Water Quality Classification of Lakes Using 250-m MODIS Data

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Abstract—The traditional method used in the water quality classification of Finnish lakes includes the collection of water samples from lakes and their analysis in laboratory conditions. The classification is based on statistical analysis of water quality parameter values and on expert opinion. It is possible to acquire similar information by using radiance values measured with the Earth Observing System Terra/Aqua Moderate Resolution Imaging Spectroradiometer (MODIS). In this letter, the classification accuracy with MODIS data is about 80%. Only about 0.2% of the 20 391 pixels were misclassified by two or more classes, as a four-class classification system is used.

Index Terms—Moderate Resolution Imaging Spectroradiometer (MODIS), remote sensing, water quality.

I. INTRODUCTION

THE QUALITY of water in Finnish lakes is monitored at several thousand monitoring stations each year (about 3400 stations during 1999). The monitoring is based on the traditional ground truth measurements, i.e., it is a combination of onsite measurements and water sample collection for laboratory analysis. The measured water quality parameters include chlorophyll-a (chl-a), nutrients, Secchi depth, turbidity, oxygen content, and various heavy metal toxins [1], [2].

From time to time, the collected data are used for classifying lakes into five quality classes ranging from excellent to poor. One advantage of this classification is that the data become easier to understand by people who are not water quality experts. Also, the amount of data is reduced into an easily manageable size and format, and it is easier to monitor the long-term changes and trends in water quality. The latest classification was completed in 1999, and it used data from 1994 to 1997. The analysis for the classification took about two years to complete, and it included over 2.5 million measurements. The next classification will be completed early 2005 (using data from 2000 to 2003).

In many ways, the traditional classification system can benefit from satellite-based information. For example, since Finland has over 56 000 lakes (surface area > 0.01 km^2), only a small numerical portion of the lakes is covered by the monitoring stations. Furthermore, many lakes have only one monitoring station; hence, the variability of water quality within those lakes is not known. Also, some monitoring stations are visited only once during the open water season. Hence, the temporal coverage of the monitoring is not good.

The only cost-efficient way to improve the spatial and temporal coverage of lake monitoring is spaceborne remote sensing. With remote sensing techniques, it is possible to first retrieve the values of some water quality parameters (e.g., chl-a, turbidity, total suspended solids (TSS), Secchi depth [3]–[5]) and then use those values to classify lakes based on the classification limits [6]. In this letter, a more direct approach is used. The quality class of a lake is assumed to be directly proportional to the radiance value detected over the lake with the Moderate Resolution Imaging Spectrometer (MODIS) sensor onboard the Terra satellite [7]. The assumption is tested using ground truth data and simulations with a biooptical reflectance model.

The atmosphere is often the most significant source of error for remote sensing measurements. In this letter, the effects of these errors on the classification method are analyzed by simulating typical atmospheric conditions with an atmospheric correction model.

II. INSTRUMENTS AND DATA

The study area is the region surrounding Lake Päijänne in southern Finland (latitude $61°$ to $62.5°$ N, longitude $24°$ to $27°$ E; the surface area is $14\,500$ km^2, of which about 19% are lakes according to the lake water quality classification data; the area of classified lakes is 2430 km^2, and the area of unclassified lakes is 350 km^2). The area was selected because it has lakes and subbasins belonging to a broad range of water quality classes (Excellent to Fair).

