywords:** Remote sensing; Lake monitoring; Water quality; SeaWiFS; EPS-a airborne sensor; Spatial and temporal inhomogeneity

## 1. Introduction

Lakes are valuable watersystems. They are, for instance, intensively used for production of drinking water, for fisheries and recreation. The ecological value of many lakes, however, has deteriorated, mainly as a consequence of eutrophication (Scheffer, 1998). The occurrence of blooms of (potentially) toxic cyanobacteria has increased globally (Chorus et al., 2000). Restoration programmes aiming at reducing the impact of eutrophication have been successful in some, but not in all cases. All of the above necessitates proper monitoring of lake water quality. Monitoring programmes have been initiated in many countries. The aim of the main national water-monitoring programme in the Netherlands (MWTL) is to: (i) establish long-term trends in the ecological quality of water systems; and (ii) to evaluate national water management policies through periodical assessment of the (ecological) quality of water systems (Ibelings et al., 1998). MWTL is based upon in situ sampling of the water systems. Algae and cyanobacteria are the principal biological receptors of eutrophication, such that changes in structure and activities of the phytoplankton determine secondary effects of eutrophication observed at higher levels. Proper monitoring of algae (for which chlorophyll is widely used as an overall estimate, despite variable cellular levels, e.g. Cracknell et al., 2001) is essential, and remote sensing of chlorophyll patterns will be emphasised in this paper.

In situ samples of spatially heterogeneous parameters like total suspended matter, chlorophyll-a, vertical diffuse attenuation of irradiance over PAR and Secchi depth are often not representative for the spatial mean of these parameters (Dekker et al., 2001; Pulliainen et al., 2001). Hence, the spatial patterns cannot be represented using traditional in situ sampling techniques. Uncertainties in lakewide estimates of the mean chlorophyll concentration results in inaccuracies in nutrient loading—chlorophyll prediction models that are extensively used in lake restoration schemes, (e.g. Galat and Verdin, 1989). For large lakes these problems are even more significant than for small lakes, since spatial heterogeneity is often more prominent in large lakes, with the lake regularly even being subdivided in several basins. Remote sensing; either by sensors on a satellite or an aeroplane; gives a (more) synoptic view of these spatially heterogeneous parameters. However, lakes are optically complex waters (Kallio et al., 2001), and extracting useful information from the images is not always straightforward. Our study focuses on the two largest lakes in the Netherlands, Lakes IJssel and Marken (1136 and 702 km², respectively). Spatial variability in chlorophyll in these lakes is mainly attributed to a patchy distribution of the zebra mussel, *Dreissena polymorpha*, an efficient filter feeder.

Fig. 1 in Schofield et al. (1999) shows the ecologically important temporal and spatial scales that affect phytoplankton blooms. The authors put forward that extracting information at all of the relevant scales requires the use of a multiplatform sampling network. In this paper we study the added value—to the standard in situ monitoring efforts—of such a multiplatform approach in the monitoring of chlorophyll and total suspended matter (TSM) in Lakes IJssel and Marken. The synoptic maps in our study are based upon SeaWiFS images, a sensor on board of the SeaStar satellite. In addition, we use hyperspectral optical data from the airborne EPS-a sensor and a shipboard PR-650 spectroradiometer (Gons, 1999; Gons et al., 1998; Rijkeboer, 1999). Hyperspectral field radiospectrometers have proven useful to validate remote sensing algorithms for retrieval of
Fig. 1. Geographical map of Lake IJssel and Lake Marken together with the EPS-a flight tracks of 31 May 2000 (dashed lines). The '*' are the positions of the standard in situ sampling from Rijkswaterstaat named 'Vrouwenzand' (Lake IJssel) and ‘Markermeer midden’.

total suspended matter and chlorophyll, and the PR-650 data will be used in such a way in this study (Hakvoort et al., 2002). Satellite and airborne sensors can be complementary to each other. Aeroplanes with hyper spectral sensors are valuable for the accurate observation of small-scale patchiness in chlorophyll in lakes (Dekker, 1993; Hoogenboom et al., 1998; Gege, 1998). However, the aeroplane cannot cover large lakes with a few flight tracks only, and the costs and personnel effort involved strongly limit the frequency of flights. Therefore, operational multi-spectral sensors on board of satellites that daily revisit Lakes IJssel and Marken are important tools for monitoring water quality. The disadvantage of SPOT and Landsat TM satellite sensors is that they miss frequency bands for chlorophyll-a detection in case II waters (see Dekker et al., 2001). The SeaWiFS sensor is also considered not to be optimal for chlorophyll-a retrieval from case II waters (Ruddick et al., 2000; Hu et al., 2000; Vos and Rijkeboer, 2000). Vos and Rijkeboer (2000) developed an algorithm that is suited for case II waters with high chlorophyll content, and this algorithm is used in this paper. Despite the frequent cloud cover in the Netherlands the frequency of good images is approximately 10 per year, which is sufficient to show the main seasonal variations. Further improvement may be achieved by combining remote sensing with computational models that may meet the demand for a sufficiently high sampling frequency by deterministic interpolation of the data in time. In our work on Lakes IJssel and Marken we compared remote sensing maps with the output of an algal growth model, DBS (van der Molen et al., 1994), and calculated a Goodness of Fit for each SeaWiFS pixel. Although the technical aspects of the model integration will
be discussed in a separate paper, we will discuss the main findings of our study.

The comparison of in situ data, airborne data and satellite data—where applicable—combined with model output—revealed problems related to the comparison of data with different spatial and temporal scales. Extrapolating individual point measurements to spatially representative values for lakes proves to be problematic. Comparison of data with different scales can lead to large differences that are not a consequence of erroneous measurements, but are a primary property of the lake system. This aspect of different scales is fundamental in problems with validation of remote sensing when ground truth data are not or insufficiently available. Even if they would be the question may be asked: ‘what is the value of the so-called ground truth?’ How to validate a SeaWiFS image of Lake IJssel, consisting of many pixels of 1.1 × 1.1 km on basis of a single or limited number of point measurements in a patchy environment? Our paper explores some ways for validation of remote sensing when ground truth data are not or insufficiently available.

2. Theory

2.1. Retrieval of water quality parameters for hyperspectral sensors

The remote sensing parameter used in this paper to derive water quality parameters is the subsurface irradiance reflectance, \( R(0-) \). Remote sensing sensors measure the water leaving radiation above water. Corrections for the effects from an air–water interface and atmospheric radiance are required to derive \( R(0-) \). Once the observed \( R(0-) \) is obtained the next step is to relate it to the optically active water constituents. This is done with an analytical optical model by fitting the observed reflectance to the modelled reflectance:

\[
R_{\text{obs}}(0-,\lambda) = R_{\text{mod}}(0-,\lambda)
\]  

with:

\[
R_{\text{obs}}(0-,\lambda) = \text{‘observed’ subsurface irradiance reflectance at wavelength } \lambda; \quad R_{\text{mod}}(0-,\lambda) = \text{‘modelled’ subsurface irradiance reflectance at wavelength } \lambda.
\]

The optically active constituents distinguished in this paper are: (i) pure water; (ii) Total Chlo- rophyll pigments (TCHL) which is the sum of chlorophyll-\(a\) and phaeopigments; (iii) total suspended matter; and (d) coloured dissolved organic matter (CDOM) which is the coloured fraction of the dissolved organic carbon (DOC).

