
MERIS observations of phytoplankton blooms in a stratified eutrophic lake

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A bstract

The use of spaceborne medium resolution imaging spectrometers with neural network algorithms has proven a large potential for application with optically complex inland waters. We make use of this approach to investigate the bio-physical dynamics in an eutrophic lake, applying three different neural networks to a dataset of 16 images acquired in June through August 2011. Concurrent in-situ data are measured by means of automatically deployed instruments from a moored platform, resolving the vertical distribution of various parameters at sub-daily temporal resolution. Phytoplankton blooms occur in different stratification layers, allowing the assessment of their influence on remote sensing estimates. A qualitative synopsis of the biophysical processes in the lake is given, but parameterization with in-situ attenuation profiles and accurate IOP estimates is needed to significantly enhance quantitative matchup comparisons. Recommendations on the combination of in-situ and satellite measurements are therefore given as an outlook.

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1. Introduction

With the latest satellite instruments and algorithms becoming available, remote sensing of chlorophyll-a (CHL-a) in inland waters is evolving towards routine operational use. Satellite retrieved CHL-a has recently complied with the monitoring requirements defined in the European Water Framework Directive (Bresciani et al., 2011). On the instrumentation side, the use of medium-resolution spectroradiometers such as MERIS and MODIS is most prevalent for this purpose. However, MERIS’ spectral resolution of red and near-infrared (NIR) wavelengths allows a more accurate retrieval of the secondary CHL-a absorption maximum than MODIS, making it more suitable for eutrophic waters (Odermatt et al., 2012). On the side of algorithms, several specific approaches have been developed for optically complex inland and coastal water types, as no universally applicable method is known (IOCCG, 2006, 2009). Neural network (NN) algorithms for MERIS (Doerffer & Schiller, 2007, 2008; Schroeder et al., 2007b) have been validated for a variety of European lakes (Koponen et al., 2008; Odermatt et al., 2010; Ruiz-Verdu et al., 2008), although other studies suggest that they may fail at very high pigment concentrations, particularly in the case of cyanobacteria (Binding et al., 2011; Giardino et al., 2010; Matthews et al., 2010).

The major asset of remotely sensed water quality is the representation of spatial variations, while the vertical representation of the water column is limited to a columnar integration whose interpretation is partly ambiguous. In contrast, traditional monitoring methods represent sparse, non-continuous geographical locations and lack the representation of spatial variations, but allow sampling of vertical variations in the entire water column. For this purpose the deployment of fluorescence probes is the most straightforward and least laborious. After appropriate calibration, such devices measure concentrations up to 50 mg/m³ CHL-a in good agreement with more expensive lab analysis techniques (Gregor & Marsalek, 2004), although not beyond other shortcomings, such as quenching-related errors in the top surface layer (Catherine et al., 2012; Lefoualanger et al., 2002). Due to these qualities, fluorescence probes find broad application in water quality monitoring programs, including the perialpine region (Odermatt et al., 2010). An improved understanding of how vertically resolved fluorescence probe measurements relate to remote sensing is necessary to help the validation of remote sensing methods by means of CHL-a monitoring data.

Water stratification and photoinhibition cause distinct vertical variations in constituent concentrations. Effects of such variations on reflectance quantities have been simulated for several hypothetical cases of vertically variable phytoplankton (Ballestero, 1999; Gordon, 2004).
1992; Stramska & Stramski, 2005) and cyanobacteria concentrations (Kutser et al., 2008). In the quest of appropriate weighting of stratified layers, Gordon and Clark (1980) initially proposed a weighting proportional to the round-trip attenuation. In this case, the weighting of the uppermost layer would always be maximal, even if it was highly translucent with a more turbid and thus more reflective layer just underneath. Zaneveld et al. (2005) suggested the use of the round-trip attenuation’s first derivative instead, an approach whose enhanced adequacy was also numerically confirmed (Piskozub et al., 2008). Sokolovský and Yacobi (2011) propose another weighting function to calculate the remotely detectable CHL-a in heterogeneous water columns with coinciding measurements of photosynthetically available radiation (PAR). Their results reveal a closer correlation with the weighting function by Gordon and Clark (1980) than with the one by Zaneveld et al. (2005), but their theoretical concept agrees with the latter in the sense that a turbid layer may contribute strongest, even if superimposed by more transparent water. Those two conceptual papers and the before mentioned simulations (Ballester, 1999; Gordon, 1992; Kutser et al., 2008; Stramska & Stramski, 2005) provide a sound theoretical understanding of the effect of vertical constituent variations on surface reflectance. However, only the study by Sokolovský and Yacobi (2011) makes use of actual in-situ measurements, and applications to air- or spaceborne sensors are lacking.