A. Surface Observations

The ground truth classification is based on a statistical analysis of the collected water quality parameter data [2]. A computer program calculates the average, minimum, maximum, and other statistical values for the parameters, which are then used to determine the initial classes of lakes according to the defined classification limits. Then other information (e.g., the occurrence of algal blooms) is used for refining the classification. This step is done by water quality experts. The end result is a map (Fig. 1) that shows the lakes classified into one of the five quality classes called Excellent, Good, Satisfactory, Fair, and Poor (numbered from 1 to 5, respectively). The number of classes used in this study is four, since lakes with class 5 (Poor) water quality were not present in the study area.
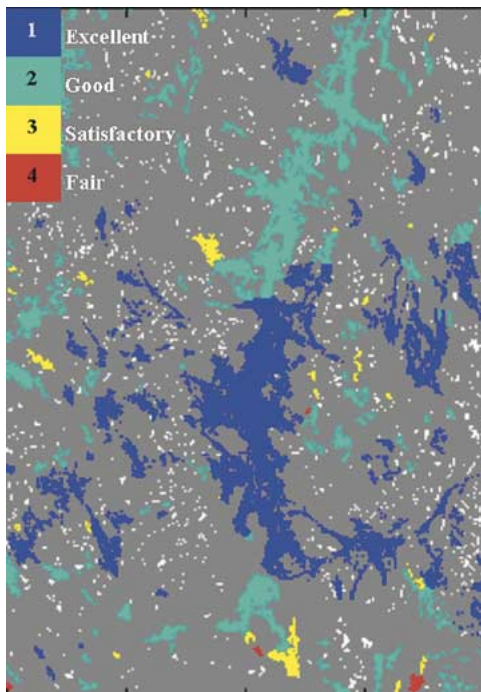
Fig. 1. Quality of water in the Lake Päijänne region (based on ground truth data from 1994 to 1997). White areas are lakes that are not classified. The width of the area is 100 km.

Fig. 2. Modis channel 1 radiance (watts per square meter per micrometer per steradian) on August 27, 2000.

B. MODIS Data

MODIS data were selected for this study because they are readily available free of charge and have a good temporal and regional coverage. The two MODIS instruments observe Finland every day, while the repeat cycle of instruments with better resolution is much longer (e.g., 16 days for Landsat Thematic Mapper). This means that the amount of available images is very large with MODIS, even though the resolution sets a limit to the size of lakes that can be monitored. Since cloud cover is often present in Finland, the amount of imaging opportunities is very important as an instrument with a long repeat cycle might not be able to get good data at all.

The MODIS data used in this analysis were acquired on August 27, 2000 at 10:00 GMT (solar zenith angle 52°, sensor zenith angle 3°). The two channels in the 250-m image (channel 1 covers the wavelength range 620–670 nm, and channel 2 covers 841–876 nm) were converted into radiance values and rectified into a national coordinate system by using the conversion coefficients and the geolocation data given in the level-1B dataset. The 250-m resolution data were selected because Finnish lakes are usually small, irregular in shape, and have islands and peninsulas that disturb measurements with low-resolution (e.g., 1 km) data. Land pixels were removed from the data by using channel 2 radiances. Land pixels are bright in channel 2, while water is almost black. By selecting a suitable threshold value, pixels can, with a high confidence, be classified as land or water. It is also possible to use a land mask based on other data. However, those may not take into account the variations in water level and the effects of shore vegetation on the measured radiance. The resulting channel 1 radiance is shown in Fig. 2.
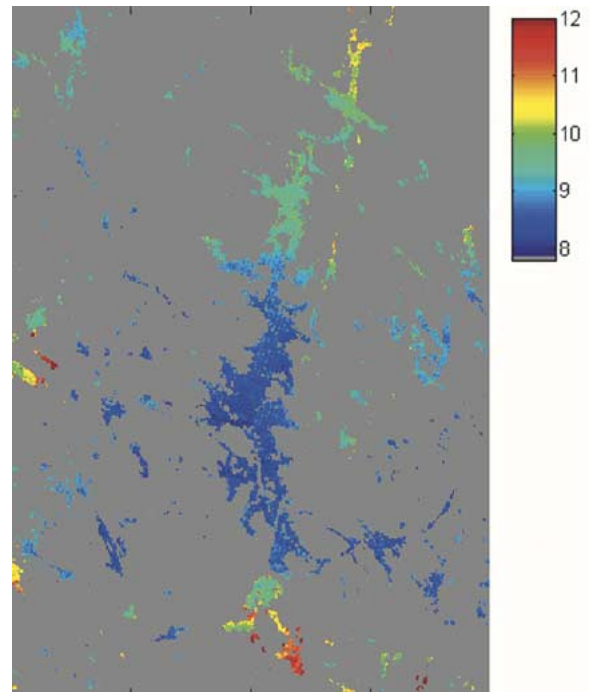
Then, the lake classification data of 1994 to 1997 were overlaid on the MODIS image, and the pixels, where both MODIS radiance and water quality class information is available, were extracted for pixel-by-pixel comparison. The number of such pixels is 20 391, and the area covered with these pixels is 1270 km^2. Hence, by using MODIS data, it is possible to classify about half of the lake area within the target region. The number of pixels, where MODIS radiance is available but the ground truth-based classification is not, is 116 (7.3 km^2).

