Koponen, S., Pulliainen, J., Kallio, K., and Hallikainen, M., Lake water quality classification with airborne hyperspectral spectrometer and simulated MERIS data. Remote Sensing of Environment, vol. 79, no. 1, pp. 51-59, 2002.

ELSEVIER

Remote Sensing of Environment 79 (2002) 51–59

Remote Sensing of Environment

www.elsevier.com/locate/rse

Lake water quality classification with airborne hyperspectral spectrometer and simulated MERIS data

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Received 7 July 2000; received in revised form 8 February 2001; accepted 21 April 2001

Abstract

We study the use of airborne and simulated satellite remote sensing data for classification of three water quality variables: Secchi depth, turbidity, and chlorophyll *a*. An extensive airborne spectrometer and ground truth data set obtained in four lake water quality measurement campaigns in southern Finland during 1996–1998 was used in the analysis. The class limits for the water quality variables were obtained from two operational classification standards. When remote sensing data is used, a combination of them proved to be the most suitable. The feasibility of the system for operational use was tested by training and testing the retrieval algorithms with separate data sets. In this case, the classification accuracy is 90% for three Secchi depth classes, 79% for five turbidity classes, and 78% for five chlorophyll *a* classes. When Airborne Imaging Spectrometer for Applications (AISA) data was spectrally averaged corresponding to Envisat Medium Resolution Imaging Spectrometer (MERIS) channels, the classification accuracy was about the same as in the case of the original AISA channels.

Keywords: Operational remote sensing; Lakes; Turbidity; Secchi depth; Chlorophyll *a*

1. Introduction

Classification systems condense large amounts of information measured on the water bodies into easily understandable information for e.g. decision makers, authorities, and general public. Finding suitable variables and classification limits for a classification system is complicated. The variables and classification limits usually depend on the geographic location, the intended use of the water, data that is available, and which organization is doing the classification. Classification can be based on physico-chemical (e.g., chlorophyll *a*, total phosphorous (TP), Secchi depth) and biological (e.g. species composition of phytoplankton, periphytic growth, macrophytes, fish fauna) variables. An extensive review of different classification systems is presented by Premazzi and Chiaudani (1992). Biological variables often describe the status of waters better than physico-chemical variables. However, since the measurement of biological variables is expensive and time consuming, the operational classification of lakes in countries with a high number of lakes, such as Finland, is usually based on physico-chemical measurements. In total, there are 56 012 lakes with a surface area larger than 0.01 km^2 in Finland.

The general quality of lakes, rivers, and coastal areas in Finland is periodically assessed by the Finnish Environment Administration. This classification is based on laboratory analysis of water samples collected from stations at selected locations. Currently, the classification is carried out nationwide every 4 years. The latest lake classification (samples collected during 1994–1997) included data from 5000 sampling stations on lakes that represent 79% of the total lake surface area of Finland (including all lakes larger than 1 km^2). However, even though the collected data set is representative, its usability is limited especially by the spatial variation of water quality in lakes.

By using remote sensing techniques, some of the important variables used in the operational classification

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0034-4257/02/$ – see front matter
PII: S0034-4257(01)00238-3

of lakes can be measured. These optically active variables include chlorophyll *a*, total suspended solids, turbidity, and Secchi depth (see e.g. Dekker, 1993; Gitelson et al., 1993; Kallio et al., 2001). Aquatic humus is also an optically active substance sometimes used in lake classification, but its estimation by remote sensing techniques in lakes has been proven difficult (e.g., Dekker, 1993; Kallio et al., 2001).

Remote sensing offers some advantages such as good spatial and temporal coverage and the possibility of measuring many lakes simultaneously. With remote sensing, some variables of lake water quality could potentially be assessed up to several times per year. This would offer valuable data on the seasonal variability of water quality. Remote sensing instruments can also reduce water sampling and lakes not monitored by traditional methods can be included in the assessment.

In order to study the usability of remote sensing for water quality measurements of Finnish lakes, the Laboratory of Space Technology of the Helsinki University of Technology, together with the Finnish Environment Institute, conducted four airborne remote sensing and ground truth measurement campaigns in Southern Finland during 1996–1998. The campaigns were part of the EU-funded SALMON project (Lindell, Pierson, Premazzi, & Zilioli, 1999) and national remote sensing projects. The main results of these projects are presented in Härmä et al. (2001), Kallio et al. (2001), Koponen et al. (2001), and Pulliainen et al. (2001).

This paper investigates the feasibility of remote sensing data for operational lake water classification by using regression algorithms. While numerous papers describe remote sensing methods used for water quality estimation, the classification of lake water quality has not been previously investigated using as many variables and as large data set as available here. In addition, the feasibility of the Medium Resolution Imaging Spectrometer (MERIS) instrument onboard the Envisat satellite for water quality classification is studied by reconstructing the MERIS channels from airborne spectrometer data.

