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Relating chlorophyll from cyanobacteria-dominated inland waters to a MERIS bloom index

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ABSTRACT

The cyanobacteria index (CI) has been applied to Medium Resolution Imaging Spectrometer (MERIS) imagery to characterize cyanobacterial biomass in diverse regions. While a consistent qualitative estimate of cyanobacterial biomass is useful, establishing universal relationships to chlorophyll a (chl) concentration, the dominant photosynthetic pigment in phytoplankton, would quantify blooms for regional comparisons. Relationships between chl concentrations were determined from water reflectance measurements and chl concentration from water samples taken from cyanobacterial blooms in eutrophic lakes in Florida, where chl ranged from 16 to 115 μg L^{-1}. When the chl relationship was applied to simultaneous satellite and field data, the chl concentration determined from satellite CI showed negligible bias and root mean square error of 27%. The generic CI-based chl algorithm presented here seems suitable for consistent quantification of chl concentration within cyanobacterial blooms.

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1. Introduction

Many coastal and freshwater ecosystems have exhibited the symptoms of cultural eutrophication over decades as a result of nutrient over-enrichment stemming from anthropogenic activities (Schindler 1974). The expansion of developed land acreage has imparted changes on sediment loading and nutrient delivery in watersheds, promoting algal blooms (Lunetta et al. 2015). Of the many types of phytoplankton that bloom in freshwater, cyanobacteria are typically the primary toxin producers (Backer 2002). Understanding spatio-temporal patterns in these blooms will aid in management strategies. A remote-sensing approach that provides synoptic imagery on higher frequency would help in screening water bodies for the occurrence of algal blooms.

A 10-year global data-set is available for the Medium Resolution Imaging Spectrometer (MERIS) sensor from April 2002 to April 2012, at 300 m resolution. Sentinel-3, the replacement mission that is expected to launch in 2015, will continue the capability into the future. An algorithm developed for MERIS, the cyanobacteria

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index (CI) (Wynne et al. 2010), uses a second-derivative computation based on reflectance in red and near-infrared wavelengths. This formulation is insensitive to most atmospheric contamination (Philpot 1991), making this algorithm highly effective for monitoring blooms in turbid water. The CI has been applied effectively to a monitoring programme for cyanobacterial blooms in Lake Erie (Wynne et al. 2010). In addition, the CI has been used to study bloom phenology in the Caspian Sea (Moradi 2014). Lunetta et al. (2015) showed that the Lake Erie relationship of CI to cell density could be used for estimating the cyanobacterium *Microcystis aeruginosa* concentrations in disparate lakes in the eastern United States. This indicates a consistent relationship between biomass and the CI, with potential global applicability. Several algorithms for estimating chlorophyll a (chl) concentration have been developed (see reviews by Kutser 2009; Matthews 2013). However, as the CI relationship was derived to estimate cell concentration (Wynne et al. 2010; Lunetta et al. 2015), the CI has only recently been applied for chl (Palmer et al. 2015b; Moradi 2014). While the CI has been applied to coastal and freshwater ecosystems on a regional scale, having an algorithm to scale CI values to chl concentration would allow for a larger inter-comparison of water bodies for management considerations. As such, the objective of this paper is to establish a relationship between the CI and chl concentration for a set of lakes, in Florida, where cyanobacteria dominate the biomass. To accomplish this, long-term *in situ* measurements for shallow stratified lakes in Florida were used to develop the chl relationships. This is a significant study area as toxic cyanobacterial blooms increasingly impact Florida's largest and most important inland waters, posing significant problems in water supplies.

2. Methods

2.1. *Remotely sensed data*

Full resolution (300 m) level 1b MERIS data were provided by NASA and processed with NASA's Sea-viewing Wide Field-of-view Sensor (SeaWiFS) Data Analysis System (SeaDAS) standard l2gen software using the 'rho_s' option (NASA 2015). The imagery was mapped to 300 m Universal Transverse Mercator with nearest neighbour sampling. The CI algorithm is used to compare with field estimates and has been defined by Wynne et al. (2010) using Equations (1) and (2). The spectral shape (SS) is defined as:

$$\mathrm{SS}(\lambda) = R(\lambda) - R(\lambda^-) + [R(\lambda^-) - R(\lambda^+)] \times \frac{(\lambda - \lambda^-)}{(\lambda^+ - \lambda^-)} \quad (1)$$

where R is the rho_s reflectance (which is dimensionless) at λ = 681 nm, λ^+ = 709 nm and λ- = 665 nm. CI is then calculated from the SS using

$$\mathrm{CI} = -\mathrm{SS}(\lambda) \quad (2)$$

where positive values of the CI indicate the presence of cyanobacteria.

