5-2020

Evaluating the Influences of Harvesting Activity and Eutrophication on Loss of Aquatic Vegetations in Taihu Lake, China

Juhua Luo
University of South Florida

Ruiliang Pu
University of South Florida, rpu@usf.edu

Hongtao Duan
Chinese Academy of Sciences

Ronghua Ma
Chinese Academy of Sciences

Zhigang Mao
Chinese Academy of Sciences

See next page for additional authors

Authors

Juhua Luo, Ruiliang Pu, Hongtao Duan, Ronghua Ma, Zhigang Mao, Yuan Zeng, Linsheng Huang, and Qitao Xiao

Int J Appl Earth Obs Geoinformation 87 (2020) 102038

Contents lists available at ScienceDirect

Int J Appl Earth Obs Geoinformation

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

Evaluating the influences of harvesting activity and eutrophication on loss of aquatic vegetations in Taihu Lake, China

Juhua Luo[a,b], Ruiliang Pu[b], Hongtao Duan[a,*], Ronghua Ma[a], Zhigang Mao[a], Yuan Zeng[c], Linsheng Huang[d], Qitao Xiao[a]

[a] Key Laboratory of Watershed Geographic Sciences, Nanjing Institute of Geography and Limnology, Chinese Academy of Sciences, Nanjing, 210008, China
[b] School of Geosciences, University of South Florida, Tampa, FL 33620, USA
[c] State Key Laboratory of Remote Sensing Science, Aerospace Information Research Institute, Chinese Academy of Sciences, Beijing, 100101, China
[d] National Engineering Research Center for Agro-Ecological Big Data Analysis & Application, Anhui University, Hefei, 230601, China

ARTICLE INFO

Keywords:
Aquatic vegetation
Floating-leaved aquatic vegetation (FAV)
Submerged aquatic vegetation (SAV)
Remote sensing
Degradation
Eutrophication
Human intervention

ABSTRACT

A rapid degradation of aquatic vegetations in Taihu Lake has roused a wide attention in recent years. Giving large-scale harvesting activity on aquatic vegetation since 2012, whether water eutrophication or the human harvest activity induced the degradation remains controversial and unclear. In this study, based on Landsat and HJ-CCD data acquired from 1984 to 2016 and a 12-year field observation (2005–2016) of water quality, a method was proposed to quantitatively assess impacts of harvesting activity and water quality change on degradations of both floating-leaved aquatic vegetation (FAV) and submerged aquatic vegetation (SAV) in Taihu Lake. First, areas of FAV and SAV covers from 1984 to 2016 in Taihu Lake were mapped using the satellite data, and then the mapped areas were modified to those on a reference date by using phenological curves of FAV and SAV covers. Next, correlations between water quality data and FAV and SAV covers were analyzed by using Pearson correlation analysis based on the data before implementing the human harvesting activity (i.e., before 2012), and multiple general linear models were established based on the selected water quality variables with p-value < 0.01 for estimating covers of FAV and SAV from 2012 to 2016. Finally, based on the predicted areas of FAV and SAV covers by the models and the modified areas mapped from satellite data, the influences of water eutrophication and the human harvesting activity on the degradation of FAV and SAV covers were quantitatively assessed. The results indicated that (1) FAV cover exhibited a significant increase from 1984 to 2011 and then a rapid decrease, while SAV cover increased significantly before 2003 and then obviously declined; (2) water level (WL) and total nitrogen (TN) showed significantly negative correlations with FAV and SAV covers, while secchi disk depth (SDD) and SDD/WL had significantly positive correlations with FAV and SAV covers; (3) the human harvesting activity made a major contribution to the loss of FAV cover, and the degradation of SAV cover was mainly due to an increased lake eutrophication and deteriorated underwater light environment. The findings derived from this study could offer a guidance for Taihu Lake ecological restoration and effective management.

1. Introduction

Submerged aquatic vegetation (SAV) and floating-leaved aquatic vegetation (FAV) are the two main types of aquatic vegetation in most shallow lakes. Both types are important for primary production and can provide multiple ecological functions such as stabilizing sediments, absorbing nutrients and purifying water, maintaining fishery production and inhibiting the growth of phytoplankton (Ozimek et al., 1990; Horppila and Nurminen, 2003; Vereecken et al., 2006; Yunkai-Li et al., 2009; SAYER et al., 2010; Rao et al., 2015; WANG et al., 2014). Previous studies indicate that the types and composition of aquatic vegetation can influence the stable state of an aquatic system in shallow lakes, especially in eutrophic lakes (e.g., Phinn et al., 2008; Carr et al., 2010; Roelfsema et al., 2014). For example, submerged macrophytes is a potential indicator of ecological quality of lakes (Søndergaard et al., 2010). When uncontrolled, rapid expansion of FAV may have a potential of causing disturbances to biodiversity, nutrient cycling, and aquatic life habitat and even an adverse shift in shallow lakes from a clear-water plant-dominated state to a turbid algae-dominated state. This is because FAV with large leaf area floating on the water surface will block the light into the water, which may induce a rapid degradation of SAV and the death of aquatic animal living on SAV due to

* Corresponding author.
E-mail addresses: jhluo@niglas.ac.cn (J. Luo), htduan@niglas.ac.cn (H. Duan).

https://doi.org/10.1016/j.jag.2019.102038
Received 10 May 2019; Received in revised form 12 December 2019; Accepted 24 December 2019
Available online 03 January 2020

lacking of light (Hofstra et al., 1999; Shekede et al., 2008; Dube et al., 2017; Palmer et al., 2015). Accordingly, understanding the dynamics mechanisms of FAV and SAV and clarifying the process driving their change mechanisms are critical to assess the health state of the water environment and guide the management of eutrophic shallow lakes.

Taihu Lake is the third largest freshwater lakes in China and is an important drinking water source, which supplies drinking water for surrounding cities with more than 10 million people (Qin et al., 2010); moreover, the lake offers other services, such as, aquaculture, tourism and recreation, and transportation (Qin et al., 2010). Taihu Lake possesses a macrophyte-dominated zone and a phytoplankton-dominated zone based on ecological characteristics and a stable state theory (Shen et al., 2011). In the phytoplankton-dominated zone, there is less aquatic vegetation and algal blooms occur frequently (Zhang et al., 2014), while in the macrophyte-dominated zone, its bottom is often covered with abundant FAV and SAV, and thus the water quality is much often better than that in the phytoplankton-dominated zone across all seasons (Luo et al., 2016a). Before 2012, there was less human intervention on aquatic vegetation in the macrophyte-dominated zone. However, a high aquatic vegetation cover produced a serious impact on the shipping and water landscape in the macrophyte-dominated zone in 2012. Thus, Ministries of Water Resources (MWR) and of Environmental Protection (MEP) appealed to harvest aquatic vegetation at a large scale in macrophyte-dominated zone using manual and mechanical harvesting ships. The approach could cut the aquatic vegetation and even dig up their roots for optimizing lake landscape, facilitating shipping and preventing secondary pollution induced by large amounts of death and decay of plants. As a result by 2015, field surveys and statistical reports indicated that aquatic vegetation decreased sharply and even disappeared in some bays in the macrophyte-dominated zone in Taihu Lake. Further, an algae bloom occurred in 2016–2017 in the macrophyte-dominated zone, where algae bloom never occurred before, suggesting that ecological balance and stable state in the zone might have been broken and water environment was deteriorating. Accordingly, whether the harvesting activity or further lake eutrophication should be responsible for the degradation of FAV and SAV had aroused a large concern and controversy from the local residents, governments and researchers. Previous studies indicated that increasing lake eutrophication and degrading underwater environment surely resulted in the loss of vegetation presence (e.g., Søndergaard et al., 2010; Kolada, 2010; Schelske et al., 2010; Zhang et al., 2017, 2016b). However, based on our knowledge, there are no studies on quantitatively assessing the influences of water quality change and harvesting activity on spatial distributions of FAV and SAV in Taihu Lake.

Satellite remote sensing technique has been proven to be the most powerful and effective tool for mapping aquatic vegetation types and species in coastal, shallow waters and monitoring their biomass at a large scale (e.g., Gullström et al., 2006a; Ma et al., 2008; Shekede et al., 2008; Villa et al., 2012; Pu et al., 2012; Roelfsema et al., 2014; Cheruiyot et al., 2014; Luo et al., 2017; Pu and Bell, 2017; Chen et al., 2018; Gao et al., 2018). Many studies have explored spectral indices derived from MODIS coarse resolution data to map aquatic vegetation in Taihu Lake, such as the floating algae index (FAI) and the vegetation presence frequency (VPF) (e.g., Liu et al., 2013; Zhang et al., 2016a; Liang et al., 2017). Moreover, using medium and high resolution satellite image data (e.g., Landsat, HJ, IKONOS, MERIS), a series of special indices, such as normalized difference aquatic vegetation index (NDAVI) and water adjusted vegetation index (WAVI), floating-leaved vegetation sensitive index (FVSI) and submerged vegetation sensitive index (SVSI), were also developed to classify FAV and SAV covers, with which classification accuracies of FAV and SAV covers could be higher than 80 % (Ma et al., 2008; Luo et al., 2014; Villa et al., 2015, 2014). Specifically, Landsat data with a long archive history can be used to trace variations in FAV and SAV covers over time (Gullström et al., 2006b; Zhao et al., 2013; Luo et al., 2016b). Meanwhile, long-term and site-specific meteorological and water quality observations are used to support such studies.

In this study, by using satellite data with a resolution of 30 m and water quality data collected from 2005 to 2016, we proposed an approach to quantitatively assesse impacts of harvesting activity and water quality change on degradations of FAV and SAV covers, respectively. Therefore, the specific objectives for this study included: 1) Mapping dynamics of FAV and SAV covers in the macrophyte-dominated zone in Taihu Lake over 33 years (1984–2016); 2) exploring relationships between FAV and SAV cover areas and water quality parameters; and 3) establishing models for assessing influences of mechanical harvesting and water quality change on FAV and SAV covers, respectively. Relevant issues on the guidance for Taihu Lake ecological restoration and sustainable management were also discussed.

2. Study area and data sets

2.1. Study area

Taihu Lake (30°55′40″– 31°32′58″N, 119°52′32″– 120°36′10″E) is a typical eutrophic shallow lake (a maximum depth of 2.6 m and mean depth of 1.9 m) with an area of approximately 2,338 km^2. It is located at the core of the Yangtze Delta, which is the most industrialized and urbanized area in China.