2. Instruments and data

The number of lakes measured during the four campaigns was 11 (all were located in southern Finland). The number of measurement days was 8. The lakes selected for the measurement campaigns had varying water quality characteristics. The trophic status varied from oligotrophic to eutrophic and two of the lakes were humic. For detailed information on the lakes, see Kallio et al. (2001).

The main remote sensing instrument employed during the campaigns was the Airborne Imaging Spectrometer for Applications (AISA) (Mäkisara et al., 1993). The main measurement characteristics of AISA are presented in Table 1.

Table 1
Measurement characteristics of AISA airborne spectrometer

Type	Pushbroom CCD-matrix sensor
Number of channels	286
Channel wavelength range	450–900 nm
Channel bandwidth	1.6–9.4 nm (sum of one to six channels)
Number of pixels (across track)	384
Field of view	21°
Pixel size from 1000-m altitude	1 m

The total number of channels that AISA has is 286. However, the instrument is not able to store data from all channels when the measurement mode suitable for airborne remote sensing is used (the amount of data generated exceeds the capabilities of the data recorder). Instead, data from a smaller number of preselected channels are stored. In the campaigns of 1996–1998, the selected channels covered most of the total wavelength range (450–900 nm) although there were some gaps. Additionally, the channel configuration varied slightly from campaign to campaign. For example, the number of stored channels was 40 in campaigns conducted in August 1996 and May 1997 and 53 in August 1997 and August 1998.

After acquisition, the AISA images were radiometrically and geometrically corrected and resampled to a pixel size of 2×2 m by the Finnish Forest Research Institute. Additional data preprocessing consisted of deriving the average radiance of each AISA channel in a 100×100-m square around each ground truth sampling point. If the ground truth point was not at the center of the measurement swath or it was close to shore or in a cloudy area, the square was moved to the closest suitable location at the center of the swath. Averaging reduces the variability of the signal due to the stripes caused by the CCD cell and the sun glitter caused by rough water surface. In order to reduce the effect of using various wavelength configurations of AISA, data from different campaigns were resampled into the same wavelength configuration by using the nearest-neighbor method (i.e., the value of a channel that did not have a value was obtained by copying the value of the channel closest to it).

The ground truth measurements included water sampling for laboratory analysis (e.g. chlorophyll *a*, turbidity, total suspended solids, aquatic humus), on-site measurements (e.g. Secchi depth, upwelling and downwelling irradiance with an underwater spectrometer), and weather observations (e.g. wind speed and direction, cloudiness). The sum of chlorophyll *a* and phaeophytin *a* (denoted here with chl-*a*) was determined with spectrophotometer after extraction with hot ethanol (ISO 10260) and turbidity by nephelometric method (based on the measurement of light, 860 nm) scattered within a 90° angle from the beam directed at the water sample (ISO 7027). In TP determination, the water sample was digested by potassium peroxodisulphate before analysis with ammonium molybdate (Murphy & Riley,

Table 2
Comparison between the variables and class limits of the general classification system developed for lakes in Finland and the OECD lake water classification scheme

Variable	Class Ultraoligotrophic (excellent)	Oligotrophic (good)	Mesotrophic (satisfactory)	Eutrophic (poor)	Hypertrophic (bad)
Secchi depth (m), Finnish	> 2.5	1–2.5	< 1		
Secchi depth (m), OECD	>12	>6	6–3	3–1.5	< 1.5
Turbidity (FNU), Finnish	< 1.5	>1.5			
Turbidity (FNU), OECD	N/A	N/A	N/A	N/A	N/A
Total phosphorous (μg/l), Finnish	< 12	< 30	< 50	50–100	>100
Total phosphorous (μg/l), OECD	< 4	< 10	10–35	35–100	>100
Mean chl-*a* in the growing season (μg/l), Finnish	< 4	< 10	< 20	20–50	>50
Max. chl (μg/l), OECD	< 2.5	< 8	8–25	25–75	>75

N/A = not applicable.

1962). The total number of points with near-simultaneous AISA and ground truth data was 127. Due to partial cloud cover and other problems, the number of usable data points is 122.

3. Methods

3.1. Classification

In this analysis, two different water quality classification systems were considered: the Water Quality Classification of Inland Waters in Finland (Heinonen & Herve, 1987; Vuoristo, 1998) and the OECD Lake Classification Scheme (OECD, 1982; Premazzi & Chiaudani, 1992). A comparison of the variables and class limits that are relevant to this study is presented in Table 2.

