



Global Lakes Sentinel Services

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GLaSS Training material, Lesson #8

Lakes with a high concentration of humic substances

What are the limits of remote sensing of water?

Annelies Hommersom (WI), Sampsa Koponen (SYKE), Kari Kallio (SYKE)



Lesson summary

Boreal lakes often contain high concentrations of colored dissolved organic matter (CDOM). This leads to strong absorption of light especially in the blue and green parts of the spectrum, so that the remaining colour is yellow/red/brownish and dark. The low reflectance complicates the use of EO methods, because a low signal easily leads to a low signal-to-noise ratio, while also small errors in for example the atmospheric correction might lead to relatively large changes in the results.

In this lesson the student will get an overview of the issues that determine the limits of remote sensing of water, with a focus on the effects of high absorption.



GLaSS training material outline

This lesson is part of the GLaSS training material. The complete training material outline is listed on http://data.waterinsight.nl/GLaSS/trainingmaterials/GLaSS_lesson_outline.pdf.

Note that the lessons logically follow up on each other, the later lessons might require skills that can be acquired during the earlier lessons.

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List of abbreviations

Abbreviation	Description
AbsF	Absorbance by filtered water sample
CDOM	Coloured Dissolved Organic Matter
Chl-a	Chlorophyll-a
EO	Earth observation
FOV	Field-of-view
MERIS	Medium Resolution Imaging Spectrometer
SNR	Signal-to-noise ratio
TOA	Top Of Atmosphere
TSM	Total Suspended Matter

1 Introduction

1.1 (Boreal) lakes with a high concentration of humic substances

In the temperate and cold regions of the boreal zone humic lakes are abundant. In Europe, boreal lakes mainly exist in Finland, Sweden and Estonia. These lakes typically have fairly low TSM and Chl-a concentrations but high concentrations of humic substances. In Finland the humic matter concentration of lakes correlates with the share of peat land in the drainage area (Kortelainen 1993). Humic lakes can also originate from peat dredging. Such lakes exist e.g. in the Netherlands.

Another typical feature of boreal lakes is that the relative number of small lakes is high. In Finland, for example, the proportion of lakes in the 0.1-1 km² size class is 23% and in the 0.01-0.1 km² size class 72% of the total number of lakes (56 000 with area > 0.01 km²) (Raatikainen & Kuusisto 1990). The number of ponds (0.0005 – 0.01 km²) is as high as 132 000. In Estonia the majority of the lakes are also small but the total number of lakes is smaller than in Finland. The total number of lakes is 2804 of which 61.3% are smaller than 0.03 km² (1720 lakes with area < 0.03 km²). In size class between 0.03-0.1 km² there are 24.4% of the lakes (684 lakes) and between 0.1-1 km² 12.3% of the lakes (346 lakes). Only 51 lakes are larger than 1 km² (Tamre 2006). Mapping of small lakes requires sensors with good spatial resolution. An additional challenge is the adjacency effect, which is stronger in small lakes than in large lakes.

The standard measure of humic substance (Coloured Dissolved Organic Matter, CDOM) concentration in water optics and remote sensing is the absorption coefficient (a) at a certain wavelength (usually between 400 and 443 nm). The absorption coefficient of CDOM is usually closely related to dissolved organic carbon (DOC, e.g. Kutser et al. 2005a, Ylöstalo et al. 2014, Brezonik et al. 2015), which is a common measure of humic substances in conventional monitoring. In countries with lakes that exhibit a wide range of CDOM concentrations determination of 'water colour' (mg Pt l⁻¹) is common in routine monitoring. The method is based on the comparison of water samples with standard cobalt chloride disks (ISO 7887). In Sweden, determination of 'water colour' has been replaced over time by more objective absorbance measurements of filtered water samples (AbsF). Absorbance is measured spectrophotometrically and should according to international standard be measured in 5 cm cuvettes at 436 nm, but is made at 420 nm in Sweden by tradition. $AbsF(420)$ (unitless) $\approx 0.03 * a_{CDOM}(440)$ (m⁻¹).



Figure 1. Example of a dilution series of water samples with increasing CDOM content (SLU, Sweden) and a photo of taking a Secchi depth in water with a high CDOM content.

1.2 The effect of CDOM on remote sensing of water quality

In this exercise we have a look at the impact of CDOM on remote sensing of water constituents. The high CDOM concentration in humic lakes increases attenuation of light in the blue and green region of the spectrum, and consequently decreases reflectance in the short wavelengths. In short, CDOM absorbs blue and green light and therefore the remaining colour is yellow/brown and much darker.

There is not any international agreement for classifying lakes according to CDOM (humic substances) level from limnological (lake typing, management) or optical point of view. Within the WFD work in Sweden and Finland lakes with water colour values $> 30 \text{ mg Pt l}^{-1}$ (corresponds approximately $a_{\text{CDOM}}(400) 3.6 \text{ m}^{-1}$) are defined as humic. Lakes with water colour $> 90 \text{ mg Pt l}^{-1}$ ($a_{\text{CDOM}}(400) 11 \text{ m}^{-1}$) are in Finland classified as humic rich lakes. Here we define 'high CDOM' lakes as lakes, in which CDOM is so high that many standard Case-2 remote sensing algorithms are not applicable.

Information on humic substances is utilized in the application of directives, lake management and climate change studies, particularly in northern Europe. For example, in Finland (and Sweden) humic level is one of the main criteria in the characterization of surface water body types according to the WFD (see GLaSS deliverable D5.7). Lakes also play an active role in the carbon cycles (e.g. Downing et al. 2006) and they were recently added to the global carbon budgets (IPCC 2013). Remotely sensed a_{CDOM} as a measure of DOC could be an aid in the assessment of carbon pool and in estimating CO_2 efflux from inland water in global carbon budget studies (Cole et al. 2007, Kutser 2012, Raymond et al. 2013).

Low remote sensing reflectance (R_{rs}) in the blue wavelengths means that the share of water leaving radiance from radiance measured by a satellite sensor is small. CDOM may also mask optical signatures of other substances. In water optics and remote sensing two types of high CDOM lakes must be distinguished. Most of the humic lakes in the boreal region have typically fairly low TSM concentration. Second type of a high CDOM lake is those with high TSM concentration. Such lakes exist in e.g. the Netherlands and in some relatively rare cases in the boreal zone. High TSM increase R_{rs} throughout the spectrum and radiance in the short wavelengths can be measured with higher accuracy than in less turbid humic lakes.

Most of the published remote sensing studies on high CDOM lakes focus on the estimation of CDOM and only a few of them include analyses on the impact of CDOM on the estimation of other water constituents such as Chl-a and TSM. However, low reflectance (as a result of CDOM) is one of the main factors limiting remote sensing of water quality.