In this study, due to less aquatic vegetation in the phytoplankton-dominated zone, we focus only the macrophyte-dominated zone, including three large bays, Gonghu, Xukou and Dongtaihu Bays, namely, regions A, B and C in Fig. 1, respectively. The study area is covered mainly with three types of aquatic vegetation, including emergent vegetation (*Phragmites communis* and *Zizania latifolia*), FAV (*Eichhornia crassipes*, *Lemna minor*, *Nymphoides peltata*, *Trapa bicornis*) and SAV (*Elodea nuttallii*, *Potamogeton crispus*, *Myriophyllum spicatum*, *Potamogeton maackianus*, *Ceratophyllum demersum* and *Vallisneria spiralis*). Since there was much less emergent vegetation distributed and only in lakeside areas, we merged it into FAV as FAV in this study.

2.2. Data sets

2.2.1. Satellite images

In consideration of data consistency and traceability, we mainly selected Landsat data (TM / OLI) with a spatial resolution of 30 m to monitor the spatial distribution of aquatic vegetation in the study area. Due to lacking Landsat TM data from 2011 to 2014, HJ-CCD images were used as the supplementary data. HJ-CCD images were acquired from the China Centre for Resources Satellite Data and Application (CRESDA). HJ-1A and HJ–1B satellites were launched by CRESDA on September 6, 2008. HJ-1A/1B CCD has similar spectral ranges and spatial resolutions to those of the first four bands of Landsat TM but a higher revisit cycle of 48 h (two days). Our previous studies (Luo et al., 2013, 2016 and 2017) using the HJ-CCD images to map FAV and SAV in Taihu Lake proved that the data had a good consistence with Landsat data in mapping aquatic vegetation types.

Previous studies demonstrate that most species of aquatic vegetation in Taihu Lake reach the maximum biomass and cover area between mid-June and mid-October (Zhao et al., 2013; Luo et al., 2016a; Luo et al., 2017). Therefore, we collected the satellite images acquired between June 26 and October 17 (Table 1). As a result, a total 28 scenes of cloud-free Landsat TM / OLI and 4 scenes HJ-CCD data were collected from 1984 to 2016.

2.2.2. Water quality measurements

In this study, the measurements of eleven water quality (WQ) parameters, including dissolved oxygen (DO), PH, total suspended matter (TSM), ammonia (NH_3-N), biochemical oxygen demand (BOD), chemical oxygen demand (COD), total nitrogen (TN), total phosphorus (TP), chlorophyll *a* (Chla), water level (WL) and secchi disk depth (SDD) were collected from 2005 to 2016. In fact, WL is not a water

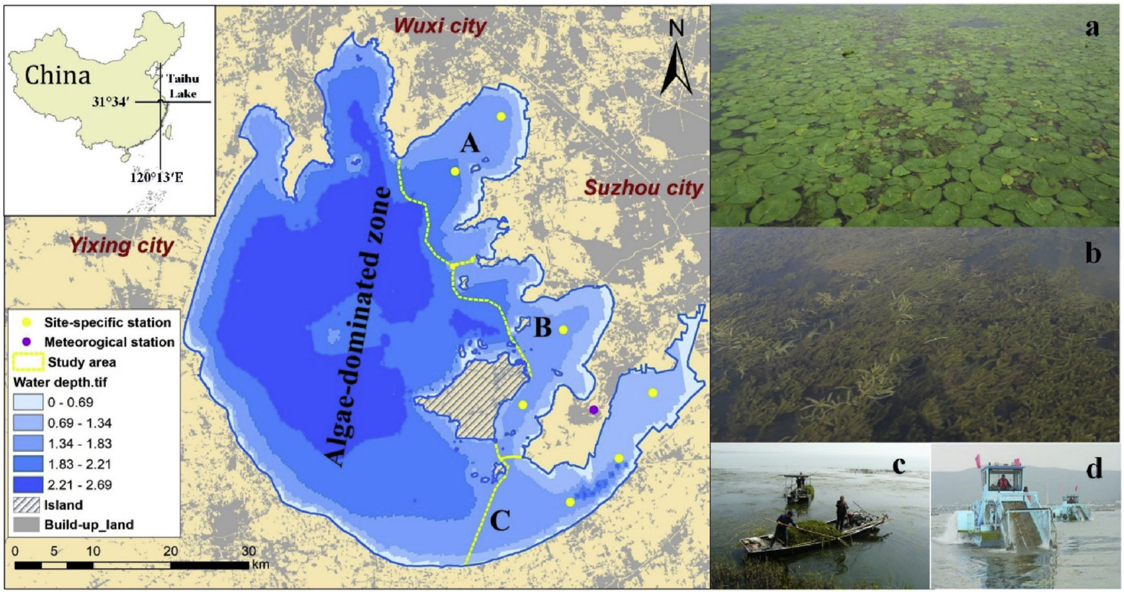

Fig. 1. A location map of Taihu Lake in China and the study area with consisting of three regions A, B and C. (a) *Nymphoides peltatum*, a dominant species of FAV in Taihu Lake; (b) *Myriophyllum spicatum,* a dominant species of SAV in Taihu Lake; (c) a manual harvesting activity scene; and (d) a mechanical harvesting activity scene.

quality parameter, but for a convenient analysis, it was called a WQ parameter in this study. The eleven WQ parameters' monthly measurements at seven regulate sampling sites from 2005 to 2016 were observed by the Taihu Laboratory for Lake Ecosystem Research and their annual observation values were calculated. The seven sampling sites include two sites located in region A, two sites in region B and three sites in region C, and the locations of sampling sites were shown in Fig. 1. The WQ sampling data in the same region were averaged to represent regions A, B and C for analyzing correlations with FAV and SAV covers in corresponding regions.

2.2.3. Meteorological data

Regular meteorological factors including annual average air temperature, wind speed, precipitation and sunshine duration from 1984 to 2016 were collected from the China Meteorological Data Sharing Service System (http://cdc.cma.gov.cn/). The location of observation station, namely Dongshan Station, was also showed in Fig. 1.

3. Methods

Fig. 2 presents a flowchart of evaluating influences of human harvesting activity and water eutrophication on the degradations of FAV and SAV covers. To achieve the goal, we divided the data into two parts: the data before and after the implementation of human harvesting activity (i.e., before 2012 and from 2012 to 2016) to conduct the research, and more components in the figure were addressed as follows. (*i*) FAV and SAV in study area were mapped from 1984 to 2016 based on satellite data using decision tree classification method, and then the cover areas of FAV and SAV were modified using a correction method to eliminate the intra-annual variations resulted from different image acquisition dates. (*ii*) The relationships between water quality (WQ) parameters and cover areas of FAV and SAV were explored by person correlation analysis based on the data collected before 2012, and then the sensitive WQ variables (p-value < 0.01) were retained. (*iii*) The multiple general linear (MGL) models for predicting FAV and SAV covers were built based on the sensitive WQ variables before implementing harvesting activity, and then the areas of FAV and SAV from 2012 to 2016 were predicted. (*iv*) With the modified monitoring areas of FAV and SAV mapped from satellite data coupling with predicted area by the models from 2012 to 2016, the influences of WQ and human harvesting activity were quantitatively assessed.

3.1. Mapping FAV and SAV

By referring to the metadata of the images (e.g., gains and offsets) and using the Fast Line-of-sight Atmospheric Analysis of Spectral Hypercubes (FLAASH) in ENVI (FLAASH User's Guide, 2004), all multitemporal Landsat and HJ CCD images were calibrated from the at-sensor radiance data to at-water surface reflectance. In this study, we used the decision tree classification and thresholds determination

Table 1
Information for acquired satellite data.

Year	Month/day	Sensor	Year	Month/day	Sensor	Year	Month/day	Sensor
1984	8/4	TM	1995	8/3	TM	2006	9/18	TM
1985	8/7	TM	1996	8/5	TM	2008	7/5	TM
1986	7/25	TM	1997	8/8	TM	2009	9/10	TM
1987	6/26	TM	1998	7/10	TM	2010	8/12	TM
1988	7/14	TM	1999	10/1	TM	2011	9/24	HJ-CCD
1989	7/17	TM	2000	9/17	TM	2012	9/2	HJ-CCD
1990	7/20	TM	2001	7/2	TM	2013	9/26	HJ-CCD
1991	7/23	TM	2002	9/23	TM	2014	9/7	HJ-CCD
1992	7/25	TM	2003	7/24	TM	2015	9/11	OLI
1993	9/30	TM	2004	7/26	TM	2016	8/28	OLI
1994	6/29	TM	2005	10/17	TM			

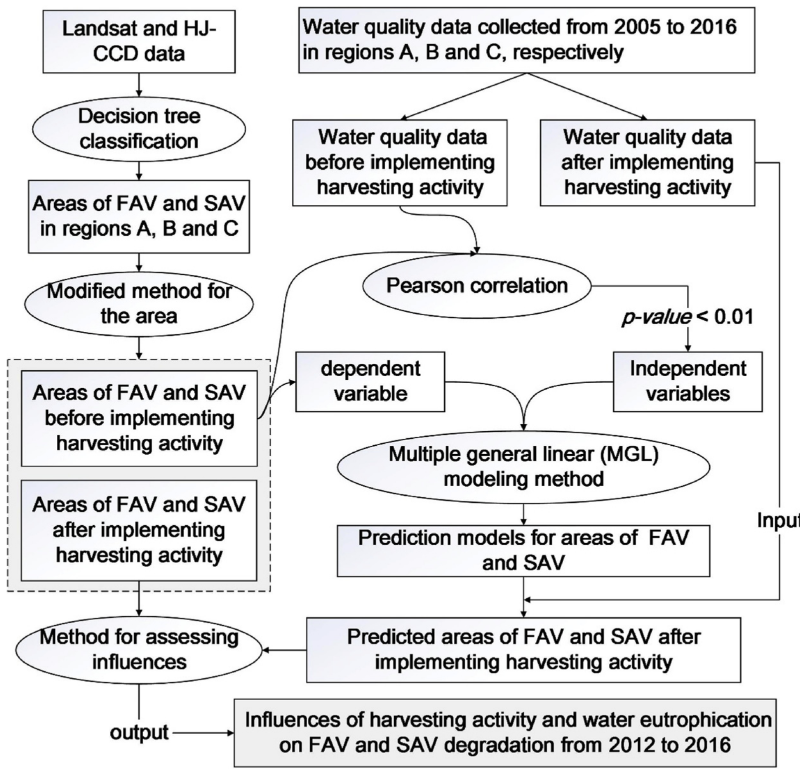

Fig. 2. A flowchart presenting a summary of the data collection, the procedure of evaluating the effects of human harvesting activity and eutrophication on FAV and SAV covers. FAV: floating-leaved aquatic vegetation; SAV: Submerged aquatic vegetation; a high-intensive harvesting activity has been implemented since 2012.

method developed by Luo et al. (2014, 2016) to map FAV and SAV covers from 1984 to 2016. More details about the classification method were provided in Luo et al. (2014, 2016). The studies indicated that the mapping method could result in classification accuracies higher than 80 % for both FAV and SAV.

