Hyperspectral imaging of toxin-producing cyanobacterial blooms in eutrophic lakes

Background

Cyanobacteria and human health

Cyanobacteria (blue-green algae) are natural and cosmopolitan inhabitants of fresh, brackish and marine waters (see Fig. 1). They are particularly well adapted for growth in nutrient-enriched lakes and other slow-flowing inland waters and often form mass populations (as blooms, scums or biofilms) during summer and autumn at temperate latitudes. These mass populations are a serious concern because they can have profound and far-reaching adverse environmental and economic impacts on natural and controlled waterbodies. They can also pose significant risks to animal and human health because several species can produce potent toxins (cyanotoxins). These toxins constitute some of the most hazardous of all waterborne biological substances and include agents with neurotoxic (anatoxin-a, beta-methylamino alanine, saxitoxins); hepatotoxic and tumour-promoting (microcystins, nodularins); cytotoxic (cylindrospermopsins) and endotoxic (lipopolysaccharides) properties (Codd et al. 2005).

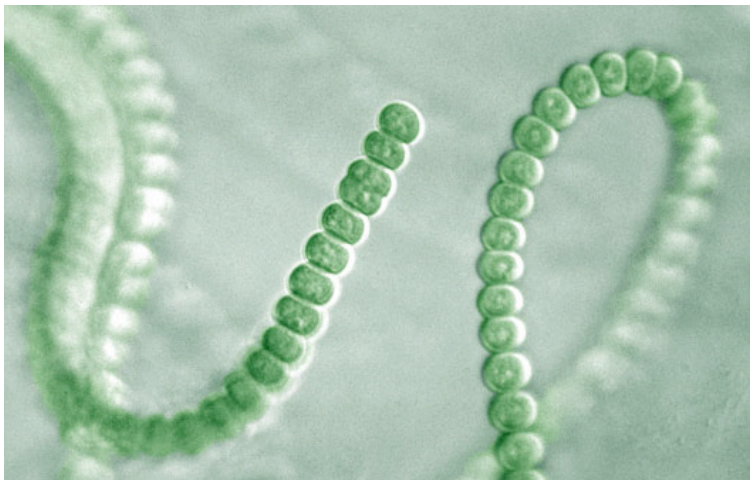

Figure 1 Micrograph image of the blue-green toxin-producing cyanobacterium *Anabaena circinalis*.

Blooms of toxigenic cyanobacteria in waterbodies used for drinking water, aquaculture, crop irrigation and recreation are increasing in abundance and spread due to eutrophication. Human exposure to bloom-forming cyanobacteria and their toxins most commonly occurs via drinking water or incidental ingestion, dermal contact and inhalation (Codd et al. 2005). Cyanotoxins have been linked with numerous incidences of ill health in humans ranging from cases of mild skin irritation and gastrointestinal illnesses to acute (and occasionally fatal) poisonings. These risks may be further exacerbated if incidences of blooms continue to increase under a warming climate.

The abundance of cyanobacteria is a useful measure of inland and coastal water quality and is one of the biological quality metrics being considered for the

assessment of lake ecological status under the European Union's Water Framework Directive (EU WFD) (2000/60/EC). Monitoring of cyanobacteria and their toxins is also necessary so that timely warnings can be provided to safeguard animal and human health. However, monitoring cyanobacterial blooms from a regulatory perspective can be problematic. Cyanobacterial blooms are often very patchily distributed in space and time which makes it difficult to get an accurate representation of their abundance through ship-based sampling alone. Moreover, ship-based sampling approaches are not conducive to regional- or global-scale monitoring. There is thus a clear need for improved monitoring and management of cyanobacteria and their toxins in inland, transitional and coastal waters for the protection of animal and human health.