The present study is to our knowledge the first attempt to combine quasi-continuous CHL-a profile measurements of multiple phytoplankton growth cycles in a stratified lake with remote sensing estimates from repeated satellite overpasses. We thereby assess the applicability of MERIS NN algorithms for eutrophic perialpine lakes. Several approaches are evaluated to account for the vertical variability in the multiparameter probe profiles, and requirements and recommendations are derived regarding how the two monitoring methods may be combined in the future.

2. Methods

2.1. Study site

Greifensee is a small dimictic lake of 8.45 km² area and 32.3 m maximum depth, located on the Swiss Plateau and surrounded by residential areas and intensive agriculture (Zurich State Agency for Waste Management Water and Air Protection & Energy, 2006). Due to nutrient emissions, Greifensee was hypertrophic in the 1970s, with the limiting phosphorus increasing to ~500 mg/m³ (Swiss Waste Management Water and Air Protection & Energy, 2006). Due to the low wind exposition and the high surface productivity, the metalimnion is thin and strongly stratified in summer, separating the phosphate-depleted epilimnion from the oxygen-depleted hypolimnion in ~5 to ~7 m depth.

2.2. In-situ measurements

From June 16 to August 30, 2011, an automated platform for phytoplankton ecology and ecosystem monitoring was moored on Greifensee (8.6785° E, 47.3663° N). The instrumentation deployed included a scanning flow-cytometer for classification and counting of phytoplankton (CytoBouy b.v., Woerden, The Netherlands) and a vertical profiling system based on OCEAN SEVEN 316 Plus CTD multiparameter probe (O7) (Idronaut, Brugherio, Italy). The 07-probe was equipped with seven sensors (pressure, temperature, conductivity, pH, oxygen, PAR and NO3) and an external Trilux fluorometer to quantify levels of CHL-a, phycoerythrin and phycocyanin (Chelsea Technologies Ltd, Surry, UK) (Pomati et al., 2011). The automated monitoring system was also mounted with a meteo station (WX7520, Vaisala, http://www.vaisala.com). Profiles were acquired at noon and midnight until July 5, and in 4 h intervals for the remaining duration of the study. Variations between day- and nighttime CHL-a measurements were observed, but were neglected since all matchup data are acquired at a similar time of the day and under cloud-free illumination. The measured CHL-a profiles were interpolated to a grid of 10 cm vertical intervals. Probe measurements were performed from 1.5 m depth to 18 m (the maximum depth on site was 19 m). Monitoring closer to the surface was not possible due to structural constraints of the automated monitoring station (Pomati et al., 2011). The mean of the two topmost profile points was thus appointed to this topmost layer, which is expected to be rather homogeneous in the mornings due to night-time convective mixing. Repeatability of the analysis with the topmost layer omitted instead of averaged did not make a significant difference. Another restriction is that the PAR sensor on the probe was strongly affected by the mooring’s shade and could not be used to derive Kd as suggested by Sokolovský and Yacobi (2011). An approximation of attenuation using CHL-a only was not possible due to independent variations in concentrations of total suspended matter (TSM) and yellow substance (Y). Therefore, attenuation-specific depth weighting of the CHL-a profiles for comparison with the surface signal derived remote sensing retrievals was not possible.

2.3. Satellite data processing

ESA’s Earth Observation Link (EOLi) listed 42 MERIS full resolution images of Greifensee in the 77 days from June 16 to August 30, 2011. About half of them were subject to cloud coverage. The remaining 20 datasets were used with the same processing chain as described by Odermatt et al. (2010), including the Case 2 Regional (C2R, version 1.3.2) algorithm (Doerffer & Schiller, 2007) and other algorithms from the BEAM toolbox version 4.5. Newer releases were evaluated but fell short of the validation results in Odermatt et al. (2010). Two other NN were applied in addition; the eutrophic lakes version of C2R (EUT, version 1.0.2; Doerffer & Schiller, 2008; Koponen et al., 2008), and the