3.2. Approach for modifying FAV and SAV areas mapped from images

In order to eliminate as much as possible the influence of the intra-annual variation caused by different image acquisition dates on our results, we used phenological curves of FAV and SAV created by Luo et al. (2016) to correct the covers of FAV and SAV mapped from the images. The phonological curves were created based on 73HJ CCD images acquired from January 2009 to December 2013 by a double logistic fitting function. Fig. 3 shows the phenological curves of FAV and SAV. Read Luo et al. (2016) for more detailed information of how to create the phonological curves. According to the phenological curves, FAV and SAV cover reach the peaks from DOY = 194 to DOY = 250 and from DOY = 245 to DOY = 275, respectively. And when DOY is 252 (September 8), the area of aquatic vegetation (FAV + SAV) reaches the maximum value. Therefore, in this study, we considered DOY = 252 as a reference date, and the FAV and SAV cover areas mapped from the satellite images from 1984 to 2016 were modified to the relative area values on the reference date by the following formulas:

$$\frac{A\_FAV_x}{A\_FAV_y} = \frac{F\_FAV_x}{F\_FAV_y} \tag{1}$$

$$\frac{A\_SAV_x}{A\_SAV_y} = \frac{F\_SAV_x}{F\_SAV_y} \tag{2}$$

Therefore,

$$A\_FAV_y = \frac{A\_FAV_x \times F\_FAV_y}{F\_FAV_x} \tag{3}$$

$$A\_SAV_y = \frac{A\_SAV_x \times F\_SAV_y}{F\_SAV_x} \tag{4}$$

where x is the image acquisition date; y is the reference date (i.e., DOY = 252); A_FAV_x and A_SAV_x are the cover areas of FAV and SAV mapped from the image acquired on date x, respectively; A_FAV_y and A_SAV_y are the modified cover areas of FAV and SAV from date x to y, respectively; F_FAV_x, F_SAV_x, F_FAV_y and F_SAV_y are the cover areas of FAV and SAV mapped from the phenological curves when DOY = x and DOY = y, respectively.

3.3. Statistical correlation analyses

Pearson correlation analysis approach was used to investigate correlation relationships between FAV and SAV covers and WQ parameters and meteorological factors.

Multiple linear regression was used to model a relationship between two or more explanatory variables and a response variable by fitting a linear equation to observation data. A multiple general linear (MGL) model takes the form:

$$Y = \sum_{j=1}^{m} \alpha_j M_j + C \tag{5}$$

where Y is the dependent variable, i.e., the cover area of FAV or SAV mapped from the satellite images; M_j is the *jth* independent variable ($j = 1,2\ldots,m$), including WQ parameters with *p-value* < 0.01 in Pearson correlation analysis and the cover area of FAV or SAV of one year before the modeling year in this study; C is the constant term.

In this study, we used MGL to establish the predicting models of FAV and SAV covers based on the data before complementing harvesting activity (i.e., before 2012).

SPSS software was adopted to carry out both Pearson correlation and MGL analyses.

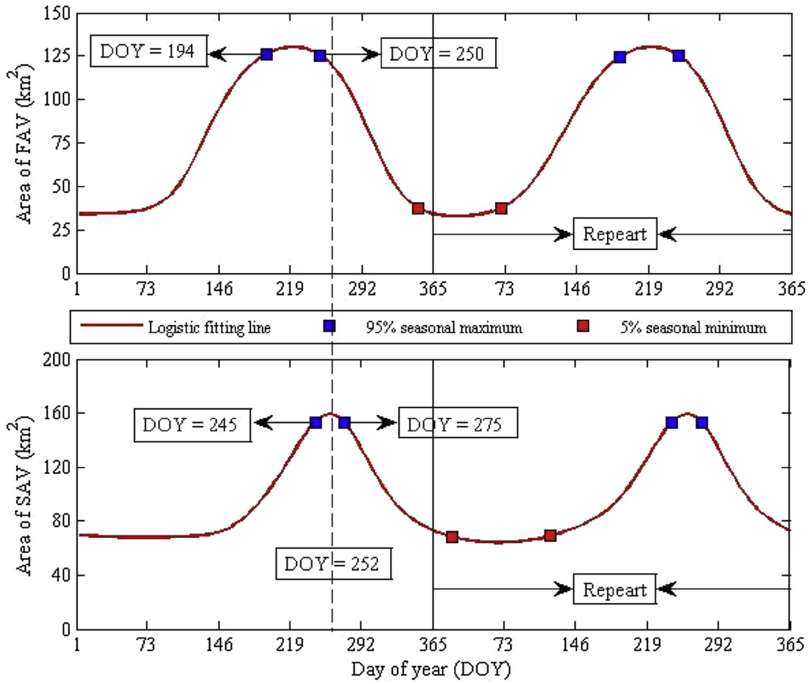

Fig. 3. Phenological curves of FAV and SAV. Black dashed line represents the reference date (DOY = 252) when the aquatic vegetation (FAV + SAV) reaches a maximum area.

3.4. Relative change rate

In order to assess the change rate of FAV and SAV covers in different regions before and after implementing the harvesting activity, we defined a relative change rate (k_i) using the modified cover areas of FAV and SAV in 2011 as a reference area. The formula is as follows:

$$k_i = \frac{A_x - A_{2011}}{A_{2011}} \times 100\% \tag{6}$$

where k_i is the relative change rate; A_x is the modified cover area of FAV or SAV in year x; A_{2011} is the modified reference cover area of FAV or SAV in 2011.

3.5. Evaluation method

The influences of harvesting activity and water eutrophication on the degradation of FAV and SAV were evaluated by the following formulas:

$$x_i = h_i + n_i = MA_i - MA_{i-1} \tag{7}$$

$$n_i = PA_i - PA_{i-1} \tag{8}$$

$$h_i = x_i - n_i = (MA_i - MA_{i-1}) - (PA_i - PA_{i-1}) \tag{9}$$

where x_i is the loss of cover area of FAV or SAV from years *i-1* to *i* (i = 2012, 2013…, 2016); n_i is the lost area of FAV or SAV induced by water eutrophication from years *i-1* to *i*; h_i represents the area loss induced by human harvesting activity from year *i-1* to *i*; MA_i and MA_{i-1} are the modified areas of FAV or SAV mapped from the satellite images in year *i-1* and *i*, respectively; PA_i and PA_{i-1} are the predicted areas of FAV or SAV estimated by the MGL models developed in this study, respectively.

The annual contribution rates of harvesting activity and water eutrophication to the loss of aquatic vegetation from 2012 to 2016 were calculated by the following formulas:

$$Q = MA_{2016} - MA_{2011} \tag{10}$$

$$n_i\ \% = \frac{PA_i - PA_{i-1}}{Q} \times 100\% \tag{11}$$

$$h_i\ \% = \frac{(MA_i - MA_{i-1}) - (PA_i - PA_{i-1})}{Q} \times 100\% \tag{12}$$

where Q is the total lost area of aquatic vegetation after implementing the harvesting activity; h_i % and n_i % are the contribution rates of harvesting activity and water eutrophication to the total lost area in year *i*, respectively.

4. Results

4.1. Spatiotemporal dynamics of aquatic vegetation

Fig. 4 exhibits that spatial distributions of FAV and SAV in the study area, and Fig. 5 shows the cover areas of FAV and SAV mapped from the satellite image and corresponding modified cover areas in regions A, B and C from 1984 to 2016. From the figures, we found the monitoring cover areas are different from those with the modified cover area, but the general change patterns and trends are similar. Overall, SAV was dominant type in Taihu Lake, and region C had the largest aquatic vegetation cover while the smallest distribution of aquatic vegetation was in region A. Over the period of 33 years, SAV experienced some changes, and the change patterns were different among three regions, which might be summarizes as follows. *i)* In region A, as shown in Fig. 5a, SAV appeared in 1991, increased to the peak around 2003 and then decreased with a large fluctuation while FAV slightly increased before 2014 and then decrease. *ii)* In region B, as shown in Fig. 5b, the modified cover area of SAV fluctuated between 1 km^2 and 5 km^2 from 1984 to 1992; and then SAV reached two peaks in 2003 and 2011, finally decreased dramatically from 104.50 km^2 in 2011 to 23 km^2 in 2016 (Fig.5b). The modified cover area of FAV increased from only 2.68 km^2 in 1984 to 45.75 km^2 in 2011, and then fell dramatically to only 3.95 km^2 in 2016. *iii)* In region C, as shown in Fig. 5c, the modified cover area of SAV fluctuated slightly before 1997, and then increased and reached the peak at 229.10 km^2 in 2003, finally decreased to 63.57 km^2 in 2016, while FAV cover area increased significantly from 55.87 km^2 in 1984 to 107.52 km^2 in 2011, and then declined to only 25.05 km^2 in 2016.