2.2. *Field chl data*

Field chl data-sets collected from six Florida lakes and the St. Johns River were provided by Florida's LAKEWATCH programme and the St. Johns River Water Management District

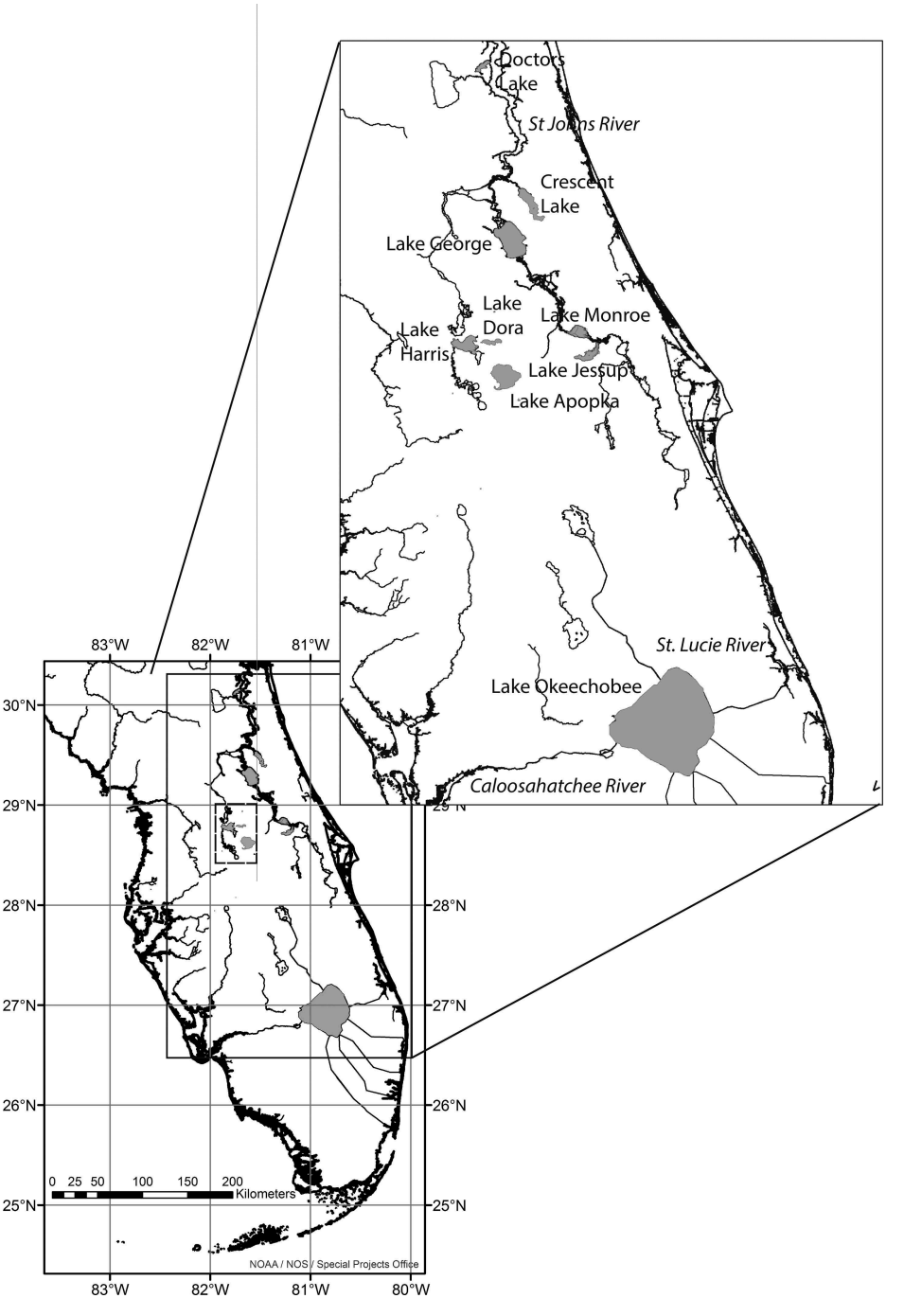

Figure 1. Map of Florida. Large solid box shows area of interest, with lakes for which data were collected. Smaller dashed box indicates region shown in Figure 4.

