1   **Trophic state assessment of global inland waters using a MODIS-**

2   **derived Forel-Ule index**

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Abstract

14   Eutrophication of inland waters is considered a serious global environmental

15   problem. Satellite remote sensing (RS) has been established as an important source of

16   information to determine the trophic state of inland waters through the retrieval of

17   optically active water quality parameters such as chlorophyll-a (Chl-a). However, the

18   use of RS techniques for assessment of the trophic state of inland waters on a global

19   scale is hindered by the performance of retrieval algorithms over highly dynamic and

20   complex optical properties that characterize many of these systems. In this study, we

21   developed a new RS approach to assess the trophic state of global inland water bodies

22   based on Moderate Resolution Imaging Spectroradiometer (MODIS) imagery and the

23   Forel-Ule index (FUI). First, the FUI was calculated from MODIS data by dividing

24   natural water colour into 21 indices from dark blue to yellowish-brown. Then the

25   relationship between FUI and the trophic state index (TSI) was established based on in-

26   situ measurements and MODIS products. The water-leaving reflectance at 645 nm band

27   was employed to distinguish coloured dissolved organic matter (CDOM)-dominated

28   systems in the FUI-based trophic state assessment. Based on the analysis, the FUI-based

29   trophic state assessment method was developed and applied to assess the trophic states

30   of 2058 large inland water bodies (surface area > 25 km^2) distributed around the world

31   using MODIS data from the austral and boreal summers of 2012. Our results showed

32   that FUI can be retrieved from MODIS with a considerable accuracy (92.5%, R^2=0.92)

33   by comparing with concurrent in situ measurements over a wide range of lakes, and the

34   overall accuracy of the FUI-based trophic state assessment method is 80.0% ($R^2 = 0.75$)

35   validated by an independent dataset. Of the global large water bodies considered,

36   oligotrophic large lakes were found to be concentrated in plateau regions in central Asia

37   and southern South America, while eutrophic large lakes were concentrated in central

38   Africa, eastern Asia, and mid-northern and southeast North America.

1. Introduction

Eutrophication represents a serious water quality challenge around the world (Jones and Lee, 1982; Le et al., 2010; Smith, 2003; Vollenweider, 1981). This process is often associated with the rapid production of phytoplankton and other microorganisms, which have important impacts on aquatic ecology and the normal functioning of water bodies (Vollenweider and Kerekes, 1982). The trophic state of inland waters is typically categorized into three levels: oligotrophic, mesotrophic, and eutrophic. Since the 1960s, attempts have been made to quantitatively evaluate the trophic state of inland waters using both single-variable and multi-variable methods (Beeton and Edmondson, 1972; Bigham Stephens et al., 2015; Burns and Bryers, 2000; Forsberg and Ryding, 1980; Rodhe, 1969). Carlson (1977) introduced a numerical *Trophic State Index* (TSI) for inland waters based on algae biomass, which can be calculated using Secchi depth (SD), chlorophyll-a (Chl-a), or total phosphorus (TP). Many studies have used Chl-a, a pigment common to almost all photosynthetic organisms, as a proxy for algal biomass and therefore also as an indicator for the trophic state of aquatic systems (Carlson, 1991; Joniak et al., 2009; Sheela et al., 2011a). The Trophic Level Index (TLI), another commonly used numerical method, is calculated from the weighted sum of either three variables (Chl-a, TP, total nitrogen (TN)) or five variables with the addition of SD and chemical oxygen demand (COD) (Burns and Bryers, 2000; Burns et al., 1999; Jin and Tu, 1990; Verburg et al., 2010).

60   Collecting systematic observations on the ecological status of inland waters in

61   aquatic systems in inland waters remains a logistical and financial challenge which with

62   conventional in-situ approaches scales proportionately with increasing geographical

63   coverage (Härmä et al., 2001; Hu et al., 2010; McClain, 2009). However, satellite based

64   remote sensing (RS) offers a potentially significant source of information for large-

65   scale monitoring of water state variables (including water trophic state).

66   Eutrophication and increased productivity typically result in changes in the optical

67   properties of water; therefore, RS approaches have been employed for water trophic

68   state assessment (Baban, 1996; Papoutsa et al., 2014), in particular through the retrieval

69   of Chl-a concentrations (Chen, 2003; Duan et al., 2007; Matthews and Odermatt, 2015;

70   Pulliainen et al., 2001; Thiemann and Kaufmann, 2000; Wang et al., 2008). In addition,

71   SD, which is one of the most commonly measured trophic state indicators, has also

72   been used to assess water trophic states (Binding et al., 2015; Knight and Voth, 2012;

73   Lillesand et al., 1983; Olmanson et al., 2008; Papoutsa et al., 2014; Sheela et al., 2011b).

74   Other studies based on RS have used multiple variables to assess water trophic states

75   (Cheng and Lei, 2001; Sass et al., 2007; Xiang et al., 2015). However, most of the RS-

76   based retrieval methods make assumptions about the biogeo-optical properties of the

77   target aquatic system and have spatial-temporal limitations or high demands on the

78   spectral resolution of RS data, due to the complex optical properties of inland waters

79   (Shen et al., 2014; Spyrakos et al., 2018; Ylöstalo et al., 2014). An additional challenge

80   is the calculation of water-leaving reflectance ($R_{rs}(\lambda)$) data globally by removing

81   various and complex atmospheric effects (Chen et al., 2013a; Wang et al., 2016),

82   although several atmospheric correction models have been developed to overcome the

83   atmospheric correction problems for different types of inland waters (Hu et al., 2000;

84   Shanmugam and Ahn, 2007; Wang and Shi, 2007; Wang et al., 2011; Zhang et al., 2014).

85   Given these challenges, the development of a globally valid Earth observation approach

86   for water trophic state assessment has been hindered (Palmer et al., 2015).

87   Here, we promote a water colour index, Forel-Ule index (FUI), as the water quality

88   parameter to assess trophic state of inland waters. We chose the FUI, which divides

89   natural waters into 21 colour classes from dark blue to yellowish brown based on the

90   traditional Forel-Ule scale due to its wide covering of water optical characteristics and

91   intimate relations with water quality (Wernand and Van der Woerd, 2010; Van der

92   Woerd et al., 2016). Indeed, water colour expressed through a single colour index is

93   generally not sufficient to retrieve variables such as Chl-a or suspended sediments

94   unambiguously (Bukata, 1983; Bukata 1995). However, studies have demonstrated that

95   water colour is closely associated with the absorption and scattering effects of water

96   constituents (including Chl-a and suspended sediments), and therefore can be used to

97   reflect the comprehensive water quality (Garaba et al., 2014; Wang et al., 2015;

98   Wernand et al., 2013a). Since the FUI can be objectively retrieved using RS

99   observations at the global scale (Li et al., 2016; Wernand et al., 2013b), it could provide

100   a feasible solution to monitoring global inland water bodies.

101   The main aim of this study was to develop an FUI-based trophic state assessment

102   approach for global inland waters using the Moderate-resolution Imaging

103   Spectroradiometer (MODIS) data, and to provide a global-scale view of the water

104   quality of large lakes and reservoirs worldwide.

105   **2. Datasets**

106   **2.1 MODIS surface reflectance product**

107   The MODIS level-3 surface reflectance product (MOD09A1) provides data of

108   mapped surface spectral reflectance at 500 m spatial resolution from 7 bands across the

109   visible and near infrared and short-wave infrared wavelengths (i.e. 469 , 555, 645, 859,

110   1240, 1640, and 2130 nm) (Vermote and Vermeulen, 1999). MOD09A1 is an 8-day

111   composite MODIS Terra product, which is spatially divided by uniform MODIS tiles

112   on the global scale, which makes it easy to calculate global time-series statistics. It has

113   been used for long-term and large-area water quality monitoring research as this dataset

114   is well georeferenced, synthesized, and cloud marked (Hou et al., 2017; Klein et al.,

115   2017; Li et al., 2016; Wu et al., 2013).

116   In order to retrieve the FUI of global inland waters, we used more than 6400

117   MOD09A1 images taken during the summer months of 2012 acquired from the

118   Goddard Space Flight Center (GSFC) of the National Aeronautics and Space

119   Administration (NASA) (http://ladsweb.nascom.nasa.gov/index.html). We chose the

120   year 2012 because of the availability of validation data from published studies and

121   online databases about the trophic state of inland waters. Summer months (i.e. from

122   June to September in the Northern Hemisphere, and from December to March in the

123   Southern Hemisphere) were used to retrieve the FUI, because the biomass of Chl-a-

124   containing planktonic algae generally peaks in this season (Singh and Singh, 2015) and

125   therefore has the greatest effect on water colour.

126   **2.2 In-situ dataset**

127   Details of the field measured Chl-a and in-situ $R_{rs}(\lambda)$ are given in in Table 1. The

128   in-situ dataset contains 469 samplings from 10 lakes in Asia, North America, and

129   Europe. The selection represents different types of inland waters, ranging from a few

130   oligotrophic and mesotrophic lakes to more eutrophic lakes, from lakes with high total

131   suspended matter (TSM, i.e. Taihu Lake) to lakes with high coloured dissolved organic

132   matter (CDOM, i.e. Lake Peipsi and Lake Winnipeg).

133   Table1 Lake Names, locations, number of samplings (N), mean Chl-a concentrations (Chl-a, μg/L)
134   and data sources of the 10 lakes and reservoirs with field measurements

Lake	Latitude	Longitude	Chl-a	N	Data Source
Lake Maggiore	46.01 N	8.67 E	2.41	3	In-situ (Giardino et al., 2013)
Lake Winnipeg	51.9 N	97.3 W	5.33	58	In-situ (Binding et al., 2013)
Lake Erie	41.9 N	82.1 W	9.34	24	In-situ (Binding et al., 2013)
Lake Peipsi	58.47 N	27.34 E	17.95	26	In-situ (Kutser et al. 2013)
Lake Erhai	25.86 N	100.15 E	19.11	21	In-situ
Yuqiao Reservoir	40.04 N	117.55 E	20.73	13	In-situ
Guanting Reservoir	40.35 N	115.73 E	26.8	31	In-situ
Taihu Lake	31.20 N	120.18 E	42.6	239	In-situ
Chaohu Lake	31.55 N	117.57 E	64.47	29	In-situ
Dianchi Lake	24.82 N	102.71 E	85.2	25	In-situ

135   Equation (1), suggested by Carlson (1977), was applied to the Chl-a dataset:

7

$$\text{TSI(Chl-a)} = 10(6 - \frac{2.04 - 0.68 \ln Chl\text{-}a}{ln2})\hspace{2cm}(1)$$

where Chl-a denotes the concentration of Chl-a in μg/L. The TSI method classifies the water trophic state as oligotrophic (TSI < 30), mesotrophic (30 ≤ TSI < 50), or eutrophic (TSI ≥ 50). The in-situ measured $R_{rs}(\lambda)$ was used to simulate MODIS bands by using MODIS spectral response functions (SRF), and then the FUI for these samplings was calculated to determine the relationship between TSI and FUI.

Concurrent MOD09 images were acquired to build the data pairs of $R_{rs}(\lambda)$. The FUI was calculated from the data pairs and compared to evaluate the accuracy of MODIS FUI. The data pairs were coincident within a ±3 hour window and the nearest MODIS image pixel was used to pair with the in-situ data. After removing concurrent MODIS data with cloud cover, noise cover, and near shoreline pixels, there were 135 pairs of $R_{rs}(\lambda)$ data from 7 of the 10 lakes. There were 73 pairs for Taihu Lake with 13 concurrent images in July and October 2006, and January and April 2007 (Wang et al., 2016); 10 pairs for Qinghai Lake with 1 concurrent image in August 2014 (Li et al., 2016); 10 pairs for Lake Erhai with 1 concurrent image in July 2012; 17 pairs for Lake Erie (Binding et al., 2013) with 3 concurrent images in August 2012; 20 pairs for Lake Winnipeg (Binding et al., 2013) with 8 concurrent images in July and August 2012; 4 pairs for Lake Peipsi (Kutser et al., 2013) with 1 concurrent image in June 2012; and 1 pair for Lake Maggiore (Giardino et al., 2013) with 1 concurrent image in July 2012.

