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1 Mapping species of submerged aquatic
2 vegetation with multi-seasonal satellite images
3 considering life history information

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14 **Abstract:** Spatial information of the dominant species of submerged aquatic
15 vegetation (SAV) is essential for restoration projects in eutrophic lakes,
16 especially eutrophic Taihu Lake, China. Mapping the distribution of SAV
17 species is very challenging and difficult using only multispectral satellite
18 remote sensing. In this study, we proposed an approach to map the distribution
19 of seven dominant species of SAV in Taihu Lake. Our approach involved
20 information on the life histories of the seven SAV species and eight distribution
21 maps of SAV from February to October. The life history information of the
22 dominant SAV species was summarized from the literature and field surveys.
23 Eight distribution maps of the SAV were extracted from eight 30 m HJ-CCD
24 images from February to October in 2013 based on the classification tree
25 models, and the overall classification accuracies for the SAV were greater than
26 80%. Finally, the spatial distribution of the SAV species in Taihu in 2013 was
27 mapped using multilayer erasing approach. Based on validation, the overall
28 classification accuracy for the seven species was 68.4%, and kappa was 0.6306,
29 which suggests that larger differences in life histories between species can
30 produce higher identification accuracies. The classification results show that
31 *Potamogeton malaianus* was the most widely distributed species in Taihu Lake,
32 followed by *Myriophyllum spicatum*, *Potamogeton maackianus*, *Potamogeton*
33 *crispus*, *Elodea nuttallii*, *Ceratophyllum demersum* and *Vallisneria spiralis*.
34 The information is useful for planning shallow-water habitat restoration
35 projects.

36 **Keywords:** Submerged aquatic vegetation (SAV); Mapping; Dominant
37 species; Remote sensing; Life history

40 **1. Introduction**

41 Submerged aquatic vegetation (SAV) has important impacts on the
42 physical, chemical and biological structure and function of aquatic
43 ecosystems, particularly in shallow lakes (Barko et al., 1991; Gumbricht,
44 1993; Hu et al., 2010). Studies indicated that shallow aquatic systems that
45 are dominated by SAV often have better water quality (clarity, total
46 suspended solid, pH, chlorophyll *a* (Chl-*a*), total phosphorus (TP) and total
47 nitrogen (TN) than other systems (Luo et al., 2014), and SAV can cause
48 aquatic ecosystems to shift from a turbid algae-dominated state to a clear-
49 water plant-dominated state (Folke et al., 2004; Soana et al., 2012), because
50 it can inhibit the growth of algae, absorb the excessive nutrients, reduce
51 water currents, accelerate the sedimentation of suspended materials,
52 stabilize sediments and prevent them from re-suspending (Depew et al.,
53 2011; Hilt et al., 2006; Luo et al., 2014; Shuchman et al., 2013). In addition,
54 it can provide food and shelter for wildlife, and habitat for spawning
55 aquatic animals.

56 In recent decades, as a consequence of rapid urbanization and human
57 activities, most of the urban and suburban shallow lakes and rivers in China
58 have experienced accelerating eutrophication followed by the loss or
59 degradation of SAV due to high total suspended matter (TSM)
60 concentration and low water transparency (Duan et al., 2012; Shi et al.,
61 2015). The restoration of SAV in phytoplankton-dominated lakes is crucial
62 for transforming the turbid states of these shallow lakes (Dong et al., 2014;
63 Hilt et al., 2006). In addition, studies have indicated that SAV can help
64 inhibit the growth of phytoplankton by competing for nutrients and light

65 (Dong et al., 2014; Lombardo and Cooke, 2003). The re-establishment of
66 SAV has been recognized as a valuable ecological engineering technique g
67 for improving aquatic systems in China. Efficient SAV restoration planning
68 requires reliable information about the physical habitat requirements of the
69 species (Angradi et al., 2013). For SAV restoration projects, mapping the
70 spatial distribution of the SAV species is important for acquiring the most
71 suitable ecology and environment conditions for the growth of the
72 dominant SAV species. Additionally, an accurate knowledge of the spatial
73 distribution of dominant species of SAV is highly valuable to many
74 scientific and management goals, including the improved parameterization
75 of shallow lake ecosystem processes and models (Zhang et al., 2013).

76 Surveying the distribution of SAV and species at a large scale is very
77 labour intensive and time-consuming due to the restriction of working in
78 the water environment. Satellite remote sensing techniques have become
79 powerful and effective tools for mapping aquatic vegetation (Liu et al.,
80 2015; Ma et al., 2008; Zhao et al., 2013). For example, Zhao et al. (2013)
81 and Luo et al. (2014) proposed methods for identifying of emergent,
82 floating-leaved and submerged vegetation and mapping their distribution
83 in Taihu Lake using Landsat TM and HJ-1A/1B CCD images, respectively.
84 Robert et al. (2015) developed a satellite-based algorithm to map SAV and
85 then successfully mapped the distribution of SAV in the Laurentian Great
86 Lakes, Lakes Michigan and Ontario. Therefore, multispectral satellite
87 remote sensing can be used to accurately map and identify emergent,
88 floating-leaved and submerged vegetation in shallow coastal waters or
89 lakes due to the large spectral difference among them.

90 For identifying SAV species, a limited number of exploratory research
91 programs have been conducted using hyperspectral remote sensing data.
92 For example, Han and Rundquist (2003) studied the spectral responses of
93 *Ceratophyllum demersum* at varying depths in both clear and algae-laden

94 water using a hyperspectral hand-held spectroradiometer. Pinnel et al.
95 (2004) gathered airborne hyperspectral remote sensing data for the spectral
96 discrimination of submerged vegetation in Southern Germany. Yuan and
97 Zhang (2006) investigated the spectral characteristics of the SAV plant
98 species *Potamogeton crispus*, *Myriophyllum spicatum* and *Potamogeton*
99 *malaianus* with the same coverage and found that their red edge peaks and
100 valleys are different. These studies suggested that there are tiny spectral
101 differences among SAV species, and it is only possible to recognize them
102 using hyperspectral remote sensing data with abundant spectral
103 information.

104 However, considering the cost and availability of hyperspectral
105 satellite data, it is infeasible to use them to continuously monitor and
106 identify SAV species. It appears to be impossible to map and identify SAV
107 species using only multispectral satellite image because the spectral
108 differences among the SAV species are tiny and therefore difficult to
109 capture using broadband remote sensing data. Fortunately, different SAV
110 species have different phenological characteristics and life histories, which
111 has made it possible to map and identify SAV species using multiseasonal
112 and multispectral satellite remote sensing data based on information on
113 their life histories, and it has been proven to be effective to identify
114 terrestrial vegetation types based on multi-temporal satellite remote
115 sensing data (Leite et al., 2011; Liu et al., 2006; Murthy et al., 2003) and
116 phenological information. However, the method has not been used and
117 tested for mapping aquatic vegetation species.

118 Therefore, in this study, using ArcGIS spatial analysis technology, we
119 developed a multilayer erasing flow for mapping SAV species in Taihu
120 Lake by combining their life history characteristics and multi-seasonal
121 satellite remote sensing data. To our knowledge, it is the first study to map
122 the dominant SAV species using satellite images.

