Koponen, S., Pulliainen, J., Servomaa, H., Zhang, Y., Hallikainen, M., Kallio, K., Vepsäläinen, J., Pyhälahti, T., and Hannonen, T., Analysis on the feasibility of multi-source remote sensing observations for chl-*a* monitoring in Finnish lakes. The Science of the Total Environment, vol. 268, nos. 1-3, pp. 95-106, 2001.

ELSEVIER

The Science of the Total Environment 268 (2001) 95–106

the Science of the Total Environment
An International Journal for Scientific Research into the Environment and its Relationship with Man

www.elsevier.com/locate/scitotenv

Analysis on the feasibility of multi-source remote sensing observations for chl-*a* monitoring in Finnish lakes

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Abstract

Chlorophyll-*a* (chl-*a*) concentration of lake water can be measured with airborne (or spaceborne) optical remote sensing instruments. The rmse obtained here with empirical algorithms and 122 measurement points was 8.9 μg/l (all points used for training and testing). Airborne Imaging Spectrometer for Applications (AISA) was used in four lake water quality measurement campaigns (8 measurement days) in southern Finland during 1996–1998 with other airborne instruments and extensive in situ data collection. As empirical algorithms are employed for chl-*a* retrieval from remote sensing data, temporally varying factors such as surface reflection and atmospheric effects degrade the estimation accuracy. This paper analyzes the quantitative accuracy of empirical chl-*a* retrieval algorithms available as methods to correct temporal disturbances are either included or excluded. The aim is to evaluate the usability of empirical chl-*a* retrieval algorithms in cases when no concurrent reference in situ data are available. Four methods to reduce the effects of temporal variations are investigated. The methods are: (1) atmospheric correction; (2) synchronous radiometer data; (3) wind speed data; and (4) bidirectional scattering model based on wind speed and sun angle data. The effects of different correction methods are analyzed by using single-date test data and multi-date training data sets. The results show that the use of a bidirectional scattering model and atmospheric correction reduces the bias component of the measurement error. Radiometer data also appear to improve the accuracy. However, if concurrent in situ reference data are not available, the retrieval algorithms and correction methods should be improved for reducing the bias error.

Keywords: Chlorophyll-*a*; Finnish lakes; Remote sensing

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0048-9697/01/$ - see front matter
PII: S0048-9697(00)00689-6

1. Introduction

Spectrometers operating on the red-to-near-infra-red part of optical wavelengths have been determined to be applicable for measuring the concentration of chlorophyll-*a* (chl-*a*). Typically, empirical algorithms developed for the retrieval of chl-*a* concentration employ ratios of reflectances and radiances measured at different bands as indices that are assumed to be linearly related to chl-*a* concentration. A ratio of results at two wavelengths X and Y where X is in the range from ~ 680 to ~ 710 nm corresponding to chl-*a* fluorescence and volume scattering from particulate matter (Gitelson, 1992; Schalles et al., 1998) and Y is below 680 nm, have been used successfully in the case of inland waters (Dekker, 1993; Gitelson et al., 1993).

The amount of chl-*a* is a good indicator of the quality of lake water as it correlates well with the total productivity of a lake and, therefore, with the nutrient load and overall condition of the lake. For these reasons, this paper is concerned with the retrieval of chl-*a* concentration from imaging spectrometer data. The specific aim is to investigate how well empirical algorithms using spectrometer channel ratios perform under varying environmental conditions. This is done by testing the retrieval algorithms using remote sensing observations representing observation days different from those used for training the algorithm. The analyses are carried out employing: (1) observed radiance spectra; (2) atmospherically corrected reflectance spectra; (3) combined airborne imaging spectrometer and microwave radiometer data; (4) surface scattering model correction for imaging spectrometer-based radiances and/or reflectances; and (5) wind speed data correction.