The Finnish water quality classification system is based on the variables and limits suitable for various water utilization purposes encountered in Finland i.e. recreational, raw water supply, and fishing. The quality class requirements for these three purposes can differ regarding both variables used and their class limit values. Therefore, the Finnish water quality classification also includes a general classification system, from which we took the classification limits for Secchi depth and turbidity. The general classification uses about 20 variables and the final class of a lake or a part of a lake is decided by the person doing the classification analysis. The most important variable in the Finnish general classification system is chl-*a* because it usually correlates best with the overall condition of a lake. Oxygen deficiency in the hypolimnion and the occurrence of toxic substances are other important variables. Aquatic humus, measured by water colour, is of special interest for water quality monitoring in Finland, since the number of humic lakes is high. For example, if the water colour (ISO 7887) is more than 50 mg Pt l^{-1} (equals about $a_{CDOM}(400) = 6\ m^{-1}$, CDOM = colored dissolved organic matter), the water quality class changes automatically from excellent to good in classification.

The OECD classification system is based on the limnological trophic state of lakes i.e. ultraoligotrophic, oligotrophic, mesotrophic, eutrophic, and hypertrophic. It uses three variables: chl-*a*, Secchi depth, and TP.

Finnish lakes are not as transparent as the lakes the OECD system was developed for. For example, about 90% of the samples in our campaigns have Secchi depth less than 3 m, which is the limit for a eutrophic lake according to the OECD system so, clearly, the limit of 3 m is not appropriate for classification of eutrophic lakes in the case of Finland. Therefore, for this analysis, the classification limits for Secchi depth were taken directly from the Finnish system.

Only the FEI system has limits for turbidity, and it has only two classes (limit is at 1.5 FNU). Fortunately, the correlation between TP and turbidity is reasonably high ($R^2 = 79.1\%$, $n = 86$, according to our data); hence, additional turbidity classes agreeing with the Finnish system can be derived from the limits defined for TP. Positive correlation between turbidity and TP has also been found in large

Table 3
Final classification limits used in the present investigation

	Class 1	Class 2	Class 3	Class 4	Class 5
Secchi depth (m)	>2.5	1–2.5	< 1		
Turbidity (FNU) [corresponding total phosphorous value in μg/l]	< 1.4 [< 12]	1.4–4.4 [12–30]	4.4–8.3 [30–50]	8.3–19.6 [50–100]	>19.6 [>100]
Chl-*a* (μg/l)	< 2.5	2.5–8	8–25	25–75	>75

water quality data sets of Finnish lakes (e.g. Mannio, Räike, & Vuorenmaa, 2000). Our data yields the following relation (Eq. (1)):

$$\text{Turbidity} = 0.0642 \times \text{TP}^{1.2423}, \quad (1)$$

where TP is expressed in mg/m^3.

The turbidity limits derived with the TP limits of the OECD system are not as well suited for the turbid Finnish waters as the national limits since the OECD values are too low.

The concentration of chl-*a* is used in both systems. However, the Finnish system uses the mean chl-*a* concentration of the growing season, while the OECD system is based on the maximum concentration. Because our data set was from August when the chl-*a* concentrations are usually at the maximum in Finland we applied the OECD classification for chl-*a*. The final class limits used in our analysis are presented in Table 3.

The observed relationship between Secchi depth and turbidity is presented in Fig. 1 and between Secchi depth and chl-*a* in Fig. 2. The correlation coefficients and the coefficients of determination (R^2) between water quality variables and their natural logarithms are presented in Table 4. Some of the variables, especially Secchi depth and turbidity are highly correlated with each other.

3.2. Retrieval algorithms

The retrieval of water quality variables with remote sensing instruments is based on analyzing the spectral features of solar radiation reflected from the water body. The substances found in natural waters (phytoplankton, suspended inorganic material and dissolved organic matter) scatter and absorb the incoming solar radiation. These processes, defined as the Inherent Optical Properties (IOP) by Preisendorfer (1976), are wavelength dependent and, therefore, influence the shape and the magnitude of the spectra reflected from water. This can be seen in Fig. 3 where the spectra measured (by AISA) at five ground truth

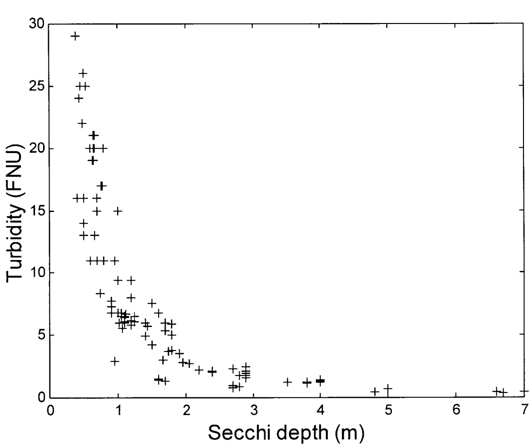

Fig. 1. The relationship between Secchi depth and turbidity.