The model used in this paper results from an analytical solution of two flow radiative transfer equations (Dirks, 1990; Krijgsman, 1994). This model (denoted as RT-model) is an extension of the well known Gordon model (Gordon et al., 1975) and is re-written here as:

\[
R(0-) = \frac{f \omega_b}{1 + \sqrt{1 - \frac{f}{\mu_u} \omega_b^2}}
\]  

\[
\omega_b = \frac{b_y}{a + b_y}
\]

with:

\( f = \) pre-factor \((-)\) given by Eq. (6);
\( \mu_u = \) average cosine of upwelling radiance \((-\sim 0.5)\);
\( \omega_b = \) backscatter albedo \((-)\);
\( a = \) total absorption \((\text{m}^{-1})\);
\( b_y = \) total backscattering \((\text{m}^{-1})\).

and where the wavelength dependency is further omitted. Krijgsman showed that this RT-model performs well for mixtures of spheres with intensive scattering \([R(0-) > 0.30 \text{ and } \omega_b > 0.85]\) and better than higher order expansions of the Gordon model. The model simplifies to the first order Gordon model in case \( \omega_b < 0.5 \), [e.g. \( R(0-) < 0.15 \)] given by:

\[
R(0-) = f \omega_b
\]

The total absorption and backscattering in this paper are:
\[ a = a_w + g_{440} \tilde{a}_{\text{cdom}} + a^*_\text{TCHL}C_{\text{TCHL}} + a^*_\text{TSM}C_{\text{TSM}} \quad (5) \]

\[ b_h = 0.5b_w + Bb^*_\text{TSM}C_{\text{TSM}} \]

with:

- \( C_x \) = concentration of component ‘x’ where \( x = \text{TSM} \) (g m\(^{-3}\)) or \( \text{TCHL} \) (mg m\(^{-3}\));
- \( a_w \) = absorption by pure water (m\(^{-1}\));
- \( b_s \) = scattering by pure water (m\(^{-1}\));
- \( a^*_x \) = specific absorption by ‘x’ where \( x = \text{TSM} \) (m\(^{-2}\) g) or \( \text{TCHL} \) (m\(^{-2}\) mg);
- \( b^*_x \) = specific scattering by ‘x’ where \( x = \text{TSM} \) only (m\(^{-2}\) g);
- \( B \) = the backscattering ratio (–) (the fraction of light scattered towards the upper hemisphere);
- \( g_{440} \) = CDOM absorption at 440 nm (m\(^{-1}\));
- \( \tilde{a}_{\text{cdom}} \) = CDOM absorption normalized by the absorption at 440 nm (\( g_{440} \)).

The asterisk indicates a specific (concentration independent) inherent optical property (SIOP) of the water constituent (CDOM, TCHL or TSM). The SIOP are the fundamental properties required for optical models. Note that in the SIOP for absorption by TSM the pigments are not included, whereas for scattering, are included. The dimensionless normalised CDOM absorption spectrum uses a tilde to indicate that it is not an SIOP but a parameter normalized by the absorption at 440 nm (\( g_{440} \)). For the satellite data as well as the airborne data we assume that the \( f \)-factor follows from:

\[ f = 0.0107Q \quad (6) \]

where \( Q \) is a factor required to convert upwelling radiance to irradiance. The \( Q \)-factor is further specified in Section 3 since it was different for the various sensors applied. In previous work, the ratio \( f/Q \) varied only within 8% approximately 0.0107 for sun zenith angles varying from 30° to 60° (Hakvoort et al., 2002). The importance of this equation is more practical than theoretical: in practice the \( Q \)-factor is often unknown. In standard software used to process raw images to \( R(0-) \) often inaccurate estimates for \( Q \) are used that may differ 25% from real values. It would have been better to start from remote sensing reflectance \([R(0-)/Q]\), and to apply \( Q \)-factors from our own estimates. However, this still might lead to inaccuracies with respect to \( Q \). In order to harmonize \( Q \)-factors Eq. (6) is used (Morel and Gentili, 1993). This also eliminates the difference between the two definitions of reflectance, and is a good choice in case \( f \) and \( Q \) cannot be measured.

The fitting problem of Eq. (1) can be solved in various ways (e.g. Hoge and Lyon, 1996; Keller, 2001; Hakvoort et al., 2002). In all cases, we must consider that the best choice for an algorithm depends on both the characteristics of the sensor and the water type. A purely mathematical solution without further model approximations is matrix inversion (Hoge and Lyon, 1996). The method used in this paper for the EPS-a airborne scanner is an improvement of the matrix inversion method that was recently found by Hakvoort et al. (2002) and is based on weighted least squares theory (denoted further as WLSQ method). The WLSQ method can be extended to the non-linear problem of Eq. (2) by applying an iterative predictor–corrector method. For each iteration the non-linear term is estimated beforehand so that a standard linear problem results. We used four iterations for conversion. An important alternative that can be applied to the airborne data (but not to the satellite data) is the colour ratio algorithm by Gons (Gons, 1999), which was tested as well.

2.2. Retrieval of TCHL from SeaWiFS for case II waters

For case II waters, neither the matrix inversion method nor the Gons colour–ratio algorithm is suitable for TCHL retrieval from SeaWiFS data. In case concentration TCHL (mg m\(^{-3}\)) \( \gg \) concentration TSM (g m\(^{-3}\)), the algorithm presented by Vos and Rijkeboer at the Ocean optics Conference (2000) is a useful alternative Vos and Rijkeboer (2000). This algorithm starts from a further approximation of the Gordon model by substituting best estimates for TSM concentrations and CDOM absorption. The CDOM absorption is kept at a fixed level since it is relatively small for Lake Marken and Lake IJssel (\( g_{440} < 1.5 \) m\(^{-1}\)). The TSM concentration follows from the
matrix inversion method shown in Section 2.1 using a fixed estimate for TCHL (and CDOM absorption). Best results with respect to in situ data were obtained by taking the spatially summer averaged TCHL concentrations from the in situ data as a first guess (i.e. a single constant TCHL estimate for the whole lake is used).

Using these estimates the concentration of TCHL now follows from the observed \( R(0-) \) at 670 nm where TCHL absorption is dominant:

\[
C_{\text{TCHL}} = \frac{a_{\text{TCHL}}(670)}{a_{\text{TCHL}}(670)}
\]

\[
a_{\text{TCHL}}(670) = \left( \frac{f b_b(670)}{R_{\text{obs}}(0-, 670)} \right) - (b_b(670) + g_{440} \tilde{a}_{\text{dom}}(670) + a_{w}(670)) + a_{\text{TSM}}(670) C_{\text{TSM}}
\]

\[
b_b(670) = b_{\text{TSM}}^a(670) BC_{\text{TSM}}
\]

Vos and Rijkeboer (2000) showed that TCHL concentrations for a cloud-free SeaWiFS image of 24 June 1999 compared well to the available in situ data of 23 June (see Section 4.1). The following restrictions for the use of the SeaWiFS algorithm were obtained from practical experience: (i) the atmosphere is free of clouds and has a low aerosol content; an estimate is that the aerosol optical thickness at 865 nm is less than 0.15; (ii) the TCHL concentration is at least higher than the TSM concentrations, and high enough in order to neglect variations in \( g_{440} \). The present algorithm is meant for lakes with a relatively high TCHL content; for Lake Marken the accuracy of the algorithm is limited due to the high TSM content. For that lake only TSM can be obtained using SeaWiFS data. A detailed sensitivity analysis of the algorithm was made by Ibelings et al. (2001).