Remote sensing of cyanobacterial blooms

There is considerable interest in the development of remote sensing-based techniques for the detection and mapping of cyanobacterial blooms from space. It has been shown that the concentration of chlorophyll a (Chl-a) within phytoplankton blooms can be retrieved from hyperspectral reflectance spectra using a simple two-band ratio:

$$\text{Chl a} \propto \frac{R_{rs}(710)}{R_{rs}(665)} \qquad [1]$$

where $R_{rs}(710)$ and $R_{rs}(665)$ is remote sensing-reflectance at wavelengths 710 and 665 nm respectively. This band ratio exploits the local Chl-a absorption maximum near 670 nm. In this region of the spectrum, interference from other optically active substances such as mineral particles and coloured dissolved organic matter (CDOM) is minimal. The depth of the absorption feature near to 670 nm is thus directly related to the concentration of Chl-a. Conversely, Chl-a absorption is minimal at near to 710 nm. Therefore, this band is used for normalisation and to minimise effects caused by non-algal backscattering and atmospheric path radiance effects. We therefore expect the value of [$R_{rs}(710)$:$R_{rs}(665)$] to increase as the concentration of Chl-a increases.

We can develop an algorithm for estimating Chl-a from this two-band [R(710):R(665)] ratio by regressing the value of the ratio against measured concentrations of Chl-a (see Fig. 2) in water samples collected from known stations concurrent to airborne remote sensing flights or satellite overpasses. This approach has been used to produce Eq. 2 for the retrieval of Chl-a using the [R(710):R(665)] band ratio. It was developed using data collected in the Norfolk Broads, UK.

$$\text{Chl a (mg m}^{-3}) = -26.2 + 40.3 \times \left[\frac{\text{R(710)}}{\text{R(665)}}\right] \qquad [2]$$

Remote sensing algorithms of the type shown in Eq. 2 have been widely used to retrieve estimates of Chl-a in inland waterbodies from remotely sensed data and provide a useful estimate of total phytoplankton biomass within the water column. However, because nearly all phytoplankton contain Chl-a, it does not provide any information on phytoplankton taxa present. This is a major limitation if we are

interested in determining the abundance of cyanobacteria within mixed phytoplankton assemblages.

However, there is a small but growing body of evidence to suggest that the identification and quantification of cyanobacteria from reflectance spectra is possible because of their unique bio-optical traits (Hunter et al., 2008). Freshwater cyanobacteria contain the accessory photopigment phycocyanin. In contrast to Chl-a, phycocyanin (C-PC) has a local absorption maximum near 620 nm. This diagnostic spectral trait provides a route to the detection and quantification of cyanobacteria in inland waters. Recently, a number of studies have sought to develop algorithms for the retrieval of C-PC from remotely sensed data (Hunter et al. 2008a, 2008b, 2009; Tyler et al. 2009) so that we can move towards global monitoring of cyanobacterial blooms from space.

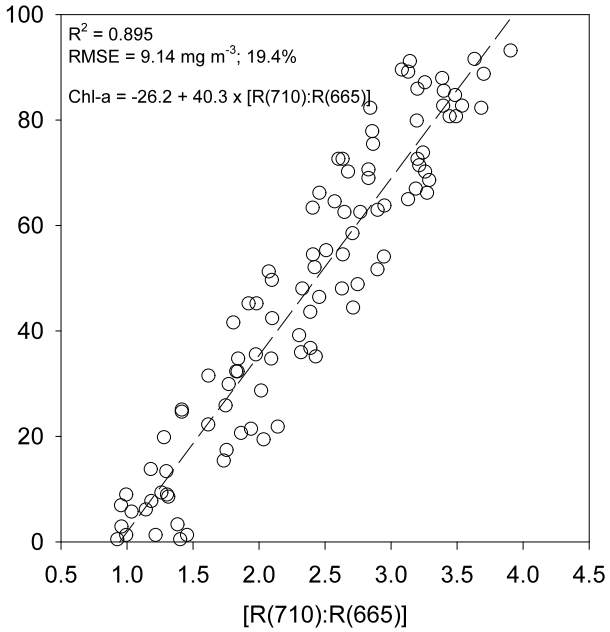

Figure 2 The relationship between the [R(710):R(665)] band ratio and the measured concentration of Chl-a in the Norfolk Broads

Study site

Esthwaite Water is a small eutrophic lake in the English Lake District (54°21′N, 3°0′W). It has a mean depth of 6.4 m and a maximum depth of around 25 m. The lake thermally stratifies in late-April, with the water column turning over again in the autumn. The lake receives nutrient inputs from a local sewage treatment works and a fish farm and these fertile conditions promote the growth of toxigenic cyanobacteria during the summer and autumn, including species such as *Anabaena*, *Aphanizomenon*, *Microcystis*, *Planktothrix* and *Woronichinia*. In April 2007, a bloom of *Anabaena circinalis* occurred in the lake; this was one of the earliest cyanobacterial blooms in Esthwaite Water on record and suggest the lake is responding to climatic forcing.