(SJRWMD) routine sampling programme. Monthly surface water samples from 2008 to 2012 were used to validate MERIS images encompassing 34 stations (Figure 1). Water samples were collected at 0.5 m in the Ocklawaha Basin region and as a 2.5-m depth

integrated sample for the lakes surrounding the St. Johns River. Up to 500 mL of sample water was filtered through a GE Healthcare – Whatman GF/C™ 47 mm Glass Microfiber (SJRWMD stations) or a EMD Millipore Glass Fiber Filters with a pore size of 0.7 µm (LAKEWATCH stations), and frozen until analysis. In the case of the LAKEWATCH data-set, uncorrected chl concentrations were calculated using the trichromatic equation for chl, Method 10200 H (Hoyer et al. 2012). For the SJRWMD data-set, chl was extracted by centrifugation (2700 rpm for 15 minutes) after filter maceration in 90% aqueous acetone. Extracts were analyzed with a Perkin Elmer UV/VIS Spectrophotometer at optical densities of 664, 647 and 630 before acid and 665 after acidification to determine total and corrected (phaeophytins removed) chl values. During the summer of 2011, the SJRWMD collected water samples and simultaneous above-water spectral radiance from the St. Johns River, Crescent Lake and Lake George (Figure 1).

2.3. *Field radiometry*

In Florida, radiance was measured at 1 nm resolution with an ASD FieldSpec radiometer. A calibrated 10% Spectralon plate was used for incident irradiance. Water and sky views were used at ~40° from vertical and at ~135° from the sun (Mobley 1999). Procedures by Gould, Arnone and Sydor (2001) were used to correct for sky and residual surface radiance and normalized for the incident irradiance to obtain remote sensing reflectance (R_{rs}) in units of sr^{-1}. The R_{rs} values were integrated to the 10-nm MERIS bandwidths using the sensor's spectral response functions, with the result multiplied by π steradians to match the (dimensionless) satellite rho_s reflectance.

2.4. *Satellite to field comparison*

The CI was calculated from MERIS data and compared with *in situ* chl concentration collected on the same day in Florida. A total of 500 same-day field to image matchups were analyzed. The same-day matchups used the average of the usable pixels in the 3 × 3 pixel block around the water sample location. Pixels flagged for clouds, land, mixed land/water and missing values were discarded. A criterion was added requiring that, for each station, the corresponding image needed at least six cloud-free pixels surrounding it to remove any artefacts missed by the cloud mask. Pixels next to land were not used in order to reduce interference from land adjacency. A root mean square error (RMSE) and relative RMSE were calculated for the CI chl calculated from satellite (chl_{CI}) vs. field chl (chl_{Fld}) where:

$$\text{RMSE} = \sqrt{\frac{\sum_{i=1}^{n} (X_i - X)^2}{n}} \tag{3}$$

$$\text{Relative RMSE} = \frac{\text{RMSE}}{\bar{X}_i} \times 100 \tag{4}$$

and X_i is the *in situ* concentration for the *i*th sample and X is the satellite-derived chl concentration, respectively, $\bar{X}$ is the sample mean and n is the sample size.

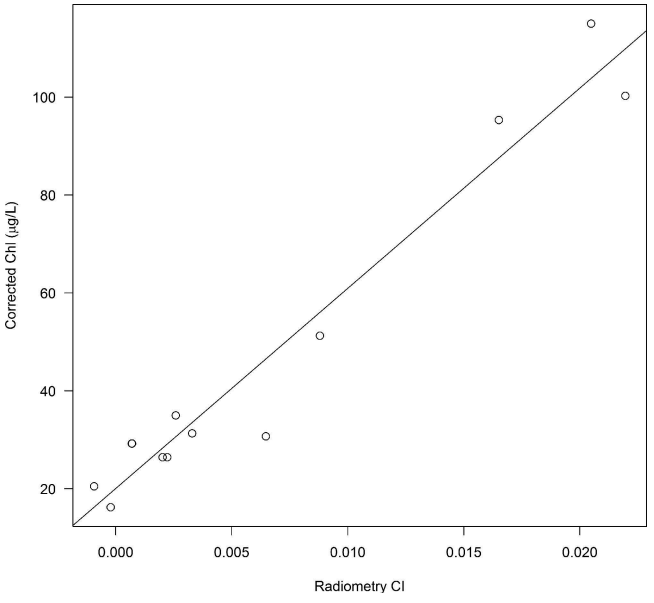

Figure 2. Relationship between chl concentration and the CI calculated using above water radiometry from sampling sites in the St. Johns River, Crescent Lake and Lake George.