3. Methods

3.1. Study sites

Lake IJssel and Lake Marken are shown in Fig. 1 together with the EPS-a flight tracks. These lakes are of prime socio-economic importance to the country through their role in the production of drinking water, recreation, shipping and fisheries. Moreover, both lakes are listed as protected wetlands (Ramsar sites) by the IUCN (International Union for Conservation of Nature and Natural Resources). Lake IJssel is a large fresh water lake of 1136 km² in the centre of The Netherlands with an average depth of 4.5 m. This lake is typical case 2 water with high total chlorophyll (TCHL, 10–120 mg m⁻³) and total suspended matter content (TSM, 5–30 g m⁻³). The lake is eutrophic, and from spring till autumn this may lead to nuisance blooms of cyanobacteria. Lake Marken is a fresh water lake of 702 km² with an average depth of 3.9 m; the lake is separated from Lake IJssel by a dam (having two sluices at either end of the dam). Most characteristic of this lake is a high-suspended matter concentration (TSM, 30–80 g m⁻³) due to a continuous resuspension of silt from the bed by wind-induced waves. Before 1990, the chlorophyll concentrations were relatively low (TCHL, 20–40 mg m⁻³) as a consequence of both light limitation as well as grazing by zebra mussels. However, since 1990 the chlorophyll content is steadily increasing (Lammens, 1999) and in the first half of 2000 mean chlorophyll-a was even above 80 mg m⁻³; the average over the last 2 years was 64 mg m⁻³. The increase in chlorophyll is probably a result of a severe reduction in the density of zebra mussels, presumably due to destabilisation of the lakebed.

3.2. Data acquisition

The following optical data of Lakes IJssel and Marken were collected during 1999 and 2000:

a. \( R(0-) \) spectra from a PR-650 handheld spectroradiometer, recorded at 10–15 stations for both lakes at 2 days during the summer half year of 1999 and 2000 (Rijkeboer, 1999);

b. Airborne EPS-a radiance images of Lakes IJssel and Marken were recorded at 25 wavelengths, on 31 May 2000; no EPS-a images were recorded in 1999;

c. SeaWiFS satellite radiance images for 10 days in 1999 and 10 days in 2000 were requested from NASA and processed; on 31 May 2000 a
SeaWiFS image coincided with the EPS-a recordings. In situ data were obtained from the following sources:
d. Data from the standard MWTL monitoring program, where available supplemented by data from a regional monitoring program (RDIJ). These data include chlorophyll-a, TSM, dissolved organic carbon (DOC) and Secchi depth, but are only available for one (fixed) location in each lake and at a limited frequency. The positions of the sampling locations are given in Fig. 1. For Lake Marken in situ data were available for 27 days for TSM and 24 days for TCHL (1999–2000). The sampling was evenly spread over this period. For Lake IJssel data were available for 31 days for TSM and 29 days for TCHL in the 2 years;
e. In situ data from additional cruises in 1999 were available for TSM and TCHL; these samples coincided with the recording of the PR-650 data, described above;
f. Between May and October 1999 in situ samples for determination of chlorophyll and cyanobacteria were taken at six dates and two locations in the southern half and two locations in the northern half of Lake IJsselmeer (CYANOTOX project);
g. SIOP for absorption by TCHL, TSM, CDOM and scattering by TSM were obtained from measurements according to a method set up by Rijkeboer et al. (1998) on the same in situ samples described under (e). Absorption by water was compiled from data by Pope and Fry (1997) for the region 400–600 nm and from Buiteveld et al. (1994) for 600–750 nm. Backscattering by water was determined according to Buiteveld et al. (1994). The backscattering ratio ‘B’ of TSM was obtained by fitting $R(0−)$ field spectra to the bio-optical Gordon model ($B=0.035$ for Lake IJssel and $B=0.030$ for Lake Marken). Comparison of SIOP for both lakes shows that the specific scattering of TSM in Lake Marken is much larger. This is probably due to a smaller particle size of the suspended matter, smaller water content and a higher mineral content.

3.3. Image processing for the EPS-a airborne scanner

The processing of radiances measured at the sensor to yield airborne water quality maps is subdivided in two steps, namely:

1. Processing of radiances measured at the sensor into maps of observed subsurface irradiance reflectance $R^{\text{obs}}(0−)$.
2. Processing of maps of $R^{\text{obs}}(0−)$ into maps of TSM, TCHL and CDOM.

The EPS-a sensor measures radiance that must be corrected for atmospheric path radiance, sunlight and diffuse skylight reflected into the sensor and refraction of light to the air–water interface. Procedures hereto are described by de Haan et al. (1997). The correction is complicated by rapid variations of the viewing angle of the instrument during the flight track. Processing large look up tables with MODTRAN IV solved this problem. Another problem is the sun glint in the image for which removal procedures were recently developed by Heege and Fisher for a Daedalus airborne sensor (Heege and Fisher, 2000). This method cannot be used since the required near-infrared bands are missing. For the EPS-a the sunglint must be minimized by planning the flight track in line with or opposite to the incident sunlight.

From the $R(0−)$ spectra, the concentrations of TCHL and TSM were retrieved using matrix inversion based on a weighted least squares approach as described in Hakvoort et al. (2002). The accuracy of the matrix inversion method was less good when using 15 or more frequency bands of the EPS-a sensor, probably since they are not evenly spaced. For the PR-650 spectrometer we used 88 evenly spaced bands, and such problems do not occur. Best results for retrieval of TCHL and TSM were obtained for an EPS-a configuration of eight bands that is close to a MERIS (sensor on board of ENVISAT) configuration, using wavelength bands centred at 414, 431, 488, 516, 563, 619, 667, 686 and 705 nm. This configuration denoted as ‘EPS-a (MERIS)’ was used for processing the EPS-a images in this paper. A validation of the accuracy of this method is shown in Section 4.1.
In Lake Marken the TSM concentrations are high, and the matrix inversion was not accurate enough for TCHL retrieval. In this case, as an alternative the Gons semi-empirical method (Gons, 1999) for TCHL retrieval was applied. This method gives, in practice, good estimates but suffers from the fact that it uses a fixed estimate for the specific chlorophyll absorption coefficient $a_{TCHL}$, and neglects CDOM absorption.

3.4. Processing of images for the SeaWiFS satellite sensor

SeaWiFS images for top of the atmosphere (TOA) radiance are processed to images of subsurface irradiance reflectance using a variant for turbid waters of the SeaDAS-software package (Ruddick et al., 2000). With this software atmospheric correction (including aerosol and ozone correction) is done, effects from the air–water interface are removed from the signal and water leaving radiance $L_w$ is converted into subsurface irradiance reflectance $R(0-)$. Finally, only $R(0-)$ at 490, 510, 555 and 676 nm are used for producing the maps of TSM and TCHL (see Section 2.2). $R(0-)$ at 756 and 865 nm bands contain little information on TSM, and were in practice also found to lead to poor results for TCHL when added to a TCHL retrieval algorithm. $R(0-)$ at 410 and 430 nm were found to be very sensitive to errors in modelling the aerosol radiance in SeaDAS and, therefore, have been omitted as well.

