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Application of spectral decomposition algorithm for mapping water quality in a turbid lake (Lake Kasumigaura, Japan) from Landsat TM data

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ABSTRACT

The remote sensing of Case 2 water has been far less successful than that of Case 1 water, due mainly to the complex interactions among optically active substances (e.g., phytoplankton, suspended sediments, colored dissolved organic matter, and water) in the former. To address this problem, we developed a spectral decomposition algorithm (SDA), based on a spectral linear mixture modeling approach. Through a tank experiment, we found that the SDA-based models were superior to conventional empirical models (e.g. using single band, band ratio, or arithmetic calculation of band) for accurate estimates of water quality parameters. In this paper, we develop a method for applying the SDA to Landsat-5 TM data on Lake Kasumigaura, a eutrophic lake in Japan characterized by high concentrations of suspended sediment, for mapping chlorophyll-a (Chl-a) and non-phytoplankton suspended sediment (NPSS) distributions. The results show that the SDA-based estimation model can be obtained by a tank experiment. Moreover, by combining this estimation model with satellite-SRSs (standard reflectance spectra: i.e., spectral end-members) derived from bio-optical modeling, we can directly apply the model to a satellite image. The same SDA-based estimation model for Chl-a concentration was applied to two Landsat-5 TM images, one acquired in April 1994 and the other in February 2006. The average Chl-a estimation error between the two was 9.9%, a result that indicates the potential robustness of the SDA-based estimation model. The average estimation error of NPSS concentration from the 2006 Landsat-5 TM image was 15.9%. The key point for successfully applying the SDA-based estimation model to satellite data is the method used to obtain a suitable satellite-SRS for each end-member.

1. Introduction

Lakes play important roles as freshwater resources for drinking water, agriculture, industry, fishing, recreation, and tourism (Giardino et al., 2001). However, accelerated eutrophication is a widespread and significant problem for lakes around the world (Jorgensen and Vollenweider, 1988; Ayres et al., 1996), and human activity has been found to be the source of this polluting process (Petrova, 1990). Therefore, an effective and convenient technique is needed for long-term monitoring of water quality in lakes.

Besides being time-consuming and expensive, conventional methods of studying water quality (e.g. water sampling by boat) frequently fail to adequately represent heterogeneous and patchy areas (Khorram et al., 1991; Liu et al., 2003). Remote sensing techniques, which have the inherent ability to provide spatial and temporal information about water, may be the only viable way to effectively monitor water quality in lakes. Even though some oceanic observation satellite sensors such as CZCS (Coastal Zone Color Scanner) and SeaWiFS (Sea-viewing Wide Field Sensor) have been designed to measure water-leaving radiance related to water quality, these datasets cannot provide detailed information about the spatial distribution of water quality in lakes. They are almost always at a small- or meso-scale, because of their coarse spatial resolution, about 1 km. Instead, terrestrial observation satellites with moderate spatial resolutions such as LANDSAT, SPOT and IRS are used for monitoring water quality in lakes (Liu et al., 2003).

Since the 1970s, many researchers have attempted to develop a robust algorithm for monitoring lake water quality from satellite data, especially for estimating chlorophyll-a (Chl-a) concentrations (e.g., using Landsat TM or ETM+data: (Dwivedi and Narain, 1987; Dekker and Peters, 1993; Mayo et al., 1995; Östlund et al., 2001; Han and Jordan, 2005). Using SPOT HVR data: (Chacon-Torres et al., 1992; Cairns et al., 1997; Dekker et al., 2002). Using NOAA AVHRR data: (Carrick et al., 1994; Bolgrien et al., 1995). Using IRS-1C LISS-III data: (Thiemann and Kaufmann, 2000). However, most of these estimation models are site- and time-specific. In addition,

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some studies have shown that Chl-a concentrations cannot be estimated using broadband satellite sensors if the water body has a high concentration of suspended sediment (Miyazaki et al., 1987; Lindell et al., 1999; Svab et al., 2005). This is because most lakes are classified as Case 2 water (water containing not only phytoplankton, but also suspended sediment, dissolved organic matter, and anthropogenic substances; (Morel and Prieur, 1977) in which concentrations of other optically active substances (OASs) are not correlated with Chl-a concentration and have complex interactions with them. For example, the presence of high levels of suspended sediment masks the spectral feature of Chl-a (Lindell et al., 1999; Svab et al., 2005).

An empirical calibration approach, based on a linear or nonlinear regression analysis needs simultaneously or quasi-simultaneously acquired reference observations to relate to the radiances observed by satellite sensors (Molo et al., 1989; Lathrop, 1992). Thus, there exist several limitations to the practical application of the approach. For example, since satellite data contain information not only on concentrations of OASs in a water body, but also on the components in the water body (e.g. species and the proportion of each component), estimation models depend on both. Therefore, it is difficult to obtain an identical estimation model in different lakes or during different periods in the same lake when satellite data (band ratio or arithmetic calculation of bands) are directly used as independent variables in the model (Liu et al., 2003). With these site- and time-specific estimation models, it is impossible to monitor water quality in other lakes that are bio-optically different, and where no reference observations are acquired concurrently with a satellite overpass. Therefore, it is desirable to have a robust model that can be used in most types of water.

