Matters Arising

Unrealistic phytoplankton bloom trends in global lakes derived from Landsat measurements

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Given its advantages for synoptic and large-scale observations, satellite remote sensing has been widely used to effectively monitor the water quality of inland and coastal environments. Using satellite-derived reflectance data from the Landsat 5 Thematic Mapper (L5TM) as a proxy for algal bloom intensity, Ho et al. [1] showed an increase in peak summertime bloom intensity in 68% of the 71 large lakes worldwide from 1982 to 2012. However, we question the veracity of their finding for at least two reasons: (1) satellite-derived reflectance in a single near-infrared (NIR) band is not a reliable proxy for bloom strength due to the strong impacts of suspended sediments and aquatic vegetation, and (2) the infrequent satellite observations from L5TM (one cloud-free image every 1-2 months) make it difficult to draw statistically meaningful conclusions. Therefore, although it is natural to speculate that more blooms may be found in lakes under changing climatic conditions, the work by Ho et al. [1] needs to be revisited before reaching any solid conclusions.

Ho et al. [1] argued that the L5TM-estimated bloom intensity (B_{NIR}) (see Equation 2 in Ho et al. [1]), which is basically the reflectance in the NIR band, is correlated with chlorophyll-a (Chla) concentration or phytoplankton biomass. However, this argument became questionable when we examined the correlations between in situ Chla and water reflectance (in situ reflectance was aggregated into the NIR reflectance equivalent of band 4 of L5TM [2]) with data collected from 15 lakes in China and from waters with varying eutrophic status (Chla ranging between 1.5 and 222.6 mg m^{-3}) (see Extended Data Fig. 1). We revealed nonsignificant relationships ($p>0.05$) between near surface Chla and NIR reflectance in three different Chla ranges (full Chla range, Chla>50 mg m^{-3} and Chla>10 mg m^{-3}). Such complex relationships between spectral reflectance and Chla concentrations were also demonstrated by Spyrakos et al. [3] when using in situ data from various inland waters around the world. Theoretically, the signal in the NIR band can be attributed to various water constituents in addition to algal blooms, and the contributions from suspended sediments and the presence of aquatic plants could be two of the most common perturbations in inland lakes. Ho et al. [1] attempted to mask out waters associated with high sediment loads with the use of hue, but as detailed later, the hue defined in Ho et al. [1] does not accurately reflect the color of a water body and is thus not effective for distinguishing phytoplankton blooms from sediment-dominated waters.

Bloom strength tends to be substantially overestimated in sediment-rich waters. Examples from two of the lakes studied in Ho et al. [1] (Songkhla Lake in Thailand and Hongze Lake in China, see Fig. 1) show that the B_{NIR} of the high-turbidity, low-algae pixels (yellowish in true-color images) was higher than that of the algae-present pixels (greenish in true-color images) within the same images. The examination of true-color and the corresponding B_{NIR} images shows that historical L5TM observations have captured sediment plumes in at least 58 (82%) of the 71 studied lakes, and these plumes could be incorrectly labeled as algal blooms due to their high B_{NIR} values (see some examples in Extended Data Fig. 2). As well supported by previous studies using in situ data from both of the studied lakes in Ho et al. [1] and other global coastal/inland waters, the NIR reflectance in turbid waters can be substantially enhanced by sediment-induced strong backscattering signals (see Extended Data Table 1). In inland lakes, episodic meteorological (e.g., wind, precipitation) and hydrological (e.g., riverine discharge) events can strongly influence sediment concentrations [4], as exemplified by previous studies in Lake Erie[5] and Lake Okeechobee in the USA [6] and Hongze Lake in China [7] (three lakes examined in their study). As such, the impacts of water turbidity on B_{NIR} should be evaluated carefully.