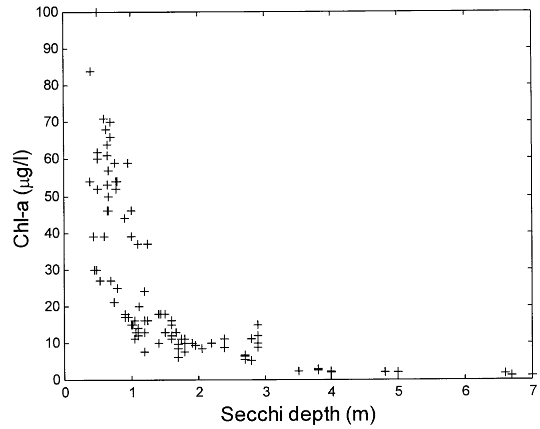

Fig. 2. The relationship between Secchi depth and chl-*a*.

data points are presented. The values of water quality variables at these points are presented in Table 5. By comparing the spectra data with the water quality variables, the following features can be observed.

• The peak at about 700 nm grows as the concentration of chl-*a* grows. This has been linked to scattering and absorption by phytoplankton (Morel & Prieur, 1977), and to chl-*a* fluorescence, which has a maximum at 683 nm (Smith & Baker, 1978). The shift to longer wavelengths as the concentration of chl-*a* grows was observed by Gitelson (1992). Just before, the peak phytoplankton has an absorption region at about 660–670 nm although it is not as clear as the peak at 700 nm in Fig. 3.

• Due to scattering from suspended matter, the detected radiance increases with the turbidity value in all parts of the spectrum in Fig. 3. Since absorption by optically active substances also influences the radiance level, it must be accounted for. One way to do this is to use wavelengths where the absorption by optically active substances (e.g. chl-*a* and CDOM) is minimal. One such region is near 710 nm (Dekker, 1993). Our data shows that at that wavelength the turbidity values in Table 5 follow the radiance values well by decreasing systematically with decreasing radiance.

The use of channel ratios for a relationship between remote sensing measurements and ground truth data is very common. The advantage of using ratios over absolute values of radiance (or reflectance) is that they correct some of the effects of measurement geometry and atmosphere. For example, Dekker, Malthus, and Seyhan (1991) showed that

Table 4
The correlation between water quality variables (99 data points)

Variables	Correlation coefficient	R^2 (%)
Secchi depth and chl-*a*	− .62	38.6
Ln(Secchi) and Ln(chl-*a*)	− .91	82.4
Secchi depth and turbidity	− .67	44.4
Ln(Secchi) and Ln(turbidity)	− .94	88.7
Turbidity and chl-*a*	.79	62.0
Ln(turbidity) and Ln(chl-*a*)	.88	76.9

Ln = natural logarithm.

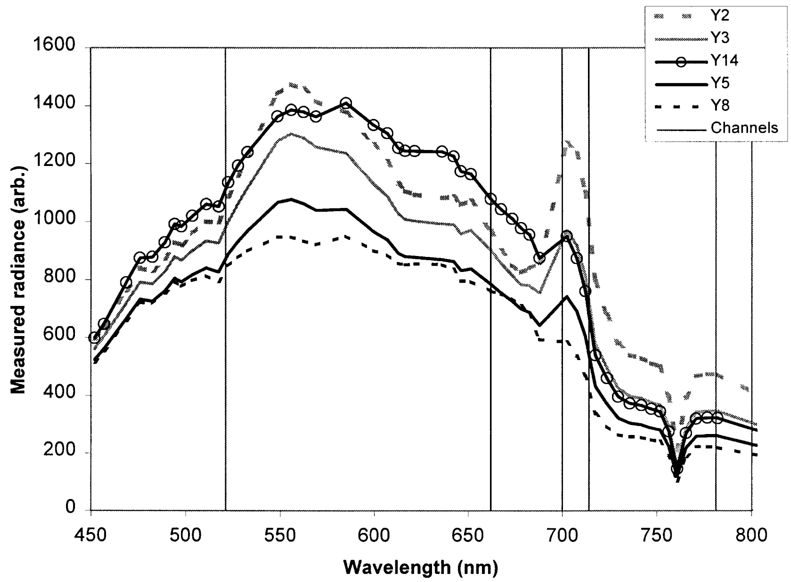

Fig. 3. Sample spectra measured at Lake Hiidenvesi with airborne spectrometer on 11 August 1998. Y2–Y14 are ground truth data points (the values of water quality variables at these points are presented in Table 5). The channels used in the retrieval algorithms are shown as vertical lines.

channel ratios yield high correlation coefficients for several water quality parameters. Dekker (1993) and Gitelson et al. (1993) concluded that for the retrieval of chl-*a* concentration a ratio of channels centered at about 675 and 705 nm is useful in several lake types (oligotrophic to hypertrophic). In addition, the previous studies on partly the same data set as used here (by Kallio et al., 2001; Koponen et al., 2001; Pulliainen et al., 2001) have showed that simple channel ratio and channel difference algorithms give high coefficients of determination for the water quality variables included here.