Fig. 6 displays the change patterns of the total of aquatic vegetation

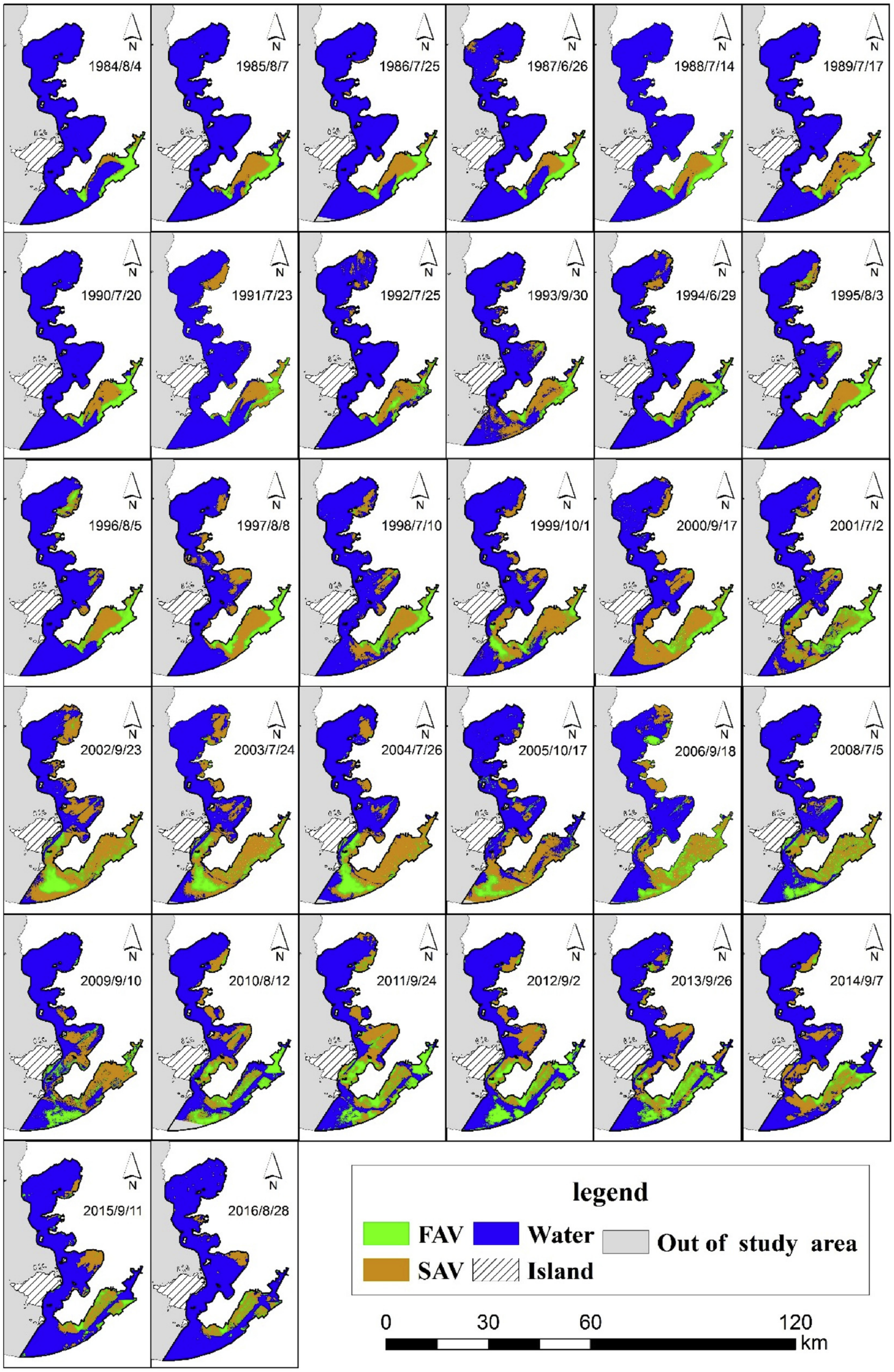

Fig. 4. Spatial distribution of FAV and SAV covers from 1984 to 2016 in Taihu Lake.

(FAV + SAV) covers mapped from the images and after correction and the separate FAV and SAV covers from 1984 to 2016 in the study area. The total cover area of aquatic vegetation first increased and then decreased with a peak around 2003 (Fig. 6a). FAV experienced a statistically significant increase from 1984 to 2011 (R^2 = 0.68) and an obvious decrease between 2011 and 2016 (R^2 = 0.94) (Fig. 6b). SAV increased significantly before 2003 (R^2 = 0. 85), and then decreased dramatically after 2003 (R^2 = 0.83) (Fig. 6c).

Fig. 7 presents the change rates (k_i) of FAV and SAV covers from 1984 to 2016 compared with those in 2011 in regions A, B and C,

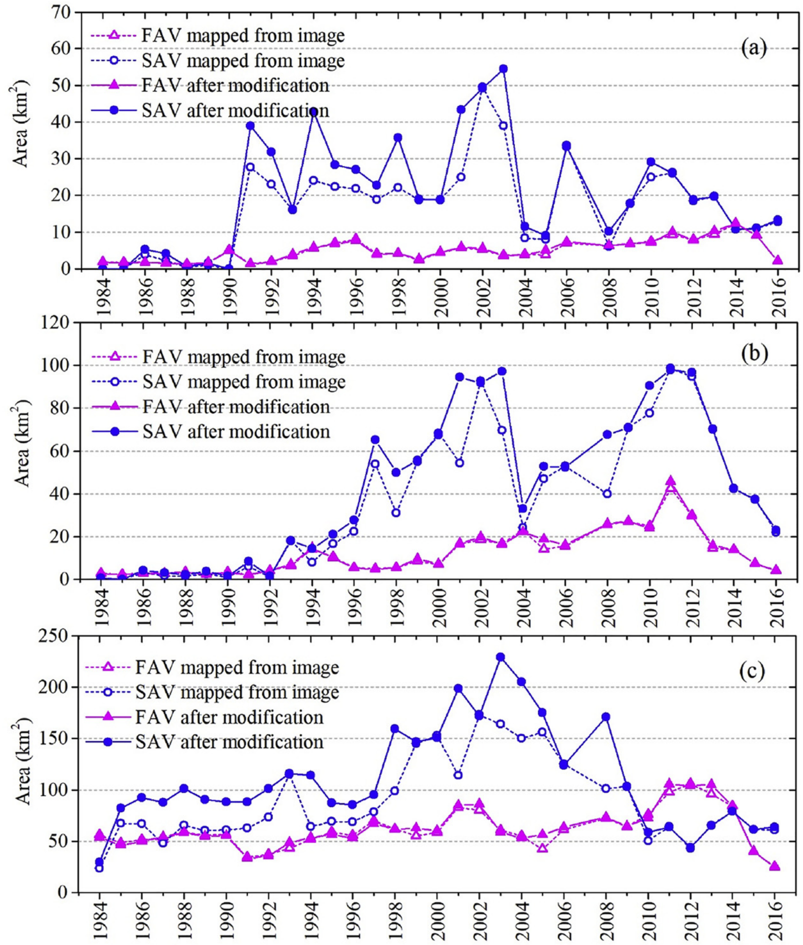

Fig. 5. Dynamics of FAV and SAV covers mapped from satellite image and after correction in regions A (a), B (b) and C (c) from 1984 to 2016.

respectively. Generally, after implementing the harvesting activity, the decrease rate of FAV was greater than that one of SAV. FAV cover in regions A, B and C was continually decreasing, and FAV in region B had the greatest decrease rate. For SAV, the decrease rate of region A was the most severe, followed by region B, and the change rate in region C was the lowest.

4.2. Correlations of FAV and SAV with water quality parameters

Table 2 lists correlations between WQ variables and the cover areas of FAV and SAV, respectively. From the table, WL and TN, respectively, had a significant negative correlation with FAV and SAV (*p-value* < *0.001*), while SDD and SDD/WL had significant positive correlations with FAV and SAV with p-value < 0.001. FAV and SAV related negatively with NH3-N, BOD and Chl*a* with p-value < 0.05. Non statistically significant correlations of other variables with SAV and SAV were observed.

4.3. Models for predicting FAV and SAV covers

Predictive models were respectively established for estimating FAV and SAV covers using MGL model with WQ data collected before 2012 and cover areas of FAV and SAV in last year as formulas.

$$Y_1 = 0.969\, X_f + 3.18\, X_1 + 20.267\, X_2 - 7.275 \quad (13)$$

$$Y_2 = 0.12\, X_s - 10.315\, X_1 + 128.57\, X_2 + 18.211 \quad (14)$$

where Y_1 and Y_2 are the predicted cover areas of FAV and SAV, respectively; X_f and X_s are the cover areas of FAV and SAV in last year; X_1 and X_2 are TN and SDD/WL, respectively.

Fig. 8 shows the relationships between the cover areas estimated from models (Eqs. (13) and (14)) and the modified monitoring areas mapped from the satellite images for FAV and SAV, respectively. The results indicated that the models had high prediction accuracies with $R^2 = 0.94$ and RMSE = 6.76 km^2 for FAV model and $R^2 = 0.95$, RMSE = 8.40 km^2 for the SAV model.

4.4. Why the degradation of FAV and SAV after 2012

According to Eqs. (7)–(12) and predictive models (Eqs. (13) and (14)), MA, PA, h, n, *x*, h%, n% and *x*% of FAV and SAV in the study area were calculated and listed in Tables 3 and 4, respectively. The experimental results indicated as follows: FAV decreased by 132.85 km^2 from 2012 to 2016, and the lost area of FAV induced by the harvesting activity (102.84 km^2, *h%* = 77.41 %) was much greater than that induced by WQ parameter change (30.01 km^2, *n%* = 22.59 %); while SAV decreased a total of 88.00 km^2 from 2012 to 2016 and the contribution rate of WQ change on the lost area (*n%* = 86.82 %) was higher than that of human harvesting activity (*h%* = 13.18 %). The lost areas of FAV and SAV varied from year to year. The area of FAV decreased the most in 2015 with a decreased amount of 56.05 km^2 and a yearly decrease rate *x%* = 42.19 %, and all the lost area was almost induced by harvesting activity. For SAV, human harvesting activity induced the decrease in 2012 and 2014, and WQ change was main driving factor resulting of SAV decrease in other years.