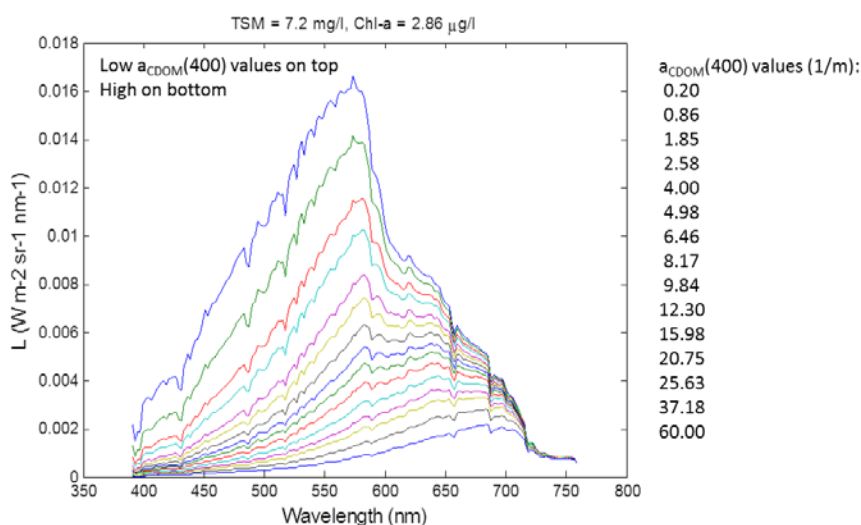


Figure 2. Effect of changing CDOM concentration on the water leaving radiance with constant TSM and Chl-a values.

1.2.1 CDOM effects on atmospheric correction

Standard atmospheric correction for Case-2 waters typically overestimates R_{rs} in the 400-550 nm region. This was demonstrated in the high CDOM Lake Pääjärvi in Finland with different versions of the Boreal processor: the original version was able to estimate the shape of R_{rs} spectrum much better than the newest version. In Lake Pyhäjärvi which represents a mesotrophic lake with low CDOM, the R_{rs} spectrum was estimated with good accuracy by both processors. $a_{CDOM}(443)$ was about 5.0 m^{-1} in Lake Pääjärvi and 1.0 m^{-1} in Lake Pyhäjärvi. The FUB processor usually underestimates R_{rs} , (a_{CDOM} was out of the training range of FUB in Lake Pääjärvi).

The estimation accuracy of low R_{rs} in humic lakes also depends on the radiometric sensitivity of a sensor. Doerffer (2008) estimated that the water-leaving radiance of the blue channels in waters with very high CDOM is near or even below the noise level and calibration uncertainty of the MERIS satellite sensor. Because of this MERIS band 1 (at 413 nm) was not included in the Boreal lakes processor. Higher concentration of scattering particles increases water leaving radiance and decreases this problem.

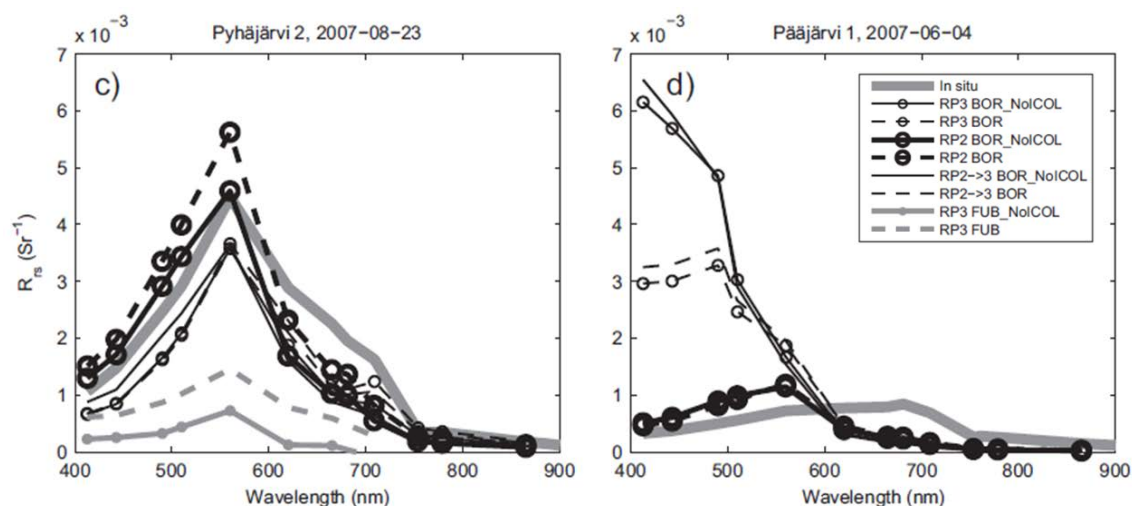


Figure 3. Reflectance (R_{rs}) spectra of Lakes Pyhäjärvi and Pääjärvi (humic lake) estimated with in situ spectrometer, BOR processor with ICOL (BOR) and without ICOL (BOR_NoICOL) correction and FUB processor with ICOL (FUB) and without ICOL (FUB_NoICOL) correction. RP2 and RP3 stand for MERIS reprocessing 2 and 3, and the first and the latest version of BOR processor, respectively. In RP2 → 3 the data from the second reprocessing was processed with the chain developed for the third reprocessing data. (Kallio et al. 2015).

1.2.2 CDOM effects on band ratio algorithms

Reports on band ratio algorithms are mostly based on airborne and field measurements with no or only small atmospheric influence. According to several reports (see e.g. review article by Matthews 2011) important wavelength regions for the band ratio algorithms are:

- TSM: 700-720 nm or 520-560 nm
- Chl-a: 660-670 nm and 700-720 nm as reference
- CDOM: 400-600 nm and 660-720 nm as reference

TSM can be estimated by a single band in NIR and is not sensitive to the variation of CDOM as demonstrated by e.g. Kallio (2006).

The widely used band ratio in **Chl-a** estimation in case-2 waters is based on the band at second absorption peak of phytoplankton and one of the NIR bands. The NIR/Red ratio usually involves wavelengths at about 665 nm and 700 nm. The key assumptions of the NIR-

red ratio algorithm i.e. $a_{ph} \gg (a_{CDOM} + a_{nap})$ in the 660–675 nm region (Gitelson et al. 2008), is critical for Chl-a estimation in high CDOM lakes. Although a_{CDOM} in the 660–680 nm region is small in comparison to shorter wavelengths, it can disturb the Chl-a algorithm by decreasing R_{rs} in the 660–680 nm region, if CDOM concentration is high. This leads to higher NIR-red ratios and overestimation of Chl-a if an algorithm calibrated for low CDOM lakes is applied (Kallio 2006).

CDOM can be estimated by a ratio of reflectance at wavelength > 600 nm to reflectance in the 400–550 nm range (e.g. Pierson et al. 2000, Kallio 2006, Del Castillo & Miller 2008, Brezonik et al. 2015). This ratio is valid in a wide range of water constituent combinations including high CDOM. Because estimation of CDOM is possible with wavelengths > 500 (550) nm, estimation of Chl-a, TSM and CDOM by band ratios in humic lakes does not require blue bands. Therefore, the accuracy of the atmospheric correction in the blue region is not important.