<table>
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<th>Table 1</th>
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<td>IOP’s ranges, corresponding concentrations and conversion methods for the training and parameterization of the NN algorithms EUT, C2R and WEW. All IOP ranges are given for MERIS band 2 (443 nm). Values of C2R are from Doerffer and Schiller (2007), those of EUT from Doerffer and Schiller (2008). Conversion of EUT and C2R use default values of BEAM 4.5. Values of WEW are from Schroeder et al. (2007b) and Bricaud et al. (1998).</td>
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<td><strong>EUT</strong></td>
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EW algorithm (version 1.2.1) developed by Schroeder et al. (2007b). All algorithms retrieved inherent optical properties (IOPs), i.e. absorption (a) and scattering (b) coefficients, in order to derive corresponding concentrations for each constituent. Algorithm specific procedures and training ranges are summarized in Table 1. All processing variations were available with and without application of the Improved Contrast between Ocean and Land (ICOL, version 1.0.4) algorithm (Santer & Schmechtig, 2000; Santer & Zagolski, 2009) for the correction of adjacency effects. In contrast to Odermatt et al. (2010), results became consistently better after application of ICOL Calculations without ICOL are thus omitted.

C2R and EUT are both based on the same algorithm architecture for the retrieval of water constituent concentrations with MERIS (Doerffer & Schiller, 2007), while WEW makes use of different models and NN inversion procedures (Schroeder et al., 2007a,b). In the scope of the MERIS lakes project, EUT was developed to account for phyco-cyanin as part of the total pigment absorption in Spanish lakes of the MERIS lakes project, EUT was developed to account for phyco-

cyanin as part of the total pigment absorption in Spanish lakes.

Apart from the constituent concentrations, C2R and EUT calculated the downwelling irradiance attenuation coefficient $K_d$ from the bulk absorption ($a$) and backscattering ($b_h$) coefficients according to Eq. (2) (Doerffer & Schiller, 2007).

$$K_d = \sqrt{a + 2b_h}$$

The euphotic depth $z_{90}$, i.e. the depth of the surface layer that accounts for 90% of the water-leaving radiance, was then calculated as the average of $1/K_d$ in the three bands with minimum turbidity. $z_{90}$ was thus derived exclusively from IOPs, and not affected by the conversion functions in Table 1. Corresponding outputs were not available from WEW.

2.4. Data matchup procedure

For the horizontal dimension, visual checking of the corresponding 300 m pixels in the MERIS images revealed extraordinarily large spatio-temporal variations along the shoreline, indicating mixed pixels and other shoreline effects that were potentially enhanced by insufficient locational accuracy. A location in the center of the Northern basin (8.6577° E, 47.3568° N) was thus chosen as reference location, about 1 km southwest of the profiling site, assuming that spatial concentration variations remain within the spatial correlation length of such a small lake. Concentrations were extracted from single pixels without spatial averaging.

In the vertical dimension, we assumed due to lack of PAR profiles that maximum and minimum concentrations of CHL-a occur with the same probability for the whole euphotic zone, i.e. $K_d$ was assumed constant. For such hypothetical circumstances, Eq. (3) describes the vertical weighting function proportional to the round-trip attenuation at evenly distributed depths $z$ (Gordon & Clark, 1980).

$$f(z) = \exp[-2K_d z]$$

The corresponding weighting function for the derivative of the round-trip attenuation is in Eq. (4) (Zaneveld et al., 2005). The factor $-2K_d$ disappears after normalizing the vertical sum of the weighting function to unity, leaving Eq. (3) for both approaches in Eqs. (3) and (4), henceforth referred to as “exponential”.

$$f(z) = -2K_d' \exp[-2K_d' z]$$

Using $K_d + c$ and thus the beam attenuation $c$ instead of $2K_d$ is more appropriate for use of hemispherical–directional quantities like the remote sensing reflectance used in C2R, EUT and WEW, but $2K_d$ is a good proxy for $K_d + c$ (Piskozub et al., 2008).

For comparison with the “exponential” weighting in Eq. (3), vertical averages were calculated as applied in a previous study on perialpine lakes and the present algorithms (Odermatt et al., 2010), and henceforth addressed as “averaged”. Both depth representations were applied for $K_d$ as retrieved by EUT and C2R, as well as for an approximated $K_d = 0.2$ m$^{-1}$ that corresponds to $z_{90} = 5$ m according to Doerffer and Schiller (2008).

3. Results

3.1. MERIS data products

After the visual pre-selection of cloud-free datasets, the C2R retrieved aerosol optical thickness (AOT) was used to assess transparency and homogeneity of the atmosphere during acquisition of the remaining twenty images. An overview of these AOT maps is given in Fig. 1. It shows that good observation conditions prevailed at the beginning and the end of the investigation period, while only few datasets were available between July 13 and August 18, 2011.