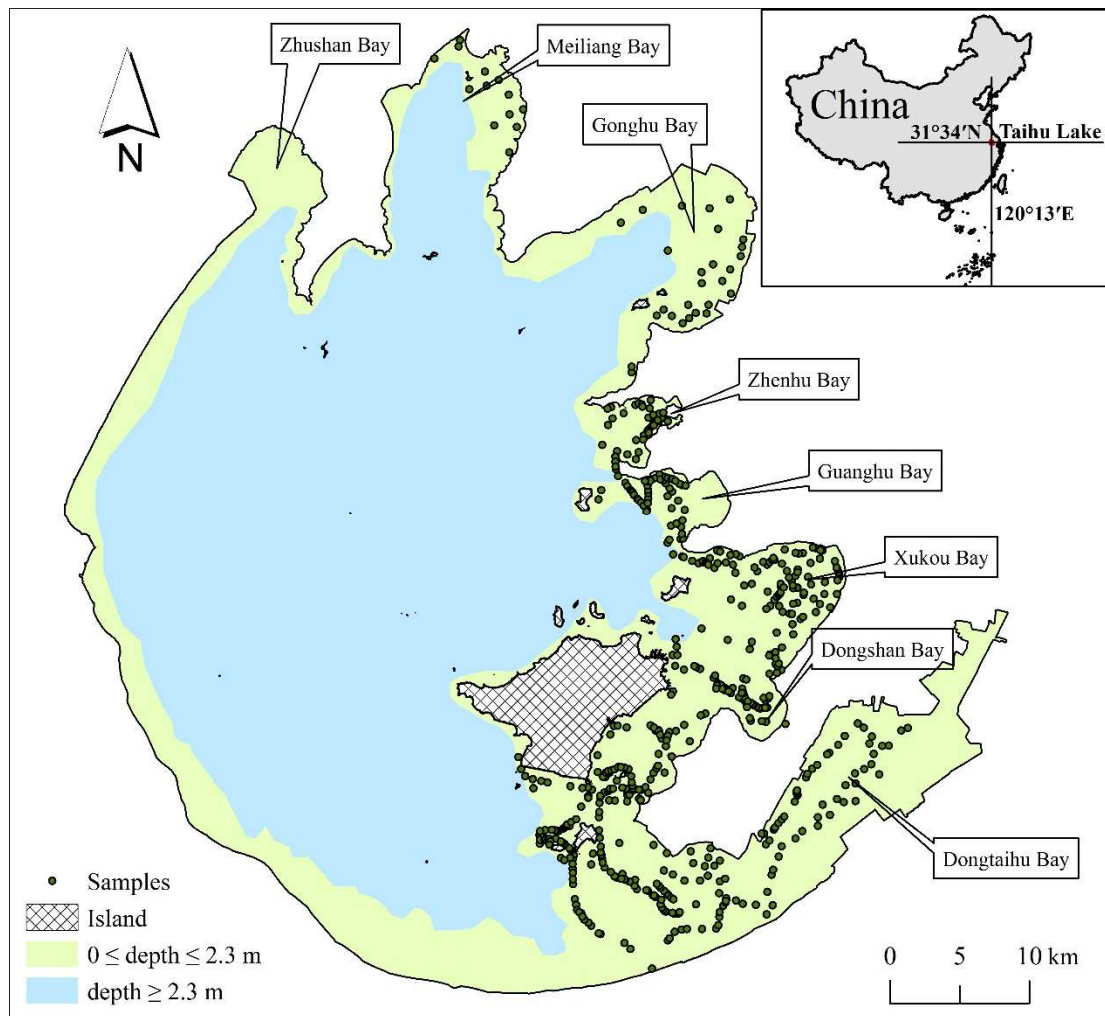
123 **2. Materials and methods**

124 *2.1. Study area*

125 Taihu Lake (30°55'40"– 31°32'58"N, 119°52'32"– 120°36'10"E) is
126 one of the five largest freshwater lakes in China and covers an area of
127 approximately 2,338 km². It is located at the core of the Yangtze Delta in
128 the lower reaches of the Yangtze River in eastern China (Figure 1). Taihu
129 Lake is a typical shallow lake with a maximum depth of less than 3 m and
130 an average depth of 1.9 m. The western and central parts of Taihu Lake
131 belong to the algal-dominated zone, where the waters are consistently
132 extremely turbid with high total nitrogen (TN), total phosphorus (TP)
133 contents and suspended matter concentration. Algal blooms occur
134 frequently in the algal-dominated zone (Duan et al., 2015). The eastern of
135 Taihu Lake, including Meiliang, Gonghu, Zhenhu, Guhuanghu, Xukou,
136 Doangshan and Dongtaihu Bays, are covered with hydrophytes and
137 therefore belonged to a macrophyte-dominated zone with much lower TN
138 and TP content and higher water transparency than did those in the algal-
139 dominated zone (Luo et al., 2016). According to previous studies (Carr et
140 al., 2010; Liu et al., 2015), no aquatic vegetation exists at water depth
141 greater than 2.3 m in the Taihu Lake. Therefore, we exacted the region with
142 water depths less than 2.3 m as the study area. Depth data was provided by
143 Taihu Laboratory for Lake Ecosystem Research (Figure 1).

144 There are four types of aquatic vegetation in the grass-type zone:
145 emergent, free-floating, floating-leaving and submerged vegetation.
146 Emergent and free-floating hydrophytes accounts for less than 5% of the
147 total aquatic vegetation area and are mostly distributed in the littoral zone
148 of Taihu Lake (Luo et al., 2014). In this study, we divided aquatic
149 vegetation into floating-leaved and submerged vegetation. According to
150 field survey and documentary records, there are approximately 17 SAV

151 species in Taihu Lake, but only seven species are dominant: *Elodea*
152 *nuttallii*, *Potamogeton crispus*, *Myriophyllum spicatum*, *Potamogeton*
153 *maackianus*, *Ceratophyllum demersum* and *Vallisneria spiralis*(Ma et al.,
154 2008; Qin, 2008; Ye et al., 2009).



155
156 Figure 1. Location of Taihu Lake within China (depth data was provided by Taihu
157 Laboratory for Lake Ecosystem Research)

158 **2.2. Field data collection**

159 Field surveys were conducted on 10-14 March, 22-24 May, 10-13 July,
160 17-22 August and 23-26 September in 2013. A total of 604 ground-truth
161 samples were collected for open water and aquatic vegetation (100 samples
162 in March, 102 samples in May, 112 samples in July, 143 samples in August
163 and 179 samples in September) in macrophyte-dominated zone of Taihu

164 Lake (Figure 1), including 405 submerged vegetation samples and 231
165 floating-leaved vegetation samples. The aquatic vegetation sampling plots
166 were limited to areas measuring at least 60×60 m (*i.e.*, four pixels of an
167 HJ-CCD image) and that had a relatively uniform distribution of
168 vegetation. We used a portable GPS receiver with an accuracy of 3 m to
169 record the centre coordinates of each sample and recorded the type and
170 percent coverage of aquatic vegetation. We also used GPS to record the
171 boundary extent of the representative floating-leaved and submerged
172 aquatic vegetation sample regions to generate a polygon vector file.

173 ***2.3. Remote sensing data collections and processing***

174 HJ-CCD images recorded from the HJ-1A/1B CCD cameras were
175 acquired from the China Centre for Resources Satellite Data and
176 Application (CRESDA). These cameras were onboard the HJ-1A and HJ-
177 1B satellites, which were launched by CRESDA on September 6, 2008.
178 Their spectral ranges and spatial resolutions are similar to those of the first
179 four bands of Landsat TM. The single CCD imagery width is 360 km, and
180 the two satellites constellation provides a wider swath width (700 km) and
181 a re-visit time of 48 h (two days). Its high re-visit cycle was of great
182 importance for mapping the dominant SAV species in this study.

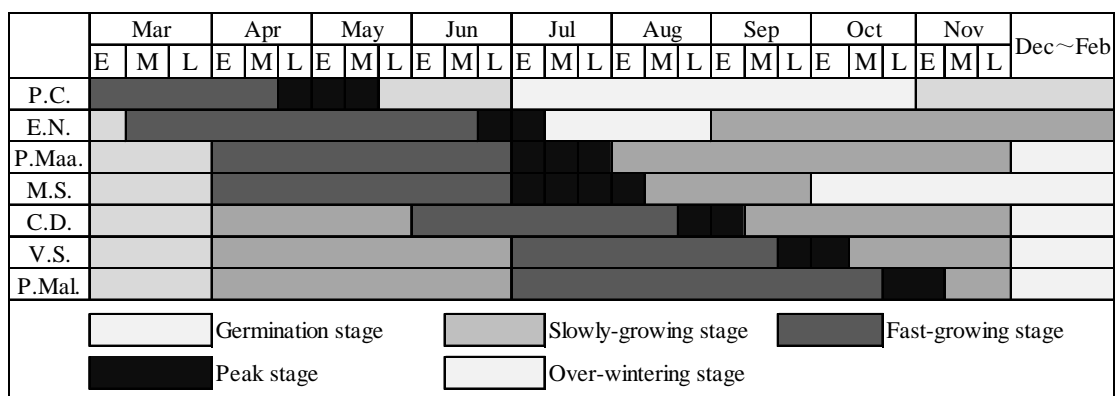
183 In this study, eight cloud-free and sun glint free HJ-CCD images
184 covering Taihu Lake and acquired on February 20, March 12, April 25,
185 May 22, July 11, August 16, September 26 and October 28, 2013 were
186 used, respectively. The ENVI software package was used to pre-process the
187 remote sensing images. Radiometric corrections were made using coefficients
188 from the metadata accompanying the images (e.g., gains and offsets).
189 FLAASH uses a robust procedure to correct for atmospheric attenuation and
190 adjacency effects (Module, 2009). Four key input parameters for the
191 FLAASH module included: the mid-latitude atmosphere model, urban

192 aerosol model, atmosphere water vapour and visibility. Based on the location
193 of the study area covered by the scenes and the satellite transit time, the first
194 two parameters were easily determined. However, water vapour and visibility
195 values may vary between the images, and these were determined by trial-and-
196 error until a typical spectral pattern of plants was observed (Pu et al., 2012).
197 The HJ-CCD images were also geometrically corrected with a previously
198 corrected Landsat TM image with a geometric accuracy of < 0.5 pixels.