Grouping of lakes have been proposed to improve the estimation of water constituents by band ratios in high CDOM lakes. Chl-a estimation in lakes with wide Chl-a variation could be improved if lakes are classified according to their CDOM concentration and band ratio algorithms with specific empirical coefficients for each class are used (Kallio 2006). Brezonik et al. (2015) proposed grouping to three classes based on CDOM, TSM and trophic status for CDOM estimation for lakes in the USA.

Application of band ratio algorithms to **satellite data** in regions including high CDOM lakes have mainly relied on TM-type sensors (e.g. Brezonik et al. 2005, Kutser et al. 2005a, Kallio et al. 2008, Brezonik et al. 2015), which have poor signal-to-noise ratio (SNR) and low radiometric resolution. These studies have primarily focused on CDOM (blue/red ratio) and Secchi disc transparency (green/red ratio) mapping and used data with and without atmospheric correction. Atmospheric correction did not always improve the estimation accuracy (e.g. Kallio et al. 2008, Kutser et al. 2012)

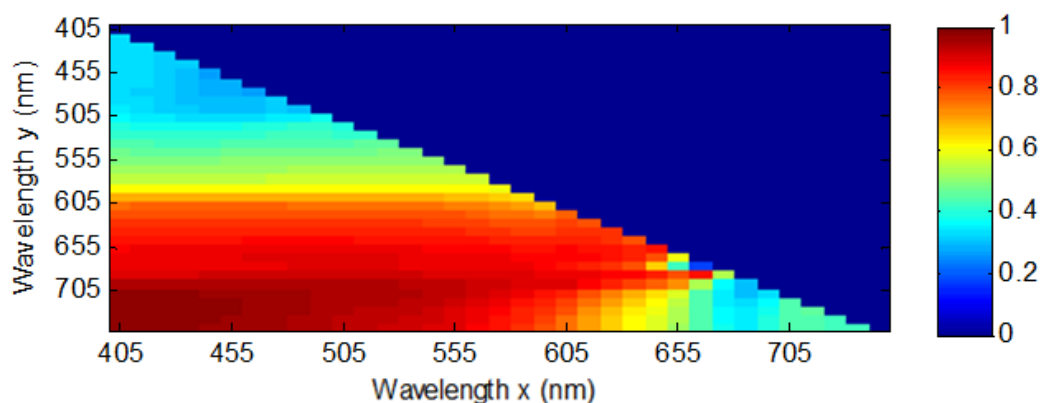


Figure 4. Surface plot of coefficient of determination (R^2) for all possible 10 nm channel ratios of simulated reflectance vs. $a_{CDOM}(400)$ (upper pane in a nationwide dataset ($N=3549$) in Finland. R^2 is indicated in colour scale and point(x,y) is R^2 for the channel ratio y/x . P_{10} and P_{90} values of the dataset are 2.1 and 19 $1/m$ for $a_{CDOM}(400)$, and 0.7 and 9.3 $mg\ l^{-1}$ for TSM. The figure is based on reflectance simulations (Kallio 2006).

Some studies have reported critical concentrations than could not be estimated from satellite data. According to Brezonik et al. (2005) high $a_{CDOM}(440)$ (between 8 and 10 m^{-1}) were outliers in Secchi transparency estimation by TM (based on the TM1 and TM3 channels) in lakes in Northern USA .

In a Landsat study in small Swedish lakes (Kutser 2012, $a_{CDOM}(412)$ between 4 and 18 m^{-1}) CDOM did not correlate with sensor data. Another reason for this result besides the radiometric characteristic of the sensor could have been strong adjacency effect of small

lakes (Kutser 2012). In Finland turbidity, CDOM and Secchi transparency were estimated with good accuracy in lakes with $a_{\text{CDOM}}(400)$ up to 12 m^{-1} using the ETM+ data. However, the high CDOM was connected to high turbidity (the correlation coefficient between $a_{\text{CDOM}}(400)$ and turbidity was +0.79), and no conclusions about the estimation accuracy in typical humic lakes (with low turbidity) could be drawn (Kallio et al 2008).

The Sentinel sensors MSI and OLCI include the critical bands for the estimation of water constituents by band ratio algorithms in high CDOM lakes.

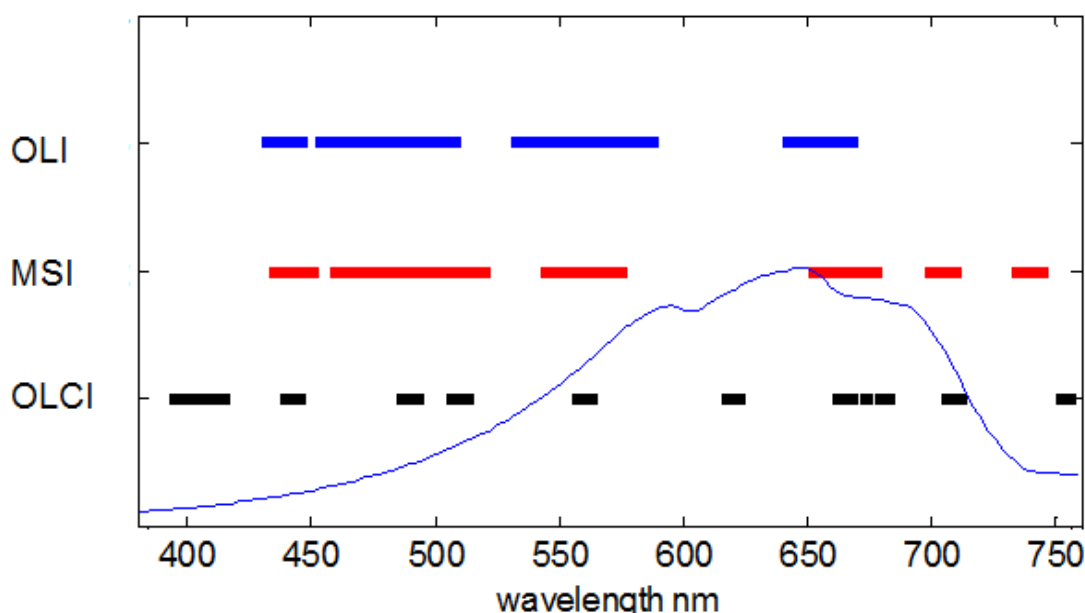


Figure 5. Band wavelengths of OLI, MSI, OLCI. Blue line is R_{rs} of Lake Pääjärvi ($a_{\text{CDOM}}(400) = 12$, $TSM=1.8$, $Chl-a=3.0$) in a relative scale. R_{rs} was simulated with the Hydrolight model (see D3.4 Adapted water quality algorithms).