3.5. Validation of the retrieval algorithms by field spectrometry

The validation of airborne and satellite remote sensing maps by in situ data is very hard to accomplish for large lakes. The standard in situ monitoring network for Lake IJssel for instance consisted of only 29 chlorophyll-a samples for 1999 and 2000 (all form one location), and for this period we obtained 20 usable SeaWiFS images. Unfortunately, only one sample was concurrent with a satellite image and this is obviously not enough for validation (in general simultaneous data from in situ sampling are rarely available—see Cracknell et al., 2001). Also, recording of airborne EPS-a reflectance, concurrent with the standard in situ sampling program failed due to unfavourable weather conditions. Furthermore, note that the positioning of EPS-a pixels has an uncertainty of 50–100 m, whereas phytoplankton patches may show gradients at smaller scales (for satellites these uncertainties are even larger both with respect to pixel size and the accuracy of the positioning). Therefore, shipborne $R(0-)$ spectra collected with a hyperspectral PR-650 spectroradiometer with frequencies at 4-nm intervals from 380 to 780 nm, and concurrent in situ data were used for validation. With this highly dense spectrum, it is possible to mimic nearly any satellite or airborne sensor by selecting the proper frequencies. In order to test the accuracy of the SeaWiFS and EPS-a algorithms for retrieval of water quality parameters these PR-650 data were used in order to simulate the SeaWiFS and EPS-a sensors. Best algorithms were selected from the validation procedure and applied for processing the reflectance data from the satellite sensor and the airborne scanner. Unfortunately, this approach does not test the quality of atmospheric correction procedures and for this we had to rely on other work that confirmed the accuracy of atmospheric correction procedures (Ruddick et al., 2000; Vos and Rijkeboer, 2000; de Haan et al., 1997). Regrettably, the PR-650 ship cruises in June and September 1999 were not on cloud-free days, so that a direct comparison between $R(0-)$ from the PR-650 and SeaWiFS images could not be made. One PR-650 dataset for Lakes IJssel and Marken could still be used for validation of SeaWiFS by neglecting a time difference of 1–2 days which a priori seemed permissible since wind was calm (but surface blooms of cyanobacteria were absent) and transport and mixing processes were limited (a time difference of 1 day between satellite overpass and in situ sampling was also used in some cases in the study of Kallio et al. (2001), but see Section 4.2 for further discussion). Results of the validation were presented at the 2000 Ocean Optics meeting (Vos and Rijkeboer, 2000) and will shortly be re-addressed in this paper.

The hyperspectral spectroradiometer held out from a boat, measures radiances above water and
these were converted to subsurface irradiances by following a standard protocol published by Gons (1999). Four radiances are measured at short time intervals: the water leaving radiances \( L_{wa} \), the sky radiance \( L_s \), the radiance from a 100% reflecting Lambertian panel \( L_{sp} \) and the same measurement but shaded for direct incident sky light which gives the fraction of diffuse down-welling light \( F_{dif} \). The \( Q \)-factor is obtained from an empirical relation fitted for turbid waters. \( R(0-) \)-spectra follow from:

\[
R(0-) = \frac{QL_u}{E_d}
\]

\[
L_u = \left( \frac{n^2}{1 - \rho_u} \right) L_{wa}(1 - S_{wa})
\]

\[
S_{wa} = \frac{\rho_s L_s}{L_{wa}}
\]

\[
E_d = \pi L_{sp}(1 - \rho_d(1 - F_{dif}) - rF_{dif}) + 0.5QL_u
\]

where:

\( L_u \) = upwelling radiance at the sensor, resulting from a water column corrected for the air–water interface (\( \text{W \ m}^{-2} \text{ nm}^{-1} \text{ sr}^{-1} \));

\( L_s \) = sky radiance (\( \text{W \ m}^{-2} \text{ nm}^{-1} \text{ sr}^{-1} \));

\( L_{wa} \) = water-leaving radiance (\( \text{W \ m}^{-2} \text{ nm}^{-1} \text{ sr}^{-1} \));

\( S_{wa} \) = fraction of radiance at the sensor that is reflected at the air–water interface \( (-) \);

\( L_{sp} \) = radiance from a 100% reflecting Lambertian panel (\( \text{W \ m}^{-2} \text{ nm}^{-1} \text{ sr}^{-1} \));

\( n \) = refractive index of water \( (-) \);

\( \rho_u \) = Fresnel coefficient of sky radiance reflected from water surface to sensor \( (-) \);

\( \rho_d \) = Fresnel coefficient for loss of upward radiance when light passes the air–water interface \( (-) \);

\( \rho_s \) = Fresnel coefficient for loss of direct sky radiance at the air–water interface \( (-) \);

\( r \) = Fresnel coefficient for loss of diffuse sky radiance at the air–water interface \( (-) \);

\( F_{dif} \) = fraction of diffuse down-welling light above water.

Default estimates for the Fresnel coefficients \( \rho_u, \rho_d \) and \( r \) are used according to Gons (1999). The measurement is done with the sensor at an angle of \( \approx 42^\circ \) with zenith, and a \( 90^\circ \) azimuth angle with incident sun light. For that angle the fraction of reflected light at the air–water interface \( \rho_s \) is minimal, and the shadowing effect of the boat is minimal. The measurement is done three-fold and the average spectrum is taken (outliers are removed). The accuracy of the measurement depends mainly on the estimate of Fresnel coefficient \( \rho_s \) (Mobley, 1999). Different values must be applied for calm, windy or cloudy weather. Simultaneously with the PR-650 measurements samples for in situ analysis of TCHL and TSM were taken at 14 locations in Lake IJssel and seven in Lake Marken.

4. Results

4.1. Validation of the retrieval algorithms by field spectrometry

The shipborne \( R(0-) \) spectra collected with a hyperspectral PR-650 spectroradiometer, were used to mimic satellite and airborne sensors in order to test the accuracy of the SeaWiFS and EPS-a algorithms for retrieval of water quality parameters. The data set (including in situ samples) was taken from Rijkeboer (1999). Retrieval algorithms were tested for various selected frequencies, namely:

a. A WLSQ algorithm using all frequency bands of the PR-650 sensor (at 4-nm intervals) from 400 to 750 nm;

b. A WLSQ algorithm for 15 bands between 430 and 705 nm, that are close to bands of the EPS-a sensor, simulating the airborne scanner;

c. A WLSQ algorithm for eight bands between 430 and 705 nm that are near MERIS bands. This configuration is denoted as ‘EPS-a (MERIS)’; it was used for a particular setting of the EPS-a sensor and not for MERIS itself, which is not studied in this paper;

d. The semi-empirical Gons algorithm that uses bands at 672, 704 and 776 nm;

e. The SeaWiFS algorithms of Section 2.2 using a selection of bands that is present on the SeaWiFS sensor.
Table 1
Performance of various algorithms (column 1) and sensor configurations (column 2) for retrieval of TCHL and TSM from PR-650 in situ measured field spectra for Lake IJssel (N=14) and Lake Marken (N=7). Relative errors (rmse given as%) are with respect to in situ samples that were collected simultaneously, (e.g. within 5 min) with the PR-650 field spectra.