3. Results

Linear regression between field chl and the CI from the field radiometry (Figure 2) gave the following empirical relationship:

$$chl = 4050(\pm 271) \times CI + 20(\pm 3) \tag{5}$$

with units of µg L^{-1} for chl. CI is dimensionless, and the standard errors in the coefficients are given by the values in brackets. The coefficient of determination (R^2) and the standard error of the estimate are 0.95 and 7.7 µg L^{-1}, respectively, for the CI and are robust for this data-set with chl concentration ranging from 16 to 115 µg L^{-1}.

The relationship of Equation (5) was applied to estimate chl concentration from the CI determined from historical MERIS images. Same day matchups of chl concentration estimated from satellite with field chl concentration from LAKEWATCH and SJRWMD were made. To avoid the use of a biased data-set, none of the SJRWMD data used to develop the relationship with the radiometry (Equation (5)) were used in the same day matchup analysis. As shown in Figure 3, the chl_{CI}: chl_{Fld} from Florida followed the 1:1 line, with a bias of only 3 µg L^{-1}. The RMSE for chl_{CI}: chl_{Fld} was 15 µg L^{-1}, with relative RMSE = 27%.

4. Discussion

The chl_{CI} seems to satisfactorily represent chl concentration for the Florida lakes analyzed in this study (Figures 1 and 3). The set of lakes evaluated here have a large range (order of magnitude) in chlorophyll and water clarity (Fulton and Smith 2008) (Figure 4).

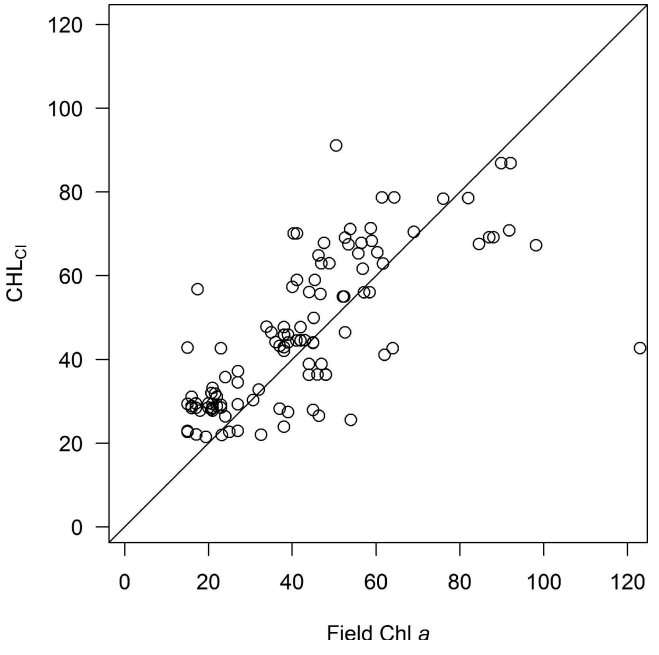

Figure 3. Comparison between field collected chl with satellite derived chl (extracted within a 3 × 3 pixel area surrounding the field measurement) calculated from satellite derived $CHL_{CI.}$