In our analysis, the best retrieval algorithm for each variable was found empirically by deriving a regression model for all possible channels and channel ratio and channel difference combinations and selecting the one with the highest R^2. The resulting algorithms and their parameters are presented in Table 6.

Secchi depth is a measure of water clarity by human eyes and all optically active substances in water affect it (Secchi depth decreases as the concentration of chl-*a*, CDOM, and other substances increases). As eyes use the whole visible band and the combined effect of all optically active substances over this region is complex, it may be difficult to find conclusive reasons for using some particular wavelengths for its retrieval. In our case, the empirical analysis yields the highest value for R^2 when a channel ratio with channels centered at 521 and 700 nm is used.

Table 5
Values of water quality variables on selected ground truth data points at Lake Hiidenvesi on 11 August 1998

Data point	Secchi depth (m)	Turbidity (FNU)	Chl-*a* (μg/l)	TSS (mg/l)
Y2	0.7	16	70	13
Y3	1	15	46	8.8
Y14	0.95	11	17	7.2
Y5	1.5	7.6	18	5.0
Y8	1.8	5.9	7.5	3.0

The absorption coefficient of filtered water at 400 nm [$a_{CDOM}(400)$, a measure of colored dissolved organic matter] was not analyzed at Lake Hiidenvesi in 1998. In August 1997, $a_{CDOM}(400)$ ranged between 5.3 and 6.0 m^{-1}. The concentration of total suspended solids (TSS, determined using GF/C glassfiber filter) is also shown although it was not used in the analysis.

In the algorithms for Secchi depth and chl-*a* the radiance of a near-infrared (NIR) channel at 781 nm is subtracted from radiance of channels at 521, 662 and 700 nm. This can be considered to be a type of coarse atmospheric correction as the reflectance of water is very low at NIR wavelength and most of the detected radiation is caused by atmospheric effects. However, with lake water this is not always true because with high concentration of suspended matter the NIR reflectance of water is not zero. Nevertheless, in our case, the subtraction improves the overall retrieval accuracy.

The feasibility of regression algorithms usually depends on the season. Therefore, the coefficients derived for May differ from those derived for August (Kallio et al., 2001). In Finland, the most important time of year in lake monitoring is August, because of high chl-*a* concentrations, the occurrence of phytoplankton blooms and low oxygen concentrations in the hypolimnion. In addition, the Finnish lake classification system generally uses in situ data from that period. Therefore, the data collected on 7 May 1997 (20 data points) was not used in the analysis.

The previous studies also showed that atmospheric correction (radiances transformed into reflectances with the MODTRAN model) only improves R^2 and root mean square error (RMSE) significantly for turbidity (Kallio et al., 2001). Since only one of the three variables used here benefited from the use of atmospheric correction, it was not applied

Table 6
Retrieval algorithms for AISA data

	Secchi depth	Turbidity	Chl-a[a]
Algorithm[b]	$a_0+a_1((L_{521}-L_{781})/(L_{700}-L_{781}))$	$a_0+a_1L_{714}$	$a_0+a_1((L_{700}-L_{781})/(L_{662}-L_{781}))$
R^2 for all data (%)	92.6	85.4	93.7
Coefficients (all data in training)	$a_0=-0.4298$, $a_1=1.0926$	$a_0=-0.9203$, $a_1=0.0155$	$a_0=-33.79$, $a_1=65.66$
Number of data points	102	99	80 (94 in testing)

[a] Data from Lake Tuusulanjärvi were not used in training.
[b] L_{xyz} is the detected radiance at a channel with a center wavelength of xyz nm.

here. For airborne remote sensing, this is an advantage since one step of the retrieval process can be eliminated.

The algorithm for chl-a does not work well for humic lakes (see e.g. Kallio et al., 2001). Therefore, two lakes (eight measurement points) were removed from the chl-a analysis. Humic lakes can be detected by analyzing the whole spectrum of the radiation reflected by lakes as shown by Pulliainen et al. (2001).