C. Biooptical Reflectance Model

The underwater irradiance reflectance spectrum was simulated with a biooptical reflectance (BOR) model developed for Finnish lakes [8]. The calculation of irradiance reflectance just beneath the water surface $R(0-, \lambda)$ is based on [9]

$$R(0-, \lambda) = C \left[\frac{b_{b,\text{Tot}}(\lambda)}{(a_{\text{Tot}}(\lambda) + b_{b,\text{Tot}}(\lambda))} \right] \qquad (1)$$

where $b_{b,\text{Tot}}(\lambda)$ is the total backscattering coefficient, and $a_{\text{Tot}}(\lambda)$ is the total absorption coefficient. C depends on the illumination and the viewing geometry. $a_{\text{Tot}}(\lambda)$ and $b_{b,\text{Tot}}(\lambda)$ are obtained by summing up the absorption and the backscattering coefficients of the optically active substances in the water. We assumed three optically active components in the model: phytoplankton, tripton, and colored dissolved organic matter (CDOM). Total backscattering was calculated without considering phytoplankton and tripton backscattering separately. The model simulates the reflectance in the 400–750-nm range with a 2-nm step.

The model was parameterized for the July–August conditions using the optical data of 11 lakes. The lake type ranged from oligotrophic to eutrophic and included humic lakes as well. The specific scattering coefficient of TSS was calculated from

absorption/attenuation meter measurements, and backscattering probability of TSS was estimated by minimizing the difference between modeled and measured reflectance spectrum (measured with Li1800UW spectrometer). The estimation of the slope factor of CDOM absorption and the specific absorption coefficient of phytoplankton and tripton were based on the spectrophotometric measurements in laboratory.

The water quality parameters used in the BOR model are not exactly the same as those used in the lake classification system. The model uses chl-a, TSS, and the absorption of CDOM at 400 nm (a400 in 1/m), while the classification is based on chl-a, turbidity, total phosphorous, and water color (among others). Fortunately, water color correlates with a400 and turbidity with TSS. Thus, it is possible to generate new limits for the classification from parameters used in the BOR model.

Before describing how the new limits are generated, it is necessary to explain what the terms turbidity and water color stand for in this study. Turbidity is a measure of optical scattering. It is affected by the type and the amount of particles suspended in water. The particles can be organic (such as phytoplankton) or inorganic (such as clay). Therefore, turbidity is partly correlated with chl-a (chl-a is a measure of the amount of phytoplankton in water). Since the limits for TSS are derived from turbidity, the TSS limits in the simulation are affected by chl-a as well. Here, turbidity was measured with the nephelometric method (unit NTU), which is based on the measurement of light (860 nm) scattered within a 90° angle from the beam directed at the water sample.

Water color is a measure of humic compounds in water. It is not to be confused with the term "ocean color." Water color (milligrams of platinum per liter) was determined by comparison with standard cobalt chloride disk [10].

The limits for TSS (milligrams per liter) were generated by using turbidity (Tur) limits presented in [6], which, in turn, are derived from total phosphorous (TotP in micrograms per liter) limits used in the ground-based classification [1], [2]. The equations are (based on our data)

$$\text{TSS} = 1.21 * \text{Tur} \quad \text{Tur} = 0.0642 * \text{TotP}^{1.24}. \qquad (2)$$

The limits for a400 were derived from water color limits with

$$\text{a400} = 0.119 * \text{Water Color}. \qquad (3)$$

The final classification limits used in this study are presented in Table I.