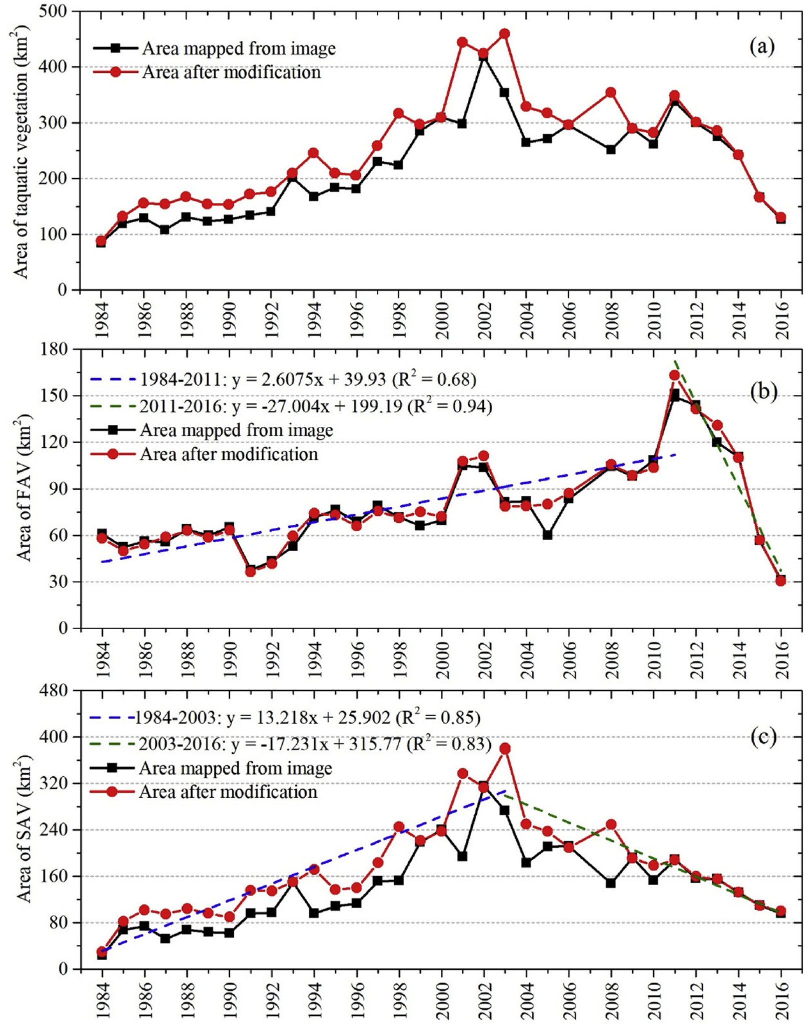

Fig. 6. Change patterns of aquatic vegetation (FAV + SAV) cover (a), FAV cover (b) and SAV cover (c) from 1984 to 2016 over the study area.

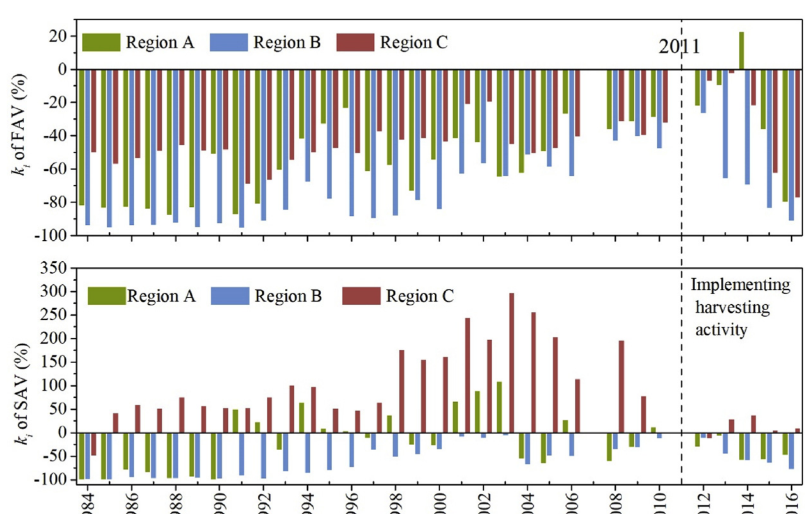

Fig. 7. Change rates (k_i) of FAV and SAV covers from 1984 to 2016 compared with those in 2011 in regions A, B and C. Positive value represents that the cover area of FAV or SAV in an interest year was higher than that in 2011, otherwise, it was negative.

Table 2
Correlations between WQ variables and the cover areas of FAV and SAV.

	FAV (n = 18)		SAV (n = 18)	
	R	*p-value*	R	*p-value*
DO	−0.136	0.590	−0.233	0.352
PH	−0.442	0.063	−0.463	0.053
TSM	−0.252	0.313	−0.096	0.706
NH3-N	−0.494*	0.037	−0.460*	0.054
BOD	−0.445	0.064	−0.539*	0.021
COD	−0.197	0.434	−0.458*	0.056
TN	−0.732**	< 0.001	−0.810**	< 0.001
TP	−0.604**	0.008	−0.619**	0.006
Chla	−0.500*	0.043	−0.599*	0.009
WL	−0.880**	< 0.001	−0.808**	< 0.001
SDD	0.730**	< 0.001	0.871**	< 0.001
SDD/WL	0.821**	< 0.001	0.934**	< 0.001

Note: ** statistically significant at α = 0.01; * statistically significant at α = 0.05.

5. Discussion

5.1. Yearly dynamics of FAV and SAV covers in Taihu Lake

Giving generally lacking history observation data of aquatic vegetation in Taihu Lake, remote sensing is an effective technique for obtaining yearly dynamics of aquatic vegetation, and has been applied in mapping aquatic vegetation dynamics. Previous studies indicated that aquatic vegetation including FAV and SAV in Taihu Lake could be mapped accurately using the Landsat and HJ-CCD data with a high accuracy of being greater than 80 %. In this study, based on Landsat and HJ-CCD images acquired from 1984 to 2016, we mapped cover areas of FAV and SAV and analyzed their dynamics. The results indicated that FAV cover first increased and then decreased with a peak value in 2011 (Fig. 5b), while SAV cover reached the peak around 2003 (Fig. 5c). Meanwhile, total cover area of aquatic vegetation (including SAV + FAV) reached the peak around 2003 (Fig. 5a). In general, the dynamics of SAV and FAV covers and all aquatic vegetation cover were consistent with previous findings in Taihu Lake (Liu et al., 2013; Zhao et al., 2013; Zhang et al., 2016a; Luo et al., 2016a; Wang et al., 2019). First, Zhao et al. (2013) mapped emergent vegetation, FAV and SAV covers using seven scenes Landsat images acquired in years 1981, 1984, 1989, 1995, 2000, 2005 and 2010, respectively, and analyzed their spatial dynamics. Their findings were that FAV was increasing from 1984 to 2010, which was consistent with our result (Fig. 5b). The SAV cover and the total area cover of aquatic vegetation increased before 2005, and it then decreased from 2005 to 2010. The peaks derived from their study were different from our results, which might be due to different mapping intervals with every five years in their study and per year in our study. Second, Liu et al. (2015) mapped aquatic vegetation in Taihu Lake from 2003 to 2013 using MODIS data and explored the spatial dynamics of aquatic vegetation. Their results indicated that aquatic vegetation was relatively larger in 2008 and 2011 and smaller in 2006 and 2007, which was consistent with our findings (Fig. 5a). Finally, Wang et al. (2019) mapped aquatic vegetation in the entire Taihu Lake from 1980 to 2017, and concluded that the cover area of aquatic vegetation first increased, and then decreased sharply with a peak value in 2015. However, the peak value was not consistent with those derived from our study and the studies mentioned above, which was because enclosure cultivation area in region C was excluded in their study.

Previous studies including those mentioned above demonstrated that the cover area of aquatic vegetation reached maximum and was steady between June and October, and thus it is reasonable that we used the satellite data acquired from the time period to map yearly dynamics of aquatic vegetation including FAV and SAV. However, given that more accurate multi-year cover data of FAV and SAV were required to build model and estimate the contribution rate of water quality change and human harvesting activity on the degradation of FAV and SAV, in this study, we needed the phenological curves of FAV and SAV to correct the areas mapped from the satellite images with different acquisition dates from 1984 to 2016 to the relative areas on the reference date (i.e. DOY = 252, September 8). Fig. 9 shows the area difference values (Δ Area) and relative errors (RE%) between the areas mapped from the images from 1984 to 2016 and the corresponding modified areas. We found that the error for SAV was greater than that for FAV, and the cover areas in most years mapped from the satellite data were underestimated for SAV and overestimated for FAV compared with the cover area of the reference date due to different image acquisition dates. Moreover, the further away from the reference date, the greater the error, e.g., the largest error was more than 45 % for SAV on June 26, 1987. Our study also indicated that although there were errors when using images with different acquisition dates to monitor yearly dynamics, the general change trends and patterns of FAV and SAV mapped from the satellite images were consistent with those after modification (Fig. 6). However, in this study, since we intended to build the accurate models for predicating the areas of FAV and SAV and further quantify the impact of WQ change and water eutrophication on their degradations, it was critical to eliminate the errors as much as possible and correct the area mapped from the images.

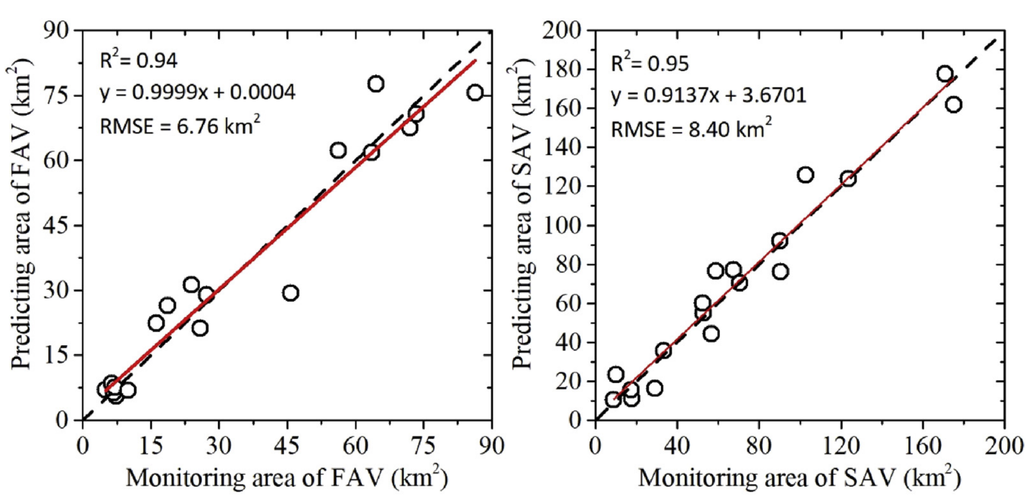

Fig. 8. Scattering plots between cover areas predicted by models and modified monitoring areas mapped from the satellite images for FAV (left) and SAV (right).

Table 3
MA, PA, x, n, h, x%, n% and *h%* of FAV in the study area (i.e. region A + B+C) from 2012 to 2016.