199 2.4. Life histories of dominant species of SAV in Taihu Lake

200 There are seven dominant SAV species in Taihu Lake: *Potamogeton*
201 *crispus*, *Elodea nuttallii*, *Myriophyllum spicatum*, *Potamogeton*
202 *maackianus*, *Ceratophyllum demersum*, *Vallisneria spiralis* and
203 *Potamogeton malaianus*. Using references and field surveys, the life
204 histories of the seven dominant species are summarized in Figure 1.
205 Detailed descriptions of the species are now discussed. 1) *Potamogeton*
206 *crispus* can tolerate temperatures below 0°C and can survive over winter.
207 It grows rapidly after March, reaches a maximum biomass in mid-May and
208 then soon dies and becomes dormancy (Nichols and Shaw, 1986; Rogers
209 and Breen, 1980). It regrows after November. 2) *Elodea nuttallii* tolerates
210 temperature below 0°C and can survive over winter, forming a dense mat
211 of vegetation just above the lake bottom (Oki, 1994). It grows rapidly after
212 May, reaches a maximum biomass in early July, and then soon died and
213 becomes dormancy. It regrows after September (Kunii, 1984). 3)
214 *Potamogeton maackianus* cannot survive over winter. It begins to rapidly
215 grow in early April and reaches a maximum biomass in July, grows slowly
216 and gradually withers (Ni, 2001). 4) *Myriophyllum spicatum* cannot
217 survive over winter. It grows rapidly from April to July and reaches its peak
218 stage from early July to early August. It begins its dormancy from
219 December to the following February (Nichols and Shaw, 1986). 5)

220 *Ceratophyllum demersum* cannot survive over winter and starts dormancy
 221 between December to following February. It grows rapidly from early June
 222 and reaches a maximum biomass from late August to early September, and
 223 then grows slowly and gradually withers (Best, 1977). 6) *Vallisneria*
 224 *spiralis* cannot survive over winter and is dormant from December to next
 225 February. It begins growing slowly from April and grows rapidly during
 226 July-September, after which it reaches maximum biomass during early
 227 October to mid-October. 7) *Potamogeton malaianus* has a similar life
 228 history, except for its peak stage. It reaches maximum biomass from late
 229 October to early November (Liu et al., 2007; Wiegleb and Kadono, 1989;
 230 Xiao et al., 2010).



232 Figure 2. Life histories of seven SAV species in Taihu Lake

233 Note: *P.C.*=*Potamogeton crispus*; *E.N.*=*Elodea nuttallii*; *M.S.*=*Myriophyllum*
 234 *spicatum*; *P.Maa.*=*Potamogeton maackianus*; *C.D.*=*Ceratophyllum demersum*;
 235 *V.S.*=*Vallisneria spiralis*; *P. Mal.*=*Potamogeton malaianus*; E=Early; M=Middle;
 236 L=Late.

237 2.5 Methods

238 2.5.1. Classification tree model for the extraction of SAV

239 Classification tree (CT) analyses are based on the dichotomous
 240 partitioning of data at certain thresholds of the value of the explanatory
 241 variables, which determine the branch a particular sample will follow
 242 (Olshen and Stone, 1984). It is considered to be especially robust when

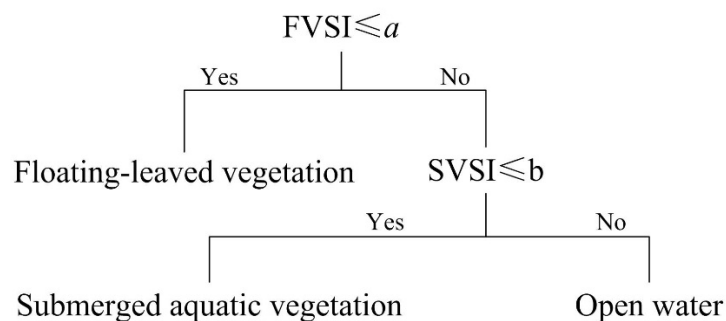
243 used with a small sample size of remotely-sensed data (Tadjudin and
 244 Landgrebe, 1996). Luo et al., (2014) developed a classification tree for
 245 mapping floating-leaved and submerged vegetation in Taihu Lake. As
 246 shown in Fig. 3, in the classification tree, floating-leaved vegetation was
 247 first extracted from other types using the floating-leaved vegetation
 248 sensitive index (FVSI), and then the submerged vegetation sensitive index
 249 (SVSI) was used to distinguish between the SAV and water. The FVSI and
 250 SVSI were defined as:

251
$$FVSI = PC_2$$
 Eq. (1)

252 where PC_2 is the second principal component of the principal component
 253 transform.

254
$$SVSI = TC_1 - TC_2$$
 Eq. (2)

255 where TC_1 and TC_2 are, respectively, the first and second components of
 256 the tasseled cap transform, which are also called the brightness and
 257 greenness (Crist, 1985; Healey et al., 2005).



258
 259 Figure 3. Classification tree of identifying floating-leaved vegetation and submerged
 260 aquatic vegetation based on FVSI and SVSI, where a and b are the threshold of FVSI
 261 and SVSI

262 In the classification tree, the thresholds, i.e., a and b , of FVSI and
 263 SVSI vary with images, because they can be influenced by aquatic
 264 vegetation conditions, environmental and physical conditions. For the
 265 image with the synchronously collected ground samples, the thresholds of
 266 FVSI and SVSI were determined and modified slightly based on field

267 survey points until the maximum classification precision was achieved. For
 268 the image without the synchronously collected ground samples, Luo et al.
 269 (2014) developed an effective algorithm to calculate the thresholds. In this
 270 study, the thresholds of FVSI and SVSI in the CT models for the image
 271 acquired on July 11 were obtained using the synchronously collected
 272 ground samples, whereas the thresholds for the images without
 273 synchronously collected ground samples were calculated according to the
 274 thresholds for the July 11 image using the algorithm developed by Luo et
 275 al. (2014) The algorithms can be expressed as:

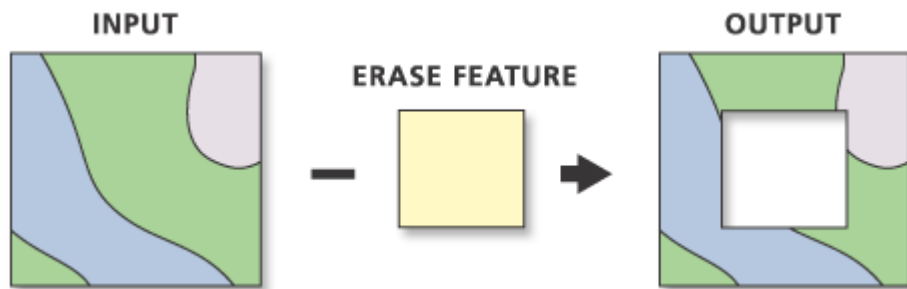
$$276 \quad CT_{m_FVSI} = k \times CT_FVSI + h \quad \text{Eq. (3)}$$

$$277 \quad CT_{m_SVSI} = p \times CT_SVSI + q \quad \text{Eq. (4)}$$

278 where CT_{m_FVSI} and CT_{m_SVSI} are the thresholds of FVSI and SVSI in
 279 the classification model, respectively, for the image acquired at time m in
 280 the absence of ground samples, which should be calculated, that is a and b
 281 in the classification tree in Figure 3; and CT_FVSI and CT_SVSI are the
 282 thresholds of FVSI and SVSI in the classification model, respectively, for
 283 the image of July 11. The CT_FVSI and CT_SVSI were obtained using the
 284 field survey data. For k and h , we first selected the same regions of interest
 285 (ROIs) with floating-leaved vegetation from the images at time m and July
 286 11, respectively. Secondly, two group FVSI values derived from the two
 287 ROIs were placed in descending order. Finally, the line fitting model was
 288 simulated using the two descending FVSI datasets, and the slope and
 289 intercept of the linear model were k and h , respectively. In a similar way,
 290 the line fitting model could be simulated by the two groups of SVSI in
 291 descending order, and then we can acquire p and q . See the work by Luo
 292 et al. (Luo et al., 2014) for the detailed test and validation of the algorithm.
 293 The thresholds and classification accuracies of SAV were assessed by the
 294 overall classification accuracy (OCA) (Luo et al., 2016; Luo et al., 2014).

295 **2.5.2. Method for identifying dominant species of SAV**

296 Based on the life history information of the dominant SAV species,
297 the dominant species were identified from the time-series SAV distribution
298 maps using the erase tool in the analysis tool of ArcGIS. The erase tool is
299 an important analysis tool in ArcGIS. As shown in Figure 4, erase creates
300 a new feature class by overlaying two sets of features. The erase features
301 polygons that define the erasing area. The input features or portions of
302 input features that overlap the erase features are not written to the output
303 feature class. The input features can be points, lines or polygons, but the
304 erase features must be polygons. The output features will be of the same
305 geometry type as the input Features. Input features or portions of input
306 features that do not overlap erase features are written to the output feature
307 class.