The signal detected by a passive optical remote sensing instrument can be divided into two main components: (1) solar radiation reflected by a target to the instrument; and (2) solar radiation scattered to the instrument by the atmosphere between the target and the instrument. The latter component is often called the path radiance (atmosphere also has another effect on the detected radiation — it attenuates the radiation reflected by the target). The receiver cell can also detect a small portion of the radiance from the neighboring pixels (this is called the adjacency effect). In the case of water quality measurements a third main component of the detected signal can be identified: the reflection of solar radiation (direct and diffuse) from the water–air interface (i.e. the water surface). Of these three compo-

Table 1
Results from the error analysis with different training/test data combinations for uncorrected data (total number of data points is 122)[a]

Date of test data	Training data R^2	Test data R^2	Number of test data points	Test data rmse (μg/l)	Bias error (model-GT) (μg/l)	Unbiased rmse (μg/l)
5 Aug 1996	0.84	0.48	12	12.5	−3.8	11.9
6 Aug 1996	0.82	0.81	11	8.4	−4.4	7.1
7 Aug 1996	0.82	0.95	3	4.4	−3.5	2.7
14 Aug 1996	0.84	0.37	8	21.2	−20.2	6.5
7 May 1997	0.82	0.74	20	7.4	6.7	3.2
11 Aug 1997	0.74	0.93	38	7.4	−0.8	7.4
18 Aug 1997	0.82	0.55	15	8.4	6.7	5.1
11 Aug 1998	0.82	0.92	15	8.5	5.0	6.9
All 1996	0.90	0.74	34	14.7	−10.0	10.8
All 1997	0.72	0.89	73	8.7	5.9	6.4
All 1998	0.82	0.92	15	8.5	5.0	6.9
Mean	0.81	0.76	–	10.0	−1.2	6.8

[a] rmse is the root mean square error and GT is ground truth.

nents only the first one contains information about the target (water quality parameters). The other two degrade the measurement accuracy by adding an unknown and temporally and/or spatially changing amount of radiative energy to the signal. That deteriorates the accuracy of retrieval algorithms especially if the algorithm is trained with data obtained under different measurement conditions.

Several parameters affect the three signal components. These can be divided into four classes: (1) water surface properties (surface roughness due to waves); (2) measurement configuration (sun and observation angles); (3) the amount and inherent optical properties of in-water substances; and (4) atmospheric factors (mainly the amount of aerosols and water vapor, also dependent on the wavelength). If these parameters are known (or can be estimated) a correction method can be used to reduce the effect of temporally varying atmosphere and water surface reflection on the water quality estimation.

2. Material and methodology

2.1. Description of data

The data used in the analysis were obtained during four lake measurement campaigns (8 measurement days). The dates of the measurement days are depicted in Table 1. Each campaign consisted of airborne and ground truth measurements. The main airborne instruments were the Airborne Imaging Spectrometer for Applications (AISA) (Mäkisara et al., 1993) and HUTRAD multi-channel radiometer system (Hallikainen et al., 1998).

Ground truth measurements included collection of water samples for laboratory analysis (e.g. chl-*a*, turbidity), on-site measurements (e.g. Secchi-depth, hand-held spectrometer) and collection of weather data (e.g. wind speed and direction, air and water surface temperature). Ground truth data was usually collected within a few hours of the airborne measurements. The total number of lake measurement points with simultaneous airborne and ground truth data is 127. However, due to instrument problems, clouds and other factors the amount of data are smaller in some cases.

For a more detailed description of measurement campaigns, acquired data and pre-processing (see, e.g. Kallio et al., 2001; Pulliainen et al., 2001). Kallio et al. (2001) also presents a few spectra measured at different lakes.

2.2. Chl-a concentration retrieval and surface reflection correction methods

AISA data sets were pre-processed by deriving the average intensity of each AISA channel in a 100×100-m or 20×20-m box around or close to the ground truth points. If a ground truth point was not at the nadir of the instrument or it was close to the shore the box was moved to a closest suitable position. This way the effect of the measurement geometry or shore vegetation on the detected radiance values was minimized.

The preprocessing reduced the amount of data and made it possible to numerically analyze (with Matlab-software) the relationship between ground truth and remote sensing data. The analysis was performed with two types of optical data: (a) the measured AISA radiances; and (b) AISA reflectances. Radiance data include all three signal components, while in the reflectance data the effects of atmospheric conditions (scattering and transmissivity) are removed with an atmospheric correction model using the HIRLAM numerical weather prediction model and MODTRAN simulations (Kallio et al., 2001). Both types of data still include the surface reflection component.

