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Estimating the biomass of unevenly distributed aquatic vegetation in a lake using the normalized water-adjusted vegetation index and scale transformation method

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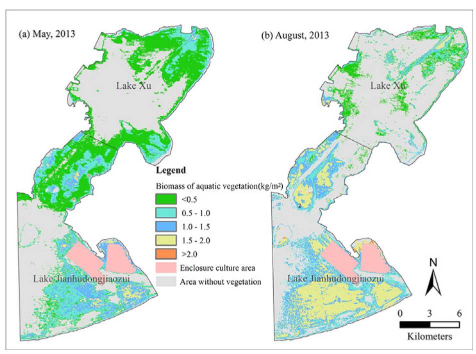
HIGHLIGHTS

- Remote sensing models for estimating biomass of aquatic vegetation were developed.
- A new normalized water-adjusted vegetation index was established.
- A new field biomass scale transformation method was proposed.
- The proposed modeling scheme had a high accuracy in biomass estimation of aquatic vegetation.

GRAPHICAL ABSTRACT



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ABSTRACT

Satellite remote sensing is advantageous for the mapping and monitoring of aquatic vegetation biomass at large spatial scales. We proposed a scale transformation (CT) method of converting the field sampling-site biomass from the quadrat to pixel scale and a new normalized water-adjusted vegetation index (NWAVI) based on remotely sensed imagery for the biomass estimation of aquatic vegetation (excluding emergent vegetation). We used a modeling approach based on the proposed CT method and NWAVI as well as statistical analyses including linear, quadratic, logarithmic, cubic, exponential, inverse and power regression to estimate the aquatic vegetation biomass, and we evaluated the performance of the biomass estimation. We mapped the spatial distribution and temporal change of the aquatic vegetation biomass using a geographic information system in a test lake in different months.

The exponential regression models based on CT and the NWAVI had optimal adjusted R^2, F and Sig. values in both May and August 2013. The scatter plots of the observed versus the predicted biomass showed that most of the validated field sites were near the 1:1 line. The RMSE, ARE and RE values were small. The spatial distribution and change of the aquatic vegetation biomass in the study area showed clear variability.

Among the NWAVI-based and other vegetation index-based models, the CT and NWAVI-based models had the largest adjusted R^2, F and the smallest ARE values in both tests. The proposed modeling scheme is effective for the biomass estimation of aquatic vegetation in lakes. It indicated that the proposed method can provide a most accurate spatial distribution map of aquatic vegetation biomass for lake ecological management. More accurate biomass maps of aquatic vegetation are essential for implementing conservation policy and for reducing uncertainties in our understanding of the lake carbon cycle.

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1. Introduction

There are 304 million natural lakes with an area greater than or equal to 0.1 ha on all continents. These natural lakes cover more than 2.8% of the land surface, not including temporary water bodies and wetlands (Downing and Duarte, 2009). Aquatic vegetation is an essential element in the life systems of most lakes and performs a number of useful functions in maintaining the productivity (Brothers et al., 2013) and biogeochemical cycles (Carpenter and Lodge, 1986) in lakes. It has been reported that macrophytes provide microhabitats for zooplankton (e.g., space and food resources, yielding positive relationships with zooplankton diversity) and that microhabitat structure determines the diversity and abundance of zooplankton communities (i.e., dry weight, species number, and plant type) (Folt and Burns, 1999; Padial et al., 2009; Choi et al., 2014). Macrophytes also provide habitat areas for aquatic insects, fish, and other resident aquatic and semiaquatic organisms and provide structure and food for mammals, birds, reptiles, and amphibians. Aquatic macrophytes can stabilize clear water conditions in shallow lakes (Scheffer et al., 1993; Hilt et al., 2011). Aquatic plants reduce the resuspension of sediment particles (Barko and James, 1998; Vermaat et al., 2000), the water turbidity (Sachse et al., 2014), the light availability for phytoplankton (Pokorný et al., 1984), the phosphorus and the nitrogen (Zuo et al., 2015). In addition, aquatic vegetation serves to anchor soft sediments, stabilize underwater slopes and soft lake bottoms and minimize shoreline erosion by dampening the effect of waves; macrophyte uptake from the interstitial waters is responsible for a significant loss of phosphorus from the sediment (Gudimov et al., 2015). Aquatic vegetation produces and stores significant amounts of carbon as biomass (Means et al., 2016) and represents a major component of the carbon balance due to its fast growth rates and high productivity (Piedade et al., 1991; Costa, 2005; Engle et al., 2008; Silva et al., 2009, 2010). All of these factors emphasize the importance of a healthy, natural aquatic plant community.