2.3 Hydrolight simulated dataset

156   A Hydrolight simulated Chl-a and $R_{rs}(\lambda)$ dataset published by (IOCCG, 2006) was

157   also used to improve the representativeness of oligotrophic to mesotrophic waters in

158   our dataset, and to illustrate the theoretical relationship between FUI and TSI in these

159   relatively clear waters. This dataset was simulated using the widely accepted

160   Hydrolight code (Mobley, 1995), with input inherent optical properties (IOPs)

161   generated from a wide range of field measurements with various bio-optical models not

162   limited to Case I water (IOCCG, 2006). The concentration of Chl-a in the simulated

163   dataset ranges from 0.03 to 30.0 μg/L with an average value of 6.08 μg/L.

164   **2.4 Independent validation dataset**

165   The FUI-based water trophic state assessment results for the summer of 2012 were

166   validated through comparison with published studies and online databases, including

167   China Environmental State Bulletin from Ministry of Environmental Protection of the

168   People's Republic of China (MEPPRC, 2012), and the National Lake Assessment from

169   the US Environmental Protection Agency (USEPA, 2016). To guarantee objectiveness

170   and fairness in the validation process, comparison data were only selected where they

171   represented the whole water body, and where the acquisition time was as close as

172   possible to the year of 2012. In total, 100 inland water bodies distributed around the

173   globe were used for validation (Figure 1).
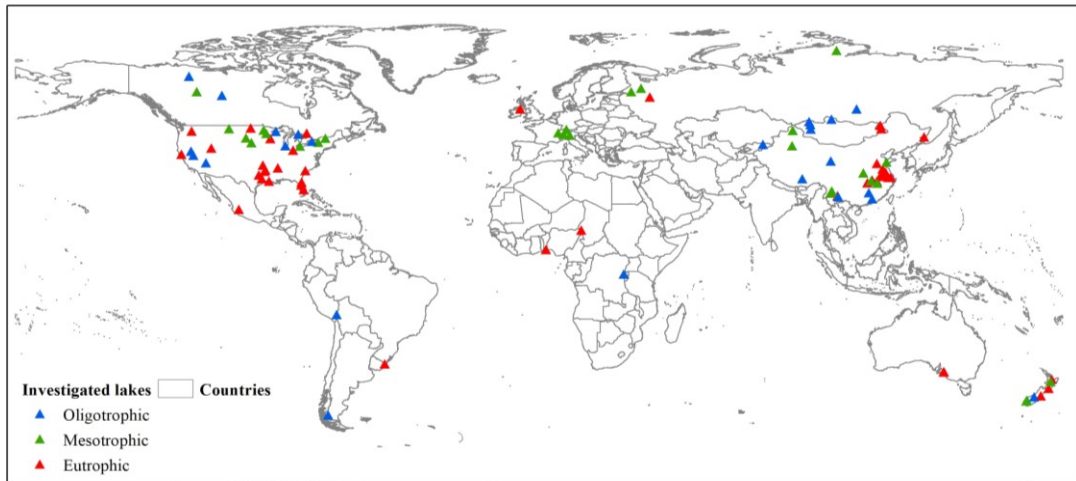
Figure 1 Spatial distribution and trophic states of 100 water bodies used for validation of the Moderate Resolution Imaging Spectroradiometer (MODIS)-derived Forel-Ule index (FUI) method. Trophic state data were obtained through literature review. Blue triangles denote oligotrophic water bodies, green triangles denote mesotrophic water bodies, and red triangles denote eutrophic water bodies.

3. Methods

3.1 Water-leaving reflectance correction

The MODIS surface reflectance products (MOD09) have been corrected for the effects of atmospheric gases, aerosols, thin cirrus clouds and adjacency from MODIS L1B data (Vermote and Vermeulen, 1999). It was found that the MOD09 reflectance was overall greater than the in situ reflectance over inland waters due to the residual noises, including the residual aerosol effect, skylight reflection, and possible sun glint (Wang, 2016). It is considered that MOD09 often fails to correct for aerosol effect because its aerosol input (the MODIS aerosol product, MOD04) usually uses a small fill value for the aerosol optical thickness for most inland waters (Wang et al., 2016; Vermote and Vermeulen, 1999). In this study, a band subtraction method based on near-

191   infrared (NIR) to short wave infrared (SWIR) bands was used to reduce the noises in

192   MOD09 data and to convert it to water-leaving reflectance ($R_{rs}(\lambda)$) (Wang, 2016). The

193   correction equation is:

194
$$R_{rs}(\lambda) = \frac{R(\lambda) - \min(R_{NIR} : R_{SWIR})}{\pi}$$
(2)

195   where $R(\lambda)$ is the original reflectance of the MOD09 band, and $\min(R_{NIR} : R_{SWIR})$ is the

196   minimum positive value of the NIR and SWIR bands. The $\min(R_{NIR} : R_{SWIR})$ was

197   subtracted from each pixel for each band to account for the residual errors (Wang and

198   Shi, 2007; Wang, 2016). This method neglects the aerosol types, but it can also avoid

199   the uncertainties in the NIR and SWIR bands being amplified by aerosol exponential

200   models. The formula is divided by π to convert the surface reflectance to water-leaving

201   reflectance by neglecting the bidirectional effects. Despite imperfections and

202   limitations, this method has been shown to achieve accuracies around 30%, and it can

203   be easily implemented in operational data processing systems for deriving $R_{rs}(\lambda)$ with

204   relative stable performances over inland waters under various conditions (Wang et al.,

205   2016).

206   **3.2 Water body identification**

207   The water bodies studied were large lakes and reservoirs (i.e., > 25 km^2 and

208   covering > 100 pixels in a MOD09A1 image). Water body extraction was taken directly

209   from satellite data rather than using a static geographic database due to the dynamic

210   nature of margins of some water bodies. The detection of water pixels in the MOD09A1

211   product was carried out using a series of processing steps on the MODIS satellite data

212   outlined in Figure 2.
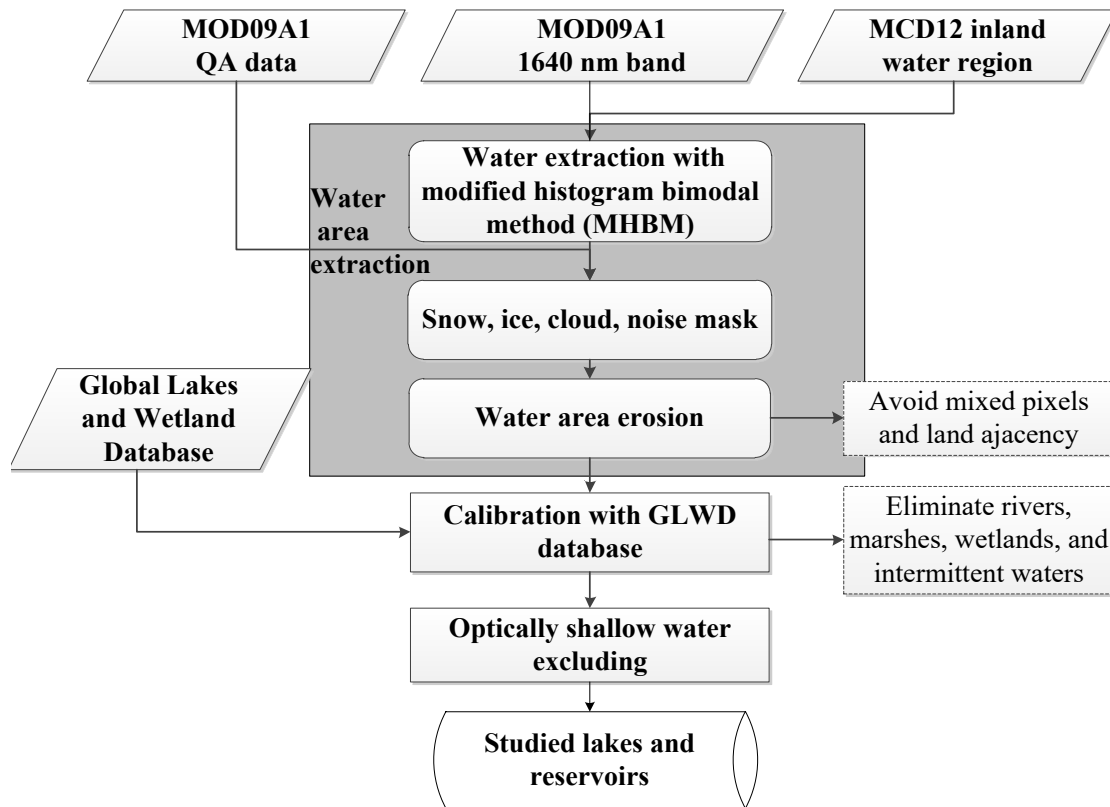
213

214   Figure 2 Flowchart of water body extraction and calibration from MOD09A1 products. MOD09A1
215   QA data is the Quality Assurance dataset that included in MOD09A1 dataset. MHBM is the
216   modified histogram bimodal method suggested by Zhang et al. (2018).

217   *3.2.1 Water body extraction and identification*

218   The modified histogram bimodal method (MHBM) suggested by Zhang et al.

219   (2018) was used to automatically segment water areas from land in the MOD09A1

220   image by using the 6th band (1640 nm) with a dynamic threshold for each water body.

221   The 1640 nm band was selected because it was strongly absorbed by water and strongly

222   reflected by terrestrial regions (Mishra and Prasad, 2015). There are six steps in the

223   segmentation process as follows:

12

224 (1) For each water body, the initial water area provided by the MODIS Land Cover

225   Type product (MCD12Q1 Type-1) (Friedl et al., 2010), which is gridded identically

226   to MOD09A1, was extended around the coastline reaching a number of 250%

227   pixels of the water area (including the initial water area).

228 (2) For each water body, a reflectance histogram of the 1640 nm band of the dilated

229   region was calculated, and the valley value of the histogram falling in the threshold

230   range was automatically determined as the threshold for the specific water body.

231   The range of thresholds from a range of representative water types was 0.005 to

232   0.11;

233 (3) Water bodies were segmented from MOD09A1 images using the determined

234   thresholds;

235 (4) MOD09A1 Quality Assurance (QA) data (Vermote et al., 2015) were used to

236   eliminate cloud, ice, and snow cover, and low quality pixels from the water areas;

237 (5) Extracted water areas were eroded with a 500 m buffer to avoid the effects of mixed

238   land-water pixels and severe land adjacency near the shoreline and to ensure the

239   quality of water pixels (Hou et al., 2017);

240 (6) Water bodies with areas of water connected with more than 100 pixels (i.e., > 25

241   km^2) were selected for this study.

242   The 500 m buffer was determined according to the comparison of MODIS $R_{rs}(\lambda)$

243 in the transects selected from the land–water boundaries; it showed that generally, one

244 pixel (500 m) near the shoreline at the visible bands was subject to detectable adjacency

245 contamination, which is consistent with the findings of Hou et al. (2017). Notably, the

246 land adjacency effect for MODIS may theoretically have an impact at much larger

247 distances offshore (Bulgarelli and Zibordi, 2018), but considering that the uncertainty

248 in MODIS $R_{rs}(\lambda)$ is already approximately 30%, the adjacency effect at distances greater

249 than 500 m may not be obvious.

250   Figure 3 shows the examples of water segmentation from MOD09A1 data. It

251 demonstrates that the water pixels have characteristically low reflectance values which

252 aids in detection against different land cover types, including small islands (Figure 3 (b)

253 and (c)), clouds (Figure 3 (f) and (g)), snow and ice (Figure 3 (e)), aquatic plants (Figure

254 3 (g)) and low quality pixels (Figure 3 (g)). The $R_{rs}(1640)$ values of the intersect lines

255 (marked in Figure 3) under different conditions are shown in Figure 4.