D. Atmospheric Model

Next, the underwater reflectance values simulated with the BOR model are transformed into top-of-atmosphere (TOA) radiances by using an atmospheric correction model developed in [11]. The model uses principal component analysis to reduce the variability of the atmosphere into one scalar variable γ. In our simulations, we used γ values -1.5, 0, and 1.5, which correspond to atmospheric visibility values of approximately 25, 40, and 60 km. Those values cover the most common atmospheric conditions.

TABLE I
WATER QUALITY CLASS LIMITS FOR EACH VARIABLE
(AND THE MIDDLE POINT VALUES USED IN FIG. 3)

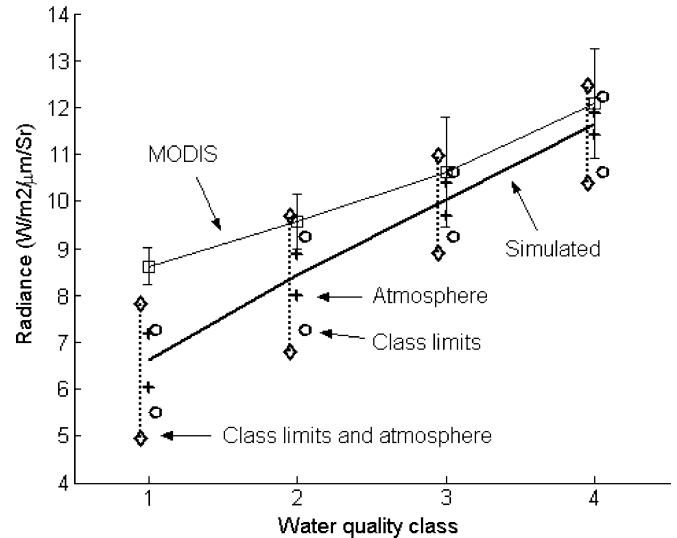| Class	Chl *a* (μg/l)	TSS (mg/l)	a400 (m^{-1})
1	0-4 (2)	0-1.7 (0.85)	0-6.0 (3)
2	4-10 (6)	1.7-5.3 (3.5)	6.0-11.9 (8.9)
3	10-20 (15)	5.3-10.0 (7.7)	11.9-17.9 (14.9)
4	20-50 (35)	10.0-23.7 (16.9)	17.9-35.7 (26.8)

Fig. 3. Simulated TOA-radiance using the minimum and maximum values of water quality parameter within each class from Table I (visibility 40 km): the simulated radiance with atmospheric variation (visibility 25 and 60 km), the combined effect of class limits and the atmosphere, and the measured mean radiance ($\pm$ standard deviation) of MODIS pixels as a function of the ground truth water quality class.

III. METHODS AND RESULTS

A. Model Simulations

The combined BOR and atmospheric model was used to simulate the TOA radiances that lakes with different water quality classes would have at MODIS channel 1 wavelengths. Fig. 3 shows the simulated radiance when the middle point values of water quality parameters for each class (from Table I) are used as input values for the model. The results show that as the class number increases (the water quality worsens), the amount of radiation reflected from the lakes grows linearly.

Fig. 3 also shows the radiance values when the water quality parameters have the maximum and minimum values within each class, the effect that different atmospheric visibilities have on the radiance, and the combined effect of the class limits and the atmosphere.