1.2.3 CDOM effects on spectral inversion algorithms

Spectral inversion algorithms applied to field spectrometer or airborne measurements of R_{rs} have usually yielded reasonable estimates of TSM, Chl-a and CDOM (e.g. Kallio et al. 2005, Laanen 2007). However, high concentrations of either Chl-a or CDOM can mask relatively low concentrations of the other (Laanen 2007). Estimation of high CDOM can be made with reasonable accuracy by spectral inversion in lakes with low (Kallio et al. 2005) and high (Laanen 2007) TSM concentration. In case of CDOM they can be more accurate than band ratios in highly varying combinations of water constituents, since they take into account the impact of other water constituents on R_{rs} (Zhu et al. 2014).

The main challenge in the application of spectral inversion algorithms to satellite data is atmospheric correction, particularly in the blue region of the spectrum. Many of the publicly available spectral inversion algorithms for satellite images (e.g. FUB, C2R) were trained with fairly low CDOM concentrations and are therefore not suitable for high CDOM cases. The Boreal lakes processor for MERIS was developed for lakes with wide range of CDOM (based on SIOPs and concentrations of Finnish lakes) and it was able to approximately estimate the shape, but not the magnitude of R_{rs} in a high humic lake. Consequently, Chl-a, CDOM and TSM were not estimated with reasonable accuracy (Kallio et al. 2015). In the non-humic lakes TSM was estimated with good accuracy, but the Boreal processor overestimated Chl-a (calculated from a_{ph}) and underestimated a_{CDOM} . However, a_{tot} was estimated correctly. The inaccuracies in Chl-a and $a_{\text{CDOM}}(443)$ estimation were therefore related to the partition of a_{tot} to phytoplankton and CDOM absorption. In high CDOM lakes, however, Boreal processor underestimated a_{tot} .

The challenges of high CDOM lakes in the estimation of water quality by EO are summarized in Table 1.

1.2.4 Conclusions of past experiences on high CDOM lakes

From the past, the following experience is obtained on remote sensing of CDOM rich lakes:

- High CDOM lakes with low TSM are more challenging for EO than those with high TSM
- TSM and CDOM (and Chl-a) in high CDOM lakes can be estimated by remote sensing, if R_{rs} can be corrected for atmospheric disturbances
- Optical signature of Chl-a can be masked by very high CDOM, particularly in low concentrations
- Wavelength region 500 (550) -720 nm is sufficient for the estimation of TSM, Chl-a and CDOM in high CDOM lakes
- Very good atmospheric correction is needed, but good atmospheric correction for high CDOM lakes does not exist.
- Atmospheric correction requires a sensor with good radiometric characteristics
- Additional challenge in small humic lakes is adjacency effect, which can be stronger in small lakes than in large lakes
- Classification of lakes (according to CDOM, TSM and/or CHL) has been proposed to improve estimation of water constituents in lakes with high CDOM variation

Table 1. Challenges of EO of high CDOM lakes and proposed solutions to solve the problems.

Challenge	Problem	Solution	Note
Low R_{rs}	High impact of atmosphere	More testing of existing AC algorithms	
	Low radiance in blue	Focus on >500 or >550 nm	Still possible to estimate CDOM, Chl-a and TSM.
	Poor SNR of sensors	Aggregate pixels Better sensors	
Interpretation	Standard algorithms may not work		
	Chl estimation	Lake type specific algorithms (based e.g. CDOM, TSM or Chl-a classes)	CDOM from other sources as input e.g. to spectral inversion
Adjacency effect	High impact in humic lakes, particularly in small humic lakes	Integrated solution with AC	

1.3 Finnish lakes

In this lesson we will work with four lakes in Finland, that differ in their relative CDOM, Chl-a and TSM concentrations. The table below illustrates the differences, based on in situ concentrations (Koponen et al, 2008).

Table 2. Differences, based on in situ concentrations (Koponen et al, 2008)

	Chl-a ($\mu\text{g/l}$)	TSM (mg/l)	CDOM ($^{-\text{m}}$ at 440 nm)
Pyhäjärvi	Low (~ 3)	Low (~ 2)	Low (~ 0.8)
Päijänne	Low (~ 2)	Very low (~ 0.8)	Intermediate (~ 1.5)
Pääjärvi	Low (~ 3)	Low (~ 1.2)	High (~ 5)
Vesijärvi	Intermediate (~ 6)	Low (~ 2)	Low (~ 0.7)