256   The extracted water areas were intersected with the Global Lakes and Wetland

257 Database (GLWD) (Lehner and Döll, 2004), which represents a compilation of

258 numerous existing maps and datasets and has been validated comprehensively for lakes >

259 1 km^2. GLWD Level 3 (GLWD-3) comprises lakes, reservoirs, rivers and different

260 wetland types in the form of a global raster map at 30-second resolution. Since the aim

261 of this study is to assess the trophic state of lakes and reservoirs at the global scale,

262 water bodies with centroid points located in the lake or reservoir type in the GLWD-3

263 database were chosen, and those located in rivers, ephemeral waters, coastal wetland

264   and other types of wetland were removed.
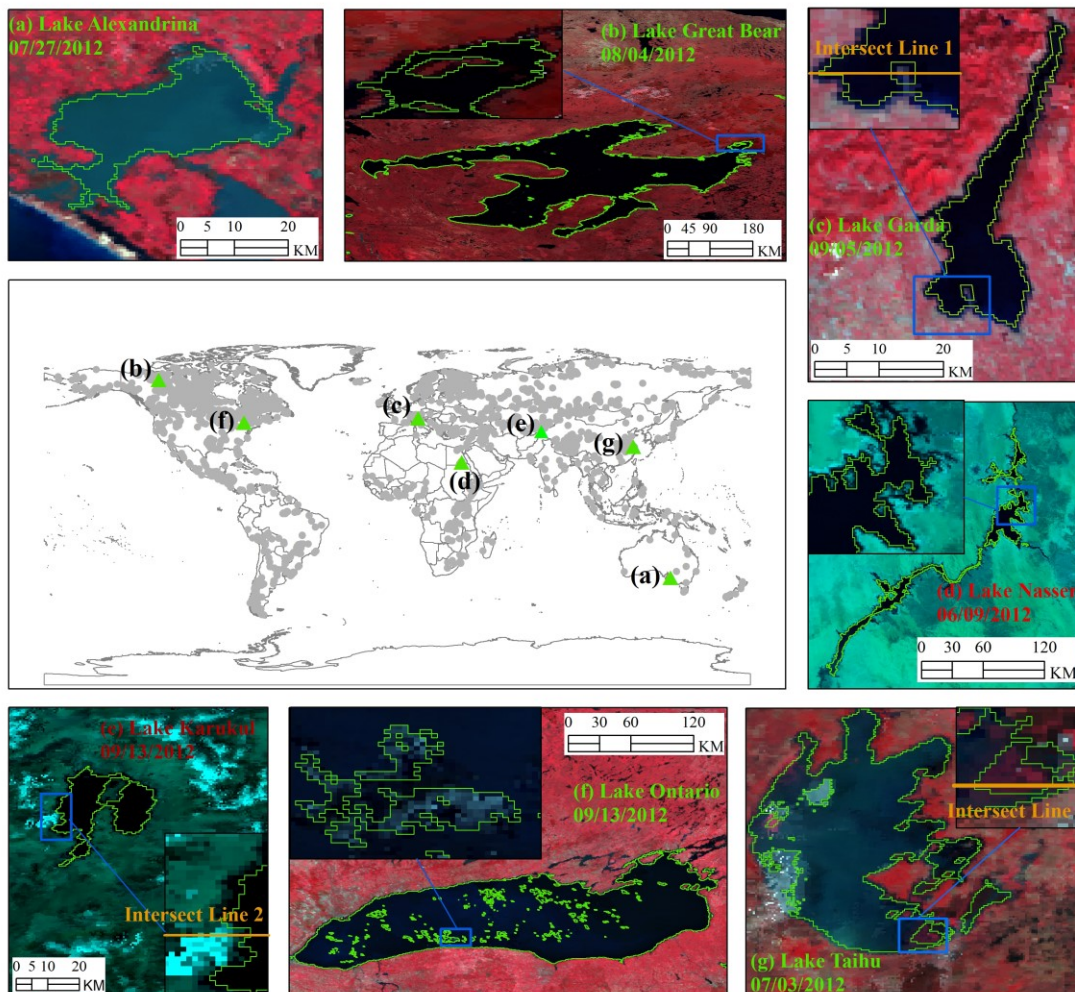
266   Figure 3 Shorelines of water bodies extracted from MOD09A1 images using the modified histogram
267   bimodal method (MHBM). (a) Lake Alexandrina in Australia; (b) Lake Great Bear in North America;
268   (c) Lake Garda in Europe; (d) Lake Nasser in Africa; (e) Lake Karukul in Asia; (f) Lake Ontario in
269   North America; (g) Lake Taihu in Asia. Green lines denote shorelines. Backgrounds are standard
270   false colour images where red, green, and blue are the 859 nm, 645 nm and 555 nm bands of the
271   MOD09A1 image, respectively. The image acquisition date is listed in each subfigure. The $R_{rs}(1640)$
272   values of the three intersect lines are shown in Figure 4.
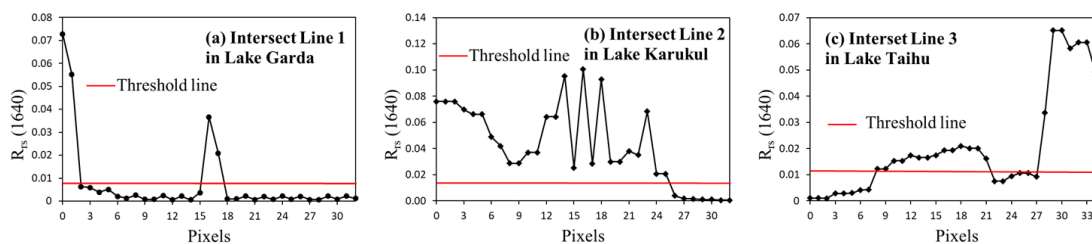
274   Figure 4 The $R_{rs}(1640)$ values of the intersect lines that marked in Figure 3. (a) Intersect Line 1

275 through Lake Garda crosses an island inside the lake; (b) Intersect Line 2 through Lake Karukul
276 crosses snow covering the shore side; (c) Intersect Line 3 through Lake Taihu crosses obvious
277 aquatic plants in the water.

278 *3.2.2 Excluding optically shallow water*

279   The extracted water pixels were tested for optically shallow water. Even though

280 optically shallow water for large inland waters (>25 km^2) is seldom found once the

281 identified wetlands in GLWD database are removed, it is possible that bottom

282 reflectance may influence observed water colour, for example in arid or semi-arid saline

283 lakes. Numerous radiative transfer models have been developed that account for the

284 effects of the bottom reflectance and water column on remotely sensed $R_{rs}(\lambda)$ (Lyzenga,

285 1978; Philpot, 1989; Maritorena et al., 1994; Lee et al., 1998; Mobley and Sundman,

286 2003). The response types of $R_{rs}(\lambda)$ spectral curves differ with changes in bottom status,

287 water depth, and optical properties of the water (Holden and LeDrew, 2002; Ma et al.,

288 2014; Lee et al., 1998；Lim et al., 2009), and there is no single method that can

289 accurately detect optically shallow water in lakes at the global scale.

290   To address these challenges, a three-stage method combining automatic

291 identification with manual-intervention was used to identify the optically shallow water

292 bodies:

293 (1) The MODIS SWIR band (1640 nm) threshold method was adopted in water area

294   segmentation, so that shallow waters with benthic aquatic plants were eliminated

295   from water area due to the higher reflectance in the SWIR band from the aquatic

296   plant that would not be presented in deeper waters (Li et al., 2009);

16

297   (2) The blue band threshold method was used as a preliminary means for identifying

298   shallow waters containing a signal from highly reflective sand and sediment

299   bottoms (Lim et al., 2009; Mobley and Sundman, 2003). The threshold (R_{rs}(469

300   nm) = 0.015 sr^{-1}) was determined by collecting and comparing a large number of

301         $R_{rs}(\lambda)$ spectra of optically shallow and deep waters derived from MOD09A1

302   images in the summer of 2012 (Figure 5);

303   (3) Shallow water bodies identified in the first two steps were reviewed using Google

304   Earth and relevant publications (Williams, 2002; Hurlbert, 2012), to remove lakes

305   and reservoirs characterized by deep waters.
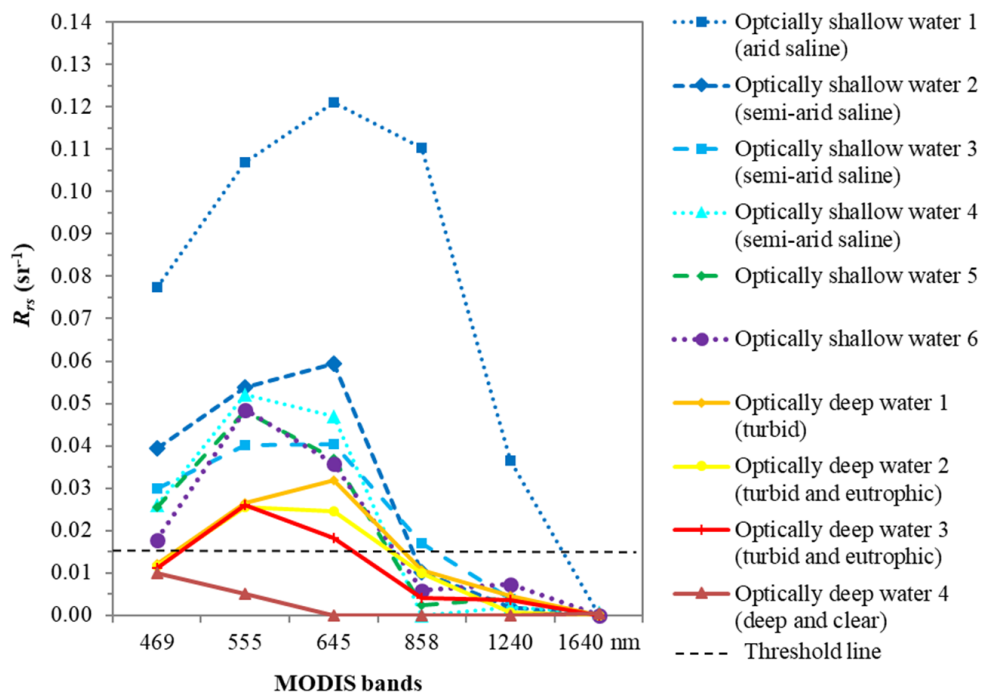
306
307   Figure 5 Typical water-leaving reflectance ($R_{rs}(\lambda)$) spectra of optically shallow waters and optically
308   deep waters derived from MOD09A1 images in the summer of 2012. The optically shallow waters
309   1-4 are Lake Beihuo Luxun, Lake Manas, Lake Margai Caka, and Lake Gasi Kule from Northwest
310   China, and they were described as arid and semi-arid saline lakes in Wang and Dou (1998). The
311   identified optically shallow waters 5 and 6 are Lake George in Australia (Fitzsimmons and Barrows,
312   2010) and shallow water near the island bank in the Bahamas, respectively (Dierssen et al., 2003);

17

313 The dotted line denotes the threshold line (0.015 sr^{-1}) of R_{rs}(469 nm) that used to separate the

314 optically shallow waters.