Lake Tuusulanjärvi was measured only during one campaign (August 1996). It contains a large amount of suspended solids (concentration typically close to 20 mg/l) and Secchi depth is low (less than 0.7 m). The 14 data points from that lake did not fit well in the regression model for chl-a and, therefore, they were not used in the training of the algorithm but were used in the testing.

At three ground truth stations, turbidity was not analyzed. Therefore, the number of data points in the turbidity analysis is 99.

Satellite remote sensing instruments can cover much larger areas than airborne sensors. Perhaps the most interesting satellite instrument is the MERIS that will be launched in the near future onboard the Envisat satellite. MERIS has several channels suitable for the estimation of water quality variables, and it has a fairly good spatial resolution of 300 m (Rast, Bézy, & Bruzzi, 1999). Here, MERIS data are simulated by calculating the mean radiance of the AISA channels that are within a single MERIS channel. The algorithms were derived by choosing the MERIS channels that are the closest to the AISA channels used earlier (e.g. 521 nm becomes the channel centered at 510 nm, 700 nm becomes the channel centered at 705 nm, and so on). As it is possible to find MERIS channels that are very close to the AISA channels, the resulting regression coefficients have about the same values as those derived with AISA data.

Table 7
Classification matrix for Secchi depth (all data in training and testing)

	RS			
GT	Class 1	Class 2	Class 3	Classification accuracy (%)
Class 1	24	0	0	100
Class 2	1	35	5	85
Class 3	0	6	31	84
All				88

RS = remote sensing; GT = ground truth.

4. Results

4.1. Secchi depth

The classification matrix for Secchi depth when all available data are used for training and testing the algorithm is shown in Table 7. The overall result is good. The total classification accuracy is 88% and the data points that were not classified correctly missed the right class by only one class.

For an operational system, concurrent ground truth data are not always available. In order to see what effects the lack of ground truth data might have, a second analysis was performed by training the retrieval algorithm with data from all but one of the measurement days and using data from that single day for testing (in this article, we call this procedure "daily testing"). This means that since we already have concurrent ground truth and remote sensing data in archive, we can use those data sets for training purposes and ground truth data may not be needed for every new campaign. This procedure was repeated with all meas-

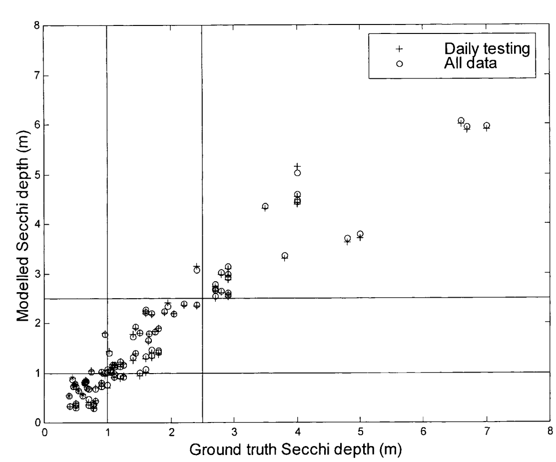

Fig. 4. Regression model for Secchi depth with AISA data. Vertical and horizontal lines represent quality class limits. Number of data points = 102. For all data, $R^2=92.6\%$; for daily testing (separate training and testing data sets), $R^2=91.8\%$.

Table 8
Classification matrix for turbidity (all data in training and testing)

	RS					
GT	Class 1	Class 2	Class 3	Class 4	Class 5	Classification accuracy (%)
Class 1	11	6	0	0	0	65
Class 2	0	16	4	0	0	80
Class 3	0	0	22	7	0	76
Class 4	0	0	0	18	2	90
Class 5	0	0	0	5	8	62
All						76

Table 9
Classification matrix for chl-*a* (all data in training and testing)

	RS					
GT	Class 1	Class 2	Class 3	Class 4	Class 5	Classification accuracy (%)
Class 1	7	2	0	0	0	78
Class 2	1	2	4	0	0	29
Class 3	0	4	39	3	0	85
Class 4	0	1	1	27	1	90
Class 5	0	0	0	1	1	50
All						81

urement dates. The classification accuracy for this case is 90%. Surprisingly, the classification accuracy is a bit better now, so the system seems not to be very susceptible to the lack of ground truth data or changes in measurement configuration or weather conditions. A scatter plot for both cases (all data in training and testing vs. daily testing) is shown in Fig. 4. The lack of concurrent ground truth observations does not appear to cause considerable change in the estimated Secchi depth values.

4.2. Turbidity

The results for turbidity are shown in Table 8 (all data in training and testing) and in Fig. 5. The number of classes is now five. The classification accuracy is again better with daily testing although the difference between the two cases (all data in training and testing vs. daily testing) is larger when the turbidity value is high. Fortunately, this did not reduce the classification accuracy.