308

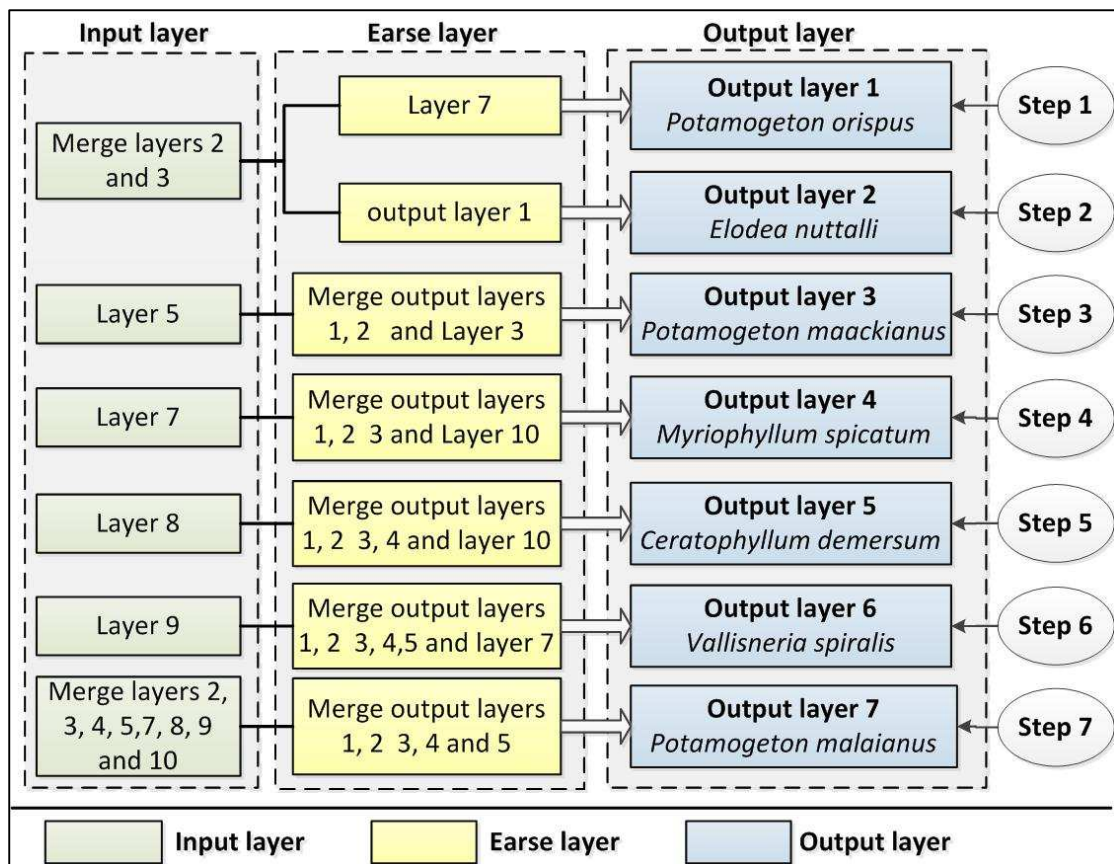
309 Figure 4. Schematic diagram of erase tool (from ArcGIS desktop help)

310 Figure 5 shows the flow chart and methods that were used to identify
311 the dominant SAV species. As shown in Figure 5, Layers 2, 3, 5, 7, 8, 9 and
312 10 are the SAV spatial distribution maps derived from the images of
313 February 20, March 12, May 22, July 11, August 16, September 26 and
314 October 28 based on the classification tree models. The methods were
315 developed according to the following general principles. 1) The dominant
316 species were extracted successively according to the time order of the
317 maximum biomass from January to December, and thus, *Potamogeton*
318 *crispus*, *Elodea nuttallii*, *Myriophyllum spicatum*, *Potamogeton*

319 *maackianus*, *Ceratophyllum demersum*, *Vallisneria spiralis* and
320 *Potamogeton malaianus* were extracted in sequence. 2) the Erase tool in
321 ArcGIS was used to extract the species. The input layer and erase feature
322 are SAV layers extracted from the images using the corresponding
323 classification tree models. To obtain the distribution layer of a species layer,
324 the input layer was derived from the image during the fast-growing and
325 peak stages of the species, and the erase feature was derived from the image
326 between the germination and slow growth stages of the species. Because
327 the species has the highest coverage and was the closest to water surface in
328 their fast-growing and peak stages, during which they can be readily
329 captured by remote sensing. In the germination and slow growth stages,
330 the species' canopies are not close to the water surface and coverage are
331 low; in these stages, very little species information can be captured by
332 remote sensing, especially in high suspended shallow lakes.

333 Therefore, based on the life histories of the seven SAV species, the
334 detailed steps for extracting the seven species are as follows: 1) extraction
335 of *Potamogeton crispus*. From February to March, *Potamogeton crispus*
336 and *Elodea nuttallii* are in the fast-growing stage, and in the germination
337 stage in July, they are the main dominant species in Taihu. The SAV layers
338 derived from March and April were merged, and then the merged layer was
339 used as the input layer, the SAV layers from July were used as the erase
340 feature, and therefore the output layer was the distribution layer of
341 *potamogeton crispus*; (2) extraction of *Elodea nuttallii*. The SAV layers
342 derived from February and March were merged, the merged layer was used
343 as the input layer, *Potamogeton crispus* layer was used as the erase feature,
344 and therefore the output layer was the distribution layer of *Elodea nuttallii*;
345 (3) extraction of *Potamogeton maackianus*. *Potamogeton maackianus* is in
346 the fast-growing stage in May and in the slowly-growing stage in March.
347 Therefore the SAV layer in May was used as the input layer; the SAV layer

348 in March and *Potamogeton crispus* and *Elodea nuttallii* layers were
349 merged, the merged layer was used as the erase feature, and the output layer
350 was the distribution layer of *Potamogeton maackianus*; (4) extraction of
351 *Myriophyllum spicatum*. This species is in its peak stage in July and in the
352 slowly-growing stage in October. The SAV layer in July was used as the
353 input layer; the SAV layer in October and the layers of *Potamogeton*
354 *crispus* and *Elodea nuttallii* and *Potamogeton maackianus* were merged,
355 the merged layer was used as the erase feature, and the output layer was
356 the distribution layer of *Myriophyllum spicatum*; (5) extraction of
357 *Ceratophyllum demersum*. This species is in its fast-growing stage in
358 August and in the slowly-growing stage in late-October. The SAV layer in
359 August was used as the input layer, the SAV layer in late-October and the
360 layers of *Potamogeton crispus*, *Elodea nuttallii*, *Potamogeton maackianus*
361 *and Myriophyllum spicatum* were merged, the merged layer was used as
362 the erase feature; and the output layer was the distribution layer of
363 *Ceratophyllum demersum*; (6) extraction of *Vallisneria spiralis*. This
364 species is in its fast-growing stage in September and in the slowly-growing
365 stage in late-October. The SAV layer in August was used as the input layer,
366 the SAV layer in late-October and the layers of *Potamogeton crispus*,
367 *Elodea nuttallii*, *Potamogeton maackianus*, *Myriophyllum spicatum* and
368 *Ceratophyllum demersum* were merged, the merged layer was used as the
369 erase feature, and the output layer was the distribution layer of *Vallisneria*
370 *spiralis*; (7) extraction of *Potamogeton malaianus*. All of the SAV layers
371 from February, March, April, May, July, August, September and October
372 were merged, the merged layer was used as the input layer, the
373 classification layers of the other six species were merged, the merged layer
374 was used as the erase feature, and the output layer was the distribution layer
375 of *Potamogeton malaianus*.



376

377

Figure 5. Flow chart for identifying seven SAV species

378

Note: Layer 2, 3, 4, 5, 7, 8, 9, 10 are the SAV distribution maps were derived from the image of February 20, March 12, April 25, May 22, July 11, August 16, September 26 and October 28,2013 using classification tree models.

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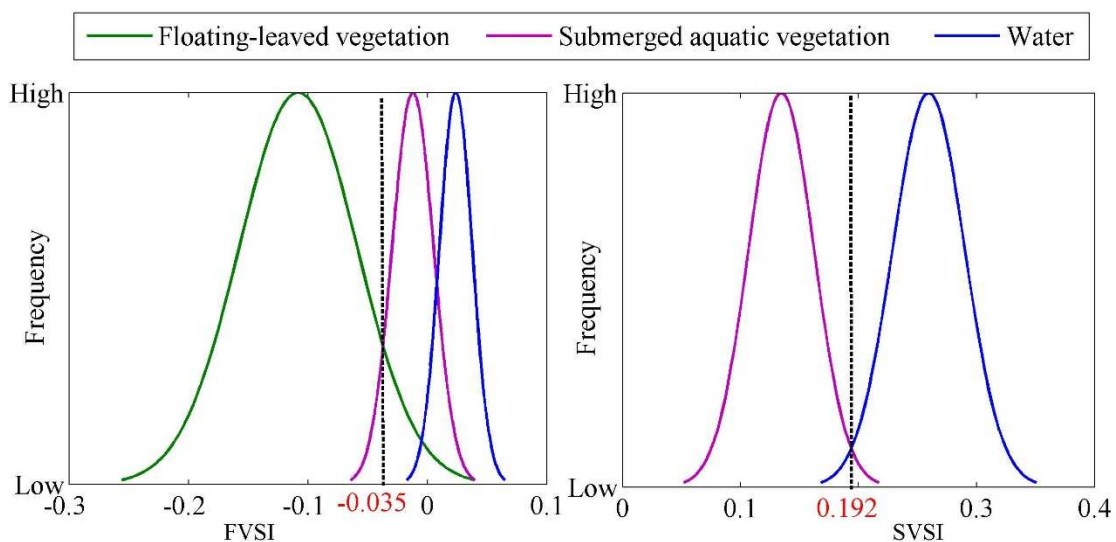
According to Figure 5, the spatial distribution of the seven SAV species in 2013 can be mapped in shallow lakes. Classification accuracies of dominant SAV species were assessed by producer's accuracy (PA), user's accuracy (UA), overall accuracy (OA) and Kappa (Congalton et al., 1983). Meanwhile, to analyse the dominant species in different seasons, we merged the SAV layers from 20 February, 12 March and 25 April 2013 as the SAV distribution layer in the spring. By combining the spatial distribution map of the seven species in 2013 and the SAV distribution layer in the spring, the spatial distribution map of the dominant species in the spring can be obtained. The SAV layers from 22 May and 11 July 2013 were merged as the SAV distribution layer in the summer, and the SAV layers from 16 August, 26 September and 28 October 2013 were merged

394 as the SAV distribution layer in the autumn. In the same way, the spatial
395 distribution maps of the dominant species in the summer and autumn were
396 built.

