Talanta 147 (2016) 422–429

Contents lists available at ScienceDirect

Talanta

journal homepage: www.elsevier.com/locate/talanta

# Estimation of chlorophyll-a concentration of different seasons in outdoor ponds using hyperspectral imaging

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ARTICLE INFO

*Article history:*
Received 1 July 2015
Received in revised form
4 September 2015
Accepted 7 September 2015
Available online 14 September 2015

*Keywords:*
Chlorophyll-a concentration
Seasons
Outdoor aquaculture
Hyperspectral imaging

ABSTRACT

Chlorophyll a (Chl-a) is regarded as one of the important components to estimate water quality and sustainability of freshwater aquaculture operations. In the current study, a hyperspectral imaging (HSI) system was used to determine the effect of season models on the accuracy of Chl-a estimation in outdoor aquaculture ponds. A visible and near infrared hyperspectral imaging system (400–1000 nm) was used to measure surface spectral reflectance (*R*) of water collected from outdoor ponds in four different seasons. Firstly, values of surface spectral reflectance (*R*) were amplified by a baseline correction (740 nm). Two-band, three-band and four-band spectral reflectance were used to compute Chl-a concentration and a new cross band ratio algorithm with six wavelengths was proposed in the study. Results indicated that two-band model established based on reflectance ratio ($R_{702}/R_{666}$) had better performances for Chl-a prediction with determination coefficients ($r^2$) of 0.908 than those by ($R_{675}^{-1}-R_{691}^{-1})^*R_{743}$ and ($R_{675}^{-1}-R_{691}^{-1})/(R_{743}^{-1}-R_{691}^{-1})$ models with $r^2$ of 0.902 and 0.896, respectively. Six optimal wavelengths (410, 682, 691, 966, 972, and 997) were identified using successive projections algorithm (SPA). The optimized regression model ($R_{410}^{-1}-R_{966}^{-1})/(R_{682}^{-1}-R_{972}^{-1})/(R_{691}^{-1}-R_{997}^{-1})$ showed best result with $r^2$ of 0.961 for Chl-a prediction. Model of cross band ratio algorithm with six wavelengths was mapped to each pixel in the image to display Chl-a component in outdoor ponds under four different seasons. The current study showed that it was feasible to use the HSI system for monitoring the influence of seasons for outdoor aquaculture water quality.



## 1. Introduction

Chlorophyll-a (Chl-a) is a main green photosynthetic pigment found in plants trapping sunlight for photosynthesis, of which the concentration in the aquaculture water is an important and effective indicator for water quality evaluation, water pollution prevention [1] and nutrient availability index evaluation such as phytoplankton abundance and biomass [2]. It is normally believed that Chl-a concentration with low levels suggests good condition while long-term persistence of high levels is a problem [3]. With the development of aquaculture, the monitoring and maintenance of Chl-a concentration in water bodies have become more and more important. However, traditional laboratory analysis of Chl-a concentration is complicated, lengthy, expensive and difficult for in situ application. In addition, the measured result is unreliable because of the optical complexity of water [4].

Recently, remote sensing has become a very valuable and virtually indispensable tool for aquaculture water quality monitoring and forecasting [5,6]. As the optical information of Chl-a can be detected by satellite [7,8], remote sensing has been successfully implemented in the application of Chl-a concentration as a convenient, rapid and low cost method in the past decade [9,10]. However, the accuracy of the extracted information of obtained satellite images was reduced and not robust due to the coarse spatial resolution and the limited range of the spectrum. Fortunately, several attempts have been made to improve the coarse spatial resolution of images using higher resolution images [11,12] and different kinds of spectrometers [13–16]. Although these attempts achieved improvement compared to the multi-spectral images, there have also been many problems in estimating freshwater aquaculture water quality, which is non-uniform. Therefore many researchers focused on using new methods to solve these problems with two-band reflectance model [17,18], three-band reflectance model [17] and four-band reflectance model [19].

Although the above researches about remote sensing have

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http://dx.doi.org/10.1016/j.talanta.2015.09.018
0039-9140/