In order to find the best chl-*a* retrieval algorithm for multitemporal AISA observations, several simple linear regression algorithms (e.g. channel difference, channel ratio) were tried with all possible AISA channel combinations (all available channels from approx. 450 nm to approx. 800 nm were used, see Härmä et al., 2001 for channel details). The best algorithm and channel combination was selected by comparing coefficients of determination for each case. As expected, the best results were obtained with an AISA channel ratio where the wavelength of the denominator is 673 nm and the wavelength of the numerator is 702 nm. This corresponds well to the findings of other authors (e.g. Dekker, 1993 or Gitelson et al., 1993). The retrieval algorithms and channel combinations for other water quality variables (e.g. Secchi depth and turbidity) are presented in Kallio et al. (2001). Channels close to 673 and 702 nm also gave fairly good result. Therefore, the algorithm is not very susceptible to errors in the wavelength calibration of the instrument.

In this case the retrieval model for chl-*a* concentration can be expressed simply as

$$\text{Chl-}a = a_0 + a_1 \frac{L(702\ \text{nm})}{L(673\ \text{nm})}, \tag{1a}$$

$$\text{Chl-}a = a_0 + a_1 \frac{R(702\ \text{nm})}{R(673\ \text{nm})}, \tag{1b}$$

where $L(673\ \text{nm})$ and $L(702\ \text{nm})$ are the measured radiances at wavelength channels 673 and 702 nm. $R(673\ \text{nm})$ and $R(702\ \text{nm})$ are the reflectances calculated using the atmospheric correction, respectively. a_0 and a_1 are coefficients determined with a linear regression model by using ground truth data.

The retrieval accuracy of the model can be estimated by dividing the available data into training and testing data sets. First, the model coefficients are derived by using the training data set (includes both remote sensing and ground truth data). Then these coefficients and the test remote sensing data set are used to derive an estimate of chl-*a* concentration. Finally the estimated values are compared with the testing ground truth data. The measurement error is simply the difference between the estimated and ground truth concentration.

The measurement error can be divided into two classes: (1) the root mean square error (rmse) represents the random repeatability of the measurement; and (2) the bias represents the systematic error due to methodology or equipment. For operational use (when large areas are measured) the bias is usually more serious since rmse can be reduced by spatially averaging measurement pixels. That is not the case for the bias and a large bias can lead into serious errors in the data interpretation (e.g. the mean chl-*a* concentration of a lake).

The accuracy of the estimates for chl-*a* concentration, when no reference data are available for the day under investigation, was investigated by excluding the observation representing the date under investigation from the test data set. Additionally, the data were divided into testing and training data sets on yearly basis.

2.3. Correction with radiometer data

A microwave radiometer measures the incoherent radiation emitted by a surface. The intensity of the detected signal mainly depends on two surface parameters: (1) temperature; and (2) roughness (reflectance/emissivity is a function of quantitative roughness parameters). Therefore, it can be assumed that radiometer data can be used to reduce the effect of spatial/temporal surface reflection variations of optical data. As it turned out to be difficult to transform radiometer data into information about the reflected solar radiation, a direct subtraction from AISA radiance/reflectance was not possible. Instead, radiometer data were used as an additional independent variable in the regression model. The retrieval model can now be expressed as

$$\text{Chl-}a = a_0 + a_1 \frac{L(702\ \text{nm})}{L(673\ \text{nm})} + a_2 T_B, \tag{2}$$

where T_B is the 'apparent temperature' measured by the radiometer and a_2 is a regression coefficient determined with training ground truth data.

2.4. Correction with bidirectional scattering model and wind speed data

A bidirectional scattering model (e.g. Kirchoff's model in Ulaby, 1982) can be used to estimate the amount of radiation scattered by a rough surface. The model is a function of sun and measurement angles, wavelength (through the dielectric properties of water) and surface roughness (which mainly depends on wind conditions) and only takes into account surface scattering. The transmitted part of the solar radiation (coming from the water through water surface) also has a strong angle dependency, which is ignored in this study.

The pre-processing method used for AISA data removed most of the variations caused by measurement angles. As the averaging boxes were located at nadir the measurement angle of the instrument can be set to 0°. At that angle the azimuth angles do not have any effect on the surface reflection. The field of view (FOV) of AISA is 22°. The view angle of a 100-m box from the flight altitude of 1000 m is less than 6°. Therefore, the anisotropy effects of the FOV within the box have been assumed to be negligible. Airborne measurements were mainly conducted a few hours before or around local noon. During that time the variation of the elevation angle of sun caused a smaller effect on the results than the wind. Therefore, a constant sun elevation angle was used. With all these simplifications the scattering model only varies as a function of wind speed, and the model for chl-*a* concentration can be expressed as

$$\text{Chl-}a = a_0 + a_1 \frac{L(702\ \text{nm})}{L(673\ \text{nm})} + a_2 \text{BD}, \tag{3}$$

where a_2 is the coefficient for bidirectional model (BD) data.