397 **3. Results**

398 **3.1. Identification of aquatic vegetation**

399 Using Eqs. (1) and (2), FVSI and SVSI were derived from the image
400 of July 11, 2013. Then, the FVSI and SVSI values of the samples collected
401 from 11-13 July 2013 were obtained. Based on the FVSI and SVSI values
402 of the different types, the histogram was obtained, and then the optimal
403 thresholds of FVSI and SVSI were quantitatively determined. As shown in
404 Figure 6, the floating-leaved vegetation could be identified from the other
405 two types when $FVSI \leq -0.035$, and then the threshold ($SVSI=0.192$) could
406 be used to distinguish the submerged aquatic vegetation from the water.
407 Using the optimal thresholds and classification tree, the floating-leaved
408 vegetation and submerged aquatic vegetation on 11 July 2013 were
409 mapped (Figure 7).



410

411

Figure 6. Histogram of FVSI and SVSI from different types

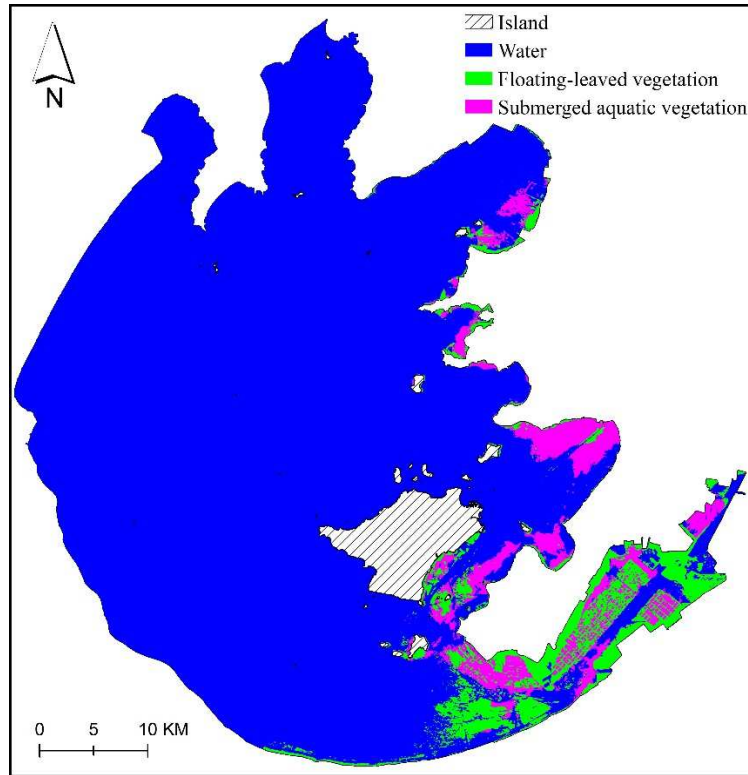


Figure 7. Spatial distribution map of aquatic vegetation on July 11, 2013

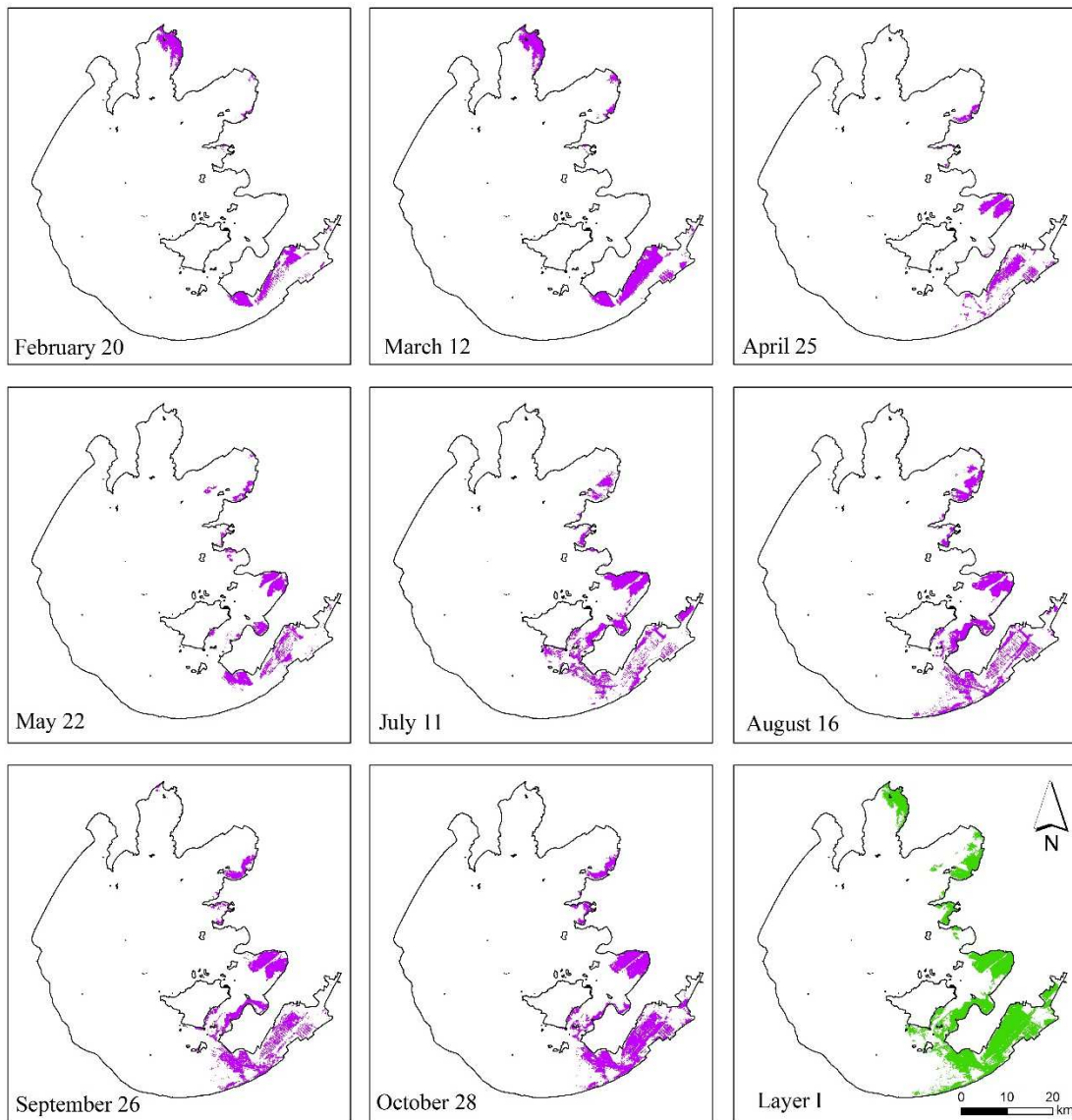
Next, based on the threshold of FVSI and SVSI for July 11, 2013, we calculated all of the thresholds of FVSI and SVSI for the other images using the algorithms (Eqs. (3) and (4)) (Table 1). The classification results for March 12, May 13, July 13, August 16, September 26 and October 28 were validated using the corresponding ground samples. The results show that the overall classification accuracies were higher than 80%, and that 83% of the misclassified samples had a coverage < 20 %, and therefore might be difficult to identify SAV with a coverage < 20% using satellite images with resolutions of 30 m.

Table 1. Thresholds of FVSI and SVSI in classification trees. a and b are the thresholds of FVSI and SVSI, respectively. OA = Overall accuracy.

Date	a	b	OA (%)	Date	a	b	OA (%)
20-Feb-13	-0.055	0.337	—	11-Jul-13	-0.035	0.192	82.1
12-Mar-13	-0.055	0.318	88.7	16-Aug-13	-0.075	0.129	85.7
25-Apr-13	-0.025	0.194	—	26-Sep-13	-0.063	0.174	84.4
22-May-13	-0.035	-0.200	85.9	28-Oct-13	-0.038	0.160	—

Eight classification trees for the eight images were established, and therefore eight SAV distribution layers were obtained (Figure 8). As shown

427 in Figure 8, the SAV was distributed mainly in the eastern bays of Taihu
 428 Lake. In February and March, there was a small amount of SAV in
 429 Meiliang and Dongtaihu Bays. From April to May, SAV existed mainly in
 430 Xukou, Dongshan and Dongtaihu Bays. The SAV distribution area
 431 gradually increased in Xukou and Dongtaihu Bays from July to October.