Year	MA (km^2)	PA (km^2)	*x* (km^2)	*n* (km^2)	*h* (km^2)	*x*%	*n*%	*h*%
2011	163.15	129.95	/	/	/	/	/	/
2012	141.39	134.58	−21.76	4.63	−26.39	16.38	−3.48	19.86
2013	129.20	127.89	−12.19	−6.69	−5.50	9.17	5.04	4.14
2014	110.11	140.36	−19.09	12.47	−31.56	14.37	−9.39	23.76
2015	54.06	113.08	−56.05	−27.28	−28.77	42.19	20.53	21.66
2016	30.30	99.94	−23.76	−13.14	−10.62	17.88	9.89	7.99
Total			−132.85	−30.01	−102.84	100.00	22.59	77.41

Note: *MA:* monitoring area of FAV mapped from the satellite image; *PA:* predicted area of FAV by GLM model. *x:* lost area of FAV in year *i* compared with the year *i*-1 (= $MA_i - MA_{i-1}$); *n: the* lost area of FAV induced by WQ parameter change in year *i* compared with the year *i*-1 (= $PA_i - PA_{i-1}$); *h*: the lost area of FAV induced by harvesting activity in the year *i* compared with year *i*-1 (= $x_i - n_i$); *x%*: the rate of the decreased area of FAV in the year *i* compared with the year *i*-1 to the total decreased area of FAV from 2012 to 2016; *n%* and *h%* are the contribution rates of WQ parameters and harvesting activity to the total lost area of FAV from 2012 to 2016. A positive contribution rate represents that the change of WQ parameters or the harvesting activity result in FAV cover decreasing, otherwise, a negative rate in FAV cover increasing.

5.2. Driving factors of changes in FAV and SAV

The change processes for aquatic vegetation are highly complex. Previous studies explored the influence factors and habitat requirements for aquatic vegetation by field observations, experiments and mechanism algorithms, and suggested that the germination, growth and death of aquatic vegetation are influenced by too many habitat factors, such as WQ, water velocity, water temperature, light regime and physical-chemical factors, human activities and so on (Koch, 2001; Kemp et al., 2004). Generally, the driving factors can be summarized as water quality parameters, meteorological factors and human interventions (Koch, 2001; Kemp et al., 2004; Körner, 2015; Phillips et al., 2016). In this study, we focused on their influences on FAV and SAV covers in our study area.

First, in Taihu Lake, existing studies exploring the relationships between WQ parameters and aquatic vegetation appearance frequency suggested that nutrient concentration and WL had a significantly negative correlation with aquatic vegetation appearance frequency, while SDD showed a significantly positive correlation (Zhang et al., 2016a; Wang et al., 2019). Our results about both FAV and SAV cover dynamics associated with WQ parameters' change confirmed the findings. Further, we also found that SDD/WL had the highest correlation with both SAV and FAV covers with correlation coefficients R = 0.923 and 0.850, respectively, which supported a conclusion reported in the previous studies that underwater light intensity was the most important controlling factor for aquatic vegetation (Schelske et al., 2010; Zhang et al., 2016a). Meanwhile, our finding also indicated that water eutrophication was the major driving factor of the loss of SAV cover from 2012 to 2016.

Second, we conducted a correlation analysis between FAV and SAV covers and four regular meteorological factor including annual average wind speed, air temperature, precipitation and sunshine duration. Table 4 shows the correlations between meteorological factors and the total cover areas of FAV and SAV in study area. The results indicated that annual average wind speed had a negative correlation with FAV and SAV covers, while air temperature showed a positive correlation with them. There was a negative correlation between annual average precipitation and SAV covers. The conclusions were consistent with the findings of the previous studies. For example, Carr et al. (1997) indicated that water temperature is a prerequisite for germination and growth of aquatic vegetation, and a high temperature can induce a high biomass and coverage. And Wang et al. (2019) suggested that the inter-month cover trend had a significant positive correlation with monthly average temperature. In addition, there were a few studies reported on the relationship between wind speed and aquatic vegetation cover, but it was well documented that waves had a significant negative impact on seagrass (e.g., Koch, 2001; Madsen et al., 2001). This is because a high wind speed can induce a high wave and thus make more sediments suspended (Carper and Bachmann, 1984; Hwang et al., 1998; Luettich et al., 1990; Lawson et al., 2007), which is not unfavorable of aquatic vegetation growth, especially for SAV (Table 5).

However, it should be noted that the meteorological factors with p-value < 0.01 were not introduced into the predicted models in this study. This is because the meteorological factor data were collected from only one meteorological station (i.e., Dongshan Station) instead of detailed data collected from regions A, B and C, respectively. Besides, WQ data in the study area were observed regularly only from 2005. Therefore, it was difficult to combine meteorological data with WQ data in spatial and time for building prediction models. In fact, wind speed was decreasing and air temperature was increasing from 2012 to 2016 (Fig. 10), which was beneficial for SAV and FAV growth and expansion instead of decreasing. Therefore, in fact, without the meteorological factors included in the models, the current contribution rates of the harvesting activity and water eutrophication to the degradations of FAV and SAV might be underestimated.

Finally, intensified human activities, such as land reclamation, aquaculture, damming, overfishing and harvesting, could also be an important driving factor of changes in aquatic vegetation (Sandjensen et al., 2000; Körner, 2015; Phillips et al., 2016). Our study also confirmed that the harvesting activity could be one of driving forces of the decrease of aquatic vegetation.

Table 4
MA, PA, x, n, h, x %, n% and *h%* of SAV in the all study area (i.e., regions A + B+C) from 2012 to 2016. See Table 3 for detailed explanations for terms: *MA, PA, x, n, h, x %, n%* and *h%*.

Year	MA (km^2)	PA (km^2)	*x* (km^2)	*n* (km^2)	*h* (km^2)	*x*%	*n*%	*h*%
2011	187.93	158.02						
2012	159.49	153.49	−28.43	−4.54	−23.90	32.31	5.15	27.16
2013	154.96	116.25	−4.53	−37.24	32.70	5.15	42.32	−37.17
2014	132.32	119.88	−22.64	3.63	−26.27	25.72	−4.13	29.85
2015	109.43	94.30	−22.89	−25.58	2.68	26.02	29.07	−3.05
2016	99.93	81.62	−9.50	−12.68	3.18	10.79	14.41	−3.61
Total			−88.00	−76.40	−11.60	100.00	86.82	13.18

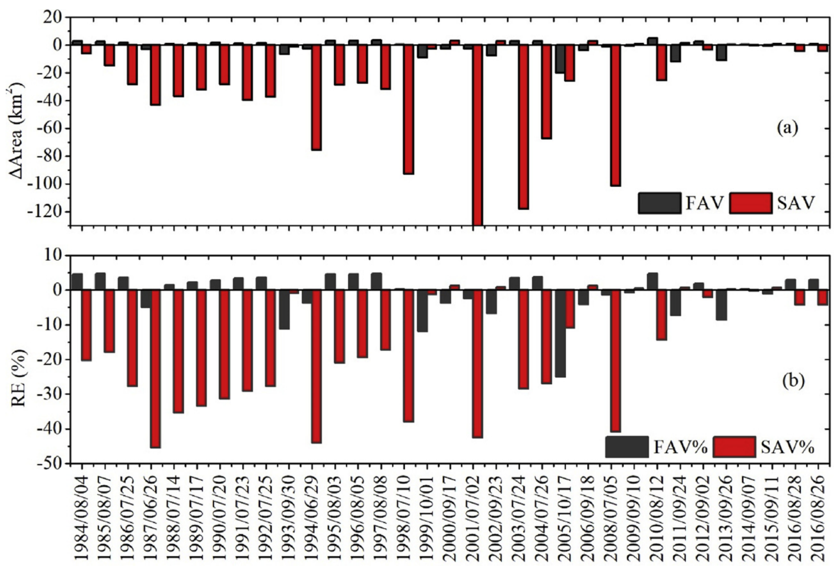

Fig. 9. ΔArea (a) and RE% (b) of FAV and SAV from 1984 to 2016. ΔArea is the difference value between the area directly mapped from the satellite images and corresponding modified area (i.e., the cover area mapped from satellite image minus the corresponding modified area); RE%, namely relative error, is the ratio of Δ Area to the corresponding modified area.

Table 5
Correlations between meteorological factors and FAV and SAV covers from 1984 to 2011.

	FAV (n = 27)		SAV (n = 27)	
	R	*p-value*	*R*	*p-value*
Annual average wind speed	−0.685**	< 0.001	−0.464*	0.015
Annual average air temperature	0.737**	< 0.001	0.715**	0.001
Annual average precipitation	−0.132	0.072	−0.548**	0.003
Annual average sunshine duration	0.147	0.465	−0.285	0.150

Note: ** statistically significant at α = 0.01; * statistically significant at α = 0.05.

5.3. Method for assessing impact factors

In Taihu Lake, aquatic vegetation cover had reduced dramatically, especially since 2012 (Fig.5a), and this issue has roused widely attentions by the public and governments. There was a controversy about the driving factors. Some reports indicated that the harvesting activity appealed by environmental departments resulted in the consequence, while others suggested that water eutrophication should have a main responsibility for it. However, based on our knowledge, there are no reports on quantitatively assessing the influences of human activities and water eutrophication on aquatic vegetation in Taihu Lake.

It is really difficult to calculate the contribution rates of human activities and water eutrophication separately using ordinary methods, such as discriminative component analysis (DCA), principal component analysis (PCA), because of the lack of actual and detailed harvesting data about aquatic vegetation. In this study, we proposed a feasible strategy to calculate the influences of human activities and water eutrophication on the degradation of FAV and SAV covers from 2012 to 2016. We divided the dynamics process of aquatic vegetation into the first phase without harvesting activity and the second one implementing the activity. We used TN and SDD/WL data acquired at the first phase to establish predicted models of FAV and SAV covers. By comparing with predicted areas from models and monitoring areas mapped from the satellite images, we could calculate the lost areas of FAV and SAV induced by water eutrophication and harvesting activity at the second phase. The method was used to assess and calculate the influence of a human importance project on regional ecology and climate change (Dai et al., 2015), and it could be used in our study due to similar situation and process. Although it was difficult to validate the results because actual lost areas induces by harvesting activity and water eutrophication could not be measured, our finding that the highest loss area induced by the harvesting activity was in 2014, which was consistent with the report that the amounts of aquatic vegetation harvested by mechanical harvesting ships reached the highest amount with 28 tons in 2014.