The classification accuracy is worse than for Secchi depth. This may result from the higher number of classes used for turbidity or from the type of algorithm that was used for turbidity estimation, or both. For other variables, the use of channel ratios reduces the effect of instrument calibration errors, atmospheric effects, seasonal effects, and other factors that may affect the measured radiance. The use of atmospheric correction improves R^2 from .85 (Table 6) to .93 (Kallio et al., 2001) and may also improve the classification accuracy. However, this was not applied, as the objective here was to test a simple classification system.

4.3. Chl-a

The classification results for chl-*a* are shown in Table 9 (all data in training and testing) and in Fig. 6. Again, the difference between daily testing and training and testing with all data is large only when the concentration of chl-*a* is high, and it did not reduce the classification accuracy significantly. Only one sample was misclassified by two classes. It represents Lake Tuusulanjärvi from which the data were not included in training the algorithm.

The ultraoligotrophic and hypertrophic classes only held nine and two samples, respectively. If those class limits were removed, the classification accuracy was about 86% for all data in training and testing and 83% for daily testing.

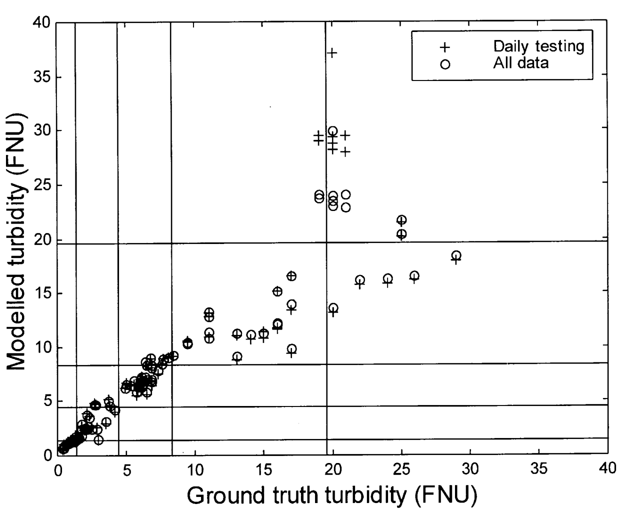

Fig. 5. Regression model for turbidity with AISA data. Vertical and horizontal lines represent quality class limits. Number of data points = 99. For all data, $R^2 = 85.4\%$; for daily testing (separate training and testing data sets), $R^2 = 76.1\%$.

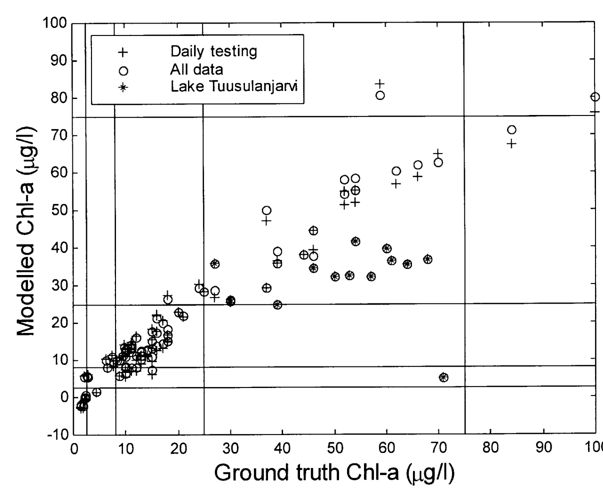

Fig. 6. Regression model for chl-*a* with AISA data. Vertical and horizontal lines represent quality class limits. Number of data points = 94. For all data, $R^2 = 93.7\%$; for daily testing (separate training and testing data sets), $R^2 = 91.9\%$.

Table 10
Classification accuracy for all cases (%)

Method	Secchi	Turbidity	Chl-*a*
AISA (all data)	88	76	81
AISA (daily training)	90	79	78
MERIS	89	77	80

When the data points were first divided into two classes according to the Secchi depth (limit at 0.9 m) and chl-*a* values were then derived with two different sets of regression coefficients the total classification accuracy changed from 81% to 84%. However, when both daily testing and Secchi depth limit was used the accuracy decreased to 77%.

4.4. Results with simulated MERIS data

The results with simulated MERIS data are very similar to those with AISA. The classification accuracies are about the same as with original algorithms using full AISA spectrum information. This is not a surprise since the MERIS algorithms are almost the same as the AISA algorithms. The only differences are wider channels with MERIS and the exact center wavelengths used in the algorithms. A summary of the classification results is presented in Table 10.