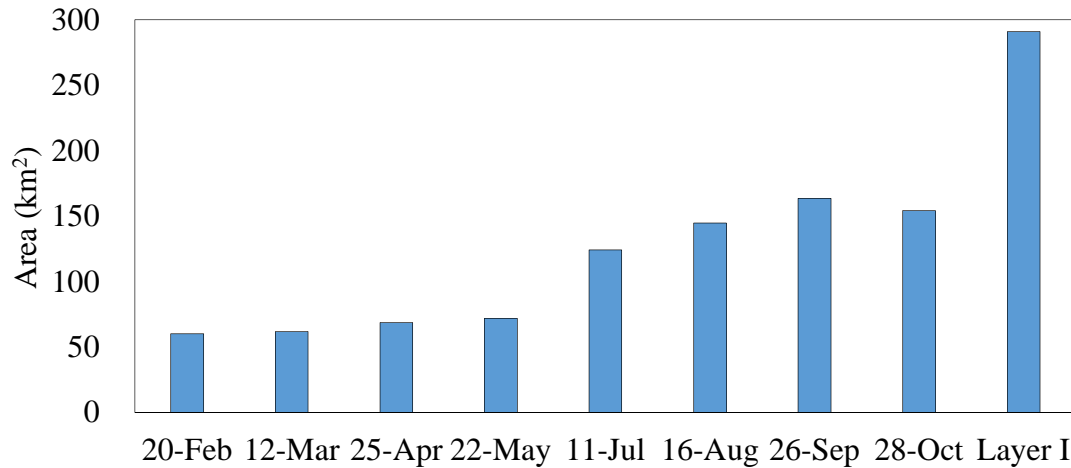


432

433 Figure 8. Spatial distribution maps of SAV with different times in 2013 in Taihu Lake
 434 Note: Layer I is the distribution map of SAV in 2013 by merging the SAV layers of February
 435 20, March 12, April 25, May 22, July 11, August 16, September 26, October 28.

436 Figure 9 shows that the area covered by SAV increased from 60.27
 437 km² in February to 163.49 km² in September. From February 20 to October

438 28, the region covered by SAV in every bay changed with time because of
439 the different life histories of the different SAV species (Figure 9).
440 Altogether, the total area covered by SAV was 291.02 km² in 2013.



441

442

Figure 9. Distribution areas of SAV from different times in 2013

443 3.2. Mapping dominant species of SAV

444 Based on the eight distribution maps of SAV in 2013 and the method
445 for identifying the dominant species of SAV shown in Figure 8, the
446 classification map with seven dominant SAV species in 2013 was obtained
447 and is shown in Figure 10.

448 The accuracy of the classification map was assessed using an error
449 matrix (Table 2). The overall accuracy was 68.4%, and kappa was 0.6306.
450 *Potamogeton crispus* and *Elodea nuttallii* have distinct life histories with
451 other species, and they therefore had high classification accuracies with PA
452 of 75.5% and 70.2%, and UA of 78.4% and 74.1%, respectively. However,
453 there were large misclassifications between *Potamogeton crispus* and
454 *Elodea nuttallii* due to their similar life histories. *Potamogeton malaianus*
455 and *Potamogeton maackianus* exhibited classification accuracies greater
456 than 68%, followed by *Myriophyllum spicatum* and *Vallisneria spirali*.
457 *Ceratophyllum demersum* had the lowest classification accuracy with PA
458 of 62.7% and UA of 60.4%, respectively, due to its small proportion in

459 Taihu Lake and inconspicuous life history. Due to their similar life
 460 histories, there were large misclassification between *Potamogeton*
 461 *malaianus* and *Vallisneria spirali*, between *Myriophyllum spicatum* and
 462 *Potamogeton maackianus*.

463 Table 2. Accuracy assessment of classification results for seven SAV species, PA = %
 464 Producer's accuracy; UA = % User's accuracy.

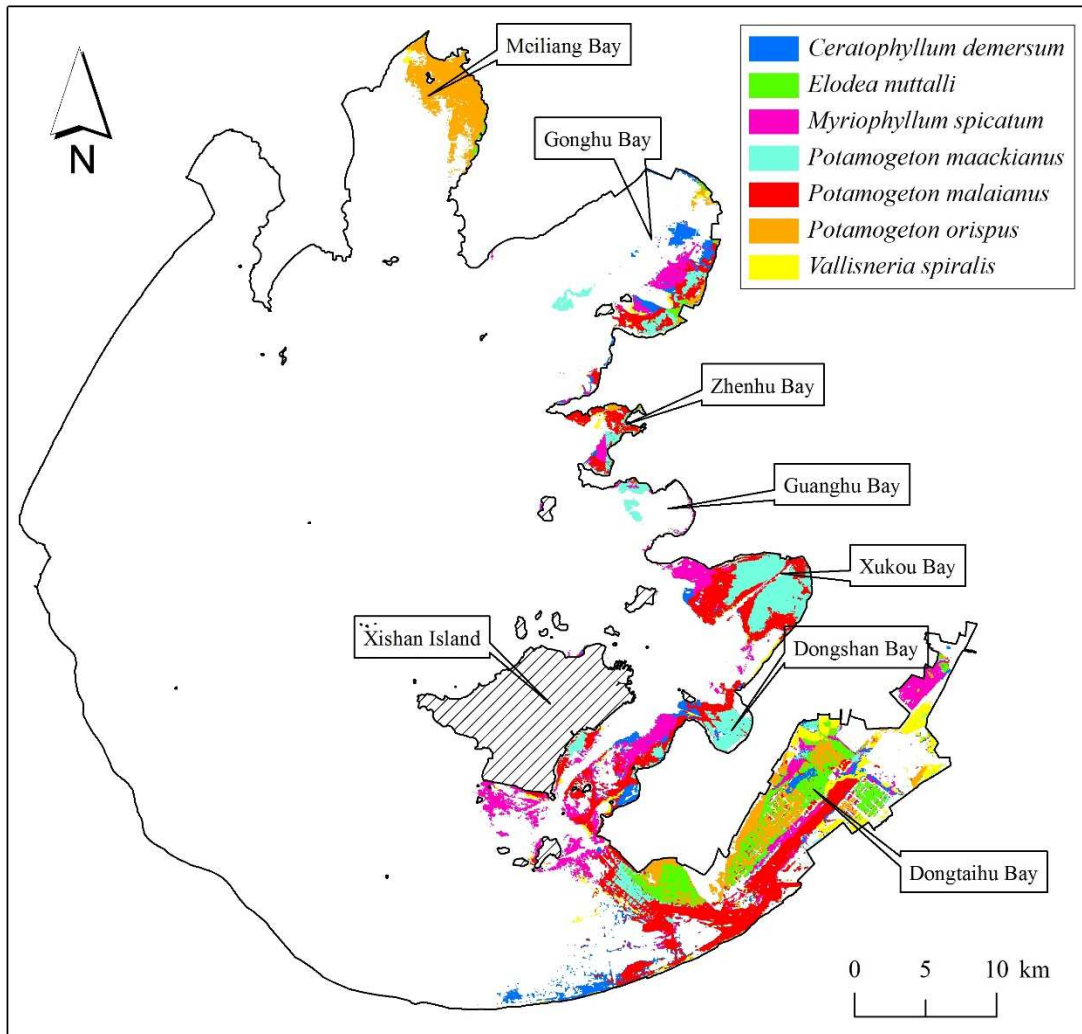
		Predicted							Total	PA
Measured	Species	P.C.	E.N.	P.Maa.	M.S.	C.D.	V.S.	P.Mal.	Total	PA
		P.C.	40	5	2	1	2	1	2	53
	E.N.	6	40	2	3	3	2	1	57	70.2
	P.Maa.	2	1	42	6	4	2	4	61	68.9
	M.S.	0	2	6	43	5	4	4	64	67.2
	C.D.	0	3	3	6	32	4	3	51	62.7
	V.S.	2	1	2	3	4	34	6	52	65.4
	P.Mal.	1	2	4	4	3	7	46	67	68.7
	Total	51	54	61	66	53	54	66	405	
	UA	78.4	74.1	68.9	65.2	60.4	63.0	69.7		

Overall accuracy= 68.4%; Kappa= 0.6306

465 Note: P.C. = *Potamogeton crispus*; E.N. = *Elodea nuttallii*; M.S.= *Myriophyllum*
 466 *spicatum*; P.Maa. = *Potamogeton maackianus*; C.D.= *Ceratophyllum demersum*;
 467 V.S.= *Vallisneria spiralis*; P. Mal.= *Potamogeton malaianus*.

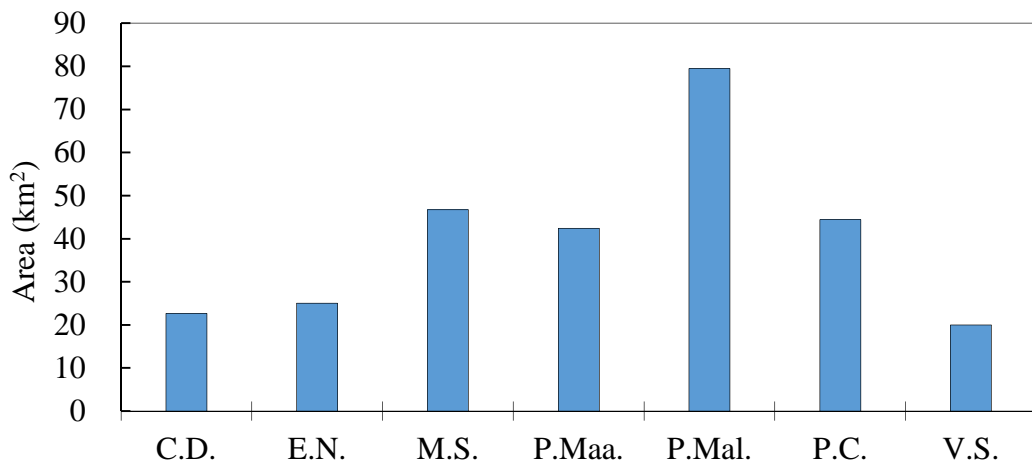
468 As shown in Figures 10 and 11, *Potamogeton malaianus* was the most
 469 widely distributed species in Taihu Lake and constituted 28.3% of the total
 470 SAV. *Myriophyllum spicatum* was the second most widely distributed
 471 species, with a percentage of 16.6% of the total SAV, and was distributed
 472 in Gonghu, Xukou, Dongtaihu Bays and the east coast of Xishan island.
 473 *Potamogeton maackianus* accounted for 15.1% of the total SAV and was
 474 mainly distributed in Xukou and Dongshan Bays. *Potamogeton crispus*
 475 was mainly distributed in Meiliang Bay in the form of single dominant
 476 species and Dongtaihu Bay in the form of accompanying species, and it
 477 constituted 15.8% of the total SAV. *Elodea nuttallii* was mainly distributed
 478 in Dongtaihu Bay, and constituted 8.9% of the total SAV. *Ceratophyllum*
 479 *demersum* and *vallisneria spiralis* accounted for 8.0% and 7.1% of the total
 480 SAV, respectively. *Ceratophyllum demersum* was scattered in the bays

481 with the exception of Meiliang and Guanghu Bays and *Vallisneria spiralis*
 482 was mainly distributed in Dongtaihu Bay.