5.4. Aquatic vegetation management implications

Requirements for the growth of FAV and SAV are almost similar, such as light available, heat and nutrition, so FAV and SAV are definitely competitors if they grow in same region or environment. When FAV expands to some amount, SAV cover will decrease and lake ecology might go detrimental, because:1) floating-leaved vegetation floats on the water surface and has dense foliage that can block the transmission of light into the underwater, which will impact SAV photosynthesis,

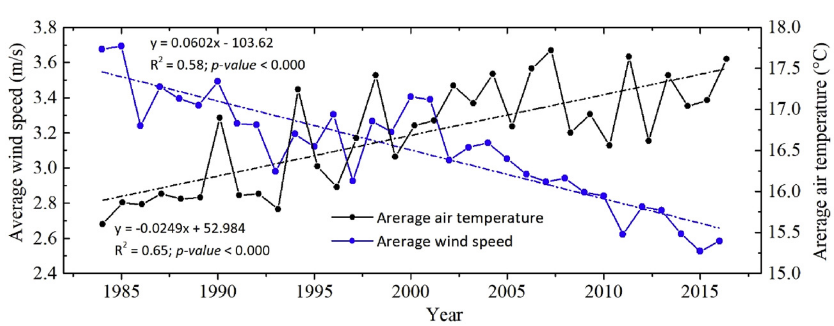

Fig. 10. Change trends of annual average wind speed and air temperature from 1984 to 2016.

and thus lead to the disappearance or even extinction of SAV (Hofstra et al., 1999); 2) excessive amounts of floating-leaved plants that die and decay quickly after reaching the maximum biomass can release pollutants and nutrient elements into the lake water (Vereecken et al., 2006), which may result in secondary pollution and further eutrophication; 3) after dying rapidly, floating-leaved vegetation will seriously affect the lake landscape and fishery activities. Therefore, moderate harvesting activity of aquatic vegetation, especially FAV, could improve the underwater light availability and be beneficial to lake ecology (Hofstra et al., 1999). In our study, this can explain why the harvesting activity induced FAV decrease and SAV increase, in some years (Tables 3 and 4). Therefore, moderate harvesting activity for FAV can be beneficial to retaining health state of aquatic ecosystem, while a blind implementing harvesting activity without consideration of ecosystem effect, might induce a rapid degradation of aquatic vegetation. Obviously, human intervention activities such as harvesting activity, especially in eutrophic shallow lakes, should be guided correctly. However, in this study, we cannot answer what is a moderate due to the limited detailed data. In the future, under a support of sufficient field data, the mechanism models of aquatic ecology should be developed to simulate and estimate the optimal FAV cover and address the issue above.

One of the most serious problems caused by eutrophication of shallow lakes is the disappearance of submerged macrophytes and switching to a turbid, phytoplankton-dominated state (Körner, 2002; Hilt et al., 2006; Phillips et al., 2016). The Taihu, a typical eutrophication lake, its water itself is detrimental to preserving aquatic vegetation cover and diversity, and a blind harvesting activity may further aggravate the degradation of aquatic vegetation. In turn, aquatic vegetation degradation and disappearance can further exacerbate water eutrophication in the macrophyte-dominated zone. In fact, it was already confirmed. As shown in Fig. 11, over recent two years, satellite images showed that algae blooms were found in the study area where there were never algae blooms found before 2015 (Fig. 11). The deteriorating water environment, may finally threaten the safety of the primary drinking-water source for approximately 40 million people.

According to our study, the driving factors resulting in the degradations of FAV and SAV were different. The human harvesting activity should take a major responsibility for the degradation of FAV, while the degradation of SAV was due to the increased lake eutrophication and degraded underwater light environment. Therefore, retaining and restoring aquatic vegetation will be really a difficult and long-term task, and more efforts should be made. Based on our analysis results, the following suggestions can be considered for sustainable management in Taihu Lake: (*i*) at present, any harvesting activities should be immediately prohibited to maintain the existing aquatic vegetation cover; (*ii*) exogenous nutrient control and watershed management should be further strengthened to improve water quality, especially increasing the SDD and lowing TN.

6. Conclusions

In this study, with a long time series of satellite data and a 12-year field observation (2005–2016) of WQ parameters, we mapped yearly dynamics of FAV and SAV covers, analyzed their correlations with relevant factors, established predictive models for FAV and SAV covers, and finally quantitatively assessed the influences of water eutrophication and human harvesting activity on the degradations of SAV and SAV covers, respectively, from 2012 to 2016. Several conclusions derived from the analysis results may include as follows:

i) FAV cover experienced a statistically significant increase from 1984 to 2011and a significant decrease in 2011–2016, while SAV cover exhibited statistically significant increase before 2002 and then obviously decrease.
ii) There were significantly negative correlations of WL and TN with FAV and SAV covers, while SDD and SDD/WL had significant positive correlations with FAV and SAV covers.
iii) Human harvesting activities had made a significant contribution to the loss of FAV cover; while the degradation of SAV was due to the increasing lake eutrophication and deteriorating underwater light environment.

In addition, harvesting activity should be correctly guided in eutrophic lake, and a blind harvesting activity might accelerate eutrophication. However, our current experimental results cannot answer whether, when and how much aquatic vegetation, especially FAV, should be harvested yet. Therefore, our on-going work will focus on addressing those questions with supports of sufficient field data and mechanism modeling in shallow lakes.

Author statement

Juhua Luo Providing methodology, formal analysis, original draft and editing.

Ruiliang Pu Providing some ideas, suggestions, editing and writing assistance to improve paper, especially in the process of paper revisions.

Hongtao Duan Providing original idea, goals and aims.

Ronghua Ma Supervising research activity planning and execution.

Zhigang Mao Offering a part of water quality data and data processing.

Yuan Zeng Providing some detailed ideas and frame of the paper.

Linsheng Huang Giving some contributions in Part Discussion.

Qitao Xiao Offering a part of water quality data and corresponding data processing.

Declaration of Competing Interest

None.

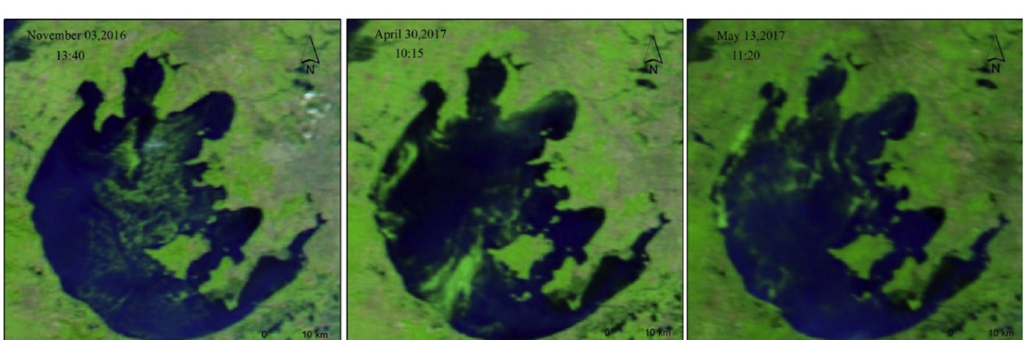

Fig. 11. MODIS RGB composite images acquired on November 3, 2016 (a), April 30(b) and May 13, 2017(c). Note: green regions are algal blooms in Lake.

Acknowledgments

The research was supported by the Open Research Fund of National Engineering Research Center for Agro-Ecological Big Data Analysis & Application, Anhui University (AE2018003); National Natural Science Foundation of China (No. 41971314, 41671358, 41971309); the National Key Research and Development Program of China (No. 2016YFC0500201-05) and Anhui Provincial Science and Technology Project (16030701091). We thank the Taihu Laboratory for Lake Ecosystem Research (TLLER) for providing with water environmental data. We also appreciate Scientific Data Sharing Platform for Lake and Watershed for providing remote sensing data (http://lake.geodata.cn), Nanjing Institute of Geography and Limnology, Chinese Academy of Sciences.

Appendix A. Supplementary data

Supplementary material related to this article can be found, in the online version, at doi:https://doi.org/10.1016/j.jag.2019.102038.