3.3 FUI retrieval method

316 In the Commission on Illumination (CIE) colourimetry system, theoretically colour

317 parameters can be calculated from hyperspectral $R_{rs}(\lambda)$ and colour-match functions by

318 using spectral integration in the visible range (C.I.E., 1932; Wang et al., 2015). As there

319 are only three red, green, blue (RGB) bands in MOD09 images (645 nm, 555 nm and

320 469 nm), the RGB conversion method was used to calculate CIE X, Y, Z using the $R_{rs}(\lambda)$

321 at the three visible bands (Wang et al., 2015; Li et al., 2016). The RGB conversion

322 equation to X, Y, Z is as follows:

323
$$X = 2.7689R + 1,7517G + 1.1302B$$

324
$$Y = 1.0000R + 4.5707G + 0.0601B$$

325
$$Z = 0.0000R + 0.0565G + 5.5934B \tag{3}$$

326 CIE chromaticity coordinates (x, y) were then calculated from the X, Y, Z by

327 normalizing them to between 0 and 1. A new coordinate system (x', y') was built based

328 on the chromaticity coordinates (x, y) as (Figure 6):

329
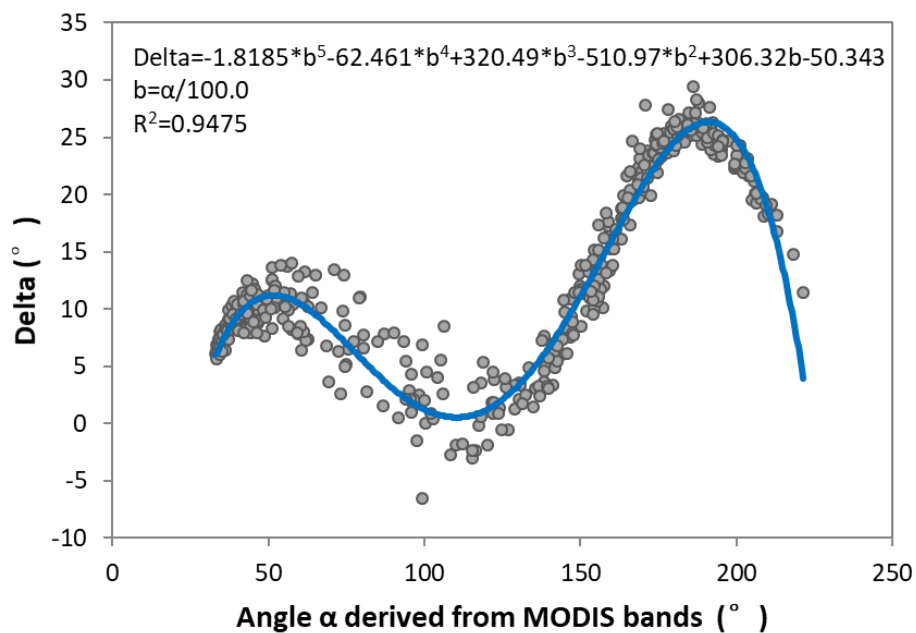$$x' = y - \frac{1}{3}$$

331
$$y' = x - \frac{1}{3}$$

330
$$\tag{4}$$

332 Based on the coordinates (x', y') in the CIE chromaticity diagram, angle α was

333 calculated, defined as the angle between the vector of coordinates (x', y') and the

18

334 negative x'-axis (at y = 1/3) in the new coordinate system. It is notable that angle α is

335 basically consistent with the definition reported in Wang et al. (2015); but for the

336 convenience of subsequent calculation, starting from the negative x'-axis, the angle α

337 is improved to remain positive now from 0° to 360°. Due to the band setting of satellite

338 sensors, there is a difference between the human eye sensed true colour and the sensor

339 derived colour (Van der Woerd and Wernand, 2015). To eliminate the colour difference

340 caused by MODIS band setting, a systematic deviation delta, defined as the difference

341 between angle α derived from hyperspectral $R_{rs}(\lambda)$ and the equivalent MODIS bands,

342 was modelled and calculated. Following the method presented in Van der Woerd and

343 Wernand (2015), the delta for MODIS was modelled with a polynomial fitting (Figure

344 7) based on the simulated dataset generated by Hydrolight (IOCCG, 2006). With this

345 delta correction, the angle α and the FUI can be transferable between satellites and

346 sensors with different spectral settings (Van der Woerd and Wernand, 2015). Finally,

347 based on angle α after delta correction, the FUI was calculated using the 21-class FUI

348 lookup table established from the chromaticity coordinates of the Forel-Ule scales

349 (Novoa et al., 2013, Figure 6).

350
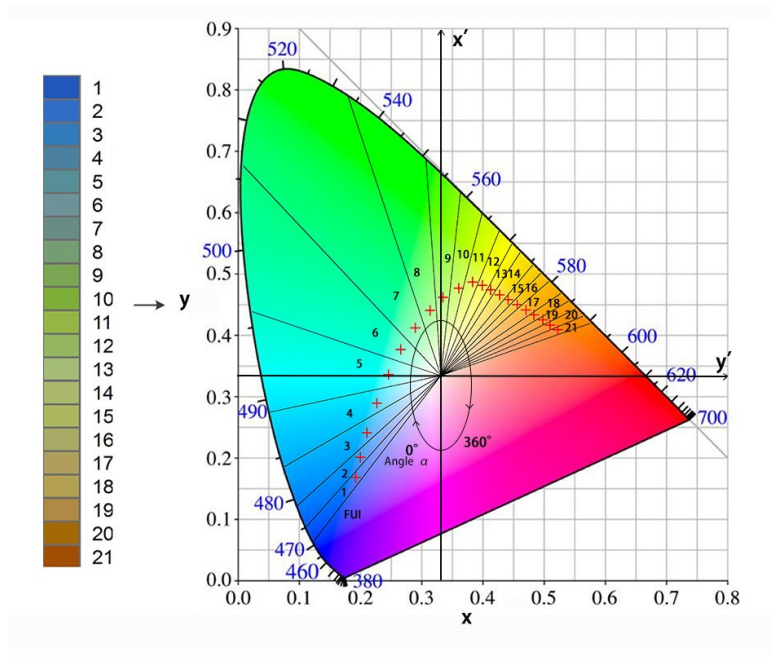
Figure 6 The FUI colours and the subdivision of the FUI from 1 to 21 in the CIE chromaticity diagram. The red crosses mark the chromaticity coordinates of the Forel-Ule scales (Novoa et al., 2013). Angle α is the angle between the vector to a point and the negative x'-axis (at y = 1/3).

Delta$=-1.8185*b^5-62.461*b^4+320.49*b^3-510.97*b^2+306.32b-50.343$
$b=\alpha/100.0$
$R^2=0.9475$

354

Figure 7 Deviation delta (°) from the hyperspectral angle α as a function of MODIS derived angle α for 0° < α < 230° (i.e., FUI ranging from 1 to 20)

### 3.4 FUI-based trophic state assessment algorithm

Calculations of the FUI and TSI were initially derived from the Hydrolight

20

359   simulated dataset to build the theoretical relationship between the two quantities in

360   relatively clear Chl-a dominated waters (Figure 8). Values for TSI ranged from 0 to 68,

361   the FUI generally increased with TSI based on the simulated dataset ($R^2 = 0.94$, N =
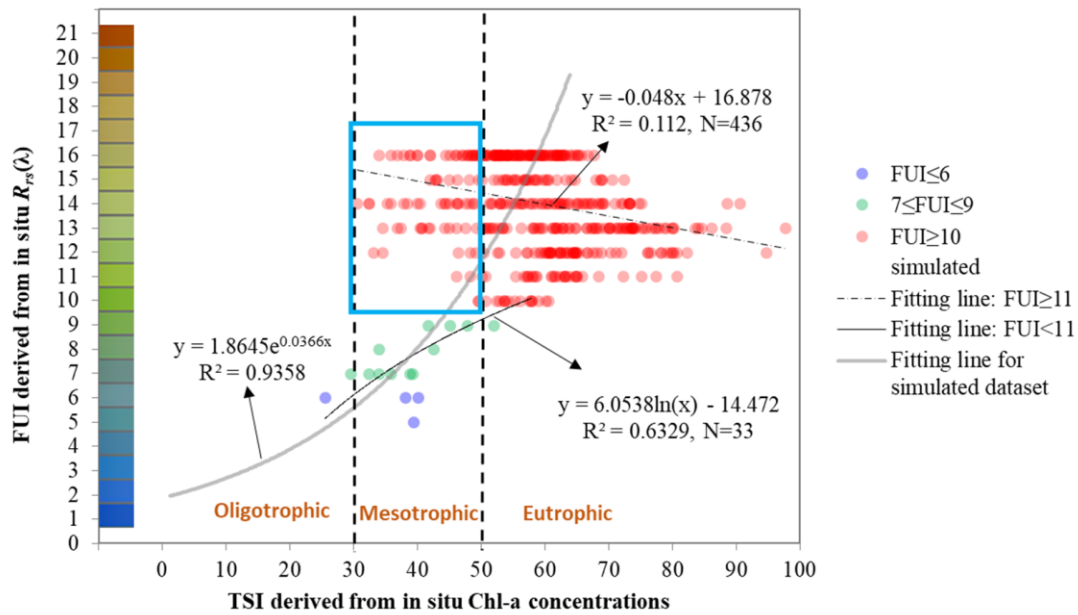
362   500).

363   However, the relationship between FUI and TSI from the in-situ dataset (Table 1)

364   showed a unimodal distribution (Figure 9): (i) similar to the simulated dataset, when

365   FUI < 10, it increased with TSI ($R^2 = 0.633$), showing that when water colour changes

366   from blue to green, the water body changes from oligotrophic to mesotrophic; (ii) TSI

367   peaked when FUI approached 10, because highly eutrophic waters generally appear

368   green owing to high Chl-a content; (iii) when FUI > 10, it showed a scattered negative

369   relationship with TSI ($R^2 = 0.112$), reflecting the shift from green to brown associated

370   with turbid eutrophic, or humic waters. Based on the in-situ dataset, the relationship for

371   FUI >10 is scattered and loose (Figure 9) because of complex constituents varying

372   independently in turbid waters, but this occasion is underrepresented in the simulated

373   dataset in Figure 8.

374   Although there are insufficient oligotrophic and mesotrophic waters in the in-situ

375   dataset, the in-situ dataset in Figure 9 showed a roughly similar overall trend as the

376   simulated dataset in Figure 8, and presented the FUI ranges for different trophic states.

377   The dataset showed that 82.7% of in-situ data points with FUI values ≥ 10 were

378   eutrophic with TSI ≥ 50; 83.3% of points with 7 ≤ FUI < 10 (i.e., 10 points out of 12)

379   were mesotrophic while the other two points had TSI values of 29.5 and 50.5. Finally,

380   data points with FUI < 7, were classified as oligotrophic, which is supported by the

381   simulated dataset. The FUI ranges were consequently used to classify the trophic state

382   of the waters.
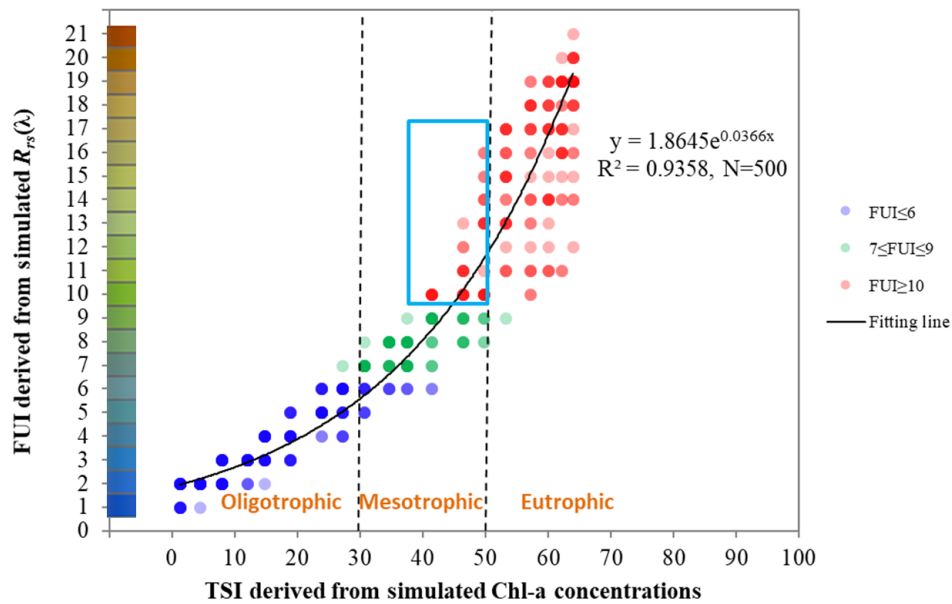
383

384   Figure 8 Scatterplot of data pairs of the Forel-Ule index (FUI) and Chl-a-based trophic state index
385   (TSI) from the Hydrolight simulated dataset (N = 500) (IOCCG, 2006). The colour bar indicates the
386   colour of the FUI indices. This simulated dataset covers a wide range of natural waters with
387   concentrations of Chl-a from 0.03 to 30.0 μg/L . The points were plotted with 60% transparency to
388   show the data density. The cyan box marks the mesotrophic points with FUI ≥ 10.

Figure 9 Scatterplot of data pairs of the Forel-Ule index (FUI) and concurrent Chl-a-based trophic state index (TSI) from in-situ measurements (N = 469). The colour bar indicates the colour of the FUI indices. Blue points denote FUI ≤ 6, green spots denote 7 ≤ FUI ≤ 9, and red spots denote FUI ≥ 10. The spots were plotted with 60% transparency to show the density of observations. The cyan box marks the mesotrophic points with FUI ≥ 10.