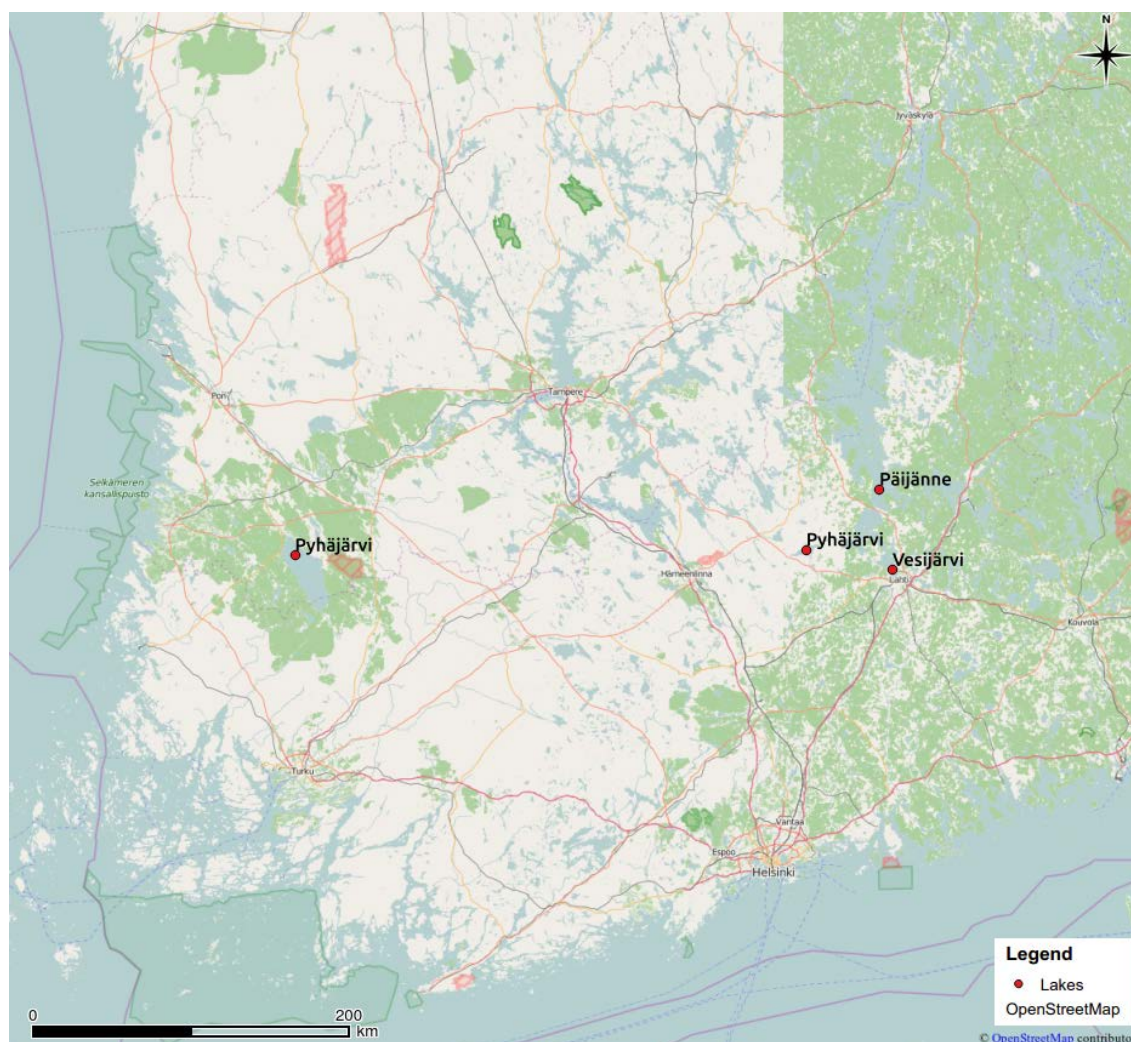


Figure 6. Map of the south of Finland with the sampling stations in the four lakes we will be working with in this lesson.

1.4 Short intro on mixed pixels and adjacency effect

Two aspects that complicate the use of EO data in the adjacency of land (either on the coast or in (relatively) small lakes, are mixed pixels and the adjacency effect.

Mixed pixels (see image below, left) occur along the shores, where land and water are 'mixed' into one pixel. Satellite sensors that are used for water quality can have pixel sizes ranging from coarse (~ 1 km) such as MODIS, which is usually not useful for small inland water, medium (~ 300 m) of MERIS or its successor Sentinel 3, to high such as Landsat 8 (30 m), Sentinel 2 (10 m) or WorldView (2 m). For each sensor at least one pixel along the shoreline will not contain useful water data because it contains a mixture of land and water. However, especially for the high resolution satellites there will be more mixed pixels because the shoreline is curved, or because of bottom visibility or surfacing vegetation along the lake shores.

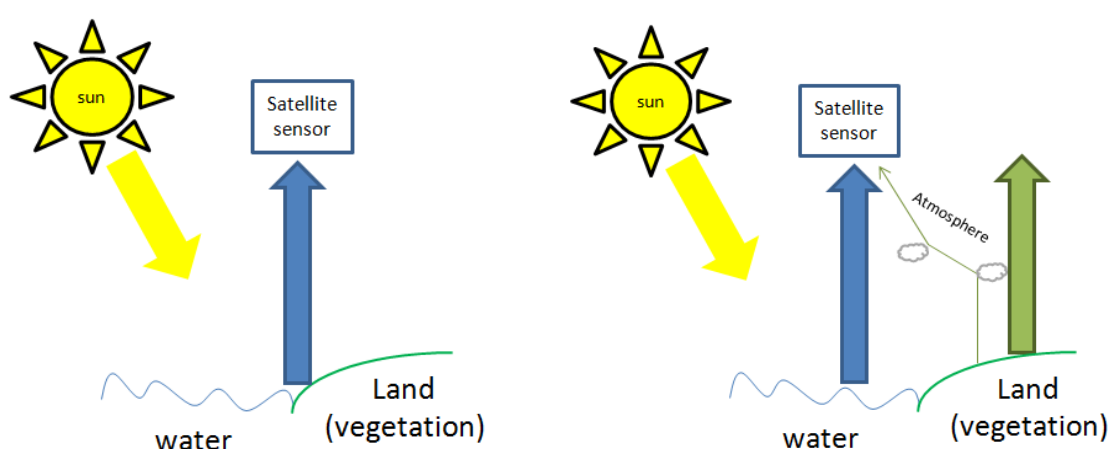


Figure 7. Left) Mixed pixel. Right) Adjacency effect.

The adjacency effect (image above, right) is what happens when an adjacent surface area reflects light, which is via atmospheric scattering observed by the satellite sensor as coming from the location it is observing. Especially in cases where the area that is being observed by the satellite is relatively dark (e.g. absorbing water), while the adjacent pixel is very bright (e.g. forested areas which reflect a large amount of near-infrared light) the 'small' fraction of light from the land that is scattered to the sensor has a relatively large effect on the observed water signal.

There are processors available that correct for this adjacency effects, for example the ICOL processor (Santer & Zagolski, 2009), which we will use in this exercise.

2 This lesson

2.1 Research question

What are the limits of remote sensing of water?

2.2 Training objectives / skills to gain in this lesson

1. Find out about the effects of absorption
2. Find out about mixed pixels and adjacency effects
3. Learn about sensitivity

2.3 Required software and data

Software and tools

To complete this lesson tasks, the following tools and software are required or suggested:

- BEAM (required, see Lesson #1).
The lakes processor that is used in this exercise is not available in the current SNAP version (v2.0). However, similar work can be done in following versions of SNAP, using other atmospheric correction processors instead.

Downloadable files

- GLaSS_Training_Lesson8.pdf
The main document of the lesson including exercises and questions.
- GLaSS_Training_Lesson8_Answers.pdf
A document containing answers to all questions proposed in the exercises.
- GLaSS_Training_Lesson8_DataAndTools.zip
Supplied data and tools, described below.

The zip-file with supplied data and tools contain:



- A folder with MERIS satellite imagery (a subset of MERIS the Finnish area in .dim format
(subset_Pyhajarvi_VesijarviArea_of_MER_FSG_1PNEPA20070604_092515_000001972058_00394_27502_0751.dim and the additional data folder) and the same image after processing with ICOL.
- A folder with additional data, which contains:
 - A file with the placemarks of the Finnish lakes that will be studied:
Finnish_lakes_locations.placemark
 - An answer template in .xls format
 - A spreadsheet with example reflectance data of different lakes
- A folder with the answer data files, containing the satellite imagery and the spreadsheets after performing the tasks in the exercises