Similarly to using bidirectional model, wind speed data can be used directly as an independent variable in the regression model.

The bidirectional model can also be used to reduce the effect of measurement angles when thematic maps are produced. In order to evaluate the angle dependence of AISA data a few intersecting flight lines were flown during the campaigns. One of the intersecting flight lines (a cross of two nearly perpendicular flight lines) was measured at sea where the effect of waves can be estimated to be fairly uniform. Furthermore, since the area of the intersection is small the signal due to chl-*a* and other substances in water can also be assumed to be uniform. Therefore, the measured signal variations can be assumed to mainly depend on factors related to water surface roughness properties and measurement angles.

Fig. 1 shows the configuration of the cross measurement. In this case the sun is in southwest (azimuth angle 215° from north) and the flight lines follow east–west (EW, heading 263°) and north–south (NS, heading 180°) directions. The wind speed was 10 m/s and the time difference between the measurement lines was 7 min. The flight altitude was 1000 m. Nine 100 × 100-m and 20 × 20-m boxes were placed on the intersection of lines as shown in Fig. 1 and the average value of measured intensity inside boxes was derived for each of the 53 AISA channels used in the measurement.

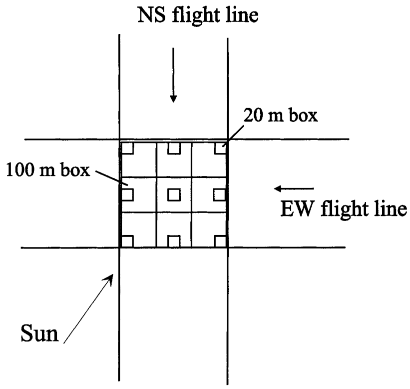

Fig. 1. AISA cross flight configuration. Solar radiation is coming from the direction indicated with the arrow.

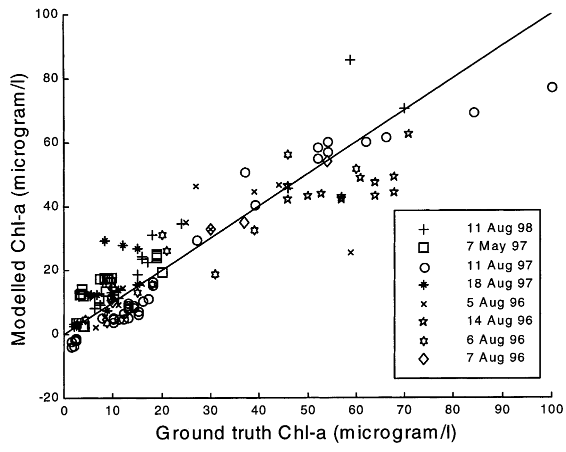

Fig. 2. Regression model of chl-*a* for all 96–98 lake observations. $R^2 = 0.82$, number of measurement points = 122, rmse = 8.9 μg/l. Different symbols represent different measurement dates. Model coefficients [for Eq. (1a)] are $a_0 = -69.1$ and $a_1 = 96.7$.

Table 2
Results from the error analysis with different training/test data combinations for data with atmospheric correction

Date of test data	Training data R^2	Test data R^2	Number of test data points	Test data rmse (μg/l)	Bias error (model-GT) (μg/l)	Unbiased rmse (μg/l)
5 Aug 1996	0.83	0.36	12	14.9	0.3	14.9
6 Aug 1996	0.79	0.84	11	7.0	−2.0	6.7
7 Aug 1996	0.79	0.97	3	3.0	−0.7	2.9
14 Aug 1996	0.81	0.14	8	20.6	−19.1	7.7
7 May 1997	0.80	0.73	20	7.5	6.8	3.1
11 Aug 1997	0.72	0.92	38	8.2	−4.5	6.8
18 Aug 1997	0.81	0.38	15	10.0	6.3	7.8
11 Aug 1998	0.79	0.92	15	8.5	5.7	6.3
All 1996	0.85	0.64	34	13.9	−6.6	12.2
All 1997	0.69	0.85	73	8.2	2.9	7.6
All 1998	0.79	0.92	15	8.5	5.7	6.3
Mean	0.79	0.70	–	10.0	−0.5	7.5

3. Results

3.1. Basic model and the effect of different measurement dates

When all available data are used for training the chl-*a* retrieval model [Eq. (1a)] the coefficient of determination $R^2 = 0.82$. This is a good result considering the simplicity of the model and all different measurement conditions (e.g. lake types, weather, season). When the model results are compared with the ground truth data the rmse is 8.9 μg/l. Fig. 2 shows the scatter plot for this case.