483

484 Figure 10. Distribution map of seven SAV species in 2013 in Taihu Lake



485

486 Figure 11. Distribution area of seven SAV species in 2013 in Taihu Lake

487 Note: P.C.=*Potamogeton crispus*; E.N.= *elodea nuttallii*; M.S. = *Myriophyllum spicatum*;
 488 P.Maa.=*Potamogeton maackianus*; C.D.=*Ceratophyllum demersum*; V.S.=*Vallisneria spiralis*;
 489 *P. Mal.*=*Potamogeton malaianus*.

490 Figure 12 shows the spatial distribution of the dominant SAV species
 491 in spring, summer and autumn. The distribution area of seven species
 492 changed with the seasons. In the spring, the dominant SAV species were
 493 *Potamogeton crispus*, *Elodea nuttallii* and *Potamogeton maackianus*, and
 494 they were mainly distributed in Meiliang, Xukou and Dongtaihu Bays. In
 495 the summer, *Myriophyllum spicatum*, *Potamogeton maackianus* and
 496 *Potamogeton malaianus* were primary dominant species. In the autumn,
 497 *Potamogeton malaianus* was covered the largest area and and was the most
 498 widely distributed species, followed by *Potamogeton maackianus*, *Elodea*
 499 *nuttallii*, *Myriophyllum spicatum*, the remaining species. The distribution
 500 rule of the species with seasons is consistent with their life histories, which
 501 was further evidence that the method proposed was reliable. As shown in
 502 Figure 13, the area covered by SAV was largest in the autumn (212.9 km²),
 503 followed by summer (153.5 km²) and spring (122.1km²)

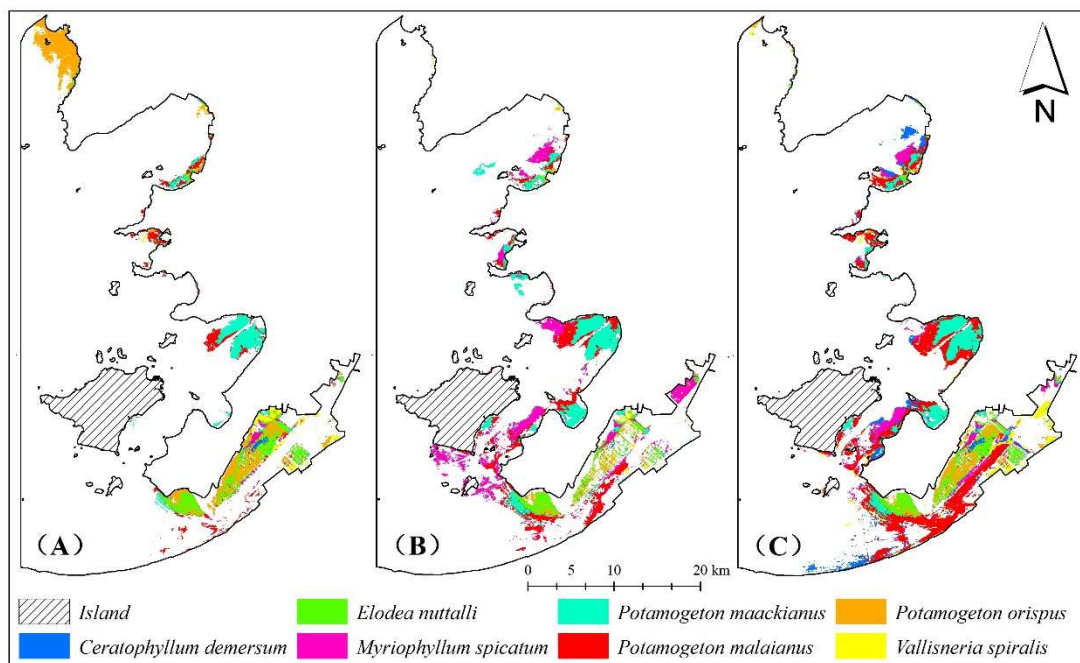
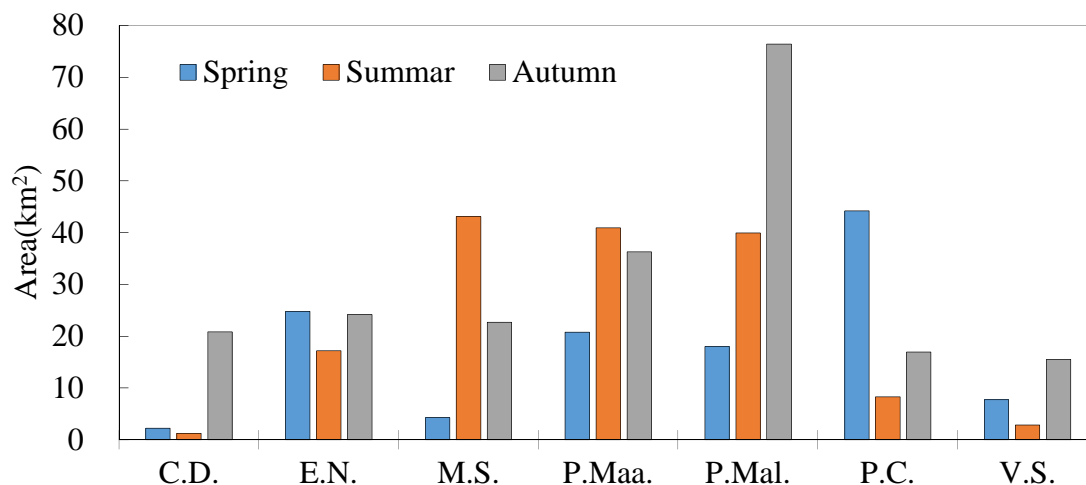


Figure 12. Distribution map of seven SAV species in Spring (A), Summer (B) and



507

508 Figure 13. Distribution area dynamics of seven SAV species with seasons in 2013 in
509 Taihu Lake

510 Note: P.C.=*Potamogeton crispus*; E.N.=*Elodea nuttallii*; M.S.=*Myriophyllum spicatum*;
511 P.Maa.=*Potamogeton maackianus*; C.D. = *Ceratophyllum demersum*; V.S. = *Vallisneria*
512 *spiralis*; P. Mal.= *Potamogeton malaianus*.

513 4. Discussion

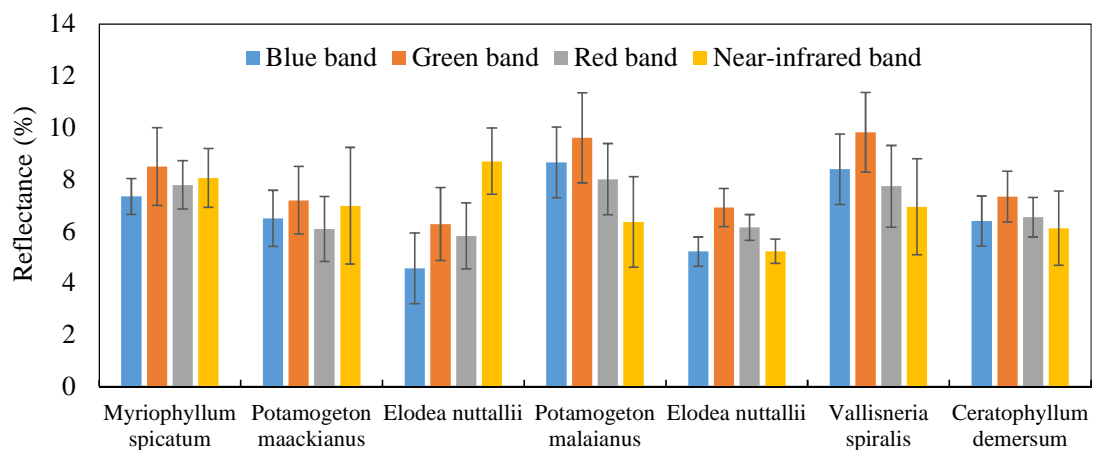
514 4.1. Uncertainties, errors and accuracies of classification

515 Mapping studies of aquatic vegetation have been conducted in
516 shallow lake. For example, Ma et al. (2008), Zhao et al (2013) and Luo et
517 al. (2014) proposed different classification methods to map the distribution
518 of emergent, floating-leaved and submerged vegetation in eutrophic Taihu
519 lakes based on moderate resolution images and achieved classification
520 accuracies greater than 80%. However, mapping SAV species is quite
521 challenging because of the limitations of remote sensing and the
522 complexity of the aquatic environment.