Some humic (i.e., high CDOM content) or turbid (i.e., high TSM content) mesotrophic waters may result in an FUI value greater than 10 with green to brown colour, such as the scattered points presented in the cyan box in Figure 8 and Figure 9. To distinguish these points, a red band (R_{rs}(645)) threshold method was implemented by comparing the $R_{rs}(\lambda)$ spectra of these points with representative $R_{rs}(\lambda)$ spectra of eutrophic waters. Even if water bodies with high CDOM but low TSM appear with a high colour index, R_{rs}(645) will be relatively low compared with other TSM-dominated yellow waters due to low backscattering of the water constituents with high CDOM and low TSM. After applying this threshold, the accuracy of eutrophic classification was increased to 86.8%. With the FUI subsection and the R_{rs}(645) threshold, a decision tree

23

405 of trophic state assessment for water bodies was developed, shown in Figure 10.

406

FUI

FUI < 7 | 7 ≤ FUI < 10 | FUI ≥ 10

$R_{rs}(645) \leq 0.00625$

Oligotrophic | Mesotrophic | Eutrophic
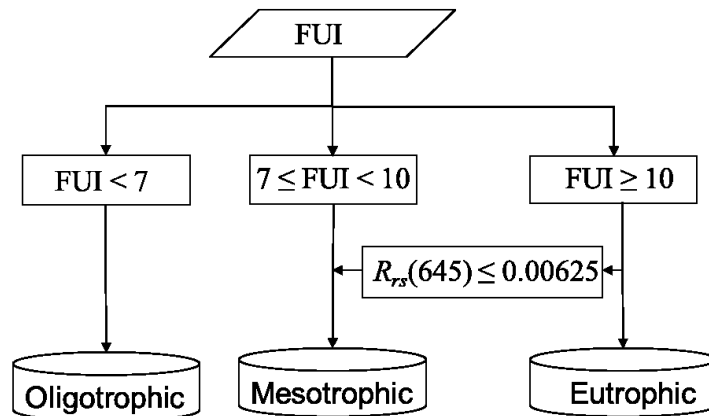
407
408 Figure 10 Forel-Ule index (FUI)-based water trophic state assessment decision tree based on the
409 classification of FUI and $R_{rs}(645)$

410   Lake-average values were considered more appropriate for global applications of

411 the method. Results showed a positive relationship between lake-average FUI and lake-

412 average TSI. For the 10 lakes sampled during 14 field campaigns, only 1 pair of

413 FUI/TSI averages was misclassified based on the FUI from the 10-lake in-situ dataset,

414 supporting the applicability of the method to lake averages.

415 **3.5 Spatial and Temporal statistics**

416   As MOD09A1 is an 8-day composite product, there are globally 16 periods of

417 MOD09A1 images over the four summer months. The seasonal average FUI for each

418 study lake was estimated and used to assess the trophic state of lakes in the summer of

419 2012. During the calculation, a standard water mask image was produced for each lake

420 by overlaying the water mask images in the same MODIS tile. This was used to check

421 the percentage of noise pixels covered by clouds, ice, snow, and other noises. If the

422 detected water pixels for a lake in an image was less than 30% of its standard water

423   mask area, then those pixels were not considered to represent the entire lake and the

424   image was not used for lake assessment. If less than 3 of the 16 images were valid for

425   a lake over the summer months, then the lake was not assessed in this study. A water

426   body spanning more than one tile of the MOD09A1 image was merged into a single

427   lake by detecting the connected area in the standard water mask images across tiles. To

428   show the variations within each lake, the spatial coefficient of variation (CV = δ/μ,

429   where δ is the standard deviation and μ is the mean) of the FUI and the temporal

430   coefficient of variation for each study lake was also calculated. The average $R_{rs}(645)$

431   for each lake was computed to aid the FUI-based trophic state assessment.

432   **4. Results**

433   **4.1 Evaluation of MODIS retrieved FUI**

434   The FUI values derived from MOD09 $R_{rs}(\lambda)$ and concurrent in-situ $R_{rs}(\lambda)$ were

435   compared to evaluate the FUI retrieved from MODIS with the water-leaving reflectance

436   correction. Despite a few scattered points (with light red colour in Figure 11(a)) that

437   may be caused by the complex atmospheric conditions (e.g. land aerosols), the paired

438   data from the seven lakes showed a strong correlation that mostly fell along the

439   approximate 1:1 line (Figure 11; R^2 = 0.87, slope = 0.92), with a mean absolute

440   difference (MAD) of 0.85 and a mean relative difference (MRD) of 7.5%. In addition,

441   the MODIS FUI produced a 10.5% difference in trophic state classification, compared

442   with the FUI derived from in-situ $R_{rs}(\lambda)$. The effects of various aerosol and

443   solar/viewing geometry perturbations on the FUI calculation are discussed in Section

444   5.1.
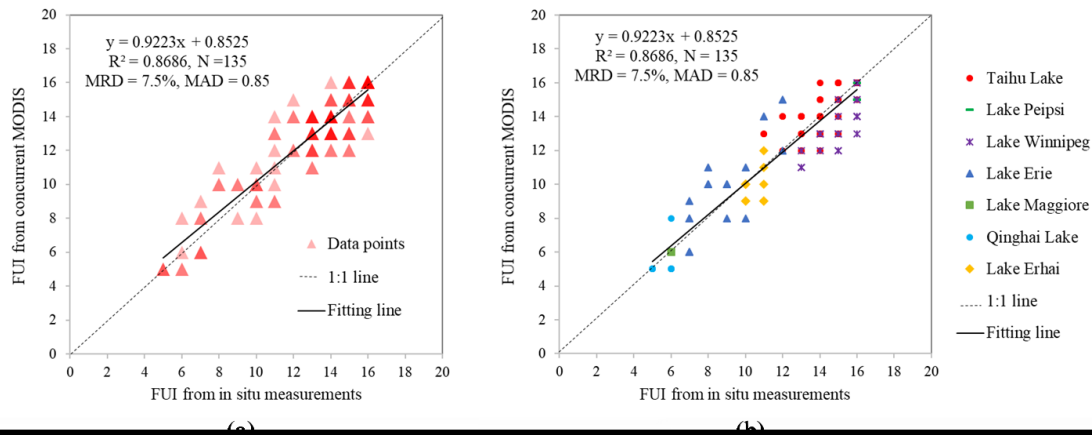
445

446 Figure 11 Scatterplots of the FUI derived from in-situ measured $R_{rs}(\lambda)$ versus concurrent MOD09
447 retrieved $R_{rs}(\lambda)$ for seven lakes with different FUI ranges. (a) Data points are coloured with 60%
448 transparency; darker spots indicate a higher data density. (b) Data points from different lakes are
449 marked with different symbols.

4.2 Validation results with independent data

451   The lake trophic state data included in the independent validation dataset, as well

452 as the sources of the trophic states data, are listed in Table S1 in Supplementary Material.

453 We found that 20 of the 100 water bodies were misclassified using the FUI-based

454 method. There were no misclassifications between eutrophic and oligotrophic water

455 bodies. Most misclassifications occurred between eutrophic and mesotrophic water

456 bodies, and to a lesser extent between mesotrophic and oligotrophic water bodies. The

457 user accuracy of the oligotrophic, mesotrophic, and eutrophic classifications was

458 100.0%, 66.7%, and 78.3%, respectively, calculated through confusion matrix analysis.

459 The overall accuracy of the trophic state assessment was found to be 80.0% ($R^2 = 0.75$),

460 while the Kappa coefficient (Landis and Koch, 1977) was 0.67 (Table 2), which

461   confirmed that the FUI-based results were substantially consistent with the comparison

462   dataset.

463   Table 2 Confusion matrix of Forel-Ule index (FUI)-based trophic state assessment for the
464   investigated 100 lakes

| Comparison Data / FUI-based Assessment	Oligotrophic	Mesotrophic	Eutrophic	Total	User accuracy
Oligotrophic	19	0	0	19	100.0%
Mesotrophic	5	14	2	21	66.7%
Eutrophic	0	13	47	63	78.3%
Total	24	27	49	100	
Producer accuracy	79.2%	51.9%	95.5%		
Kappa coefficient	0.67				
Overall accuracy	80.0%				

465

4.3 Trophic state assessment for global inland waters in 2012

467   Among the water bodies studied (N = 2058, total surface area = 1.73 million km^2),

468   the MODIS FUI of the lakes in the summer of 2012 ranged from 2.0 to 17.0, the spatial

469   CV of the water bodies ranged from 0.0% to 41.2% with an average value of 12.9%

470   and the temporal CV ranged from 0.0% to 54.3% with an average value of 9.9%. The

471   season-averaged FUI values of the studied large lakes were found to vary between 3.1

472   and 16.0, and the mean FUI was 11.1 with a worldwide CV of 26.6% (Figure 12). Based

473   on these data, the results presented that large lake trophic states were not equally

474   distributed around the globe, shown in Figure 13. Eutrophic water bodies accounted for

475   63.1% of the total number but only 30.5% of the total surface area, mesotrophic water

476   bodies accounted for 26.2% of the total number and 39.4% of the total surface area, and

477   oligotrophic water bodies accounted for 10.7% of the total number but 30.1% of the

478   total surface area.
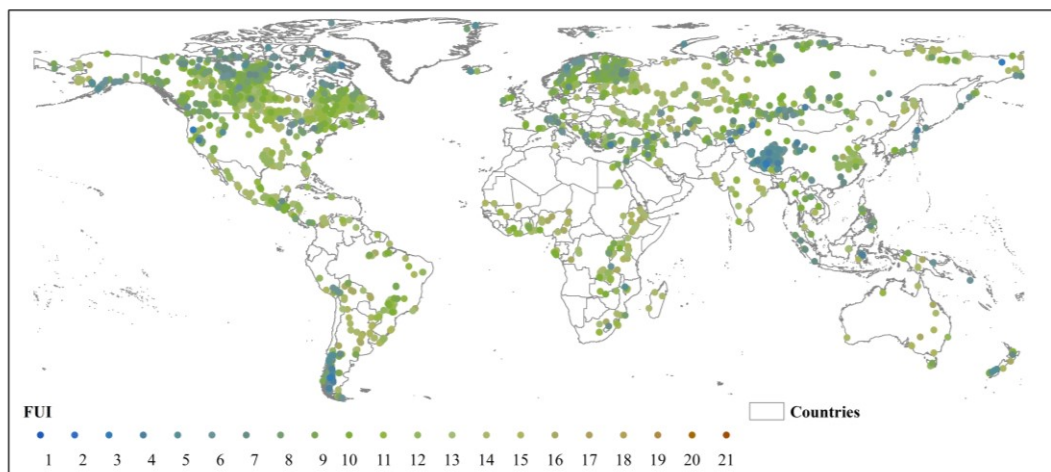
479

480   Figure 12 MODIS FUI values for global inland waters in the austral and boreal summers of 2012.
481   Each point represents a single water body of > 25 km^2 in surface area. The FUI of each point
482   represents averaged values from all lake pixels across the summer months rounded to the nearest
483   integer.
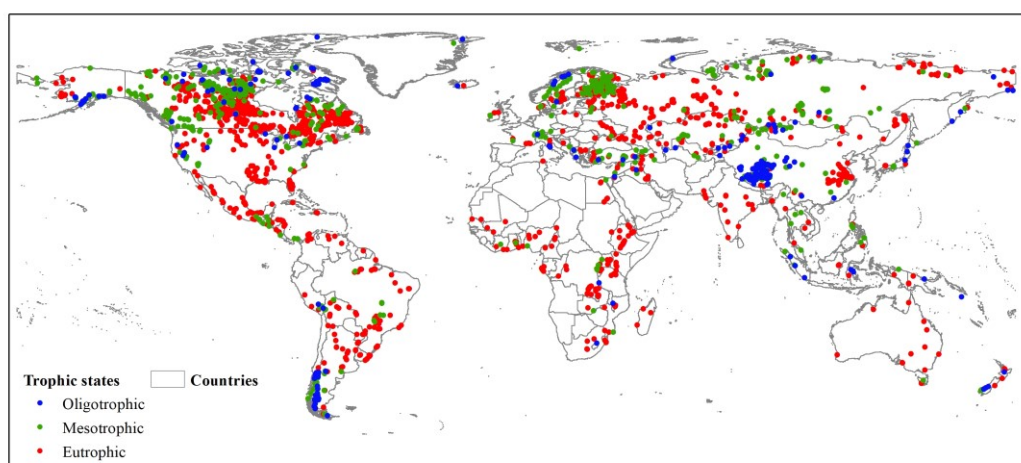
484

485   Figure 13 Trophic state classification of global inland waters in the austral and boreal summers of
486   2012 assessed using the FUI-based method. Blue spots denote oligotrophic water bodies, green spots
487   denote mesotrophic water bodies, and red spots denote eutrophic water bodies.