The spatial distribution of AOT in Fig. 1 shows that the largest variations occurred in the littoral zone, and were probably due to shoreline effects. Around the reference location in the Northern basin however, the retrieval was homogeneous. When comparing AOT maps with corresponding CHL-a, TSM and Y outputs, the overestimation of AOT (yellow, −0.2) along the shoreline usually leads to very low constituent concentrations (Fig. 2, blue areas). In more pelagic regions, spatial variations of all constituents’ concentrations were low. Differences may occur between the upper and lower basins, as e.g. indicated in the CHL-a and TSM maps in Fig. 2. However, regarding variations within the large basin, significant errors due to the displacement of in-situ measurements and matchup pixel location are not expected.

The influence of allochthonous matter is expected to cause independently varying constituent concentrations in Greifensee, apart from periods where autochthonous processes dominate the optical properties. High correlations between CHL-a and the other two constituent concentrations may therefore indicate insufficient separation of IOPs. Unlike EUT and C2R (all $R^2 \leq 0.32$), significant correlations occurred for WEW. CHL-a and TSM were correlated with $R^2 = 0.77$, CHL-a and Y with $R^2 = 0.82$.

3.2. Biophysical dynamics

In-situ measured CHL-a profiles in Fig. 4 displays background concentrations of 3 to 10 mg/m$^3$ CHL-a, and several algal proliferation events with distinct pigment compositions. The first bloom in the second half of June was at 6 to 12 m depth and of up to 50 mg/m$^3$ CHL-a. A less intense bloom followed in the first days of July at a
**Fig. 1.** Spatial distribution of AOT for twenty MERIS images, using C2R for Greifensee (Switzerland) in June to August 2011. Gray indicates cloud cover; white pixels are neither recognized as water nor as cloud cover, indicating retrieval errors. Images with gray date labels are discarded because of clouds (July 9, August 16) or retrieval errors (July 26 and 31).

**Fig. 2.** Spatial distribution of surface CHL-\(a\), TSM and Y retrieved using C2R for Greifensee (Switzerland), August 24, 2011. The red box in the CHL-\(a\) map indicates the pelagial location of the pixel extracted for matchup comparisons; the red cross indicates the littoral position of the mooring.

**Fig. 3.** Photo of the surface of Greifensee, taken on August 12. A relatively constant amount of surface scum remained on the water surface during several days.
shallower depth (maximum concentrations at 2 to 4 m depth), but still didn’t reach the surface. The most dynamic period we recorded occurred between July 20 and August 30, with several variations between 10 and 50 mg/m³. The peak productivity of phytoplankton was observed between the 9th and the 20th of August, which was characterized by a cyanobacteria bloom caused by Microcystis aeruginosa. Between August 10 and 15, the bloom even formed surface scum (Fig. 3). This surface event was not directly documented by the in-situ instruments due to lack of surface measurements. In spite of its obvious effect on the waters’ optical properties, no further peculiarity than maximum CHL-α was found in the MERIS estimates, either. During the subsequent period of clear weather from August 19 to 25, the Fig. 4. Measured CHL-α profiles with remotely sensed $z_{\text{sec}}$ (top panel), and time series of water constituents for EUT, C2R and WEW (bottom panel) for the dates indicated in 2011.
center of phytoplankton productivity (35 to 50 mg/m³ CHL-a, still cyanobacteria) descended to about 3 m depth at the end of our time series.

The optical properties of TSM are the most distinctive and concentrations by EUT, C2R and WEW therefore coincided well. TSM increased steadily until August 19, and declined rapidly within the next three days. In the case of Y, large offsets occurred between C2R and EUT on one hand, and WEW on the other hand, especially in the last weeks of the record. Nevertheless, the general increase of Y in August followed plankton blooms as expected, and indicated a realistic temporal development.

The retrieved z90 was primarily related to TSM and CHL-a, as Y absorption plays a minor role at the wavelengths of least attenuation (490 to 560 nm). In mid-July for example, z90 remained low due to increased TSM concentrations, in spite of decreasing CHL-a. The values of z90 by C2R and EUT agreed with R² = 0.96, but the estimates by C2R were 1.18 to 1.76 times those by EUT. The main shortcoming of z90 was that it is an estimate for a homogeneous column. It indicated low penetration when high CHL-a was retrieved through a transparent, superimposing layer (e.g. June 20 and 26), but could strongly overestimate the actual penetration if this layer was not sensed (e.g. C2R on June 19). Estimates for the descending bloom in late August agreed better.