Aim

The aim of this project is **to evaluate the efficacy of hyperspectral imaging as a tool for monitoring and managing toxic cyanobacterial blooms in lakes** through an analysis of data collected at Esthwaite Water in 2007 during the spring bloom of *Anabaena circinalis*. This is to be achieved through the following objectives:

1. Determine the accuracy of the existing Chl-a retrieval algorithm (Eq. 2) using the AISA Eagle-Hawk data from Esthwaite Water.

2. Design a band-ratio algorithm for the retrieval of C-PC and use regression analysis to develop an algorithm that can be applied to the AISA Eagle-Hawk image for the discriminative mapping of cyanobacteria in Esthwaite Water.

3. Compare the performance of the empirical algorithm for Chl-a retrieval against a semi-analytical model (if time permits).

Datasets

The available datasets include hyperspectral AISA (Airborne Imaging Spectrometer for Applications) Eagle and Hawk images of Esthwaite Water in the English Lake District acquired by the Natural Environment Research Council's Airborne Research and Survey Facility (NERC ARSF). The Eagle and Hawk data have been appended together into a single file named **AISA_EH_Est_26042007.img**. This hyperspectral image is composed of 335 contiguous bands between 394 and 2451 nm and has a spatial (pixel) resolution of 5 m. The image was acquired between 11:51 and 11:57 h UTC on 22 April 2007 under clear skies and minimal atmospheric haze.

Water samples were collected at the same time as airborne overflights and the locations of the sampling stations were recorded using a GPS (± 5 m). The water samples were analysed for the concentrations of Chl-a and C-PC. The water quality data is provided in the spreadsheet named **Water Quality Data.xls**.

Remember to set your user preferences at the start of each session and save all your files to your home folder as you progress

Task 1: Preliminary image processing

The AISA Eagle-Hawk image has been georegistered to UTM WGS-84 coordinates. The data has also been atmospherically corrected to remote sensing-reflectance [$R_{rs}(0+,\lambda)$] using the FLAASH model in ENVI. $R_{rs}(0+,\lambda)$ is the reflectance signal as measured immediately above the water column without the contribution of sky radiance or specular reflectance from the water surface itself. The AISA Eagle-Hawk data is therefore directly compatible with the reflectance-based Chl-a retrieval algorithm presented in Eq. 2.

- Create a region-of-interest (ROI) around the shore of Esthwaite Water (you can also include the two smaller waterbodies if you wish) and use this to build and apply a Mask Band to the AISA Eagle-Hawk image to remove all non-water pixels from the scene (or alternatively spatially subset the image). This will prevent you applying the retrieval algorithms to terrestrial pixels.

Task 2: Test the existing Chl-a retrieval algorithm

The Chl-a retrieval algorithm presented in Eq. 2 was developed from data collected in the Norfolk Broads. However, to rigorously test the performance of this algorithm it is important that we apply it to datasets collected from different lakes with differing optical properties. The optical properties of Esthwaite Water are likely to be markedly different from those of the Norfolk Broads.

- Use either the band math or band ratio tool to calculate the value of [R(709):R(665)] band ratio for the subset image of Esthwaite Water created in Task 1.

- Use the band math function to apply the Chl-a retrieval algorithm to the [R(709):R(665)] band ratio image. This will create a further image depicting the estimated Chl-a concentration on a pixel-by-pixel basis across the lake.

- The locations of the sampling stations on Esthwaite Water are provided in **Water Quality Data.xls**. Use the pixel locater and cursor location/value (or another appropriate method) to determine the estimated Chl-a concentrations at each sampling station.

- Compare the estimated Chl-a concentrations from the AISA Eagle-Hawk image to those measured in the lake. Create a scatter plot of Estimated Chl-a vs. Measured Chl-a in MS Excel (or similar) and calculate the coefficient of determination (R^2) and the RMSE (mg m^{-3}, %) for the retrieval.