488   It was found that oligotrophic large lakes concentrated in high mountains and

489   plateau regions of Central Asia (Qinghai-Tibet Plateau region) and southern South

490   America (Patagonia Plateau region), while eutrophic large lakes concentrated in central

28

491   Africa, eastern Asia (East China), and mid-northern and southeast North America

492   (south Canada and southeast U.S.). In terms of lake numbers, Oceania had the highest

493   proportion of oligotrophic large lakes (23.1%), Europe had the highest proportion of

494   mesotrophic large lakes (35.2%), and Africa had the highest proportion of eutrophic

495   large lakes (88.8%). In terms of surface area, North America had the highest proportion

496   of oligotrophic water (49.8%), Asia had the highest proportion of mesotrophic water

497   (71.2%), and Africa still had the highest proportion of eutrophic water (Figure 14).
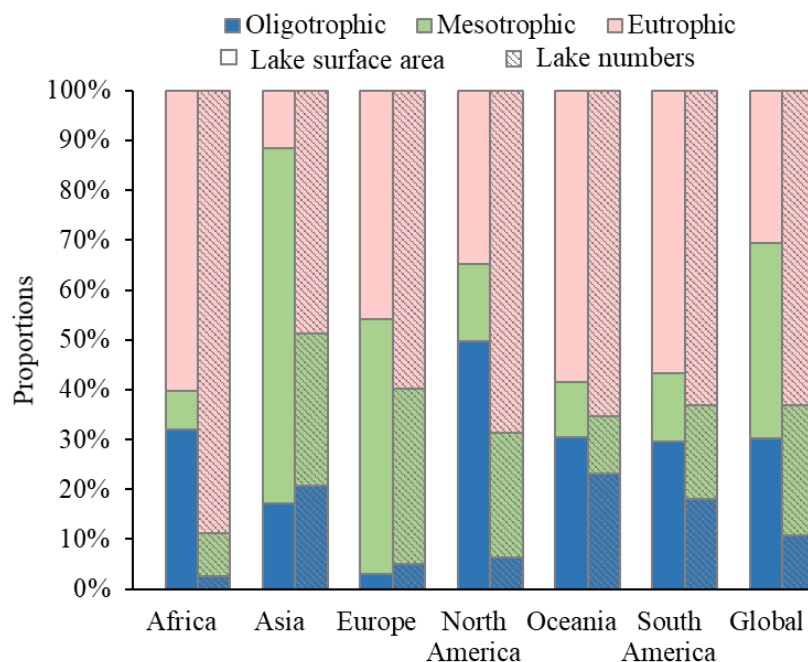
498
499 Figure 14 Proportion of large lakes with each trophic state in terms of lake number and lake
500 surface area across continents.

4.4 Trophic state assessment for regional groups of lakes

502   To further validate the FUI-based trophic state results, data from five regional

503 groups of lakes around the world were analyzed (Figure 15): the North America Great

504 Lakes region (oligo-mesotrophic dominated), the African Great Lakes region

505 (mesotrophic dominated), the central south European region (mesotrophic dominated),

506 the east Asian middle-lower Yangtze region (eutrophic dominated), and the Tibet

507 Plateau (oligotrophic dominated).
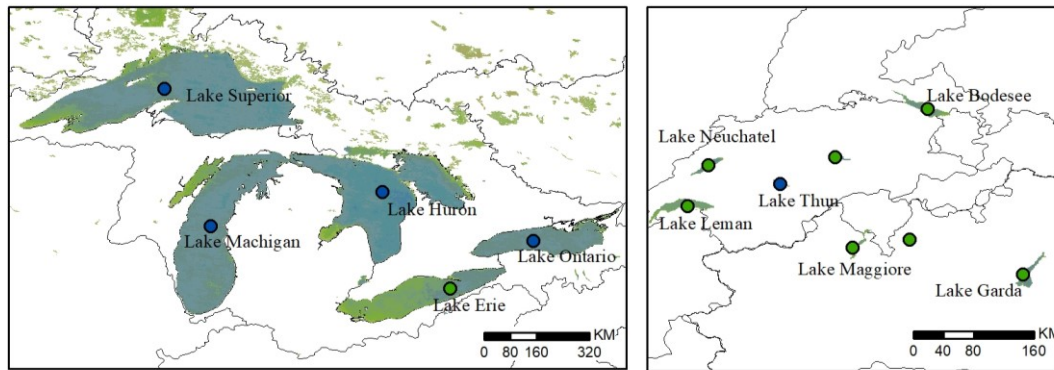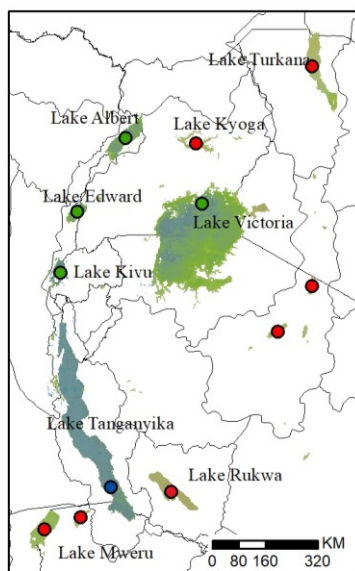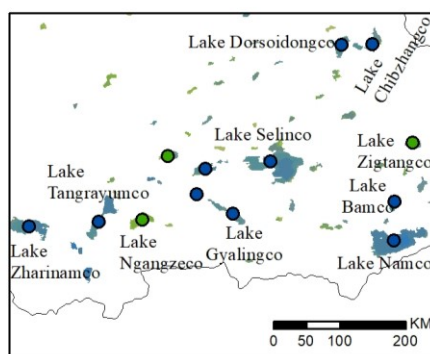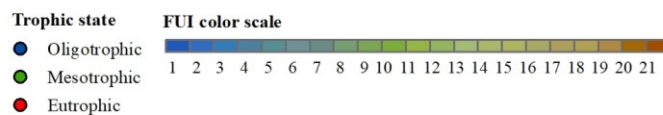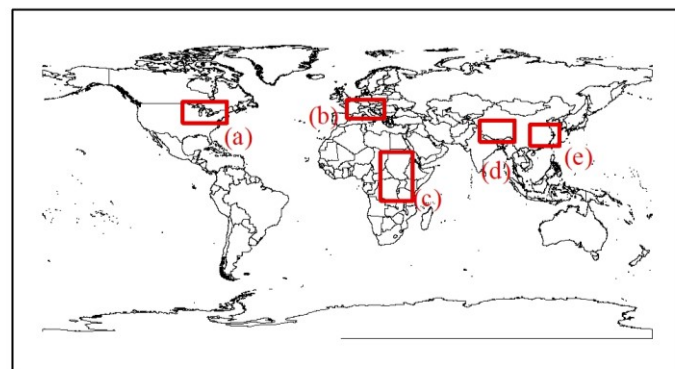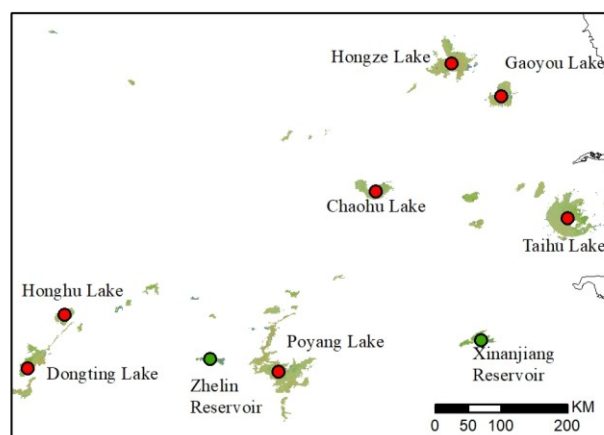
508

509　Figure 15 Trophic states and Forel-Ule index (FUI) values of large lakes within typical lake regions
510　in the austral and boreal summers of 2012: (a) North America Great Lakes region; (b) central south
511　European; (c) African Great Lakes region; (d) Tibet Plateau; (e) middle-lower Yangtze region.
512　Coloured points represent the mean trophic state of the water body (blue spots denote oligotrophic
513　water bodies, green spots denote mesotrophic water bodies, and red spots denote eutrophic water
514　bodies).

515

516　　　　The FUI of lakes in the North America Great Lakes region mainly ranged from 5

517　to 10, corresponding to a cyan water colour. Lake Superior, Lake Michigan, Lake

518　Ontario and Lake Huron were found to be oligotrophic, while Lake Erie was found to

519　be mesotrophic. The water colour of western Lake Erie is greener than the other lakes

520　and had an FUI of ~11 (i.e., eutrophic). These results are consistent with those of past

521　studies (Auer et al., 2004; Barbiero et al., 2012; Bridgeman et al., 2013; Chaffin et al.,

522　2011; Holeck et al., 2015; Mukherjee et al., 2016; Shuchman, 2013).

523　　　　The FUI of lakes in the central south European region mainly ranged from 7 to 9,

524　corresponding to a cyan water colour and a mesotrophic state. This is consistent with

525　past studies, which have classified water bodies in this region as oligo-mesotrophic

526　(Coci, et al., 2015; Rimet et al., 2015; Fuentes et al., 2013; Giardino et al., 2014; Jaquet,

527　2013; Stich and Brinker, 2010; Vollenweider and Kerekes, 1982).

528　　　　The FUI of lakes in the African Great Lakes region, which constitutes part of the

529　Rift Valley and East African Rift, mainly varied from 4 to 16, corresponding to a water

530　colour of cyan to green and a wide range of trophic states (oligotrophic, mesotrophic,

531　and eutrophic). Lake Victoria, the second largest freshwater lake in the world, is

532   mesotrophic with eutrophic sections. Lake Turkana, one of the largest desert lakes in

533   the world and the most important regional source of fish, is eutrophic. Lake Tanganyika,

534   the deepest lake in Africa, is oligotrophic. These results are consistent with the past

535   studies (Hecky et al., 2010; Okullo et al., 2011; Avery, 2012; Velpuri et al., 2012;

536   O'Reilly, 2003; Verburg, 2006).

537   The FUI of lakes on the Tibet Plateau ranged from 2 to 7, corresponding to a water

538   colour of blue to cyan and trophic states that are mainly oligotrophic. Lake Namco,

539   which lies at an elevation of 4718 m and experiences low impact from human activity

540   (Wang and Dou, 1998), was shown to have a very low FUI (2–4) and be oligotrophic.

541   Compared with Lake Namco, the FUI of Lake Selinco was higher (4–7), and its trophic

542   state was oligotrophic but approaching mesotrophic (Li et al., 2016). The FUI of Lake

543   Ngangzeco and Lake Zigtangco were found to be even higher and their trophic states

544   were mesotrophic. Few studies have been implemented for the water trophic states on

545   the Tibet Plateau due to the poor weather conditions. The results in Figure 15 (d) can

546   fill the knowledge gap in this region.

547   The FUI of the lakes in the middle-lower Yangtze region mainly ranged from 9 to

548   14, corresponding to a water colour of green to yellow-green, and the trophic states

549   were mainly eutrophic. This is consistent with past studies, which have demonstrated

550   that Lake Taihu, Lake Chaohu, Lake Poyang, and Lake Dongting are typical eutrophic

551   and turbid lakes in China (Chen et al., 2013a, 2013b; Shi et al., 2015; Wang et al., 2011;

552　Wu et al., 2013; Yang et al., 2013). The trophic states of the Xin'anjiang and Zhelin

553　reservoirs, the two largest reservoirs on the middle-lower reach of the Yangtze, were

554　found to be mesotrophic, which agrees with the results of published literature (Chen,

555　2009; Sheng et al., 2015).