To address these problems, several approaches based on spectral mixture modeling were recently proposed (Svab et al., 2005; Tyler et al., 2006; Novo et al., 2006; Oyama et al., 2007). For example, Svab et al. (2005) demonstrated that shallow lake water can be characterized by spectrally unique end-members, using principal component analysis (PCA). Their results indicated that a spectral linear mixture modeling approach combined with multivariate regression analysis can be used to estimate Chl-a concentrations independently of suspended sediment concentrations. Tyler et al. (2006) applied Svab et al.'s (2005) findings to Landsat TM data to quantify phytoplankton in Lake Balaton, Europe's largest shallow lake, which is characterized by high levels of suspended sediments. The modeled image-derived results of Chl-a in September 2000 demonstrated an excellent correspondence ($R^2 = 0.95$) with ground-based measurements. Moreover, this estimation model was then successfully applied to a July 1994 Landsat TM image, demonstrating the model's temporal stability and robustness. Similar to those two studies, Oyama et al. (2007) developed another new algorithm, called the spectral decomposition algorithm (SDA) for estimating Chl-a concentrations from multispectral satellite data in Case 2 water. They also considered the mixed reflectance spectrum of a given pixel as a linear combination of three basic components, i.e. clear water, non-phytoplankton suspended sediments (NPSS), and phytoplankton as represented by the environmental conditions of Lake Kasumigaura, Japan. These are the same as the end-members used in Svab et al. (2005) and Tyler et al. (2006). However, the use of only the corresponding end-member's decomposition coefficient (similar to the end-member relative abundance in Tyler et al. (2006) as the independent variable of the regressive estimation model, is different from the use of all end-member relative abundances for obtaining an estimation model based on multivariate regression analysis in Svab et al. (2005) and Tyler et al. (2006). Oyama et al. (2007), found that the SDA-based estimation model can be prepared based on a tank experiment because its independent variable (decomposition coefficient C) contains only information on the concentration of the corresponding end-member, and this concentration is not related to the size of the tank. Their results also showed that the SDA-based estimation model can potentially be applied to different Landsat TM images if the lake is dominated by the same phytoplankton and NPSS (Oyama et al., 2007). However, these findings have not been validated by satellite images.

Therefore, the objectives of this research are as follows: (1) to test the applicability of the SDA-based estimation model obtained from a tank experiment to a satellite image, (2) to show the potential possibility of using a bio-optical model to determine the three SRSs of end-members for satellite images, and (3) to demonstrate the potential robustness of the SDA-based estimation model with different Landsat-5 TM images of Lake Kasumigaura, Japan.

2. Study area

Lake Kasumigaura is located in the eastern part of Japan's Kanto Plain. With a surface area of 171 km^2 and an average depth of 4 m (maximum depth of 7.3 m), it is the second largest lake in Japan after Lake Biwa. The lake is considered eutrophic, because it has a high load of nutrients, and because of its shallow depth (Fukushima et al., 1996). Although the average Chl-a concentration decreased from 87 to 61 μg l^{-1} during the last three decades, the mean total phosphorus concentration increased from 116 to 138 μg l^{-1}. Secchi disk depth decreased from 70 to 52 cm during the last two decades (CGER, 2006). Total suspended sediment (TSS) concentrations increased from 14.1 to 26.4 mg l^{-1} during the last decade, due mainly to the resuspension of bottom sediments (Fukushima et al., 2005). Diatoms (e.g., *Cyclotella sp.* or *Synedra sp.*) are generally observed during winter, spring, and autumn, while harmful blooms (blue green algae, e.g., *Microcystis sp.* or *Anabaena sp.*) are sometime observed during summer. The concentration of dissolved organic carbon (DOC), which is often correlated with CDOM concentration, is always low (2.9–4.2 mg l^{-1}, (Fukushima et al., 1996; Imai et al., 2003)) compared with other lakes such as Lake Taihu (8.8–20.2 mg l^{-1} in Zhang et al. (2005)) and Finnish lakes (6.0–12.3 mg l^{-1} in Kutser et al. (2005)). The absorption coefficients of CDOM at 420 nm ranged from 0.5 to 0.6 m^{-1} when DOC concentrations ranged from 1.9 to 2.7 mg l^{-1} (CGER, 2006), which was lower than the absorption coefficients of CDOM at 420 nm in Finnish lakes (1.7–7.7 m^{-1} in Kutser et al. (2005)).

3. Materials

3.1. Satellite data

Two Landsat-5 TM images (path: 107/row: 35) were acquired; one on February 18, 2006 and the other on April 22, 1994. Weather conditions during the image acquisitions included cloudless skies over the lake and low wind speeds (approximately 2.0 m s^{-1} in 1994 (Oki and Yasuoka, 1996) and almost 0 m s^{-1} in 2006).

3.2. Field data

Field work in 2006 was timed to coincide with the acquisition of the Landsat image. Water samples were collected at 25 sampling stations in Lake Kasumigaura on February 18, 2006 within 1.5 h of the satellite overpass (Fig. 1). The locations of the sampling stations were identified using the global positioning system (GPS) installed on eTrex Vista (Garmin, Olathe, KS, USA), with a positional error of less than 5.0 m. Water samples were directly collected from the water surface (0.2 m depth) using 4.0 l polycarbonate bottles at each station. From each bottle, a 100 ml sub-sample was immediately transferred to another bottle to which 5.0 ml of a glutaraldehyde solution (20% concentration) was added to fix the phytoplankton for their later identification, using a