Similar to high sediment loads, the growth of aquatic vegetation can lead to the overestimation of bloom severity. Pixels with high B_{NIR} values – in particular, vegetated waters (darkish in true-color images) rather than bloom areas – were also found within the same lakes (see Songkhla Lake in Fig. 1), where massive submerged plants have previously been reported [8]. The reason is that algal blooms and submerged vegetation share similar spectral curvatures and comparable magnitudes of NIR reflectance values, as demonstrated by the in situ hyperspectral measurements for Taihu Lake in China (a shallow lake that is ~200 km from Hongze Lake) (see Extended Data Fig. 3). Moreover, previous studies with datasets collected across various global regions and plant species also showed markedly increased NIR reflectance due to the presence of submerged vegetation (see Extended Data Table 2). Currently, challenges still exist when one attempts to distinguish submerged plants from algal blooms with multispectral satellite images, not to mention using a single NIR band [9]. Indeed, a literature search revealed that of the 71 studied lakes, 41 (58%) were found to contain abundant aquatic plants (see Extended Data Table 3), and their impacts on B_{NIR} should have been considered.

A hue-based mask (Equations 3 & 4 in Ho et al. [1]) was designed to exclude potential contamination from sediments. However, this approach has failed in numerous cases (see examples in Extended Data Fig. 2). This is mainly due to the inclusion of the atmospheric signals in the calculation of hue, i.e., the hue was estimated using the top-of-atmosphere (TOA) reflectance. Thus, this hue reflects the color of the combined signal of the atmosphere and the water, not the hue of the water itself. As shown in Extended Data Fig. 4, atmospheric molecular scattering (or Rayleigh scattering) alone could dominate the TOA reflectance for water bodies in the blue band [10]. Even worse, the method (i.e., Fmask [11]) used to determine lake surface area could lead to substantial underestimations of bloom severity. As the examples in Fig. 1c-e and Extended Data

Fig. 5 show, when true-color images reveal in vivo bloom occurrences, such areas failed to pass the Fmask and were excluded in further B_{NIR} calculations. Indeed, the examination of their studied lakes showed that most of the severe blooms with surface scum were missed due to the improper use of Fmask. This is because intense blooms often cause high normalized difference vegetation index (NDVI) values that can exceed the threshold used by Fmask (e.g., NDVI<0.1) to identify water pixels [11]. Since the Fmask algorithm was originally designed for cloud and cloud-shadow detection [11], further considerations are required when it is used for water area identification.

Furthermore, the infrequent L5TM observations are well known for their limitations in terms of capturing the short- and long-term dynamics of lacustrine algal blooms. Such limitations could be exacerbated by frequent cloud distributions, which also pose one of the challenges associated with optical satellite remote sensing. Statistically, the global mean daily cloud-free probability is 33%, with seasonal differences of <5% [12]. In other words, when L5TM overpasses 23 times within a year because of its 16-day revisit period, the annual mean number of cloud-free observations for a given location is only ~7.5 even without any other unfavorable observational conditions (such as sun-glint). As a compromise between data availability and result fidelity, Ho et al [1] excluded those years with fewer than 3 valid images in five summer months. We replotted a time series of algal bloom areas in Taihu Lake that was produced by Hu et al. [13] (see Extended Data Fig. 6), which was obtained using cloud-free images from daily Moderate-resolution Imaging Spectroradiometer (MODIS) satellite observations (revisit period of ~1 image per day) between 2000 and 2008. Of the >300 cloud-free daily MODIS images within the 9-year period, only 24 shared the same overpassing dates as L5TM. Furthermore, detecting a bloom on the basis of remote sensing imagery depends strongly on wind, as the fraction of the satellite-observable surface bloom in relation to the total phytoplankton biomass is also a function of wind speed [14,15]. Due to the unpredictable nature of cloud occurrence and wind speed, the temporal dynamics of bloom features were difficult to characterize with L5TM datasets.

Our results have clearly demonstrated that the use of L5TM-based B_{NIR} by Ho et al. [1] as a proxy for algal bloom strength is questionable for the majority of the lakes examined in their study. The incorrect use of a water mask algorithm (i.e., Fmask) also leads to the omission of the most severe blooms with floating scum. The use of limited Landsat observations (often one cloud-free image every 1-2 months) is problematic for drawing statistically meaningful conclusions. Therefore, the trends in phytoplankton blooms for the 71 global lakes derived by Ho et al. [1] appear unrealistic. In summary, a significant amount of work, including the development of reliable algorithms for bloom detection and the use of statistically meaningful observations, is still required to estimate the multidecadal changes in bloom conditions before any attempt is made to interpret such “changes.”