5. Discussion

556

5.1 FUI sensitivity to aerosol perturbations and observation conditions

557

558　　　The significant positive correlation between the concurrent FUIs over a wide range

559　of lakes, and the relatively low uncertainties suggest that MODIS surface reflectance

560　data and the water-leaving correction method can be used for FUI retrieval and the FUI-

561　based trophic state assessment of water bodies. Moreover, it is notable that in

562　comparison with concurrent in-situ data (Figure 11), the accuracy of the MODIS FUI

563　(~90%) was greater than that of MODIS $R_{rs}(\lambda)$ (Wang et al., 2016), indicating that the

564　FUI calculation process can reduce uncertainties introduced in MODIS $R_{rs}(\lambda)$.

565　　　However, the MOD09 $R_{rs}(\lambda)$ retrieved still theoretically contains some of the

566　uncertainties induced by the effects of aerosol types and bidirectional properties as a

567　result of the MOD09 data and the water-leaving correction method. Hence, the

568　sensitivities of FUI to these uncertainties within the input data were investigated using

569　radiative transfer model simulations. These simulations verified the general global

570　applicability of FUI calculated with this method.

571　　　Based on the radiative transfer theory and assuming a non-coupling water-

572   atmosphere system, Rayleigh-corrected reflectance (R_{rc}) can be expressed as:

573 $$R_{rc}(\lambda) = \rho_t(\lambda) - \rho_r(\lambda) = \rho_a(\lambda) + \pi t(\lambda)t_0(\lambda)R_{rs}(\lambda) \qquad (5)$$

574   where $\rho_t(\lambda)$ is the top-of atmosphere (TOA) reflectance, $\rho_r(\lambda)$ is the reflectance due to

575   Rayleigh scattering, $\rho_a(\lambda)$ is the aerosol reflectance including that from aerosol

576   scattering and aerosol-Rayleigh interactions, $t(\lambda)$ is the atmospheric transmittance from

577   the target to the satellite sensor, and $t_0(\lambda)$ is the atmospheric transmittance from the Sun

578   to the target. These unknowns can be calculated from SeaDAS LUTs (look-up tables)

579   for variable aerosols and solar/viewing geometry. Thus, the relationship between $R_{rs}(\lambda)$

580   and the $R_{rc}(\lambda)$ containing various aerosols can be established through simulations. To

581   determine whether the FUI is sensitive to the considered perturbations, the FUI

582   calculated directly from $R_{rc}(\lambda)$ at MODIS RGB bands were compared with the FUI

583   calculated from the corresponding $R_{rs}(\lambda)$ with the same band setting.

584   Figure 16 shows the comparison results for maritime and coastal aerosols at the

585   scene center and scene edge. The overall relationship between R_{rs}-based FUI and R_{rc}-

586   based FUI under all light conditions is quite robust ($R^2 = 0.967$) with an MRD of 10.9%,

587   even though the relationship deteriorates a little under coastal aerosols with larger

588   aerosol optical thickness at 869 nm ($\tau(869)$) towards the scene edge. These

589   perturbations resulted in 9.5% of the data indicating a different trophic state to that

590   indicated by the FUI calculated from the original $R_{rs}(\lambda)$ data. The results illustrate that

591   the FUI algorithm is generally insensitive to perturbations due to aerosols and

592 observation conditions. This may be because of the normalization process in the

593 chromaticity coordinate calculation and the clustering process in the 21-indices

594 classification, which may reduce the uncertainties caused by different aerosol types.
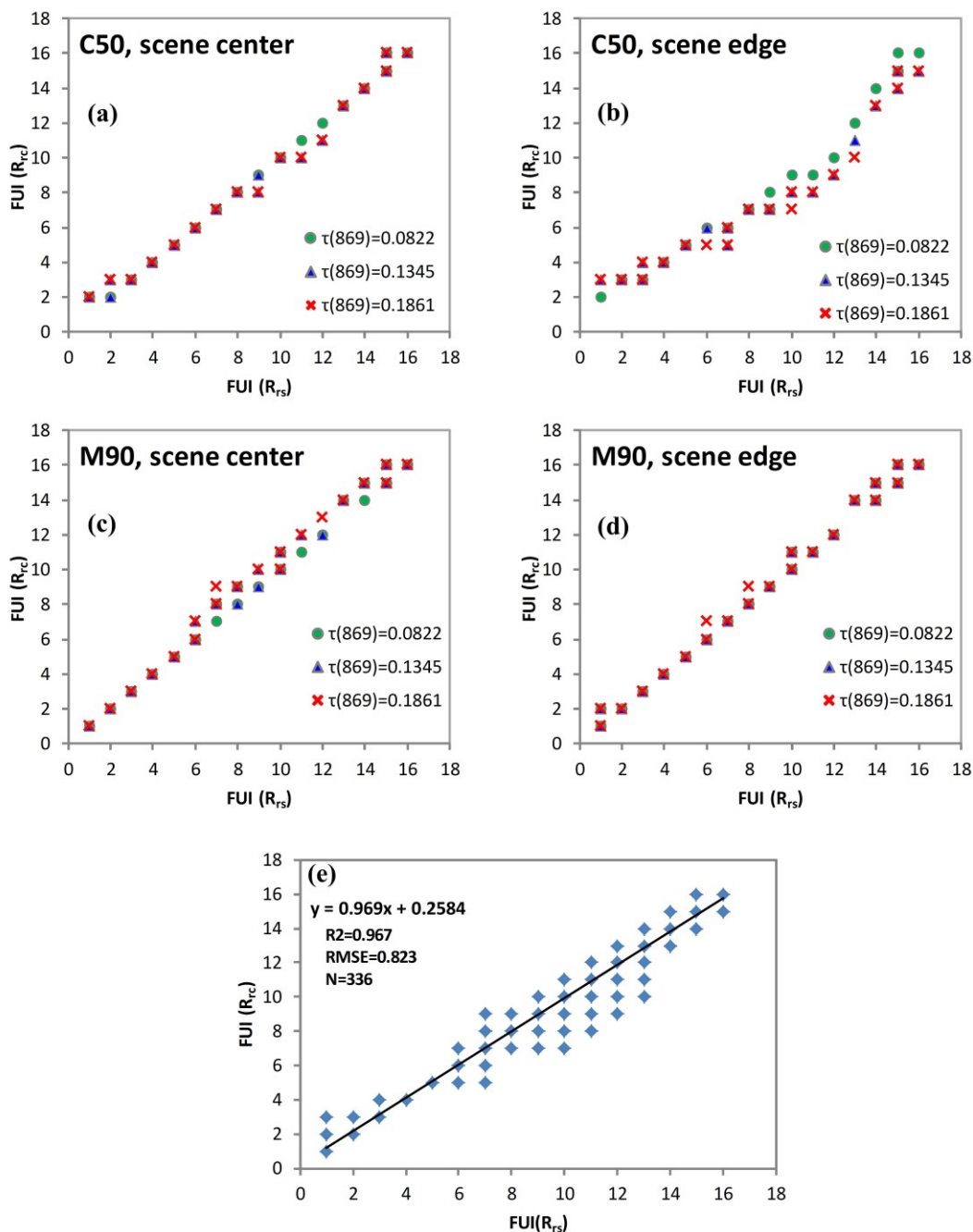
595

596 Figure 16 Relationship between R_{rc}-based FUI and R_{rs}-based FUI with various atmospheric
597 conditions (i.e., aerosol type and optical thickness at 869 nm (τ(869))) and solar/viewing geometry,
598 based on model simulations. Two aerosol types were used in the simulations: (a and b) coastal

599 aerosol with 50% relative humidity (C50) and (c and d) maritime aerosol with 90% relative humidity
600 (M90). Two solar/viewing geometries were performed in the simulations: (a and c) near scene center
601 and (b and d) near scene edge. (e) Relationship between R_{rs}-based FUI and R_{rc}-based FUI under all
602 considered conditions ($R^2 = 0.967$, MRD = 10.9%, RMSD = 0.823, n = 336). MRD denotes the
603 mean relative difference and RMSD denotes the root mean square difference.

604 **5.2 Relationship between the FUI-based method and traditional trophic state**

605 **assessments**

606   Our FUI-based trophic state assessment method depends on water colour

607 information derived from satellite imagery, which is in contrast to traditional

608 assessment methods that depend on one or several biophysical variables (i.e., Chl-a, SD,

609 TP, TN, COD and biomass; Burns et al., 1999; Vant, 1987). To compare the FUI-based

610 method with traditional variables, we compared our results with data in the NLA2007

611 report (USEPA, 2009), which contains both Chl-a based trophic state assessments, and

612 additional trophic state assessments based on SD, TP, and TN. Using the 20 lakes found

613 in both datasets, the results showed that the FUI-based classifications were better

614 correlated with SD and Chl-a ($R^2 = 0.80$, 0.65, $p < 0.05$, RD (relative error) = 30%;

615 Figure 17), reflecting the importance of water clarity and Chl-a in controlling water

616 colour. The correlation between the FUI-based results and TP-based trophic state

617 assessments was also strong ($R^2 = 0.29$, $p < 0.05$, RD = 35%). However, the TN-based

618 results had a weak relationship with the FUI-based results ($R^2 = 0.03$, RD = 55%).

619 Similarly, the TN-based results had an insignificant relationship with the Chl-a-based

620 results ($R^2 = 0.03$), as there is usually a weak relationship between TN and Chl-a in

621 lakes (Guildford and Hecky, 2000).

622   Of the 20 U.S. lakes compared, none were classified as oligotrophic in the FUI-

623   based results (Figure 17), but 5 lakes were classified as oligotrophic in the Chl-a-based

624   NLA results. This misclassification of oligotrophic lakes as mesotrophic was also seen

625   in the validation comparison data (Table 2), which will be discussed in Section 5.3.
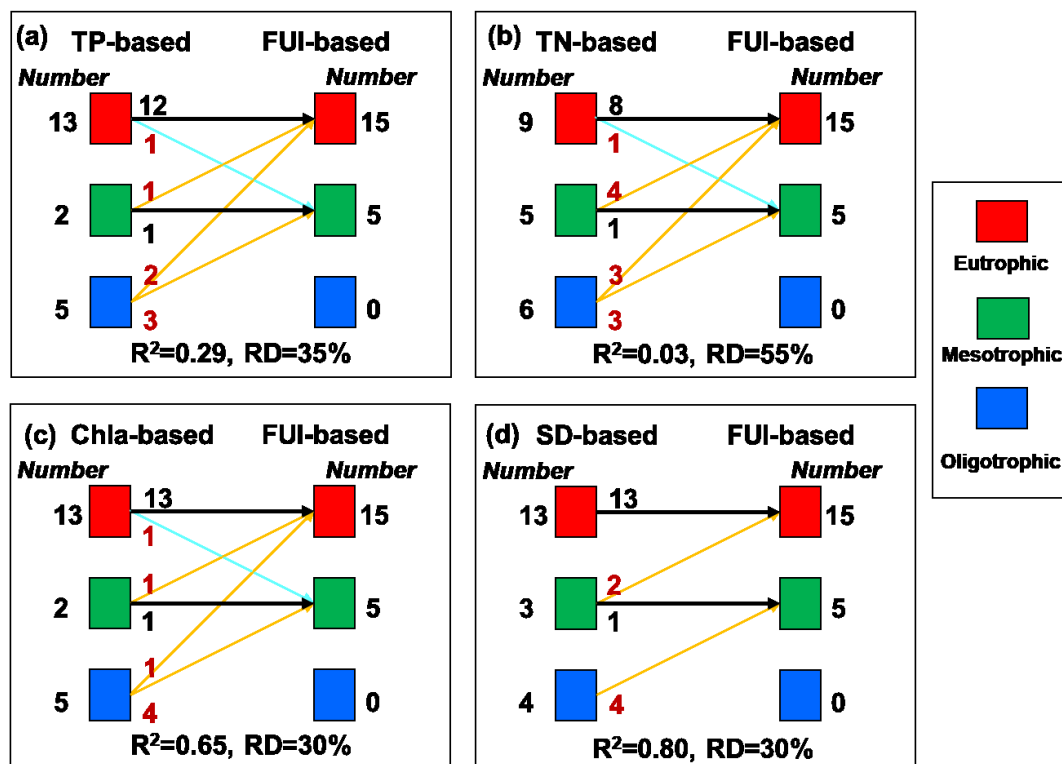
626
627   Figure 17 Comparison of lakes classified as different trophic states using the Forel-Ule index (FUI)-
628   based trophic state results and National Lake Assessment 2007 (USEPA, 2009) results based on (a)
629   total phosphorus (TP), (b) total nitrogen (TN), (c) chlorophyll-a (Chl-a), and (d) Secchi depth (SD),
630   for the 20 matched lakes. R^2 denotes the determination coefficient and RD denotes the relative error.