### 3.3. Comparability of MERIS estimates and CHL-a profiles

EUT, C2R and WEW estimated CHL-a from default conversion functions (Table 1) achieved quite similar correlations, in spite of e.g. the cyanobacteria-specific parameterization of EUT (Fig. 5). The extreme CHL-a value retrieved by WEW on August 11 (40.6 mg/m³) avoided a better correlation of R² = 0.83, but it cannot be identified as an outlier since it is ironically one out of only two WEW retrieved matchup points that was not flagged as erroneous. The agreement of MERIS estimates and in-situ measurements remains thus relatively low for all assessed weightings. This corresponds to effects of vertical heterogeneity and phytoplankton absorption efficiency as assessed below. Furthermore, the lack of in-situ measurements of the top 1.5 m is expected to be a large error source compared to other studies where measurements are available from a minimum depth of 0.5 m (Odermatt et al., 2010).

Vertical heterogeneity caused large offsets between MERIS estimated and in-situ measured CHL-a during the first two weeks of the observed period. On June 20 and 26 for example, MERIS estimated CHL-a was relatively high, and z90 accordingly between only 3 and 4 m. The increase in CHL-a may however refer to a phytoplankton bloom at more than 5 m depth, and therefore outside all types of reference data weighting. As a consequence, the comparison of vertically averaged and exponentially weighted CTD measurements versus MERIS estimates by the different algorithms revealed to be quite consistent, yet rather small effects were observed. The 5 m approximation was always more accurate than z90-adjusted representations. Averaging outperformed exponential weighting for EUT and C2R, but not for WEW (Table 2).

With the default phytoplankton absorption efficiency of EUT and C2R (Table 1), in-situ CHL-a was underestimated by a factor of 2–5 (Fig. 5). The same C2R algorithm tended to overestimate CHL-a in larger, oligo- to mesotrophic lakes in the perialpine area (Odermatt et al., 2010). Regressions between in-situ measurements and aCHL-a were calculated for each algorithm in order to remove the effect of variable phytoplankton absorption efficiency (Fig. 6).

According to Eq. (1), power correlations are expected for relationships between aCHL-a and CHL-a. This implies that the regression conditions in Fig. 5 correspond widely to those in Fig. 6, but the latter achieves generally increased R² as the coefficients A and B from Eq. (1) were introduced as additional regression variables. The largest enhancement achieved in this way was for WEW. However, in the case of WEW the values of A were exceptionally small, and surprising-ly is B > 1, although packaging effects were expected to decrease absorption efficiency with increasing concentrations. Approximate, yet not quite as extreme values have only been measured for Lake Taihu (Zhang et al., 2010), with A = 0.019 and B = 1.066, whereas other measurements indicated a much lower variability around A = 0.058 and B = 0.735 (Bricaud et al., 2004; Cannizzaro et al., 2008; Wang et al., 2010), as retrieved for EUT and C2R (Table 3). Altogether, this indicates that the regression of in-situ measured CHL-a and satellite retrieved aCHL-a is prone to over-fitting without corresponding aCHL-a measurements.

### 4. Conclusions

Ambiguity in the vertical representativeness of remotely sensed constituent concentrations is a potential concern to end users and hence hindering its use in operational water quality monitoring. Probe profiles are the fastest way to measure the vertical distribution of CHL-a, and are a standard in-situ monitoring approach. The present work combines the two, demonstrating the potential of their combination, and allowing several recommendations for synoptic monitoring approaches in the future. It is shown that MERIS and the evaluated neural network algorithms are
Table 3 Coefficients derived for customized CHL-α conversion according to Eq. (1).

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<tr>
<th>Coefficient</th>
<th>EUT</th>
<th>C2R</th>
<th>WEW</th>
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<td>5 m averaged</td>
<td>A_{CHL-α} = 0.043, B_{CHL-α} = 0.430</td>
<td>A_{CHL-α} = 0.056, B_{CHL-α} = 0.339</td>
<td>A_{CHL-α} = 0.050, B_{CHL-α} = 0.376</td>
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<tr>
<td>5 m exponential</td>
<td>A_{CHL-α} = 0.057, B_{CHL-α} = 0.338</td>
<td>A_{CHL-α} = 0.066, B_{CHL-α} = 0.470</td>
<td>A_{CHL-α} = 0.072, B_{CHL-α} = 0.568</td>
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References


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