Data availability The Landsat data can be obtained from the U.S. Geological Survey at https://glovis.usg.gov. The in situ spectral and Chla data will be provided to the public upon acceptation of this manuscript.

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Competing interests Declared none.

Additional information

Supplementary information accompanies this Comment.

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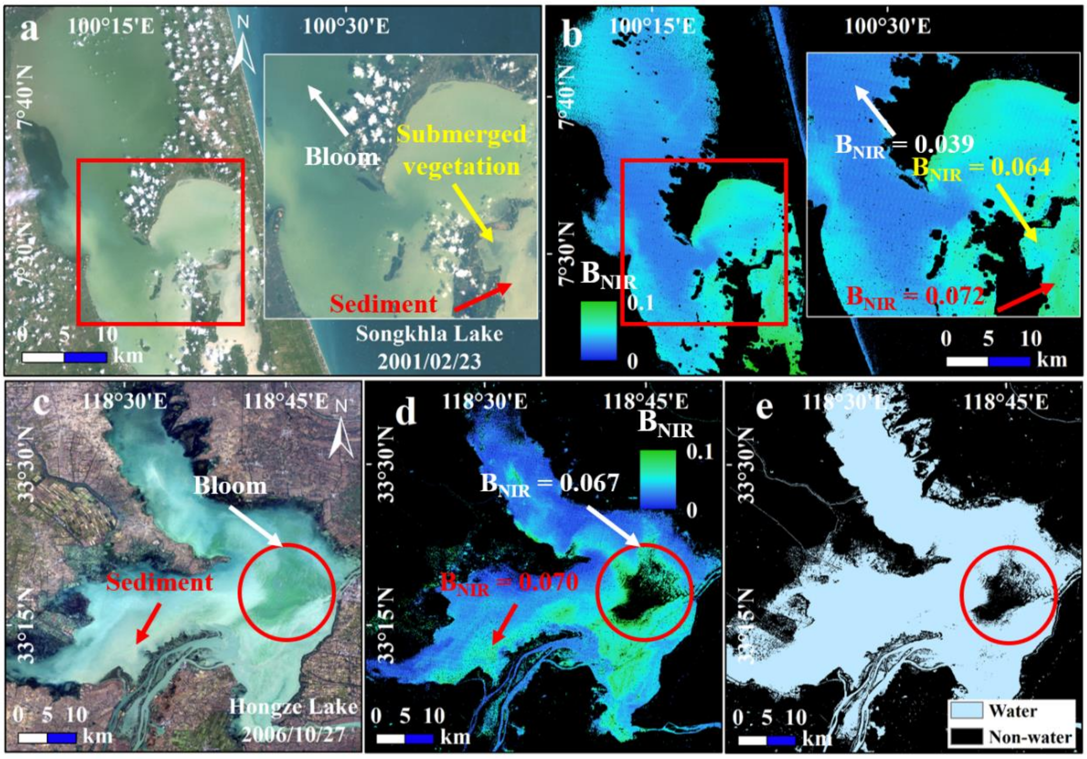

Figure 1 | Examples showing the problems associated with L5TM-based bloom intensity (B_{NIR}, estimated with Equation 2 in Ho et al. [1]) in global lacustrine phytoplankton bloom detection. L5TM true-color composites and corresponding B_{NIR} map for Songkhla Lake in Thailand (**a-b**) and Hongze Lake in China (**c-d**). (**e**) Water mask determined by Fmask[11] for Hongze Lake using the same image in **c**. Areas with either high sediment loads (yellowish in true-color images, indicated by red arrows) or the presence of submerged vegetation (darkish in true-color images, indicated by yellow arrows) exhibit higher B_{NIR} values than the bloom-occurring pixels (greenish in true-color images, indicated by white arrows), leading to erroneous interpretation of algal blooms. An intense bloom in Hongze Lake (within the red circle) has been erroneously classified as non-water by Fmask and excluded in the B_{NIR} map (**d**). More examples of these problems in many other lakes studied in Ho et al [1] are available in the Extended Data Figs. 2&5. The red squares within panels a & b indicate inset location.