Q How well did the Chl-a retrieval algorithm perform? Did it perform better or worse than in Esthwaite Water compared to the Norfolk Broads? Do your results suggest this algorithm could be used routinely to estimate Chl-a in Esthwaite Water and other eutrophic lakes with acceptable error terms (e.g., ± 20%)?

Task 2: Develop a new algorithm for C-PC retrieval

You have now applied a Chl-a retrieval algorithm to the AISA Eagle-Hawk data and used this to produce spatially synoptic estimates of the Chl-a concentration across the lake. However, we cannot infer cyanobacterial abundance directly from the retrieved Chl-a concentration. To do this, we need an algorithm that specifically estimates the concentration of a diagnostic biomarker pigment such as C-PC.

- Devise a simple band ratio model for the retrieval of C-PC, carefully selecting the bands to be used in the model to optimise retrieval. [Hint: all the information you need is contained in this handout!].

- Use the band math or band ratio function to calculate your new band ratio for C-PC retrieval from the original AISA Eagle-Hawk image.

- Use the pixel locater and cursor location/value (or another appropriate method) tools to extract the band ratio values at each sampling station.

- Use regression analysis in MS Excel to determine the relationship between the band ratio value and the measured C-PC concentrations for the 10 sampling stations on Esthwaite Water. [Make sure that you use C-PC as the independent (response) variable].

- Use a band math function to apply the resulting regression equation to the AISA Eagle-Hawk image and retrieve estimates of C-PC on a pixel-by-pixel basis across the lake.

- Produce a calibrated map depicting the concentration of C-PC in Esthwaite Water either in ENVI or by exporting the processed image to a package such as ArcGIS. Include a scale bar (in kilometres), north arrow and legend on your output map.

Q How well did the retrieval algorithm for C-PC perform? What was the coefficient of determination and RMSE for the retrieval? Do your results suggest this algorithm could be used routinely to estimate cyanobacterial abundance in eutrophic lakes with acceptable error terms (e.g., ± 20%)?

Time to spare? Optional task: Testing semi-analytical algorithms

You have now developed and applied empirical algorithms for Chl-a and C-PC retrieval. While empirical algorithms are attractive in the sense that they are relatively easily to derive, they tend to have limited transferability between different lakes types and conditions. Analytically-based algorithms that adopt a more tangible physics-based approach tend to be far more robust when applied across different waterbodies. Several analytically-based algorithms have been proposed for the retrieval of Chl-a, and recently a semi-analytical algorithm has been proposed for the estimation of C-PC in Case II waters.

Gons et al. (2005) proposed the following algorithm for the retrieval of Chl-a from MERIS data.

$$a_{chl}(665) = \left(\left\{ \left[a_w(708.75) + b_b \right] \times \left[\frac{R_{rs}(708.75)}{R_{rs}(665)} \right] \right\} - b_b^{\,p} - a_w(665) \right) \quad [3]$$

where $a_{chl}(665)$ is the absorption coefficient of chlorophyll at 665 nm; $a_w(665)$ and $a_w(708.75)$ are the absorption coefficients of pure water at 665 (0.401) and 708.75 nm (0.727) respectively; $R_{rs}(708.75)$ and $R_{rs}(665)$ is the measured remote-sensing-reflectance at 708.75 and 665 nm respectively; p is an empirical constant equal to 1.062. The algorithm assumes a white (spectrally neutral) backscattering coefficient; this can be calculated using a wavelength located in the near-infrared as follows:

$$b_b = \frac{1.61 \times R_{rs}(779)}{0.082 - 0.6 \times R_{rs}(779)} \quad [4]$$

where $R_{rs}(779)$ is the remote sensing-reflectance at 779 nm. The true concentration of Chl-a can then be calculated by dividing the value of $a_{chl}(665)$ by the specific chlorophyll absorption coefficient at 665 nm = 0.0161 m^{-1}.

If you have sufficient time implement the algorithm above algorithm using the AISA Eagle-Hawk data from Esthwaite Water and see how it compares with the locally-optimised empirical algorithm. See Hunter et al. (2010) for further information.

Some useful references

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Dr Peter D. Hunter
University of Stirling