References

Carper, G.L., Bachmann, R.W., 1984. Wind resuspension of sediments in a prairie lake. Can. J. Fish. Aquat. Sci. 41, 1763–1767.
Carr, J., D'Odorico, P., McGlathery, K., Wiberg, P., 2010. Stability and bistability of seagrass ecosystems in shallow coastal lagoons: role of feedbacks with sediment resuspension and light attenuation. J. Geophys. Res. 115.
Chen, Q., Yu, R., Hao, Y., Wu, L., Zhang, W., Zhang, Q., Bu, X., 2018. A new method for mapping aquatic vegetation especially underwater vegetation in lake Ulansuhai using GF-1 satellite data. Remote Sens. 10, 1279.
Cheruiyot, E., Mito, C., Menenti, M., Gorte, B., Koenders, R., Akdim, N., 2014. Evaluating MERIS-based aquatic vegetation mapping in Lake Victoria. Remote Sens. 6, 7762–7782.
Dai, Z., Liu, J.T., Wei, W., Chen, J., 2015. Detection of the Three Gorges Dam influence on the Changjiang (Yangtze River) submerged delta. Sci. Rep. 4.
Dube, T., Mutanga, O., Sibanda, M., Bangamwabo, V., Shoko, C., 2017. Testing the detection and discrimination potential of the new Landsat 8 satellite data on the challenging water hyacinth (Eichhornia crassipes) in freshwater ecosystems. Appl. Geogr. 84, 11–22.
Gao, Y., Li, Q., Wang, S., Gao, J., 2018. Adaptive neural network based on segmented particle swarm optimization for remote-sensing estimations of vegetation biomass. Remote Sens. Environ. 211, 248–260.
Gullström, M., Lundén, B., Bodin, M., Kangwe, J., Öhman, M.C., Mtolera, M.S.P., Björk, M., 2006a. Assessment of changes in the seagrass-dominated submerged vegetation of tropical Chwaka Bay (Zanzibar) using satellite remote sensing. Estuar. Coast. Shelf Sci. 67, 399–408.
Gullström, M., Lundén, B., Bodin, M., Kangwe, J., Öhman, M.C., Mtolera, M.S.P., Björk, M., 2006b. Assessment of changes in the seagrass-dominated submerged vegetation of tropical Chwaka Bay (Zanzibar) using satellite remote sensing. Estuar. Coast. Shelf Sci. 67, 399–408.
Hilt, S., Gross, E.M., Hupfer, M., Morscheid, H., Mählmann, J., Melzer, A., Poltz, J., Sandrock, S., Scharf, E., Schneider, S., van de Weyer, K., 2006. Restoration of submerged vegetation in shallow eutrophic lakes – a guideline and state of the art in Germany. Limnologica 36, 155–171.
Hofstra, D.E., Clayton, J., Green, J.D., Auger, M., 1999. Competitive performance of Hydrilla verticillata in New Zealand. Aquat. Bot. 63, 305–324.
Horppila, J., Nurminen, L., 2003. Effects of submerged macrophytes on sediment resuspension and internal phosphorus loading in Lake Hiidenvesi (southern Finland). Water Res. 37, 4468–4474.
Hwang, P.A., Teague, W.J., Jacobs, G.A., Wang, D.W., 1998. A statistical comparison of wind speed, wave height, and wave period derived from satellite altimeters and ocean buoys in the Gulf of Mexico region. J. Geophys. Res. Oceans 103, 10451–10468.
Kemp, W.M., Batiuk, R., Bartleson, R., Bergstrom, P., Carter, V., Gallegos, C.L., Hunley, W., Karrh, L., Koch, E.W., Landwehr, J.M., Moore, K.A., Murray, L., Naylor, M., Rybicki, N.B., Stevenson, J.C., Wilcox, D.J., 2004. Habitat requirements for submerged aquatic vegetation in Chesapeake Bay: water quality, light regime, and physical-chemical factors. Estuaries 27, 363–377.
Koch, E.W., 2001. Beyond light: physical, geological, and geochemical parameters as possible submersed aquatic vegetation habitat requirements. Estuaries 24, 1–17.
Kolada, A., 2010. The use of aquatic vegetation in lake assessment: testing the sensitivity of macrophyte metrics to anthropogenic pressures and water quality. Hydrobiologia 656, 133–147.
Körner, S., 2002. Loss of submerged macrophytes in shallow lakes in North-Eastern Germany. Int. Rev. Hydrobiol. 87, 375.
Lawson, S.E., Wiberg, P.L., McGlathery, K.J., Fugate, D.C., 2007. Wind-driven sediment suspension controls light availability in a shallow coastal lagoon. Estuaries Coasts 30, 102–112.
Liang, Q., Zhang, Y., Ma, R., Loiselle, S., Li, J., Hu, M., 2017. A MODIS-based novel method to distinguish surface cyanobacterial scums and aquatic macrophytes in Lake Taihu. Remote Sens. 9, 133.
Liu, X., Zhang, Y., Yin, Y., Wang, M., Qin, B., 2013. Wind and submerged aquatic vegetation influence bio-optical properties in large shallow Lake Taihu, China. J. Geophys. Res. Biogeosci. 118, 713–727.
Luettich, R.A., Donald, R.F.H., Somlyody, L., 1990. Dynamic behavior of suspended sediment concentrations in a Shallow Lake Perturbed by episodic wind events. Limnol. Oceanogr. 35, 1050–1067.
Luo, J., Duan, H., Ma, R., Jin, X., Li, F., Hu, W., Shi, K., Huang, W., 2017. Mapping species of submerged aquatic vegetation with multi-seasonal satellite images and considering life history information. Int. J. Appl. Earth Obs. Geoinf. 57, 154–165.
Luo, J., Li, X., Ma, R., Li, F., Duan, H., Hu, W., Qin, B., Huang, W., 2016a. Applying remote sensing techniques to monitoring seasonal and interannual changes of aquatic vegetation in Taihu Lake, China. Ecol. Indic. 60, 503–513.
Luo, J., Li, X., Ma, R., Li, F., Duan, H., Hu, W., Qin, B., Huang, W., 2016b. Applying remote sensing techniques to monitoring seasonal and interannual changes of aquatic vegetation in Taihu Lake, China. Ecol. Indic. 60, 503–513.
Luo, J., Ma, R., Duan, H., Hu, W., Zhu, J., Huang, W., Lin, C., 2014. A new method for modifying thresholds in the classification of tree models for mapping aquatic vegetation in Taihu Lake with satellite images. Remote Sens. 6, 7442–7462.
Ma, R., Duan, H., Gu, X., Zhang, S., 2008. Detecting aquatic vegetation changes in Taihu Lake, China using multi-temporal satellite imagery. Sensors 8, 3988–4005.
Madsen, J.D., Chambers, P.A., James, W.F., Koch, E.W., Westlake, D.F., 2001. The interaction between water movement, sediment dynamics and submersed macrophytes. Hydrobiologia 444, 71–84.
Ozimek, T., Gulati, R.D., van Donk, E., 1990. Can macrophytes be useful in biomanipulation of lakes? The Lake Zwemlust example. Hydrobiologia 200–201, 399–407.
Palmer, S.C.J., Kutser, T., Hunter, P.D., 2015. Remote sensing of inland waters: challenges, progress and future directions. Remote Sens. Environ. 157, 1–8.
Phillips, G., Willby, N., Moss, B., 2016. Submerged macrophyte decline in shallow lakes: what have we learnt in the last forty years? Aquat. Bot. 135, 37–45.
Phinn, S., Roelfsema, C., Dekker, A., Brando, V., Anstee, J., 2008. Mapping seagrass species, cover and biomass in shallow waters: an assessment of satellite multi-spectral and airborne hyper-spectral imaging systems in Moreton Bay (Australia). Remote Sens. Environ. 112, 3413–3425.
Pu, R., Bell, S., Meyer, C., Baggett, L., Zhao, Y., 2012. Mapping and assessing seagrass along the western coast of Florida using Landsat TM and EO-1 ALI/hyperion imagery. Estuar. Coast. Shelf Sci. 115, 234–245.
Pu, R., Bell, S., 2017. Mapping seagrass coverage and spatial patterns with high spatial resolution IKONOS imagery. Int. J. Appl. Earth Obs. Geoinf. 54, 145–158.
Qin, B., Zhu, G., Gao, G., Zhang, Y., Li, W., Paerl, H.W., Carmichael, W.W., 2010. A drinking water crisis in Lake Taihu, China: linkage to climatic variability and lake management. Environ. Manage. 45, 105–112.
Rao, W., Ning, J., Zhong, P., Jeppesen, E., Liu, Z., 2015. Size-dependent feeding of omnivorous Nile tilapia in a macrophyte-dominated lake: implications for lake management. Hydrobiologia 749, 125–134.
Roelfsema, C.M., Lyons, M., Kovacs, E.M., Maxwell, P., Saunders, M.I., Samper-Villarreal, J., Phinn, S.R., 2014. Multi-temporal mapping of seagrass cover, species and biomass: a semi-automated object based image analysis approach. Remote Sens. Environ. 150, 172–187.
Sayer, C.D., Burgess, A., Kari, K., Davidson, T.A., Peglar, S., Yang, H., Rose, N., 2010. Long-term dynamics of submerged macrophytes and algae in a small and shallow, eutrophic lake: implications for the stability of macrophyte-dominance. Freshw. Biol. 55, 565–583.
Schelske, C.L., Lowe, E.F., Kenney, W.F., Battoe, L.E., Brenner, M., Coveney, M.F., 2010. How anthropogenic darkening of Lake Apopka induced benthic light limitation and forced the shift from macrophyte to phytoplankton dominance. Limnol. Oceanogr. 55, 1201–1212.
Shekede, M.D., Kusangaya, S., Schmidt, K., 2008. Spatio-temporal variations of aquatic weeds abundance and coverage in Lake Chivero, Zimbabwe. Phys. Chem. Earth Parts A/B/C 33, 714–721.
Shen, J., Yuan, H., Liu, E., Wang, J., Wang, Y., 2011. Spatial distribution and stratigraphic characteristics of surface sediments in Taihu Lake, China. Chin. Sci. Bull. 56, 179–187.
Søndergaard, M., Johansson, L.S., Lauridsen, T.L., Jørgensen, T.B., Liboriussen, L., Jeppesen, E., 2010. Submerged macrophytes as indicators of the ecological quality of lakes. Freshw. Biol. 55, 893–908.
Vereecken, H., Baetens, J., Viaene, P., Mostaert, F., Meire, P., 2006. Ecological management of aquatic plants: effects in lowland streams. Hydrobiologia 570, 205–210.
Villa, P., Boschetti, M., Morse, J.L., Politte, N., 2012. A multitemporal analysis of tsunami impact on coastal vegetation using remote sensing: a case study on Koh Phra Thong Island, Thailand. Nat. Hazards 64, 667–689.
Villa, P., Bresciani, M., Bolpagni, R., Pinardi, M., Giardino, C., 2015. A rule-based approach for mapping macrophyte communities using multi-temporal aquatic vegetation indices. Remote Sens. Environ. 171, 218–233.
Villa, P., Bresciani, M., Braga, F., Bolpagni, R., 2014. Comparative assessment of broadband vegetation indices over aquatic vegetation. IEEE J. Sel. Top. Appl. Earth Obs. Remote. Sens. 7, 3117–3127.
WANG, C., ZHENG, S., WANG, P., QIAN, J., 2014. Effects of vegetations on the removal of contaminants in aquatic environments: a review. J. Hydrodynam. B 26, 497–511.
Wang, S., Gao, Y., Li, Q., Gao, J., Zhai, S., Zhou, Y., Cheng, Y., 2019. Long-term and inter-monthly dynamics of aquatic vegetation and its relation with environmental factors in Taihu Lake, China. Sci. Total Environ. 651, 367–380.
Yunkai-Li, Chen, Y., Song, B., Olson, D., Yu, N., Liqiao-Chen, 2009. Ecosystem structure and functioning of Lake Taihu (China) and the impacts of fishing. Fish. Res. 95, 309–324.

Zhang, Y., Jeppesen, E., Liu, X., Qin, B., Shi, K., Zhou, Y., Thomaz, S.M., Deng, J., 2017. Global loss of aquatic vegetation in lakes. Earth-Sci. Rev. 173, 259–265.
Zhang, Y., Liu, X., Qin, B., Shi, K., Deng, J., Zhou, Y., 2016a. Aquatic vegetation in response to increased eutrophication and degraded light climate in Eastern Lake Taihu: implications for lake ecological restoration. Sci. Rep. 6.
Zhang, Y., Liu, X., Qin, B., Shi, K., Deng, J., Zhou, Y., 2016b. Aquatic vegetation in response to increased eutrophication and degraded light climate in Eastern Lake Taihu: implications for lake ecological restoration. Sci. Rep. 6.
Zhang, Y., Ma, R., Duan, H., Loiselle, S.A., Xu, J., Ma, M., 2014. A novel algorithm to estimate algal bloom coverage to subpixel resolution in Lake Taihu. IEEE J. Sel. Top. Appl. Earth Obs. Remote. Sens. 7, 3060–3068.
Zhao, D., Lv, M., Jiang, H., Cai, Y., Xu, D., An, S., 2013. Spatio-temporal variability of aquatic vegetation in Taihu Lake over the past 30 years. PLoS One 8, e66365.