The results for different training/test data combinations are shown in Table 1. As can be seen the rmse usually includes a fairly large bias component (systematic error) when the training data set does not include observations from the testing date. Some of these biases can be ex-

Table 3
Regression coefficients for radiance and reflectance data [Eqs. (1a) and (1b)]

Date of test data	Radiance				Reflectance			
	Coefficient a_1 for Eq. (1a) ± 95% confidence interval		Coefficient a_0 for Eq. (1a) ± 95% confidence interval		Coefficient a_1 for Eq. (1b) ± 95% confidence interval		Coefficient a_0 for Eq. (1b) ± 95% confidence interval	
5 Aug 1996	98.2	±8.1	−70.9	±7.7	94.1	±8.0	−78.9	±8.7
6 Aug 1996	96.9	±8.6	−69.7	±8.2	90.8	±8.8	−75.6	±9.6
7 Aug 1996	96.6	±8.4	−69.1	±8.0	90.5	±8.4	−75.1	±9.2
14 Aug 1996	89.7	±7.3	−63.9	±6.9	83.8	±7.7	−69.1	±8.3
7 May 1997	94.9	±8.8	−66.3	±8.6	88.8	±8.9	−72.2	±9.9
11 Aug 1997	104.3	±13.5	−76.4	±12.7	92.6	±12.7	−78.7	±13.8
18 Aug 1997	95.9	±8.6	−67.6	±8.3	91.1	±8.6	−74.9	±9.4
11 Aug 1998	100.6	±9.2	−72.1	±8.7	93.8	±9.3	−77.9	±10.0
All 1996	89.9	±6.6	−65.5	±6.2	86.0	±7.6	−72.1	±8.1
All 1997	96.4	±17.5	−65.3	±17.5	88.1	±17.4	−70.7	±20.1
All 1998	100.6	±9.2	−72.1	±8.7	93.8	±9.3	−77.9	±10.0
Mean	96.7	9.6	−69.0	9.2	90.3	9.7	−74.8	10.6
S.D.	4.3	3.1	3.7	3.2	3.4	2.9	3.4	3.5

plained with large differences in the water quality of the measured lakes (for details, see Pulliainen et al., 2001; Kallio et al., 2001). For example, all data points obtained during 14 August 1996 (bias error over 20 μg/l) are from the same very eutrophic lake (Lake Tuusulanjärvi). This lake contains blue-green algae (although it was not dominant), which may explain the bias. Some of the others are more likely to be due to the differences in measurement conditions as the testing data include observations from several lakes which are all also represented in the training data set.

3.2. Atmospheric correction

Table 2 shows the results for AISA data that has been converted to reflectance indices by using an atmospheric correction model. As can be seen the atmospheric correction does not improve the rmse significantly. However, the bias error is reduced in seven of the 11 cases. This is an important result as the bias component is usually more harmful for an operational system.

Table 3 shows the regression coefficients (a_0 and a_1) derived from training radiance and reflectance data by using Eqs. (1a) and (1b). The coefficients are fairly stable. The standard deviation of coefficients is approximately 5% of the value of the mean. Atmospheric correction seems to reduce the standard deviation of both coefficients.

3.3. Radiometer correction

Table 4 shows the results when radiometer data have been used as an additional independent variable in the regression model (Table 4 also shows the best channel for each day). All data from an individual date are used for both training and testing the algorithm. Unfortunately, due to technical problems the availability of radiometer channels varied greatly between measurement campaigns. Furthermore, radiometer measurements were not conducted during the campaign in August 1998. Therefore, an analysis with the complete data set was not possible. Instead, each day was analyzed separately by comparing the coefficients of determination with and without radiometer data. The improvement in R^2 is statistically significant in five of the eight cases. Furthermore, radiometer data seem to improve R^2 significantly in cases where it was low initially (e.g. cases 14 August 1996 and 18 August 1997).