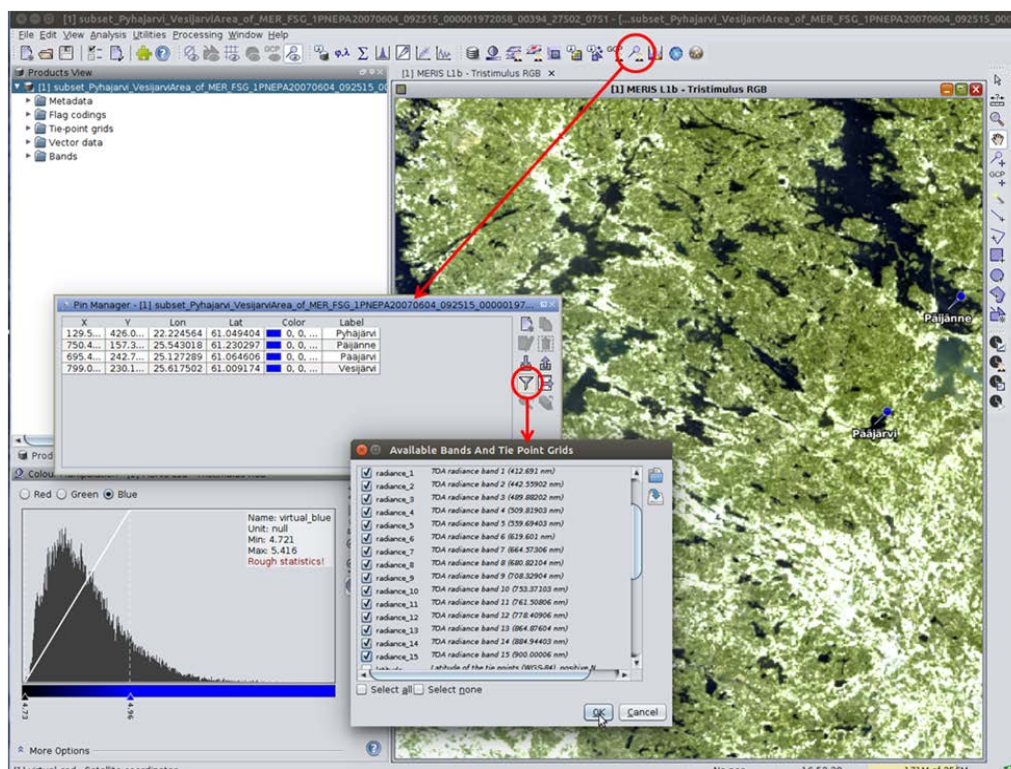
3 Exercise


Part 1 The effects of absorption

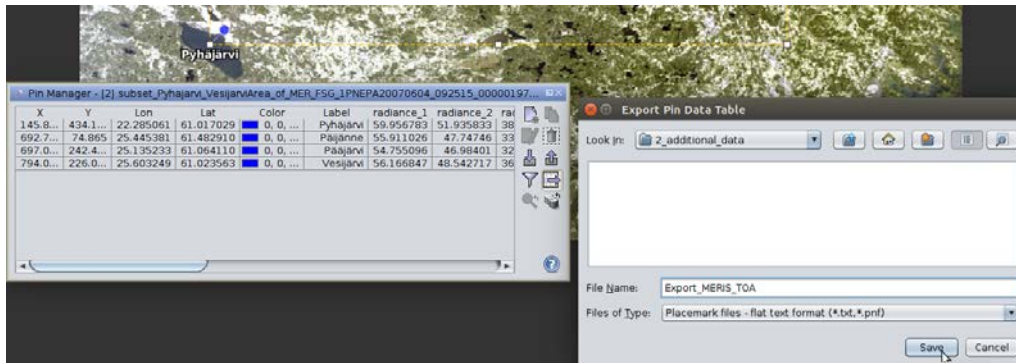
- Start BEAM
- Open the MERIS image of 4th June 2007
(File > Open Product > select the image subset_Pyhajarvi_VesijarviArea_of_MER_FSG_1PNEPA20070604_092515_000001972058_00394_27502_0751.dim)
- View > Open RGB Image View. Note that the area of interest is already selected and that the 'pins' of the lakes we are interested in are already there.
- Scroll around to find already some obvious differences in brightness between the lakes

To see how dark these lakes are, we will compare the total reflection recorded by the satellite (on top of the atmosphere, TOA) with the atmospherically corrected data. For more information on atmospheric correction, see lesson #3.

- Open the Pin Manager () and click-hold-drag the window to a convenient location
- Select the funnel icon () > select all "radiance" bands (scroll down) > OK

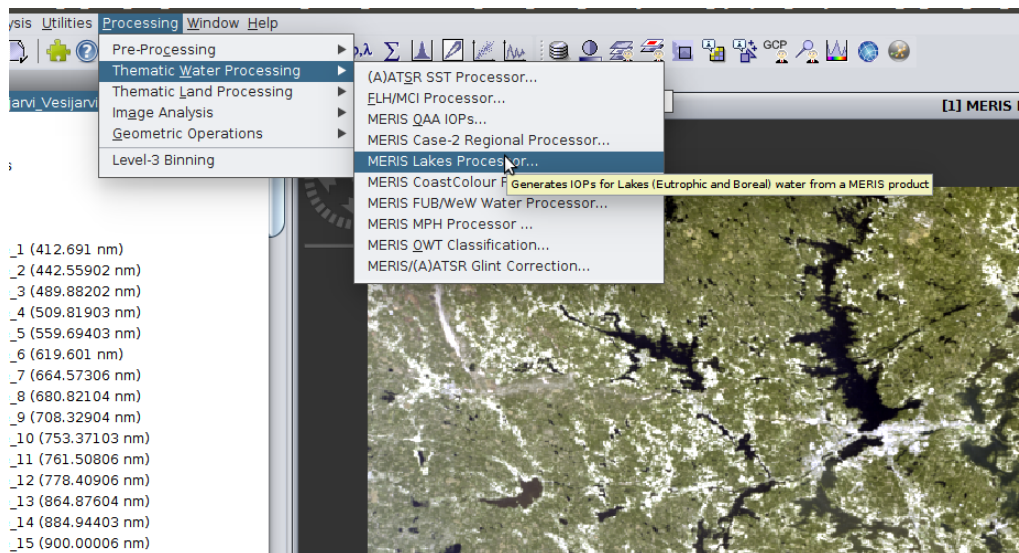


- Export the data () to a text file and call it Export_MERIS_TOA.txt

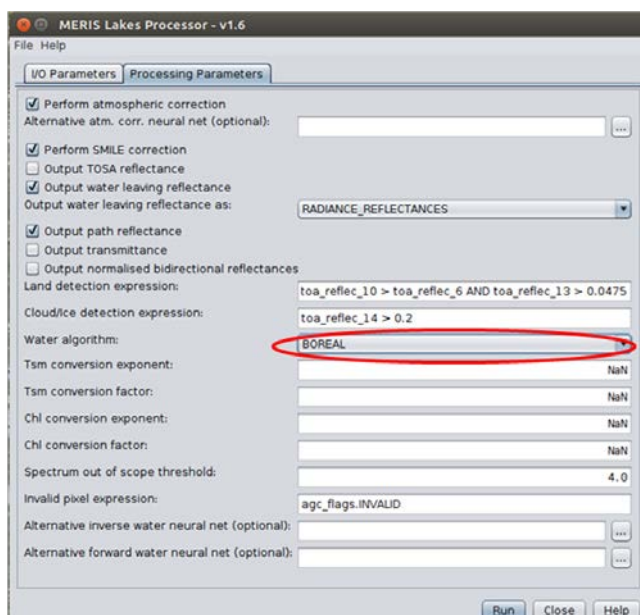



Now apply a suitable atmospheric correction method.