631   **5.3 Uncertainties of trophic state assessment using FUI**

632   Since there is currently no single RS algorithm applicable for the global inland

633   waters to retrieve the trophic state related parameters (i.e.Chl-a), as a relatively easy-

634   to-produce image product, the FUI-based method makes it possible to assess the trophic

635   states of global inland waters. Although the trophic state of the waters across the in-situ

37

636   dataset and independent dataset could be classified with relatively high accuracy (~80%)

637   with the FUI, the confusion matrix of the FUI-based classification for 100 investigated

638   lakes (Table 2) shows that the FUI method led to an over-estimation of the trophic state

639   of a small proportion of lakes. This may be explained by differences in the division of

640   the trophic states by different different assessing methods. The trophic state

641   classification in this study adopted the boundaries of 1 and 7 μg/L, based on Carlson

642   (1977). However, the USEPA (2016) adopted the boundaries of 2 and 7 μg/L. Hence,

643   there may be some over-estimation in the mesotrophic state when using the FUI method

644   because of the lower boundary. The other reason might be that the FUI of waters may

645   appear larger when there are other optically active constituents in addition to Chl-a that

646   dominate these optically complex inland waters.

647   We identified the mesotrophic waters from the eutrophic waters with FUI ≥ 10 by

648   using a red band (R_{rs}(645)) threshold method, because the relatively high CDOM

649   content in water changes the water colour to green and yellow, and the backscattering

650   of the water in the red band is quite low because of the low TSM content. In the cyan

651   box in Figure 9, there were a few other situations that result in the misclassification of

652   mesotrophic waters, which are shown in Figure 17. For these mesotrophic waters with

653   FUI ≥ 10，the optical properties are generally dominated by abundant CDOM or TSM.

654   Mesotrophic water dominated by relatively high CDOM and with very low TSM can

655   be identified from eutrophic water using the red band threshold method. However, for

656   water dominated by high CDOM with relatively high TSM, the $R_{rs}(\lambda)$ spectra is similar

657   to eutrophic waters and cannot be distinguished using the MODIS bands. It is difficult

658   to distinguish between mesotrophic and eutrophic waters when dominated by high TSM

659   with the MODIS imagery. Further assessment of the trophic state of these two specific

660   situations will require platforms with superior spectral resolution.
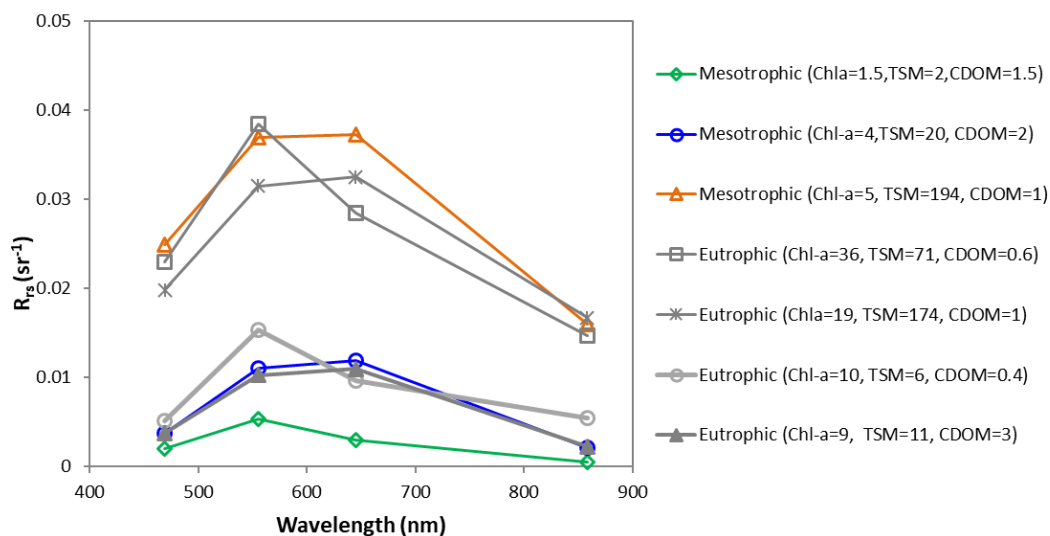
661
662   Figure 17 Different types of water-leaving reflectance ($R_{rs}(\lambda)$) spectra of waters with FUI≥10,
663   including eutrophic and confusing mesotrophic waters. The unit for Chl-a is µg/L, for TSM is
664   mg/L, for CDOM is m^{-1} which means the absorption coefficient at 440 nm.

665   As the summer-average FUI of each water body was used to assess the trophic

666   state of the water body, the averaging processes may result in the loss of spatial and

667   temporal characteristics of some water bodies, whilst reducing the occurrence of

668   unexpected errors and uncertainties. In this case, a water body that is partly eutrophic

669   and partly mesotrophic may be classified as mesotrophic after the averaging process.

670   The timing of the images also affects the results, as the trophic state of lake may change

671   during the summer months. Therefore, a threshold for the number of images of no less

672   than three over the summer months is therefore considered necessary and avoids the

673   cases where two consecutive images may produce a biased result against the average

674   state. From the global results, the spatial CV of the water bodies ranged from 0.0% to

675   41.2% with an average value of 12.9%, and the temporal CV ranged from 0.0% to 54.3%

676   with an average value of 9.9%. Large variations in these waters might in part be related

677   to the impact of cloud cover influencing or biasing the pixel coverage for a lake for

678   different areas, whilst some may also be related to extreme events such as sudden algae

679   blooms or sediment plumes following heavy rainfall.

680   The data quality of MODIS Terra was often considered not adequate for ocean

681   colour applications (Franz et al., 2008). But around 2010, NASA started reprocessing

682   of all the MODIS Terra products and produced good agreement with MODIS Aqua by

683   using improved radiometric calibration to account for sensor degradation (Li et al.,

684   2017; Lyapustin et al., 2014; Meister and Franz, 2011). In addition, for inland waters,

685   the water signal has a greater contribution in the TOA radiance, which tends to be much

686   greater than that associated with open ocean waters.

687   There may be some uncertainties induced by the calibration of Terra MODIS and

688   the artefacts of atmospheric correction in the derivation of $R_{rs}(\lambda)$ and FUI from Terra

689   MOD09 products in this study. Nevertheless, following the simple water-leaving

690   reflectance correction, the comparison between MODIS FUI and in-situ derived FUI

691   and the evaluation of the FUI sensitivity to remaining data perturbations produced good

692 results and demonstrated the validity and practicability of the MOD09 product and the

693 simple correction method for a wide range of inland waters. As might be expected, the

694 producer accuracies (Liu et al., 2007) in the confusion matrix (Table 3) for darker waters

695 like oligotrophic and mesotrophic waters, are relatively low (79.2% and 51.9%). As

696 described, this is likely associated with calibration errors and artefacts introduced from

697 atmospheric correction over dark waters (Wang et al., 2016). Hence, for global inland

698 waters with various optical properties, a more robust atmospheric correction for satellite

699 products remains a high research priority.

700 Moreover, we chose Terra MOD09 as the main data source rather than Aqua

701 MYD09 because of the frequent stripe noise. The stripe noise in band 6 (1640 nm) is

702 severe in the Aqua MYD09 and Aqua MYD02 (the Level-1B Calibrated Geolocation

703 Data Set), which is induced by the detectors in Aqua MODIS band 6 and has been

704 reported in numerous studies (Rakwatin et al., 2009; Wang et al., 2006; Doelling et al.,

705 2015). Band 6 is a useful SWIR band used in this study to detect water areas and

706 atmospheric noises; however, the stripe noise in this band in Aqua would result in

707 inaccurate water area masks and water-leaving reflectance.

708 **5.4 Applicability to new satellite sensors**

709 The FUI retrieval algorithms from the water-leaving reflectance spectra have been

710 established for various satellite sensors such as MODIS, MERIS, Landsat-8 OLI,

711 Sentinel-3 OLCI (Wang et al., 2015; Wernand et al., 2013; Van der Woerd and Wernand,

41

712 2015, 2018). There are two main approaches for calculating CIE tristimulus X, Y, Z.

713 One is to rebuild the spectral data using an interpolation approach (Van der Woerd and

714 Wernand, 2015, 2018). The other approach is specific to sensors with only RGB bands

715 in the visible range, and it converts RGB to CIE X, Y, Z using the conversion equation,

716 as shown in Equation (3) (C.I.E., 1932; Wang et al., 2015). However, despite whether

717 an interpolation approach or the RGB conversion approach is used, there would be

718 colour differences from the human eye sensed true colour caused by the band setting of

719 the sensors (Van der Woerd and Wernand, 2015). To remove this difference, a delta

720 correction method was introduced by Van der Woerd and Wernand (2015) and adopted

721 in this study which models the difference between the sensor results and the true colour

722 results using polynomial fittings. Therefore, with the delta correction, the FUI and the

723 angle α calculated can be comparable and transferable between different satellite

724 sensors (Van der Woerd and Wernand, 2015, 2018). It is notable that the definition for

725 angle α enables it increase with FUI in this study, while the definition for angle α in

726 Van der Woerd and Wernand (2015) results in a decrease with FUI considering the

727 different start and revolving direction of angle α adopted. A transfer is first required

728 when comparing angle α derived using the different definitions. Regardless of the

729 definition of angle α, the FUI calculated are consistent because the same set of

730 chromaticity coordinates of the Forel-Ule scales were used (Novoa et al., 2013).

731 Furthermore, the FUI calculated from new sensors, like Landsat-8 OLI and Sentinel-3

732 OLCI, could be generally comparable with that from MODIS using a proper correction

733 method for the band settings (Van der Woerd and Wernand, 2018). With recently

734 launched sensors such as the Landsat-8 OLI and Sentinel-2(A & B), smaller lakes can

735 be added to the dataset to achieve more comprehensive global results.

6. Conclusions

737   In this study, the trophic states of global large inland waters were assessed using

738 an FUI-based remote sensing algorithm. The successful outcome can be attributed to

739 two factors: (1) the water colour index, FUI, can be calculated from MOD09A1 data

740 with considerable accuracy (~90%) through comparison with in-situ data, and it is

741 nearly immune to aerosol perturbations and variations in observation conditions. Such

742 tolerances lead to significantly increased validity, which is critical to FUI's application

743 on the global scale; (2) The FUI-based trophic state assessment algorithm was

744 developed based on the analysis of the relationship between FUI and TSI from 469

745 samples from in-situ measurements at 10 lakes around the world, which contain a wide

746 range of optical and water quality properties. This led to a robust trophic state

747 assessment method for inland waters on large scales, and an overall accuracy of 80%

748 was achieved. This algorithm could be applied to other satellite sensors with the

749 establishment of FUI retrieval algorithms from various sensors.

750   The assessment algorithm was implemented on MODIS images collected in the

751 austral and boreal summers of 2012, and the trophic states of the water bodies were

752 classified as oligotrophic, mesotrophic, or eutrophic. Of the 2058 water bodies

753 considered, eutrophic water bodies accounted for 63.1% of the total number but only

754 30.5% of the total surface area, mesotrophic water bodies accounted for 26.2% of the

755 total number and 39.4% of the total surface area, and oligotrophic water bodies

756 accounted for 10.7% of the total number but 30.1% of the total surface area.

757 Oligotrophic large lakes were found to be concentrated in plateau regions in Central

758 Asia and southern South America, while eutrophic large lakes were concentrated in

759 central Africa, eastern Asia, and mid-northern and southeast North America.

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