3.4. Bidirectional correction

Ground truth wind speed data were not available for the 1996 campaign and for some of the measurement points in 1997. Therefore, those points were eliminated from the bidirectional and wind speed correction analyses. As an outcome, a set of 80 observations was available for analyses. The results were determined similarly to those shown in Tables 1 and 2. Thus, as algorithms were tested for a certain date of observation, observations from all other measurement dates were used for training the algorithms.

Table 5 shows the results when only the data with wind speed and no correction method was used in the analysis. The results are better (mean $R^2 > 0.9$) than when all measured data points were used (Table 1). This is probably due to smaller differences in the AISA channel configuration (see Härmä et al., 2001 for details) and measurement conditions (e.g. atmospheric effects).

Table 6 shows the results when the bidirectional correction method is used for the same data. In three of the four cases the bidirectional correction reduces rmse slightly (compared with the results in Table 5). The bias error is also reduced in three cases although the mean of biases increases.

For comparison, Tables 7 and 8 show the results for the same data set when the wind speed and atmospherically corrected data are used, respectively. Using wind speed data directly in the algorithm does not seem to improve the retrieval result. Atmospheric correction is also less useful for the dates in question (the same can be seen in Table 2).

An additional correction attempt was made to use bidirectional model data with atmospherically corrected data by subtracting the surface reflection derived with the bidirectional model from

Table 4
Correction of AISA measurements with radiometer data

Date of test data	Number of points	R^2 without radiometer data (%)	R^2 with radiometer data (%)	Model coefficients ($\pm$95% confidence)			Best radiometer channel
				a_0 [Eq. (2)] (μg/l)	AISA ratio a_1 (μg/l)	Radiometer data a_2 (μg/l)	
5 Aug 1996	12	50.0	51.2	-96 ± 177	81 ± 69	0.35 ± 1.47	h6.8
6 Aug 1996	13	46.3	50.9	-204 ± 307	-97 ± 93	0.89 ± 2.05	v18
7 Aug 1996	5	98.0	98.9	-196 ± 385	79 ± 118	1.14 ± 3.82	h18
14 Aug 1996	12	30.1	64.3	159 ± 178	164 ± 93	-1.97 ± 1.52	h6.8[a]
7 May 1997	20	73.9	87.9	-64 ± 58	75 ± 16	-0.70 ± 0.33	v24[a]
11 Aug 1997	42	93.0	94.2	24 ± 28	97 ± 9	0.38 ± 0.27	h18[a]
18 Aug 1997	15	54.6	74.8	-238 ± 149	85 ± 36	-0.92 ± 0.65	v36[a]
All Aug 1997	57	90.2	93.5	-47 ± 43	98 ± 7	-0.99 ± 0.38	h10[a]

[a]The contribution of radiometer data is statistically significant.

Table 5
Results from the 1997 to 1998 measurements with radiance data

Date of test data	Training data R^2	Test data R^2	Number of test data points	Test data rmse (μg/l)	Bias error (model-GT) (μg/l)	Unbiased rmse (μg/l)
7 May 1997	0.93	0.74	20	5.9	5.0	3.1
11 Aug 1997	0.91	0.95	33	9.3	−7.1	6.1
18 Aug 1997	0.91	0.63	12	3.5	2.4	2.5
11 Aug 1998	0.92	0.92	15	7.0	2.8	6.5
Mean	0.92	0.81	–	6.4	0.8	4.5

Table 6
Results from the 1997 to 1998 measurements with bidirectional correction

Date of test data	Training data R^2	Test data R^2	Number of test data points	Test data rmse (μg/l)	Bias error (model-GT) (μg/l)	Unbiased rmse (μg/l)	Regression coefficient of BD data [Eq. (3)]
7 May 1997	0.94	0.80	20	5.2	4.4	2.8	50 ± 26
11 Aug 1997	0.91	0.95	33	10.9	−9.0	6.1	-21 ± 49
18 Aug 1997	0.93	0.63	12	3.3	−2.1	2.5	64 ± 30
11 Aug 1998	0.94	0.92	15	6.3	−1.6	6.1	62 ± 28
Mean	0.93	0.82	–	6.4	−2.1	4.4	–