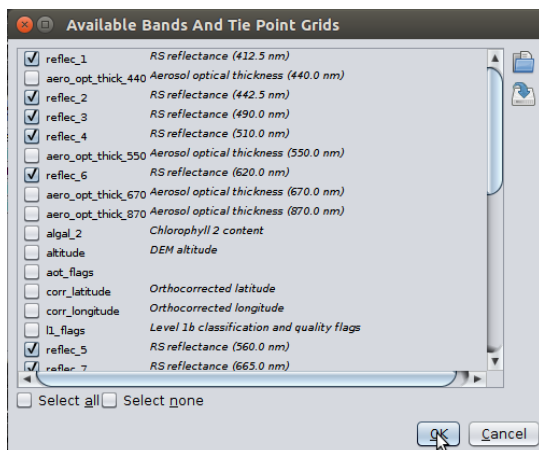
- Processing > Thematic Water Processing > MERIS Lakes Processor



- In the second tab, select the Boreal processor. Leave all other parameters to the standard.



- After running the processor, open the Pin Manager, Import () the in situ station locations (File: Finnish_lakes_locations.placemark (in the folder Additional data)) > open
- Export the reflectance ('reflec') and call the file Export_MERIS_L2Lakes.txt



Now we will compare the TOA radiance with the surface reflectance. (Note: these are different units! TOA radiance is the light captured by the satellite, while reflectance is a ratio of light traveling towards to satellite divided by downwelling irradiance from the sun)

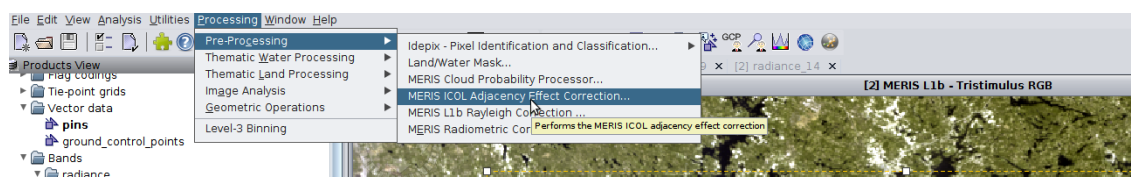
- Open the answer template.xls file (in the folder Additional data)
- Import the exported data files and paste the data at the locations for MERIS TOA and MERIS Lakes. Note the large difference in shape between the TOA radiance and the surface reflection.
- In the second tab, compare the retrieved reflectance data with the in situ measured reflectance spectra.
 - Does the atmospheric correction with the Boreal Lakes processor work well?
 - Can you explain these results using the information of section 1.3?

Part 2 Mixed pixels and the adjacency effect

First we will have a short look at mixed pixels:

- Go back or re-open the RGB view of the original image (first steps of part 1)
- Zoom in to lake Pääjärvi
- Open the Colour Manipulator window and move the Red Green and Blue sliders so that some details become visible
 - Where do you notice (potential) mixed pixels?

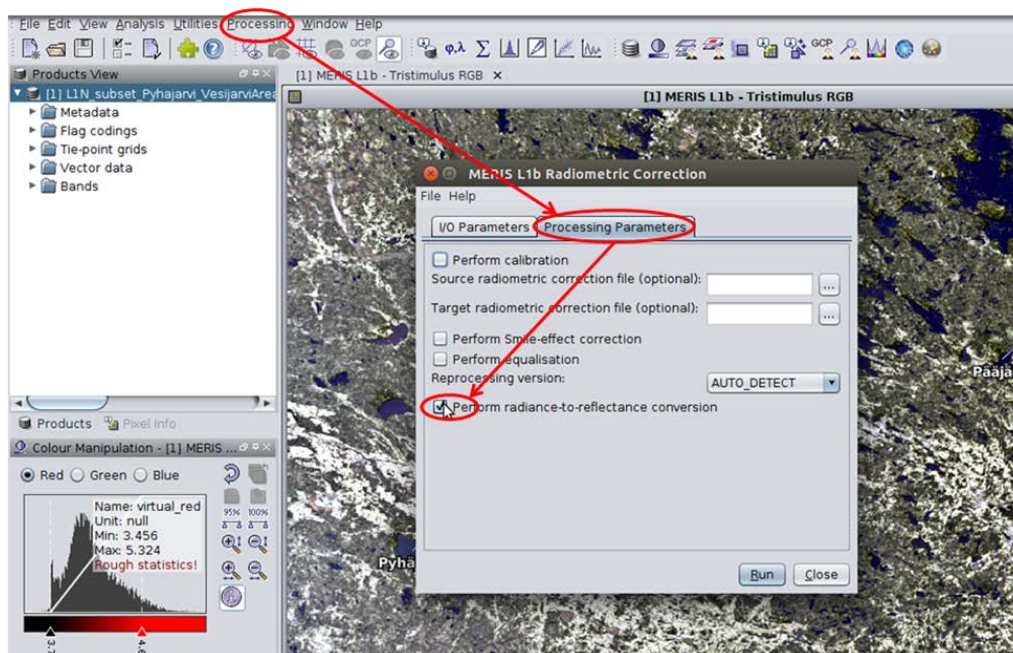
The next step is to apply the adjacency correction algorithm, ICOL. You can find ICOL under 'Processing' > 'Pre-Processing' > 'MERIS ICOL Adjacency Effect Correction'. However, ICOL processing requires a large memory and is relatively slow, so we have prepared an ICOL processed image for you.



- Open the ICOL processed MERIS image
L1N_subset_Pyhajarvi_VesijarviArea_of_MER_FSG_1PNEPA20070604_092515_00001972058_00394_27502_0751.dim
- Repeat the steps of Part 1 using the Pin Manager, the Boreal Lakes processor and the answer template spreadsheet:
 - export the reflectances on top of atmosphere after ICOL processing: MERIS_TOA_ICOL.txt
 - process the image that was corrected for adjacency effect with the Boral Lakes processor
 - export the reflectances obtained with the combination of adjacency correction plus atmospheric correction: MERIS_ICOL_L2Lakes.txt
 - *Did the results improve by using the ICOL adjacency correction processor?*

Apparently, even dedicated atmospheric correction methods currently fail for the darkest lakes. To get an idea of how this is possible, check how large the correction actually is.

- (Re) open the MERIS image that was not processed with ICOL
- Go to tools > Pre-Processing > MERIS L1b Radiometric Parameters. In the pop-up window select the tab “Processing Parameters” and check the box “Perform radiance-to-reflectance conversion” > Run



- Open a random band of the just created image, which now contains TOA reflectance (instead of radiance) data
- Import the Finnish_placemarks via the Pin Manager
- Export the “reflectance” data
- Use the last tab in the Answer template spreadsheet to calculate the percentage reflectance per wavelength that is caused by water (the percentage of the in situ of the TOA reflectance).