<table>
<thead>
<tr>
<th>Method</th>
<th>Sensor simulated</th>
<th>No. bands</th>
<th>Lake IJssel</th>
<th>Lake IJssel</th>
<th>Lake Marken</th>
<th>Lake Marken</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td></td>
<td>% error TSM</td>
<td>% error TCHL</td>
<td>% error TSM</td>
<td>% error TCHL</td>
</tr>
<tr>
<td>WLSQ PR-650</td>
<td>88</td>
<td>28</td>
<td>25</td>
<td>31</td>
<td>30</td>
<td></td>
</tr>
<tr>
<td>WLSQ EPS-a</td>
<td>15</td>
<td>30</td>
<td>25</td>
<td>31</td>
<td>33</td>
<td></td>
</tr>
<tr>
<td>WLSQ EPS-a (MERIS)</td>
<td>8</td>
<td>24</td>
<td>25</td>
<td>30</td>
<td>34</td>
<td></td>
</tr>
<tr>
<td>Gons</td>
<td>PR-650</td>
<td>3</td>
<td>–</td>
<td>21</td>
<td>–</td>
<td>15</td>
</tr>
<tr>
<td>2 Steps SeaWiFS</td>
<td>4+1</td>
<td>38</td>
<td>27</td>
<td>25</td>
<td>29</td>
<td></td>
</tr>
</tbody>
</table>

* EPS-a bands at 414, 431, 488, 516, 563, 619, 667, 686 and 705 nm were used.
* Four bands are used for TSM retrieval and one band for TCHL retrieval, see Section 2.2.

To quantify the accuracy of methods a–e the average relative error between TCHL and TSM concentrations retrieved from PR-650 data and TCHL and TSM from in situ samples—for the 14 stations at Lake IJssel and seven stations at Lake Marken—was calculated. The relative root-mean square error (rmse, expressed as a percentage) of these methods is given in Table 1.

For Lake IJssel, all methods are within 20–30% accuracy for TCHL retrieval. The differences in accuracy for TSM retrieval are larger which is partially due to the fact that TSM concentrations in Lake IJssel are relatively low compared to TCHL concentrations. For the EPS-a sensor, the TSM can best be retrieved using the EPS-a method close to a MERIS configuration of eight bands. For Lake Marken, the TCHL concentrations obtained for the Gons method clearly have the smallest error (15%). The other methods all have an error ~30%. For these methods, the sensitivity of the modelled reflectance for TCHL is smaller at high TSM concentrations and, therefore, larger errors in TCHL are found. The error for TSM is comparable for all methods (~30%) and similar to the error for Lake IJssel. The present validation showed a negligible difference between the accuracy of the RT-model and Gordon model for all cases but one. In the latter case, \( R(0-1) > 0.15 \) and the fit with the RT-model was better.

Given the results of the validation the following algorithms were considered to be of sufficient accuracy for further use:

a. for the EPS-a the use of EPS-a-(MERIS) band configuration is preferred, except for TCHL retrieval at Lake Marken where Gons method can be used as an alternative. We put forward that, in general, this semi-empirical algorithm must be used as an alternative to matrix inversion when the TCHL (mg m\(^{-3}\)) \( \ll \) TSM (g m\(^{-3}\));
b. for SeaWiFS algorithm e is used, but we refrained from processing TCHL of Lake Marken since for high TSM we know that the algorithm can fail due to atmospheric disturbances not incorporated in the results given in Table 1. Errors for Lake Marken shown in Table 1 are valid for TSM concentrations in the range 20–40 g m\(^{-3}\), hence do not apply to the upper limits of the TSM range in this lake (up to 80 g m\(^{-3}\)).

The relative errors given here correspond broadly with those recently published for extensive data sets collected for Finnish Lakes (Kallio et al., 2001; Koponen et al., 2001; Harma et al., 2001). However, none of the algorithms in those papers is multi-temporally valid or applicable to a larger range of lakes, with different water quality parameters, like the matrix inversion method (see Kutser et al. (2001)). Kutser results, however, show significant underestimation of modelled TSM and Chl-a concentrations, which is probably due to the fact that not all specific inherent optical properties (SIOP) were derived from local in situ measurements as is done in our work. For our
study, we must know if the applied SIOP are valid at different times of the year. Analysis of the SIOP data set showed that the spatial variation of SIOP at various stations is larger than the temporal variation (Rijkeboer, 1999). The error related to the spatial variation in SIOP is already included in the errors given in Table 1, so we feel that relative errors in Table 1 also are valid for different seasons.

4.2. EPS-a flights

In Figs. 2 and 3 the TSM and TCHL maps for the tracks flown by the EPS-a over Lake IJssel are shown. The tracks were flown on 31 May 2000 (see also Fig. 1). In Fig. 5 the track is shown for Lake Marken. All these maps are projected onto the SeaWiFS maps, also for 31 May 2000. First we will discuss the EPS-a tracks, and then compare the results with the SeaWiFS images.

The TCHL map for Lake IJssel in Fig. 3 shows a sharp TCHL gradient, which is also visible in the TSM map in Fig. 2. However, the TSM concentrations increase again towards Lake Ketel (at the bottom right hand corner of the image) whereas the TCHL map is zero (or negative) in this south-eastern part of Lake IJssel. Zero or negative TCHL concentrations imply that TCHL < 3 mg m$^{-3}$, and that the algorithm is not suited for retrieval of these low TCHL concentrations. A histogram of TCHL concentrations for the northern half of the track flown over Lake IJssel is shown in Fig. 4 and clearly shows two distinct water masses present. The TSM map for Lake Marken in Fig. 5 shows patterns with plumes extending from east to west. The TCHL map for Lake Marken was obtained with the Gons method and since it shows no gradients and relatively low TCHL concentrations of 20–30 mg m$^{-3}$ it is not further shown here. Comparison of these maps to in situ data that were collected 1 day (Lake Marken) or 2 days (Lake IJssel) before may be risky given the dynamic behaviour of TSM and TCHL in these lakes, mainly depending on wind conditions. Especially for Lake Marken, the TSM map in Fig. 5 clearly shows dynamic sediment
Fig. 4. Normalised histograms of TSM and TCHL values observed along the track at 31-05-2000. Two distinct water masses are visible: one with TCHL below 10 mg m$^{-3}$ and TSM of $5 \text{g} \text{m}^{-3}$, and one with TCHL 25–50 mg m$^{-3}$ and TSM of $>10 \text{g} \text{m}^{-3}$.

plumes in the image and this indicates that concentrations may vary instantly. The concentration of TSM sampled at the standard location (Markermeer Midden) on 30 May 2000 was $56 \text{g} \text{m}^{-3}$ and this is in the right order of magnitude. TCHL was $67 \text{mg} \text{m}^{-3}$ and is much higher than the concentrations from the Gons colour ratio algorithm (20–30 mg m$^{-3}$). TCHL at Vrouwenzand (Lake IJssel) was sampled on 29 May 2000 and was $165 \text{mg} \text{m}^{-3}$, which is also much higher than the TCHL map in Fig. 3 indicates. Also TSM was much higher 2 days before (75 mg m$^{-3}$) than the TSM map in Fig. 2 indicates. As will be shown in Section 4.3 TSM and TCHL at Vrouwenzand are highly variable in time and thus a time difference of 2 days is too large for validation of EPS-a on basis of in situ data.