Table 7
Results from the 1997 to 1998 measurements with wind data correction

Date of test data	Training data R^2	Test data R^2	Number of test data points	Test data rmse (μg/l)	Bias error (model-GT) (μg/l)	Unbiased rmse (μg/l)	Regression coefficient of wiin data
7 May 1997	0.94	0.44	20	15.3	14.6	4.7	1.56 ± 0.75
11 Aug 1997	0.92	0.95	33	9.5	−7.2	6.3	-0.32 ± 0.29
18 Aug 1997	0.92	0.63	12	5.6	5.0	2.5	-0.52 ± 0.52
11 Aug 1998	0.92	0.92	15	7.8	4.4	6.5	-0.44 ± 0.44
Mean	0.93	0.73	–	9.6	4.2	5.0	–

Table 8
Results from the 1997 to 1998 measurements with atmospheric correction (reflectance data)

Date of test data	Training data R^2	Test data R^2	Number of test data points	Test data rmse (μg/l)	Bias error (model-GT) (μg/l)	Unbiased rmse (μg/l)
7 May 1997	0.90	0.72	20	6.9	6.1	3.2
11 Aug 1997	0.90	0.94	33	11.4	−8.8	7.2
18 Aug 1997	0.88	0.45	12	3.7	1.5	3.3
11 Aug 1998	0.89	0.92	15	8.5	5.3	6.7
Mean	0.90	0.76	–	7.6	1.0	5.1

Table 9
Total rmse (including bias) and bias error (in μg/l) for 1997–1998 measurements with various correction methods

Date of test data	No correction		Atmospheric correction		Bidirectional correction		Wind speed correction	
	rmse	Bias	rmse	Bias	rmse	Bias	rmse	Bias
7 May 1997	5.9	5.0	6.9	6.1	5.2	4.4	15.3	14.6
11 Aug 1997	9.3	−7.1	11.4	−8.8	10.9	−9.0	9.5	−7.2
18 Aug 1997	3.5	2.4	3.7	1.5	3.3	−2.1	5.6	5.0
11 Aug 1998	7.0	2.8	8.5	5.3	6.3	−1.6	7.8	4.4
Mean	6.4	0.8	7.6	1.0	6.4	−2.1	9.6	4.2

AISA reflectance indices before deriving the channel ratio. However, that did not improve the retrieval results.

All rmse and bias errors for different correction methods are summarized in Table 9. Bidirectional correction seems to reduce the bias most.

3.5. Measurement angle correction of thematic maps

Fig. 3 depicts the mean intensity measured by all AISA channels as a function of measurement angle (within the FOV of AISA) for EW and NS flight directions. For EW the positive angles are on the side of the sun and for NS the negative angles are on the side of the sun. As can be seen the angle dependence is considerable for EW direction and smaller in the NS direction. The smaller angle dependence for NS data is due to the smaller sun azimuth angle relative to the flight direction. With EW flight direction the intensity difference between the image edges is approximately 30%.

The use of channel ratios for chl-*a* estimation (702/673 nm) reduces the effect of measurement angle (Fig. 4). For EW direction the relative angle dependence is reduced by approximately 20% when compared to the relative dependence of the non-ratio measurement.

The results for the bidirectional surface scattering model are shown in Fig. 5. The shape of the theoretically derived curves follows the shape as the measured curves well (Fig. 3). However, the magnitude of the change is not as dramatic. Therefore, the bidirectional model does not explain all of the observed behavior. Most of the observed angle dependence is probably caused by the angle-dependent signal propagating from below the water surface. The surface scattering model does not account for that. In any case, it seems to be possible to use the surface scattering model for removing part of the errors caused by angular effects.

The aircraft did not have attitude determination at the time of the measurements. Therefore, the exact tilt and roll angles of AISA are not known. This may change the theoretical curves slightly.

4. Discussion

The results confirm that an airborne spectrometer is a useful tool for chl-*a* monitoring of Finnish lakes. The ratio of radiances at channels

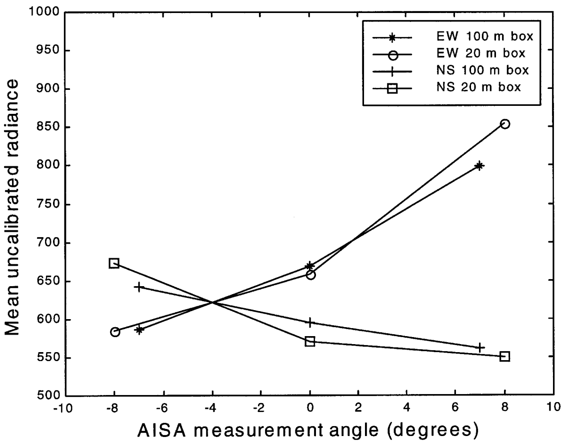

Fig. 3. Mean AISA intensity (linear scale) as a function of measurement angle (measured on 4 August 1998). The azimuth angle between sun and the instrument is 48° for EW (sun is on the side of positive measurement angle) and 35° for NS (sun is on the side of negative measurement angle). Wind speed is 10 m/s.