solved some problems, the bands chosen to estimate Chl-a vary differently because of several factors, such as phytoplankton taxonomic composition, illumination conditions and nutritional status. Moreover, the biggest application problem is the uncertainty of modeling bands. In addition, in situ sampling is costly and not suitable for the day-to-day monitoring of a small-scale operation. Hyperspectral imaging (HSI) technology, which is an integration of computer vision [50–53] and spectroscopic techniques and has been investigated for many applications [54–62], is a good solution to some of the above problems. With the development of HSI technology, there have been many studies about measuring the spectral reflectance of low Chl-a concentration in different inland water bodies using in situ spectroradiometric measurements [20]. Abd-Elrahman et al. determined Chl-a concentrations in working aquaculture ponds by a ground-based HSI sensor with coefficient of determination ($r^2$) values of 0.833 and 0.862 for the two-band and three-band models, respectively [21]. Recently, Cheng et al. estimated Chl-a concentration in pond water and Taihu lake in China using a similar field system by developing models with separating spectra based on Gaussian parameters with $r^2$ values of 0.78 and root mean square errors (RMSE) of 4.80 mg/m$^3$ [22]. However, all these research works were in working aquaculture ponds, and the applied HSI sensors were expensive and accuracy of measurement was relatively low. Therefore, development of a laboratory-based hyperspectral imaging could be an alternative solution to the above problems. It should be noticed that Chl-a concentration in laboratory condition water samples should be homogeneous and therefore spectroscopic technique alone should be well sufficient for completing the analysis, however, aquaculture ponds are different and the water is actually non-uniform and heterogeneous. In addition, natural influence such as geographical location, precipitation and temperature, as well as sunshine can also cause the heterogeneity of Chl-a concentration in the ponds. As the result, it would be not feasible to use the spectroscopy technique alone to measure Chl-a concentration. To our best knowledge, no researches of Chl-a measurement using laboratory-based hyperspectral imaging have been reported. Therefore, in this study, the main objective was to analyze the feasibility of laboratory-based HSI technique for Chl-a concentration prediction and mapping in outdoor ponds of different seasons. The specific objectives of the current study were to (1) establish a satisfactory approach to extract spectral data from hyperspectral images of water samples acquired in the visible range (400–1000 nm); (2) apply the baseline correction to improve the robustness of prediction models; (3) build prediction models with two-band, three-band and four-band algorithms; (4) identify the most significant wavelengths linked to Chl-a predictions by successive projections algorithm (SPA); (5) build new quantitative prediction model with the selected important wavelengths, and (6) apply the optimal wavelengths model to hypercubes to obtain distribution maps depicting the variation of Chl-a within water samples from four different seasons.

## 2. Materials and methods

The experimental procedure consisted of seven main steps, including taking water samples, acquiring hyperspectral image, measuring Chl-a by traditional methods, processing acquired hyperspectral image, extracting spectral information, developing two-band, three-band and four-band models, building prediction model with the selected important wavelengths and obtaining Chl-a distribution map.

**Table 1**
Chl-a concentrations in four different seasons as measured by a traditional spectrophotometer.

| Season models | Samples number | Chl-a range, μg/L |
|---|---|---|
| Winter | 100 | 1.119–32.216 |
| Spring | 100 | 28.097–53.360 |
| Summer | 100 | 100.162–196.403 |
| Autumn | 100 | 49.241–83.933 |

### 2.1. Sample preparation and measurement of Chl-a

Water samples were obtained from outdoor ponds in Freshwater Fish Seed Breeding Center, Guangzhou, China on the 15th of every month from December 2013 to November 2014. In total about 120 water samples obtained from December 2013 to February 2014, from March 2014 to May 2014, from June 2014 to August 2014, and from September 2014 to November 2014 were collected as winter, spring, summer and autumn samples, respectively. At last, a total of 400 water samples from all 480 samples were selected with 100 repeats for each different season. Water samples (surface water) were taken in high density polyethylene flasks (500 mL) and covered with aluminum foil paper and were transported to the laboratory. Firstly, Chl-a concentrations (μg/L) were determined by traditional spectrophotometer method with extracting pigment after dissolving in the 90% ethanol for overnight [23]. The results are shown in Table 1, indicating Chl-a concentrations across four seasons being 1.119–32.216 μg/L, 28.097–53.360 μg/L, 100.162–196.403 μg/L, and 49.241–83.933 μg/L for winter, spring, summer and autumn, respectively.

### 2.2. Hyperspectral imaging system

In the current study, the hyperspectral images of water samples were acquired by a line-scanning visible and near infrared hyperspectral imaging system. The details of the system were the same as described previously [24]. The system was made up of hardware components and data acquisition software. The hardware mainly consisted of an imaging spectrograph (Imspector V10E, Spectral Imaging Ltd., Oulu, Finland), a visible spectral camera (DL-604M, Andor, Ireland), a camera lens (OLE23, Schneider, German), and two 150-W lamps (3900-ER, Illumi-nation Technologies Inc., New York, USA) and a mobile platform operated by a stepper motor (IRCP0076-1COMB; Isuzu Optics Corp., Taiwan, China). The spectral ranges before 400 nm and after 1000 nm included a large amount of noise and thus were discarded, therefore the final spectral range selected was between 400 nm and 1000 nm with a total of 381 bands (1.57 nm spectral increment between two contiguous bands). Because of high reflectance of water surface, the exposure time was adjusted to just 20 ms and the speed of conveyer belt was fixed at 1.4 mm s$^{-1}$ in order to avoid distortion of images.

### 2.3. Image processing and spectral data extraction

Before obtaining hyperspectral images by scanning line by line, the transparent water samples were shaken well and poured into a transparent rectangle-shaped container (4 cm × 3 cm × 7 cm), which was placed on the conveyer belt and then moved to the center under camera (Fig. 1). A total of 100 multi-sample hyperspectral images were scanned with four water samples in every image simultaneously. A series of image processing steps for the obtained images were taken before developing prediction models, which included image corrections to obtain relative reflectance images, image segmentation and identification of region of