The image contains approximately 2 million pixels of which 95% of the spectra were accurately inverted (the other 5% is at the edges of the image or at pixels contaminated by ships tracks and/or foam). To illustrate the accuracy of the inverted spectra two representative pixels in the Lake IJssel EPS-a image are shown (Fig. 6). One pixel is for high TCHL (north of the front), and one is for low TCHL (south of the front). Since no in situ data were available, the accuracy of the results can only be checked from the difference between the modelled EPS-a $R(0-)\text{spectra}$ and the observed PR650 $R(0-)\text{spectra}$. Fig. 6 shows that the difference between modelled and observed spectra
is small and this is an indication that the retrieved concentrations are accurate. Modelled and observed $R(0-)$ spectra are shown for the southern part of Lake Marken in Fig. 7. Reflectance is very high (22% at 555 nm) but the accuracy of the fit is as good as for Lake IJssel when the non-linear RT-model (Eq. (2)) is applied. For the linear first order Gordon model (Eq. (4)) the results are not as good. Fig. 7 also shows that the RT-model fits better than a Gordon model expanded to third order in $\omega_0$ using coefficients by Gordon et al. (1975) for clear skies.

4.3. Comparison of EPS-a data with SeaWiFS data

Since in situ data close to the time of the EPS-a flight are not available (see Section 4.2) we can only ‘validate’ these maps with the SeaWiFS satellite maps (see Figs. 2, 3 and 5). The satellite overpass was within 2 h of the EPS-a flights for both lakes. The SeaWiFS TSM maps of 31 May 2000, 12:08:05 GMT for Lake IJssel and Lake Marken compare well with the EPS-a maps. The range in TSM is 5–15 g m$^{-3}$ for Lake IJssel for both images. For Lake Marken, the range is 45–70 g m$^{-3}$ for EPS-a scanner and 50–75 g m$^{-3}$ for SeaWiFS. The satellite image of Lake Marken shows a clear east–west gradient in TSM (Fig. 5), which is not observed by the EPS-a since the track covers only part of the lake. However, the EPS-a track shows distinct features not observed in the satellite image since its spatial resolution is much better.

The $R(0-)$ at 555 nm for SeaWiFS at Lake IJssel is in the range of 6–8% reflectance, which is in agreement with the EPS-a observations for $R(0-)$ at 563 nm. However, taking into account the different $Q$-factors that were applied ($Q = \pi$ and $Q = 3.75$, see Section 3), the SeaWiFS $R(0-)$ at 555 nm should have been 7–9% reflectance. We consider the EPS-a observations to be more accurate since they did not suffer from the large aerosol optical thickness at high altitude caused by cirrus (0.3 at 865 nm). Compared to the EPS-a results, the satellite TSM values will be underestimated since in these waters TSM is strongly correlated with the $R(0-)$ peak at 555 nm. This leads to an overestimated TCHL concentration in the algorithm of Eqs. (7) and (8) as was shown by studying the sensitivity for errors by Ibelings et al. (2001). The satellite image indeed shows (30–40
mg m$^{-3}$) higher TCHL content than the EPS-a map as a consequence of cirrus. Although this particular satellite image turns out not to be very accurate, important features like the occurrence of a gradient in chlorophyll in the southern half of the lake are still present in the satellite map of Fig. 3. The satellite map also shows inaccurate values for pixels near land boundaries in Figs. 2 and 3, so within 1 km from shorelines the satellite cannot be used.

4.4. Seasonal variations in TSM and TCHL—SeaWiFS 1999 and 2000

SeaWiFS TSM maps (Fig. 8) and TCHL maps (Fig. 9) for 2000 give an idea about the seasonal variations in chlorophyll and suspended matter in these lakes. TSM in Lake IJssel shown in Fig. 8 increased during the season due to increase in the abundance of algae (see the concurrent increase of TCHL in Fig. 9). Lake Marken shows the opposite trend where TSM decreases during the season due to reduced wind resuspension in summer. TCHL maps of Lake IJssel show that the algal bloom in spring (diatoms) is much less intensive than the cyanobacterial bloom in summer. In February and April the TCHL concentration is higher in the north than in the south, which is in accordance with observations by Lammens (1999). In August and September 2000, the spatial distribution of TCHL in Lake IJssel shows that phytoplankton is most abundant in the north-eastern or south-eastern part of the lake (SeaWiFS images for 1999 show the same). The average TCHL distribution for summer inferred from interpolation of 23 years of in situ data (1972–1995) shows a chlorophyll maximum in the north-eastern part of the lake only (Lammens, 1999), concentrations in the
Southeast are much reduced. Algal blooms observed in the south in the summer of 2000 indicate a (partial) inversion of the south to north chlorophyll gradient that is commonly observed. For 1999, in situ data from the six CYANOTOX field cruises show that indeed in August and September cyanobacteria/algae are predominantly found in the southern part of the lake, whereas in May the situation is clearly reversed and in correspondence with the long-term trend. To illustrate this, in situ data from these cruises are shown in Fig. 10. From our data, we conclude that the inversion in the chlorophyll gradient probably sets in at the middle of August when water temperatures reach their maximum (23–24 °C). Wind driven transport of surface scums of cyanobacteria (Ibelings et al., in press), who peak in this same period, may obscure the ‘real’ chlorophyll patterns that result from locally enhanced growth of phytoplankton. An alternative explanation may be that

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Fig. 9. TCHL maps (mg m\(^{-3}\)) for Lake IJssel for 2000.

Fig. 10. TCHL (mg m\(^{-3}\)) at a station at the southern part of Lake IJssel (Houtrib) compared to a station at the Northern part of Lake IJssel from in situ data for 1999.
in very warm water the grazing of mussels slows down. Zebra mussels are mainly present in the south and are thought to be responsible for the reduction of chlorophyll levels in this part of Lake IJssel (Lammens, 1999).

Satellite data for $K_D^{\text{PAR}}$ in 2000 are given in Fig. 11. They were derived from: (i) SeaWiFS satellite data on TCHL and TSM; (ii) best estimates for CDOM absorption (1.0–1.5 m$^{-1}$ at 440 nm, depending on the season), which is fairly constant in space for Lake IJssel; and (iii) the inherent optical properties and the optical model given in Section 2. All these data were processed according to Buiteveld (1995) to get satellite maps for $K_D^{\text{PAR}}$ (m$^{-1}$). $K_D^{\text{PAR}}$ data are very useful for calibration of algal bloom models. The images show that the heterogeneity of $K_D^{\text{PAR}}$ is very large. In the Netherlands where lakes are often highly eutrophic, algal growth is very sensitive to $K_D^{\text{PAR}}$, so synoptic and frequent data on this parameter are essential for carefully calibrated and realistic modelling of algal biomass.