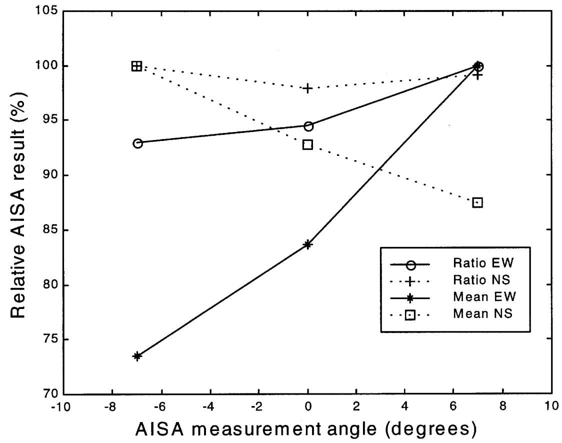

Fig. 4. Relative channel ratio (702/673 nm) and mean AISA derived intensity.

702 and 673 nm alone gives good retrieval accuracy despite the simplicity of the algorithm. However, a bias error component is usually present in the rmse.

The use of atmospheric correction reduces the bias but only slightly. The wavelength channels used in the chl-*a* retrieval algorithm are relatively close to each other and, therefore, the atmospheric correction does not affect the ratio of the channels much.

The analysis performed for radiometer correction did not allow for the calculation of rmse or bias error, so a direct comparison with other correction methods was not possible. However, the comparison of coefficients of determination with and without radiometer data (Table 3) indicates that the use of synchronous radiometer data can improve the retrieval accuracy.

Correction with a bidirectional scattering model reduced both bias and rmse (Table 9) but again the accuracy improvement was fairly small. Clearly, the model can be improved by removing the simplifications it now has.

The use of bidirectional correction for reducing the relative differences in different measurement angles seems possible even though the use of channel ratios reduces the angular effects significantly. The field of view of space-borne spectrometers is much higher than that of airborne AISA (FOV of AISA = 22°). For example, the forthcoming MERIS instrument has a FOV of 68.5°. Therefore, the effect of measurement angle can be assumed to be much larger. The bidirectional correction method can also be used reduce the error in satellite data.

The remote sensing system presented here contains two main instruments (i.e. spectrometer and radiometer). The results from the measurement campaigns prove that the instruments can be used at the same time and that their data can be combined. The radiometer used here is still under development and suffered from occasional failures. After the radiometer development is completed (commercial radiometers could also be used) and after the retrieval algorithms are developed this system should be suitable for operational monitoring of water quality.

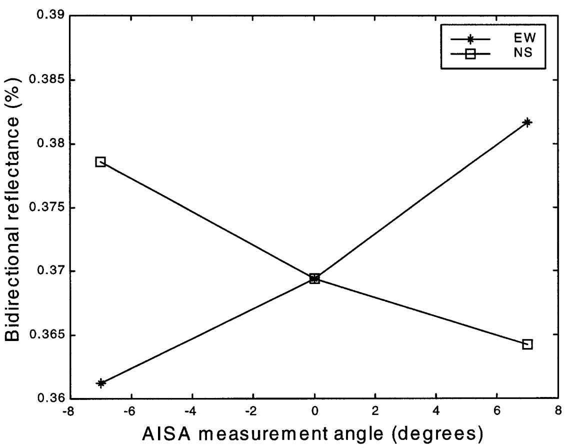

Fig. 5. Bidirectional reflectance as a function of AISA measurement angle calculated with Kirchoff's scattering model. Wind speed 10 m/s.

5. Conclusions

The obtained results indicate that the bias error is a major problem in the estimation of chl-*a* concentration from imaging spectrometer data as nearly concurrent in situ reference data are not available and as empirical retrieval algorithms are applied. Some of the correction methods evaluated here do improve the measurement accuracy of chl-*a* slightly. However, a significant amount of bias error usually remains, which reduces the feasibility of spectrometer observations for operational monitoring. A system employing several algorithms (one for each lake type) might give better results.

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