Information on the areal biomass and distribution of aquatic vegetation is necessary for the monitoring, management and understanding of lake aquatic ecosystems (Vis et al., 2003). However, determining the properties of aquatic plants such as biomass is difficult at both small and large spatial scales because of the spatial heterogeneity of aquatic plant communities (Duarte and Kalff, 1990; Vis et al., 2003; Silva et al., 2008). Traditional field-based mapping and monitoring of aquatic vegetation biomass at large spatial extents presents several challenges, including the inaccessibility of some areas for field sampling; rapid changes in aquatic plant location, extent, and density; and high costs and travel time. Furthermore, such mapping and monitoring is labor intensive and destructive to sensitive lake ecosystems (Zhang et al., 1997; Jakubauskas et al., 2002), resulting in reduced sampling effort and/or incomplete data sets with limited spatial and temporal coverage (Vis et al., 2003). Given these limitations, biomass estimation through satellite remote sensing is a feasible alternative (Costa, 2005; Silva et al., 2010; Goetz and Dubayah, 2011; Byrd et al., 2014). Remote-sensing methods offer the ability to continuously monitor growth and phenology on the same individuals and can reduce the effort involved in biomass harvesting, but these methods depend on strong relationships between the predictor variables and plant biomass (Armstrong, 1993; Peñuelas et al., 1993; Daoust and Childers, 1998; Zhang, 1998; Silva et al., 2010). Estimating the biomass of aquatic vegetation using remote sensing and statistical regression involves two important parameters: the biomass values of the field sampling-site quadrats and the spectral data. These two parameters directly determine the accuracy and precision of the biomass estimation of aquatic vegetation obtained through satellite remote sensing. Due to the large spatial heterogeneity and uneven distribution of aquatic vegetation in lakes, areas of continuous and uniformly distributed aquatic vegetation that are 30 × 30 m or larger are uncommonly found in field investigations. Thus, the biomass values of field sampling-site quadrats cannot be regarded as identical to those of field sampling-site pixels. If the biomass values of field sampling-site quadrats were directly used to build a model, serious errors or large deviations would result in the biomass estimation based on remote sensing. Therefore, it is necessary to apply a scale transformation to the biomass values of the field sampling-site quadrats before building a statistical model of biomass based on remote sensing. The other parameter used for biomass estimation is the spectral data of the remote-sensing imagery, which mainly include the bands or band combinations (ratios, indices) (Armstrong, 1993; Peñuelas et al., 1993; Zhang, 1998; Silva et al., 2008). To date, published studies (e.g., Peñuelas et al., 1993; Zhang, 1998; Payton, 2001; Schweizer et al., 2005; Ma et al., 2008; Robles, 2009; Byrd et al., 2014; Massicotte et al., 2015) on the use of vegetation indices to estimate the biomass of aquatic vegetation are limited to the normalized difference vegetation index (NDVI), the enhanced vegetation index (EVI), and the normalized difference green index (NDGI). However, these vegetation indices were established mainly for terrestrial vegetation, and the question remains as to whether a new aquatic vegetation index can be established that is more suitable for the remote-sensing estimation of aquatic vegetation biomass in lakes.

The remote-sensing estimation of aquatic vegetation biomass in lakes remains rare, and few studies have used scale transformation and the aquatic vegetation index in the remote-sensing estimation of aquatic vegetation (including floating-leaf and submergent vegetation and excluding emergent vegetation, as described below) biomass in a lake. In the following, we proposed a scale transformation (CT) method of converting field sampling-site biomass from the quadrat to the pixel scale for remote-sensing biomass estimation and a new normalized water-adjusted vegetation index (NWAVI) based on remote-sensed imagery for the biomass estimation of aquatic vegetation. Then, we tested whether it was possible to estimate the biomass of aquatic vegetation in a lake using the proposed CT- and NWAVI-based method and evaluated the performance of the biomass estimation. Finally, we mapped the spatial distribution and temporal change of the aquatic vegetation biomass in a test lake in different months.

2. Materials and methods

2.1. Study area

Lake Taihu, the third largest freshwater lake in China, is located in the south of Jiangsu Province, China (119°53′49″–120°35′25″E and 30°55′32″–31°32′50″N) (Fig. 1). It has a surface area of 2338 km^2 and average and maximum water depths of 1.89 m and 2.6 m, respectively. Before the 1960s, Lake Taihu had a large area of aquatic vegetation (Nanjing Institute of Geography, Chinese Academy of Sciences, 1965). According to recent field surveys, the distribution of aquatic vegetation was widest for submerged vegetation, followed by floating-leaf vegetation and finally, emergent vegetation; the distributions and biomass were greatest at the end of the summer for all of the vegetation types (Yang, 1998; He et al., 2008). Field surveys have also indicated significant changes in the distribution of aquatic vegetation during the past decades (Zhao et al., 2012). Currently, the aquatic vegetation is mainly distributed in Lake Xu, Lake Jianhudongjiaozui, Lake Gong and East Lake Taihu. Our study area covers the entire Lake Xu and the entire Lake Jianhudongjiaozui, they are parts of Lake Taihu and lies in the southeast of Lake Taihu (Fig. 1).

2.2. Field measurements

In this study, a total of sixty-one field sampling sites were established as shown in Fig. 1. Among them, thirty-five ground-truth samples were obtained in May 2013 and twenty-six were obtained in August 2013. Each sampling site was geographically located using a Global Positioning System device with 3–6 m of precision. The aquatic vegetation was collected using plant clips developed by the Taihu Laboratory for Lake Ecosystem Research, Nanjing Institute of Geography and Limnology, Chinese Academy of Sciences, the size of a single sample