4.5. Comparison of SeaWiFS with in situ data

TSM and TCHL in situ data from the MWTL monitoring programme are compared (Figs. 12 and 13) to data from the pixel in the SeaWiFS image that contains Vrouwenzand (see Fig. 1). The size of this pixel is 1.1×1.1 km$^2$. A comparison of TSM derived from SeaWiFS to in situ data from samples taken at Markermeer Midden is presented in Fig. 14. Both satellite and in situ data, although not exactly overlapping in time, show similar seasonal trends for TCHL at Vrouwenzand (Fig. 12) and TSM at Markermeer Midden (Fig. 14). In order to illustrate the seasonal trends more clearly (the scatter in the in situ data is large), 2-
monthly average TCHL concentrations were calculated for the combined data sets of 1999 and 2000 (Fig. 15). Also, the standard deviations (S.D.) for the in situ data for these 2-monthly periods were obtained. The number of remote sensing data in periods 1 and 2 were too small to get representative S.D. for the remote sensing data, so these are not shown. Fig. 15 shows a better seasonal trend from low TCHL in January–February (period 1) to high TCHL in July–August (4), and September–October (5) than Fig. 12. The spread for the in situ data is large except for the period September–October (5). The SeaWiFS mean is only just outside the plotted range of the in situ TCHL concentrations (mean –

S.D., mean + S.D.) for March–April (2) and July–August (4). The SeaWiFS mean for March–April (2) is low, and probably underestimates the ‘true’ mean for this period.

The TSM at Vrouwenzand (Fig. 12) from the in situ sampling is highly variable and seasonal trends are difficult to recognise, making the 2-monthly averages here not giving a better picture. On the contrary, the trend shown by satellite remote sensing is clear, and shows much similarity to the trend in TCHL: a steady increase in late spring and summer, much lower in autumn and winter. In general, the variability of TSM and
TCHL is much higher for the standard in situ monitoring stations, than for the satellite image which must be a consequence of the high variability of suspended matter at small spatial scales, (i.e. scales smaller than a satellite pixel). The high spatial variability resulting in a high temporal variability in the in situ data obscures the real seasonal trends and hampers the interpretation of these data. The satellite images proof to be a valuable addition to the in situ monitoring program for determination of seasonal and long-term trends in TCHL and TSM. As an example, we compared the summer average for Chl-$a$ determined from all available in situ samples from April–September, to TCHL determined from SeaWiFS. In order to harmonise both data sets, we first determined the monthly average of all available in situ samples and of the satellite images. From the six numbers we determined the summer average and a S.D., which represents the temporal variability. In 2000 (1999 values given within brackets) the summer average was $69 \pm 40 \ (68 \pm 34) \ \text{mg m}^{-3}$ calculated from in situ data and $61 \pm 25 \ (63 \pm 22) \ \text{mg m}^{-3}$ from remote sensing data. Note that the S.D. for in situ data is considerably larger than for remote sensing data (in 2000: 58 vs. 41%) as expected from Fig. 12. So the temporal variability of the in situ data is much larger, but the summer mean of both data shows good agreement.

Satellite data give a synoptic view and thus can be used to indicate the most representative sampling location for a lake. The SeaWiFS TCHL maps for Lake IJssel show that such a unique location need not exist since spatial patterns change every month. The summer mean of TCHL for Lake IJssel was again determined, but now taking all pixels of the satellite image into account. The summer average then is $65 \pm 23 \ (67 \pm 10) \ \text{mg m}^{-3}$. This is in good agreement with the station values at Vrouwenzand so from these results it emerges that Vrouwenzand seems indeed representative for the whole of Lake IJssel.

5. Discussion

The main national monitoring program for aquatic ecosystems in the Netherlands (MWTL) is based upon a wide range of variables, ranging from concentrations of heavy metals to abundance of macrophytes or birds. In our study, we focus solely on the monitoring of phytoplankton. Phytoplankton abundance has increased in many Dutch lakes as a result of eutrophication; nuisance cyanobacteria have become the dominant group in many lakes in (late) summer. It follows that the key incentives for monitoring phytoplankton in inland water systems are the general evaluation of eutrophication policies, and more specifically, (early) warning for potentially toxic blooms of cyanobacteria. Specific recognition of cyanobacteria in the bulk reflectance is possible, but difficult at low concentrations. An early warning—at the early stages of a bloom—on basis of a remote sensing image—remains elusive in most cases, let alone the recognition of individual nuisance species or the assessment of toxicity from space (see Schofield et al., 1999 for a discussion). Our current study focuses on general monitoring of chlorophyll and especially, on a reliable inclusion of spatial patterns that may otherwise obscure long-term trend analysis. The synoptic view that is acquired through the use of a platform like SeaWiFS is commonly cited as the strongest argument in favour of remote sensing. Remote sensing, however, cannot be the definite answer to studying spatial patterns at all relevant scales. The analysis of relatively large scale patterns as one would observe with SeaWiFS demands an understanding of the variability at smaller scales, for which different sensors and/or models are required (Guichard et al., 2000).

There are three instruments that are used more or less widely in the evaluation of eutrophication policies. In situ sampling is still the basis for most monitoring efforts. In addition, many authorities now (routinely) apply water quality models to integrate and interpret the monitoring data. In our study, we aim to show the added value of remote sensing in monitoring lakes. When considering the characteristics of the three aforementioned information sources (in situ, model, remote sensing) it becomes clear that the instruments are complementary:

a. In situ monitoring has a long tradition in lake management. It is a reliable way of monitoring
individual points in a water system, but fails to give synoptic spatial cover. In situ monitoring programmes can be time consuming and costly, especially in larger water systems;
b. Water quality and ecological models are mass conserving, have a relation to in situ data via adequate calibration, and may contribute to a better understanding of system dynamics or spatial and temporal variation. Whereas remote sensing is capable of showing spatial patterns, models are able to provide insight into the underlying causes of the observed variability (Hedger et al., 2002). Their best-known quality probably is the predictive capacity of models. The quality of the model output, however, varies widely, and is much dependent on the quality of the model input, (e.g. van der Molen, 1999).
c. Remote sensing data are extensive in spatial (and increasingly in temporal) cover. The use of the optical models like matrix inversion improves the quality of the analysis, and reduces the necessity for individual calibration of each image. Information, however, is restricted to the optical depth of the water column and pixels at the land–water interface cannot be used.

We have used a combination of shipboard, airborne and satellite optical detection. Such a multisensor approach proved to be beneficial since the different sensors monitor phenomena at a different scale, e.g. compare EPS-a and SeaWiFS. Most remote sensing studies suffer from a lack of simultaneous in situ data—often referred to as ground truth. For testing the quality of our data retrieved from remotely sensed signals we had to rely on a cross validation between the three available optical sensors. This may appear to be a weak option, but in a way, modellers sometimes use a similar approach. The validity of the output by a certain model may be questioned, but if more than one model gives comparable results one may rightly gain confidence in the models used (Schef-fer, 1998). We found a good fit between observed (PR650) and modelled (EPS-a) $R(0–)$ spectra, which gave us confidence in the quality of the data retrieval from the EPS-a. A comparison between EPS-a and SeaWiFS showed more variation, but the important (seasonal) phenomena were reproduced by both sensors.

The SeaWiFS satellite sensor can serve as an important additional tool for monitoring the highly variable seasonal patterns of TCHL for Lake IJssel as a whole. The two step algorithm for retrieval of TSM and TCHL led to acceptable results when compared to in situ data (collected for the PR-650 surveys). An accuracy in the order of 30% may not seem impressive, but is acceptable given a spatial variation in SIOPs of at least 15%. Moreover, one aspect of monitoring in general, regardless of the technique chosen is that every source of information has its own inherent errors. Chlorophyll analyses from in situ samples taken less than 2 km apart near Vrouwenzand in the IJsselmeer showed a comparably large (16–55%) relative difference. This difference either reflects the spatial inhomogeneity of the lake—in which case, remote sensing is the only serious alternative if one is interested in basin wide information or the difference reflects an accumulation of errors in sampling and estimation of the chlorophyll concentration.