523 Fortunately, different SAV species have different phenological
524 characters and life histories. Therefore, based on multi-temporal remote
525 sensing images and the life histories of SAV species, we have proposed a
526 method for mapping and identifying SAV species, but the overall accuracy

527 was only 68.4% (Table 2) due to many uncertainties. The uncertainties that
528 affect the classification accuracy can be summarized as follows: 1) the
529 limited of the resolution of remote sensing data. On the one hand, spatial
530 resolution can affect classification accuracy because of mixed pixels.
531 Lower spatial resolution can cause more serious mixed pixel phenomena
532 and thus result in larger deviations between the classification and the
533 measured results. On the other hand, the spectral resolution of remote
534 sensing data also directly affects the SAV species mapping accuracy. Figure
535 14 showed band reflectance of seven SAV species exacted from HJ-CCD
536 image of July 11, 2013. The result showed that it is difficult to classify
537 seven SAV species only using multispectral image. Meanwhile, we also
538 acquired their corresponding situ spectral measurements on July 13, 2013
539 (Figure 14). It is indicated that there are large differences between the SAV
540 species. Thus, it is possible to classify some species by hyperspectral data.
541 Meanwhile, the studies also suggested that there are tiny spectral
542 differences between SAV species (Han and Rundquist, 2003; Yuan and
543 Zhang, 2006), and only hyperspectral remote sensing data could capture
544 the differences and to then identify SAV species. Therefore, to reduce and
545 eliminate these uncertainties, the resolution of remote sensing data,
546 including spatial resolution and spectral resolutions, must be improved. In
547 future, with the constantly emerging of the hyperspectral sensors,
548 combining our approach, classification accuracies of SAV species would
549 be expected to be further improved. 2) Uncertainty in the aquatic
550 environment. Taihu Lake has experienced significant pollution with high
551 suspension, TN and TP contents, low water transparency, which have
552 caused serious eutrophication and frequent algal blooms. In such a
553 complex aquatic environment, the depth of SAV species from the surface
554 of the water has a significant influence on the classification accuracy. A
555 larger depth can lead to a lower spectral signal-noise ratio and therefore a

556 lower classification accuracy. For example, *Ceratophyllum demersum*
 557 grows at a greater depth from the water surface than other species in even
 558 its fast-growing and peak stages, and therefore had the lowest classification
 559 accuracy(62.7%). 3) Similar life histories of SAV species. Based on the
 560 differences of their life histories, we developed the method for mapping
 561 SAV species. Therefore, larger differences of life histories between them
 562 can produce higher identification accuracies and vice versa. For example,
 563 *Potamogeton crispus* had the highest classification accuracy because it has
 564 a distinctly different phenology than the other species. *Myriophyllum*
 565 *spicatum* and *potamogeton maackianus* tended to be misclassified because
 566 of their similar life histories. Fortunately, as shown in figure 15, there are
 567 significant differences in the red edge and near-infrared region between
 568 these species. So it may be a feasible method for reducing the uncertainty
 569 and improving their classification accuracies by using hyperspectral data
 570 on the basis of our classification results, which would be carried out in our
 571 future research.

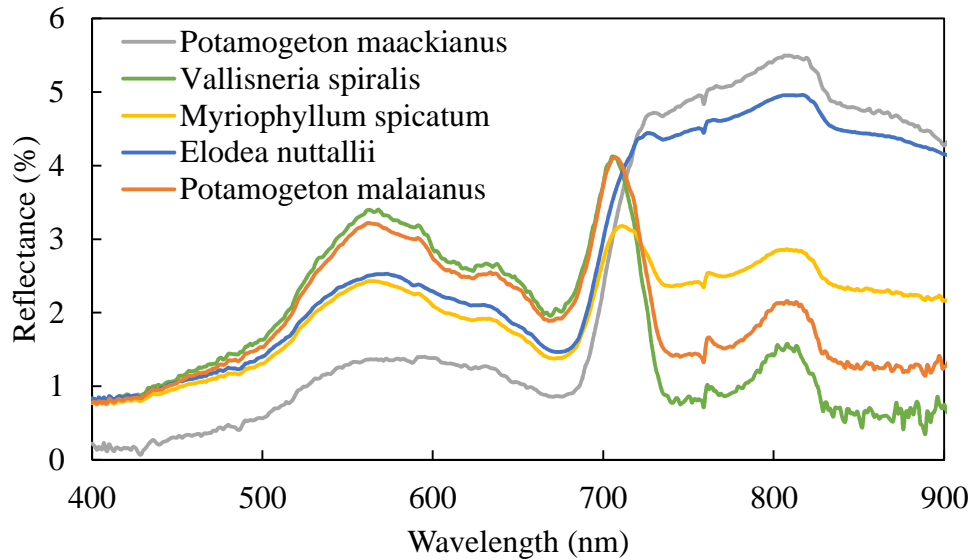


572

573 Figure 14. Band reflectance of seven SAV species from HJ-CCD image of July 11,

574

2013



575

576 Figure 15. Situ spectral measurements of SAV species on July 13, 2013

577 *4.2. Management and application*

578 Shallow lakes are among the most complex aquatic systems and are
 579 known to switch between two stable states: a macrophyte-dominated clear-
 580 water state and a phytoplankton-dominated turbid state (Scheffer and van
 581 Nes, 2007). Taihu is a typical large, shallow lake, both macrophyte-
 582 dominated and phytoplankton-dominated areas exist simultaneously (Liu
 583 et al., 2015). However, in recent years, algal blooms have gradually
 584 extended its coverage and persisted over longer durations in Taihu Lake.
 585 The eutrophication of shallow lakes is characterized by the disappearance
 586 of diverse SAV and the dominance of phytoplankton, because SAV and
 587 phytoplankton compete for nutrients and light (Dong et al., 2014). Studies
 588 have indicated that reasonable distribution of diverse SAV can cause
 589 aquatic ecosystems to shift from a turbid algae-dominated state to a clear-
 590 water plant-dominated state (Depew et al., 2011; Dong et al., 2014; Hilt et
 591 al., 2006). Therefore, the restoration of SAV is an effective method for
 592 relieving eutrophication in shallow lakes. Knowing and extracting the
 593 physical habitat requirements of the SAV species from their existing
 594 habitats is quite crucial for efficient SAV restoration planning. The

595 interpretation of satellite remote sensing data is the most effective method
596 for mapping the existing habitats of SAV species across an entire lake. In
597 this study, SAV species in Taihu Lake were mapped by combining the
598 characteristics of their life histories and multi-temporal satellite remote
599 sensing data. Although the overall accuracy was only 68.4%, the most
600 suitable ecology and environment conditions and characteristics of the
601 SAV species can be derived from the mapping results. Meanwhile, future
602 work will focus on developing knowledge bases of different SAV species
603 that contains their most suitable ecologies and environment conditions
604 according to their distribution characteristics for guiding SAV restoration
605 work. It is also important determine the historical succession and assess
606 health status and the paludification process of Taihu Lake, based on the the
607 method proposed by this study.

608 **5. Conclusion**

609 Mapping SAV species can capture their most suitable ecology and
610 environment characteristics, which is extremely useful in restoration and
611 management of eutrophic shallow lakes. In this study, the life histories of
612 seven SAV species in Taihu Lake were summarized based on field
613 observations and the literature, and then a multilayer erasing approach for
614 mapping the SAV species mapping was developed based on the life
615 histories of SAV species and multi-temporal satellite remote sensing
616 imagery. Using this approach, the SAV species were mapped in Taihu Lake
617 with an overall accuracy of 68.4% and a kappa coefficient of 0.6306.
618 *Potamogeton crispus* had the highest classification accuracy (PA =75.5%
619 and UA=78.4%), followed by *elodea nuttallii* (PA=70.2% and UA=74.1%),
620 *potamogeton maackianus* (PA =68.9% and UA=68.9%), *potamogeton*
621 *malaianus* (PA =68.7% and UA=65.2%), *myriophyllum spicatum* (PA
622 =62.7% and UA=60.4%), *potamogeton maackianus* (PA =65.4% and

623 UA=63%) and *ceratophyllum demersum* (PA =62.7% and UA=69.7%).
624 *Potamogeton malaianus* was the most widely distributed species,
625 followed by *Myriophyllum spicatum*, *Potamogeton maackianus*,
626 *Potamogeton crispus*, *Elodea nuttallii*, *Ceratophyllum demersum* and
627 *Vallisneria spiralis*. The distribution area of the seven species changed with
628 the seasons due to their phenological differences. The area covered by SAV
629 was largest in the autumn (212.9 km²), followed by summer (153.5 km²)
630 and spring (122.1km²).

631 The classification method presented, which is based on multi-
632 temporal satellite images and life histories, is a novel and effective means
633 for identifying SAV species. The classification results should be very
634 helpful for aquatic ecosystem recovery and lake management.

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