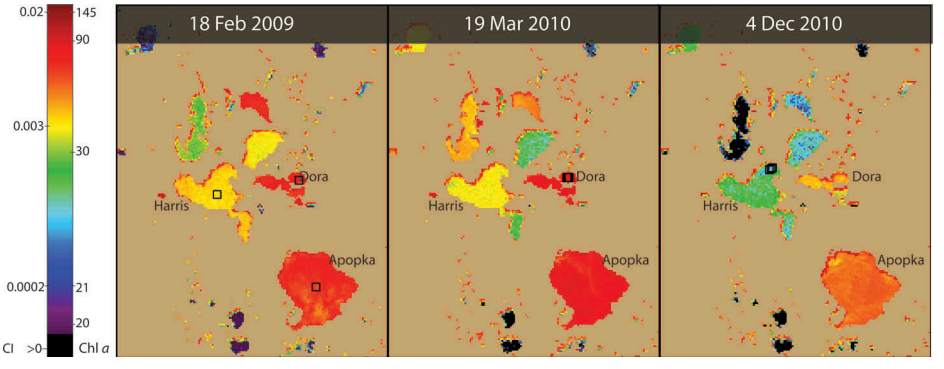

Figure 4. Example full-resolution MERIS CI images for Florida showing the location of blooms and associated CI imagery scaled to that of the chl_{CI} (μg L^{-1}). Area shown is indicated by dashed box in Figure 1.

Therefore, the low bias and RMSE observed with the chl_{CI}: chl_{Fld} relationship when used to quantify chl concentration in cyanobacterial blooms in lakes with varying conditions may indicate a wider applicability of the algorithm. Future application of this relationship will determine whether regional tuning is necessary. With the available field data (16 to 115 μg L^{-1}), we cannot confirm the use of this relationship below 16 μg L^{-1} chl; however, a threshold of 10 μg L^{-1} was indicated by Palmer et al. (2015a).

When compared with other phytoplankton, the absorption overwhelms the fluorescence signature in cyanobacteria due to a variety of factors. Cyanobacteria have most of

their chl in non-fluorescing photosystem I; conversely, most of the chl in algae is in fluorescing photosystem II (Seppälä et al. 2007). In addition, fluoresced light can be reabsorbed by adjacent cells in dense bloom conditions (Huot, Brown, and Cullen 2005). Finally, cyanobacteria have higher scattering owing to their small cell size, which overwhelms the fluorescence signature, and the presence of gas vacuoles in some species (including *Microcystis* spp.) may exacerbate this phenomenon (Wynne et al. 2010). As a result, the CI is quite effective for measuring the chlorophyll associated with cyanobacteria. While MERIS had a 620-nm band that coincides with phycocyanin absorption peak at 620 nm, using phycocyanin to estimate total cyanobacterial biomass (vs. presence) can be challenging. The cell content of phycobilins varies with nutrients and light availability (Tandeau de Marsac 2003), and the chlorophylls also absorb 620-nm light, requiring additional corrections to phycocyanin algorithms (Simis et al. 2007). Lunetta et al. (2015) and Matthews and Odermatt (2015) use phycocyanin (620 nm) only as an indicator of presence.

Palmer et al. (2015b) found a relationship between SS(681) based on radiance and chlorophyll in order to examine the phenology of blooms in Lake Balaton, Hungary. However, a radiance-based calibration cannot be examined for potential utility at other latitudes and seasons as the magnitude of the SS(681) will change with sun angle.

The large variability in the matchups between satellite and field data is an inherent problem with cyanobacterial blooms. Kutser (2009) described the large spatial variability within a pixel in cyanobacterial blooms. Sometimes, the variability applies even around a vessel, leading to large differences between satellite and water sample comparisons. Much of the RMSE of the satellite/field matchups (Figure 3) probably results from this problem of spatial variability. Lunetta et al. (2015) confirmed that a relationship between CI and cyanobacteria cell counts applies to lakes in several regions of the United States. This result indicates that a stable relationship between CI and cyanobacteria biomass is likely. Therefore, the relationship between CI and chl_{Fld} established in this study may be widely applicable. Further validation will confirm the stability of the relationship; however, the CI can be used for monitoring of large lake regions for water quality and climate analyses on a larger spatial scale. Recent results from Moradi (2014) and Palmer et al. (2015b) demonstrate this potential.

As this study has shown, the CI algorithm used to track cyanobacterial blooms in Lake Erie can quantify blooms in Florida lakes. The quantification of cyanobacteria biomass, as it relates to chl concentration, is reasonable for this region and may better guide managers and researchers as they use the CI products (Wynne et al. 2010; Lunetta et al. 2015). Future work will determine the wider applicability of the CI to chl relationship to blooms in lakes on a more global scale. Larger-scale studies will also be appropriate to evaluate the stability and relative merits of the CI against other operational algorithms for cyanobacteria (such as the MPH, Matthews and Odermatt 2015) with minimal regional tuning.

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Disclosure statement

No potential conflict of interest was reported by the authors.

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