B. MODIS and Lake Classification

In addition to the simulated results, Fig. 3 shows the mean of observed MODIS channel 1 radiances for each water quality class as a function of the ground truth class number. The class versus mean radiance curve behaves like the simulated data: the amount of radiance grows as the class number grows. There are differences between the two curves though. The simulated radiances are lower than the measured ones. However, the difference
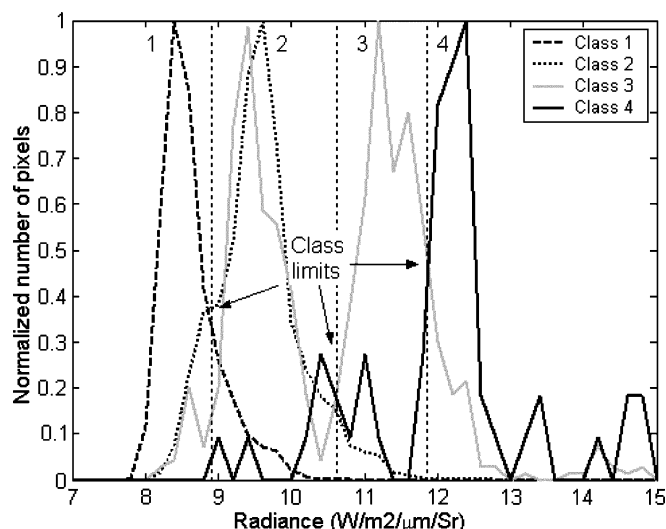
Fig. 4. Normalized histograms of MODIS radiances (August 27, 2000) found within each ground truth water quality class (data from 1994 to 1997).
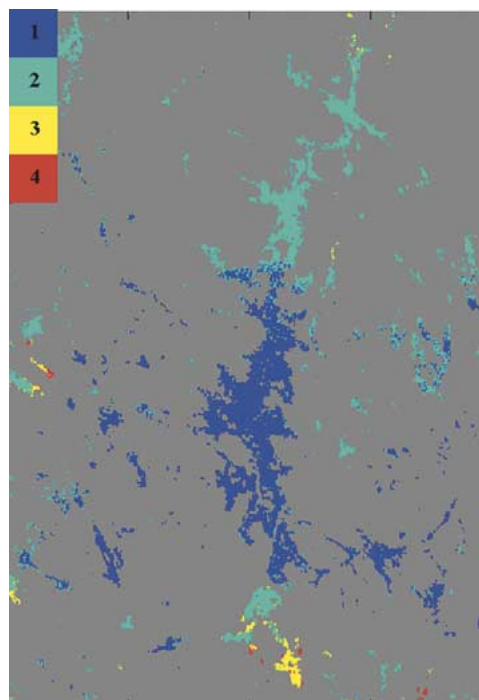

Fig. 5. Lake classification with MODIS data (August 27, 2000). The colors of the classes are the same as in Fig. 1. The width of the area is 100 km.

TABLE II
ERROR MATRIX (NUMBER OF PIXELS). TOTAL CLASSIFICATION ERROR: 19.8%; CLASSIFICATION ACCURACY: 80.2%; ERROR MORE THAN ONE CLASS: 45 PIXELS (0.22% OF ALL PIXELS). THE TOTALS COLUMN AND ROW ARE THE TOTAL NUMBER OF PIXELS BELONGING TO EACH CLASS (THE COLUMN IS FOR THE MODIS DATA, AND THE ROW IS FOR THE GROUND TRUTH DATA)

MODIS	Ground truth					
	Class1	Class2	Class3	Class4	Totals	Error %
Class1	**9903**	954	24	0	10881	9.0
Class2	2325	**6128**	276	7	8727	29.8
Class3	1	364	**282**	6	653	56.8
Class4	0	13	73	**44**	130	66.2
Totals	12229	7459	646	57	20391	
Error %	19.0	17.8	56.3	22.8		19.8

is not very large and can in most part be explained with the atmospheric variations. Only with class 1 lakes do the radiance ranges not overlap.

Fig. 4 shows the histogram of the MODIS radiances found within each ground truth water quality class. The radiance histograms of each class are quite well defined with a single peak, except the histogram of class 3, which also has a peak in the class 2 radiance range. That peak is caused by the class 3 (according to the ground truth data) water near the center of Fig. 1 (the yellow area), which is classified as class 2 water with MODIS data. The experts who make the classification decided to classify the area as class 3 due to industrial waste water and agricultural loading, although the values of the water quality parameters are usually within the class 2 limits [12]. Also, water quality in the area has been improving during the past years. If the area is removed from the analysis, the extra peak in the histogram disappears.