The most apparent shortcoming of satellite data is the lack of a sufficient frequency in images of good quality, mainly due to cloud cover. This shortcoming can be overcome by deterministic interpolation of satellite maps with computational water quality models, as was included in our study on Lakes IJssel and Marken. This issue will be addressed in a separate article. Here we briefly mention the main outline of the study. We ran cross-checks between the TCHL maps on basis of the SeaWiFS images and output from a deterministic algal growth model, DBS (described by van der Molen et al., 1994). We applied a cost function that quantifies the misfit between model results and observations. Cost functions provide an easy way of quantitatively and objectively comparing two data sets. Input for the cost function were the observations (SeaWiFS images) and their uncertainties (see Vos et al., 2001). The uncertainty for SeaWiFS in TCHL was estimated to be 30% (for example $50 \pm 15 \text{ mg m}^{-3}$). If the model result falls within the uncertain range of the observations the model and observed data are supposed to be in good agreement. Similarity was poor in spring,
but generally good in summer. Misfits between image and model enhanced our understanding of ecosystem functioning. For example, models helped to investigate why the gradient in the spatial distribution of TCHL in the IJsselmeer reverses in the middle of August when water temperatures reach their peak. The chlorophyll gradient in Lakes IJssel and Marken is thought to be related to a (reverse) gradient in density of zebra mussels—Dreissena polymorpha. In recent years, a serious reduction in the abundance of Dreissena has been observed in Lake Marken, perhaps as a result of shifts in silt sedimentation/resuspension patterns. The reduction in mussel densities correlates with an increase in chlorophyll. Satellites should be able to monitor—and in combination with models event reconstruct the history of—the events resulting in the changing patterns in turbidity and chlorophyll distribution in Lake Marken. Similarly, Budd et al. (2001) used satellite remote sensing to establish a distinct correlation between patterns of grazing mussels (D. polymorpha) and remote sensing reflectance for Lake Huron.

The combination of satellite data and models is synergistic (Plummer, 2000; Dekker et al., 2001; Ibelings et al., 2001). Plummer classified approaches for linking remotely sensed data and ecological process models into four different categories: (i) to use remote sensing data to provide estimates of variables required to drive ecological models; (ii) to use remotely sensed data to validate predictions of ecological models, Ibelings et al. (in press) used 12 years of NOAA satellite data to validate the output of a model predicting the occurrence of cyanobacterial surface waterblooms in the IJsselmeer; (iii) to use remote sensing to update, constrain or adjust models, e.g. in a process called data assimilation (Schofield et al., 1999); and (iv) to use ecological process models to understand remotely sensed data.

The requirement for the use of up-to-date and basin wide information in calibration is due to the fact that the water quality is not stationary but highly dynamic as clearly emerges from the remote sensing maps shown here. The satellite does not show local variability at the smallest scales—because it integrates a larger area of 1.1 km² in one pixel. In addition, the present temporal frequency is no more than 10 good SeaWiFS images per year, i.e. only sufficient for general purposes, like deriving a mean chlorophyll concentration. For more specific goals like following the wax and wane of nuisance algal blooms a higher frequency of good quality images would be required. Combining data from different sensors attributes to solving this problem. Gregg and Woodward (1998) combined SeaWiFS with MODIS and showed a 40–47% increase in global coverage. This approach has the additional advantage that the different sensors pass at different times of the day. Hence, in the presence of a broken cloud cover more meaningful images could be acquired (Joint and Groom, 2000).

It is obvious that the scales of detection of satellites and aeroplanes can be complementary. The EPS-a airborne sensor shows details in TSM and TCHL distributions that cannot be monitored with any other technique. For instance, the airborne sensor showed the location of a sharp TCHL gradient in Lake IJssel that could not be detected accurately by satellites or field spectrometers. We conclude that the airborne sensor can serve as an excellent tool to monitor shorelines, river plumes and fronts for which a much higher spatial resolution is required. In very turbid waters like Lake Marken, the low sensitivity of the SeaWiFS TCHL algorithm makes that TCHL detection with the airborne sensor is presently preferred over the satellite sensor. However, this might change with the advent of MERIS. MERIS has up to 15 spectral bands in the visible and near infrared (NIR) part of the spectrum. Compared to SeaWiFS that lacks a band in the red/NIR end of the spectrum near 705 nm, MERIS should be better suited for retrieval of TCHL from turbid waters. The standard spatial resolution is 1 × 1 km, but a high-resolution mode of 250 × 250 m is available. This combination of good spectral and spatial resolution makes MERIS a valuable addition to the existing sensors (see Gons et al., in press for further information). Yet even the arrival of new, better-equipped sensors is not sufficient to attain the full potential of remote sensing, which is still unrealised (Plummer, 2000). We endorse a conclusion by Behrenfeld and Falkowski (1997) who published global estimates of productivity in the oceans, based upon
satellite derived chlorophyll concentrations. They concluded that: ‘improvement of productivity algorithms is dependent not on improved mathematical formulation or finer detail in the physics of light attenuation and absorption, but on improvement in our understanding of phytoplankton ecology and photophysiology’. This paper shows that for shallow lakes in situ sampling, shipboard, airborne and satellite remote sensing are representative for different spatial scales and this may in some cases lead to different results. It implies that monitoring programs must take into account which spatial scales are relevant to the end-users of the data. The new EU policy directive on water quality (EU directive 2000/60/EC, 22-12-2000) may be a stimulus to improve the present monitoring programmes. We have restricted ourselves to monitoring of eutrophication. This still proves difficult enough in a spatially and temporally variable lake. One step up would be the detection of different phylogenetic groups or even species in the bulk chlorophyll signal—in inland waters there is a pressing need for the detection of nuisance cyanobacteria. Ultimately, it should be possible to predict the occurrence of harmful algal blooms (see Schofield et al., 1999; Ibelings et al., in press). If prediction is a bridge too far, the real time monitoring of eutrophication processes would be a good alternative, but here as well an improvement of the current remote sensing (and modelling) infrastructure is required.

Acknowledgments

We thank BCRS, RWS-WONS and Meetstrategie 2000+ for financial support of the study. We acknowledge the help of Harry Hosper (RIZA – Lelystad) in completing the final report of the study, which formed the basis for this publication. We thank Directorate IJsselmeergebied of Rijkswaterstaat (Lelystad) for use of their in situ data for Lake IJssel and Lake Marken. Pascal Boderie of Delft Hydraulics set up the algal growth model that was used in a Goodness of Fit test with SeaWiFS. We also thank Macheltl Rijkeboer of NIOO-CL (Nieuwersluis) for collecting some of the in situ data. We thank the NASA Goddard Space Flight Center for approving us the status of authorized research user of SeaWiFS data. We thank Kevin Ruddick of MUMM (Brussels) for supplying us with the MUMM variant of the SeaDAS software package and Reinold Pasterkamp of IVM\VU (Amsterdam) for his assistance with the MATLAB software. Finally, we would like to thank an anonymous referee for his or her constructive comments that helped us improve the paper.

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