Part 3 Sensitivity

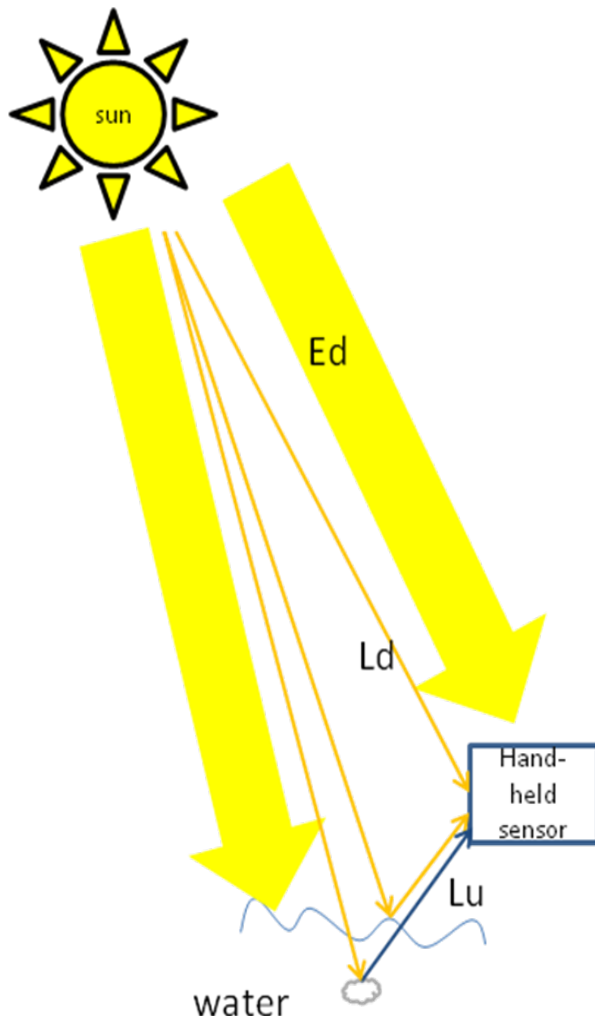
Another important property that determines the potential and limits of remote sensing, especially of lakes with a high content of absorbing materials, is the sensitivity of the sensor.

The lower the signal, the higher the signal-to-noise ratio. This also explains why a similar sensor with a smaller pixel size will have a lower sensitivity: it either registers the light that is reflected from a large or a small surface. The light reflected by a large surface will be a higher signal and therefore lead for the same sensor to a better signal-to-noise ratio. In areas with a high reflection, a smaller pixel size will therefore generally have advantages (see also Lesson #6). For areas with a low reflection, the disadvantage of a smaller pixel size as a lower sensitivity, plays a more important role. In GLaSS deliverable 5.5 (2015), a theoretical exercise is carried out to show the maximum potential differences in Chl that can be retrieved from MERIS Full resolution (300 m pixels) and MERIS Reduced resolution (1200 m pixels) imagery.

Repeating this exercise here would take too much time and it is also difficult to visualize the effects of sensitivity of a satellite sensor. Instead, we prepared a spreadsheet (Different_lakes.xls) which contains the in situ measurements of three lakes:

- Lake Markermeer (Lesson #6): a turbid, highly reflecting lake with high Chl and TSM
- Lake Garda: a clear lake, which contains low concentrations of Chl, TSM and CDOM
- Lake Lake Pääjärvi (see section 1.3): a highly absorbing lake

The spreadsheet contains the measurements of a hand-held radiometer which measures the water-leaving reflectance. Such hand-held instruments usually consist of three radiometers to derive the reflectance of the water. See the image below.



This figure shows the measurement of the reflectance of water with a hand-held sensor, using the above-water method (reflectance can also be measured below the surface).

The reflectance is a measure of 'the colour of the water'. The colour of the water can be measured as a ratio of the light that leaves the water divided by the light that enters the water. By using a ratio, the measured water colour is compensated for e.g. a cloudy day, with less blue light.

The light entering the water at a specific spot is the sum of the direct radiance at that spot (L_d , which stands for downwelling radiance) and the diffuse downwelling light (E_d). Part of the light reflects at the surface, part of it enters the water. A small portion of the radiation that enters the water, backscatters on e.g. particles and then leaves the water.

The light leaving the water in a certain direction, as seen by an instrument, is therefore the sum of the light that is reflected at the water surface (which is not interesting) and the light which has passed through the water (the interesting part).

To derive all the light that is needed to calculate the reflectance, the above-water instruments usually measure E_d , L_d and L_u .

Finally, the reflectance is calculated as:

$$R_{rs} = (L_u - \rho L_d) / E_d$$

Where ρ is the fraction of light that is reflected at the water surface (e.g. Mobley, 1999).

- Open the spreadsheet *Different_lakes.xls* from the Additional data folder
- Check out the tabs to find the E_d , L_d and L_u measurements and the calculation of R_{rs} .
 - *Are the E_d and L_d and L_u measurements of these lakes comparable?*
 - *And R_{rs} ?*
- Copy the plot and adjust the y-axis to be able to see also the Lake Pääjärvi reflectance measurement better.
 - *Is the shape of R_{rs} of Lake Pääjärvi as expected? (Check the Answer template file to compare)?*
 - *Do you see any effects that might be due to sensitivity?*
 - *Can you think of factors that would improve in situ reflectance measurements? This could be environmental, hardware etc.*
 - *Would any of these also apply to satellites?*

4 More information and further reading

This lesson is based on the following report:

- GLaSS Deliverable D5.5, 2015. Global Lakes Sentinel Services, D5.5: Boreal lakes case study results. SYKE, WI, TO, BG.. Available via: www.glass-project.eu/downloads

The report is suggested for further reading. It contains:

- A review of past experience using EO data for highly absorbing boreal lakes
- Tests with new SIOCCS and FUB processors in Finland, Sweden and Estonia
- An exercise to find out how the noise characteristics of a satellite sensor affect the estimation of Chl-a, and if it is possible to find Chl-a, TSM and a_{CDOM} combinations where the estimation of Chl-a is no longer reliable due to the low signal-to-noise ratio.
- A small experiment with a WISP-3 in situ sensor methods to apply for absorbing waters

For more information on GLaSS, and to download all public reports: www.glass-project.eu.

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Colophon

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Lakes with a high concentration of humic substances

What are the limits of remote sensing of water?

Annelies Hommersom (WI), Sampsa Koponen (SYKE), Kari Kallio (SYKE)

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GLaSS Consortium

No	Name	Short Name
1	WATER INSIGHT BV	WI
2	SUOMEN YMPARISTOKESKUS	SYKE
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