Next, the classification limits were selected by locating the radiance values where the histogram curves of classes 1 and 2; 2 and 3; and 3 and 4 cross. These points are also shown in Fig. 4. The MODIS image was then classified using these limits, and the result is shown in Fig. 5. The MODIS classification was compared with the ground truth classification, and these results are shown in Table II. The overall classification accuracy is 80.2%, and only 0.22% of the data were misclassified by two classes. None of the data points were misclassified by three classes.

The distribution of the classification error is not even. In cases where the MODIS classification is wrong, it is more likely that the remotely sensed data suggests a lower water quality class than the class based on ground measurements than the other way around. So, the MODIS-data-based method seems to give more pessimistic estimates on water quality.

IV. DISCUSSION

The overall classification accuracy is good considering the simplicity of the classification method. Some amount of clas-

sification error is inevitable when a parameter with continuous values is classified, as even a small change in the radiance value can change the class into which the pixel belongs. One important result in this study is that very few pixels (about 0.22%) were misclassified by more than one class.

There is a time difference of three to six years between the ground truth data collection and MODIS data acquisition. It is possible that the water quality class of some lakes has changed during this time (based on data collected from 1985 to 1993, the portions of good and excellent quality lakes are growing slowly [2]). That may explain some of the errors in the MODIS classification (e.g., the peak in the class 3 histogram). The other likely source of errors is the atmosphere. According to the simulations, the atmosphere can have a large effect on the radiance and can, therefore, disturb the classification. Local variations in the atmosphere (e.g., thin clouds) can increase the radiance detected over a lake, and this will cause the remotely sensed class to be worse than the real class actually is. One method to remove or

minimize these kinds of errors is to use, for example, median radiance values or maximum-likelihood classification for several images.

For a limited area, the effects of the atmosphere (and the viewing geometry) can usually be assumed to be homogenous (aside from the effects discussed above), and if ground truth data are available, it is not necessary to perform atmospheric correction. However, when images acquired on different dates are compared with each other, some kind of correction is usually necessary. One possible method for reducing the errors caused by the atmosphere on the classification method used here is to use supervised classification.

The radiances obtained with model simulations follow the same behavior as the measured data. This supports the initial assumption and confirms the results obtained with ground truth data even though there still are differences between the measured and simulated radiance curves shown in Fig. 3.

The main difference is that MODIS radiance levels are slightly higher. One reason for these differences may be the direct reflectance from water surface, which is not currently included in the BOR/atmospheric model. The adjacency effect (radiation from bright nearby pixels) can also be a contributing factor to the difference.

In this study, it was possible to classify about half of the lake area using MODIS data. The rest were masked by the infrared-land mask. The masked pixels are water pixels (or partial land pixels) so close to the shore that the signal from them is likely to be contaminated by land and therefore unusable. The smaller a lake is, the more difficult it is to get a good measurement from it. The buffer zone at the shore is roughly one to two pixels, so a lake has to be about 1 km in diameter before it can be reliably measured with MODIS.

Remote sensing techniques are not able to retrieve all water quality parameters that are used in the ground-truth-based classification. Those include, for example, different heavy metal concentrations, oxygen depletion, and defects in the taste of fish. Also, the ground truth classification is based on expert opinion, which does not always follow the exact class limits. Therefore, remote sensing data alone cannot be used for the final classification of lakes, and ground-truth-based monitoring is still required. However, if the data provided with the methods presented here are used together with ground-based data, more detailed classifications can be made more often and with better spatial coverage than with ground-based data alone.

V. CONCLUSION

The results of this study indicate that a direct classification of lakes based on the radiance detected at MODIS channel 1 wavelength is feasible. The accuracy of the classification is approximately 80%. The factors that contribute to the error include: 1) the time difference between remote sensing and ground truth data; 2) the atmosphere; 3) the classification of a continuous variable into discrete classes; and 4) the use of water quality parameters that cannot be measured using remote sensing techniques in the ground-truth-based classification.

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