5. Discussion

The airborne water quality classification system was able to classify the target lakes with good accuracy despite different measurement configurations and lake types. This indicates that remote sensing is a useful tool for water quality classification. However, airborne remote sensing is quite expensive and its use will be limited in operational monitoring of large areas. Fortunately, the simulated Envisat MERIS data also gave good results.

For satellite instruments, atmospheric correction is more important than for airborne instrument since the radiance originating from below the water surface is very weak compared to the radiance from the atmosphere. This may reduce the estimation accuracy when satellite data is used instead of airborne data. On the other hand, the measurement conditions (e.g. solar angle, weather) will be more constant as the image is acquired in a single moment, which should improve the retrieval accuracy. Using retrieval algorithms based on channel ratio or difference indices reduces the effect caused by the atmosphere, but some kind of correction may still be necessary. For MERIS data, possible atmospheric correction methods are presented by Antoine and Morel (1999) and Moore, Aiken, and Lavender (1999).

The classification accuracy remained high for all three variables even when the retrieval algorithms were tested using separate test data sets neglecting the nearly simultaneous reference data in training the algorithms. This suggests that the current database should be large enough for operational monitoring of the lakes used in the survey. The results are only valid for August. The limited data from May indicate that the algorithms may vary seasonally (Kallio et al., 2001). Therefore, the algorithms presented here should be first thoroughly tested before applying them to other seasons. The system developed here for August should also work well for lakes that are similar to the ones used here. For other lake types, more concurrent ground truth and remote sensing data are needed. However, Finnish lake types are fairly well covered in the present data set.

The division of data into two classes based on Secchi depth did not improve the accuracy of an operational chl-*a* retrieval system. However, the preclassification of the data may still be reasonable, because it allows the use of optimal algorithms for different lake types. For example, Kallio et al. (2001) demonstrated that the use of radiance measured at shorter wavelengths 685–691 nm instead of 699–705 nm in the numerator of the chl-*a* algorithm improved the accuracy of estimations for the oligotrophic and mesotrophic lakes.

The classification limits used here were selected by combining two classification systems, each of which has its strengths and weaknesses. For example, the national system was developed for Finnish lakes, but it is not used elsewhere and, therefore, comparison with results from other areas may be difficult. The OECD system, on the other hand, was developed for European lakes and comparison is easier, but some of the variable limits are not well suited for Finnish lakes. Chl-*a* classification was here based on the OECD system that is applicable for European lakes, while the classification limits for Secchi depth and turbidity follow the practically more suitable national system.

The current operative lake classification system used in Finland is based on the measurements at fixed stations (laboratory analyses of water samples). These stations (or in some cases just one station per lake) may not always present the actual condition of a lake in the best possible way. Perhaps the worst flaw of the current classification system is that the spatial resolution is limited. With remote sensing instruments, it is possible to see how the values of water quality variables are distributed spatially and, thus, get information on the complete status of the lake. Information on the relative spatial variations of water quality variables is also interesting even though the absolute accuracy is not as good as with laboratory techniques.

The accuracy of a classification system also depends on the number classes the system uses. In this analysis, the number of classes is only five or less and part of the success may be attributed to that. However, in most cases, no information at all is available from smaller lakes so even a coarse classification is useful. Furthermore, the experts who generated the operative classification systems discussed here have only used at most five classes.

One problem with low and medium resolution satellite data (e.g. MERIS) is that Finnish lakes are typically small and irregular in shape and may include small islands. The radiation reflected from the shore and the vegetation near the shore is usually stronger than the radiation from water. Therefore, if even a small portion of a pixel is covered by land the retrieval of water quality variables may not be possible. However, the 300-m nadir resolution of MERIS should be good enough for large and medium size lakes if the rectification accuracy is good.

When variables that have continuous values are classified, some misclassifications at the edges of class limits are inevitable. This is also probably the reason why the classification accuracy for turbidity and Secchi depth is better when not all data are used for training as a slight change in the value of a data point can change the class. In any case, the system used here seems to work well since only one data point for chl-*a* was misclassified by more than one class.

6. Conclusions

The classification of lake water quality, using parameters Secchi depth, turbidity, and chl-*a*, is possible with airborne imaging spectrometers. The class limits were obtained from two operational classification standards and a combination of them was determined to be most suitable when remote sensing data is used. In most cases, the classification is possible even without concurrent ground truth data. This indicates that operational classification with remote sensing data is possible. The classification accuracy ranges from 76% to 90%.

The main advantage of remote sensing over the traditional lake monitoring method based on water sample collection is its good spatial and temporal coverage. Monitoring can be carried out several times per year and lakes not included in the traditional sampling can be also monitored. The channel configuration of the Envisat MERIS instrument also appears to be suitable for the classification of turbid lakes, such as Finnish lakes.

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