Assessments of trophic state in lakes and reservoirs of Wuhan using Sentinel-2 satellite data

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ABSTRACT

With the rapid development of economy, many lakes in Wuhan have been polluted to different degrees and suffer from eutrophication. The main objective of this study was to conduct the monthly trophic state assessments of waters in Wuhan from March 2019 to June 2020 using 111 Sentinel-2 images. The Forel-Ule index (FUI) and empirical Gaussian process regression (GPR) were, respectively, applied to obtain monthly area percentage (AP) of waters with each trophic state. Both FUI-derived and empirical GPR-retrieved results showed that majority of water bodies (>90%) in Wuhan were in mesotrophic and eutrophic states. The GPR-retrieved results based on FUI-derived water types were more reliable than the retrieval without classification, which reduced RMSE of trophic-level index (TLI) from 9.2 to 5.8, and MAPE from 14% to 9% (N = 213). Severe eutrophication occurred in the summer and early autumn (June–October). Stepwise multiple linear regression analysis indicated that temperature and wind speed were the two most important meteorological factors influencing eutrophication variability: the temperature accounted for 63% and 55% dynamic eutrophication from FUI-derived and GPR-retrieved results, respectively; the wind speed explained 44% and 52% variability of FUI-derived and GPR-retrieved results.

KEYWORDS

Sentinel-2; Wuhan; Forel-Ule index (FUI); trophic level index (TLI)

Introduction

Water eutrophication has long been recognized as a threat to the health of aquatic ecosystems worldwide (Carpenter, 2005; Schindler, 2012). As nutrients and organic matter increase, the trophic state of water bodies ranges from oligotrophic to mesotrophic and finally eutrophic. Eutrophication is mainly due to increased nutrient supply, particularly the nitrogen (N) and phosphorus (P) elements (Prepas & Charette, 2003; Schindler, 2012). The trophic assessments of water trophic state is necessary to support planning of conservation and management strategies (Opiyo et al., 2019; Sharma et al., 2010). Remote sensing (RS) provides information on surface water conditions over large geographic area (Olmanson et al., 2008; Palmer et al., 2015; Tyler et al., 2006). Several RS-based studies have assessed water trophic state assessments by biooptical modelling (Feng et al., 2005; Shi et al., 2019). Many researchers monitored water trophic state by using a water quality parameter (WQP) retrieved from satellite data, i.e., through satellite-retrieved chlorophyll-a (Chl-a) (Duan et al., 2007; Matthews & Odermatt, 2015; Thiemann & Kaufmann, 2000), or Secchi disk depth (SDD) (Christiana et al., 2014).

The use of multi-source indicators allows the integration of diverse aspects of trophic state (Sheela et al., 2011); for example, the Carlson’s Trophic State Index (TSI) (Carlson, 1977; Hadjimitis et al., 2010), calculated from the weighted sum of several WQPs, is a commonly used numerical method for assessing the particular variations occurring in the aquatic ecosystems (Aizaki et al., 1981; Opiyo et al., 2019; Sheela et al., 2011; TiBeBe et al., 2019). Closely associated with the absorption and scattering effects of water constituents (e.g., Chl-a and suspended sediments), water colour can be used to describe the comprehensive water quality (Wang et al., 2018; Wernand, Hommersom et al., 2013). The Forel-Ule index (FUI) divides natural waters into 21 colour classes from dark blue to yellowish brown through water reflectance, and therefore can be used to reflect water quality. Since FUI can be objectively retrieved using remote sensing reflectance (Rrs), it has been applied to retrieve the overall water quality through water trophic state assessment (Li et al., 2016; Wang et al., 2018; Wernand, Hommersom et al., 2013) and proved a feasible solution for monitoring water quality (Chen et al., 2019; Giardino et al., 2019; Wang et al., 2018; Wernand, Hommersom et al., 2013).
Since in optically complex inland waters constituents vary in space and time, a single model is not able to describe all water types (Smith et al., 2018; Sun et al., 2014), hence retrieval algorithms have been developed based on the optical water type (OWT) classification (Cui et al., 2020; Du et al., 2018; Huang et al., 2014; McKee et al., 2007; Neil et al., 2019; Sun et al., 2014). The majority of OWT algorithms has focused on WQPs retrieval, but a little attention has been paid to TSI methods despite their performance in depicting water trophic state. In addition, there are few researches on the comparison of FUI-derived trophic state assessments and the empirical model - retrieved TSI.

With a high spatial resolution (10–20–60 m) and a revisit frequency of 5 days, Sentinel-2A and 2B – MSI sensors offer advanced opportunities for lake monitoring (Alba et al., 2019; Bresciani et al., 2018; Pahlevan et al., 2017). This work presents the trophic state assessment of waters in Wuhan using Sentinel-2 multi-spectral instrument (MSI) data from March 2019 to June 2020. The objectives are (1) to identify different trophic states and to evaluate monthly variability of each state; 2) to retrieve the trophic-level index (TLI) for each FUI-derived water type based on empirical Gaussian process regression (GPR); 3) to compare the results of FUI-derived trophic state and GPR-retrieved TLI; 4) to assess the trophic state of waters in Wuhan and analyze spatio-temporal variations.

**Study area**

Wuhan, the capital city of Hubei Province, is the most populated city in China (Asghar et al., 2018). It is located at the confluence of the Yangtze River and its tributary, the Han River (Figure 1). There are 166 lakes in Wuhan City, of which 40 are distributed in the urban areas (W. Wang et al., 2017). The total water area in Wuhan is 2217.6 km², accounting for one-fourth of the total city. Population density, industries, and agriculture are the major pressure factors negatively affecting trophic state of Yangtze River and lakes in the southernmost regions of the basin.

![Figure 1](image_url). The location of Wuhan, China, and sampling sites of seven cruises. Detailed information of available data for each cruise is listed in Table 1.
Materials and methods

Sample collection, and meteorological dataset

In *situ* data were collected in Wuhan from 2017 to 2020 during seven field campaigns. The SDD and Chl-a concentration were captured in the field measurement, with a Secchi Disk and YSI EXO-2, respectively. At the same time, we took all water samples ($N = 437$, Table 1) to laboratory analysis for concentration of total phosphorus (TP), total nitrogen (TN) and chemical oxygen demand (COD). The number of samples varied with the date due to weather conditions. Finally, TN was determined by Alkaline potassium persulfate digestion UV spectrophotometric method; TP was determined using Ammonium molybdate spectrophotometric method; and COD was measured by dichromate method.

Meteorological data, including wind speed, air temperature, precipitation, and length of daylight, were downloaded from the China Meteorological Data Network, http://data.cma.cn/site/index.html. The corresponding 12 factors and information are shown in Table 2.

| Categories | Sample time | $N$ | $S2$ image acquisition |
|------------|-------------|-----|------------------------|
| Part I     | 8:20 – 11:30, Nov. 1–7 November 2017 | 105 | 10:58, Nov. 1, 2017 (S2A) |
|            | 8:40 – 15:30, Mar. 5–9 March 2018   | 57  | 11:05, 9 March 2018 (S2B) |
|            | 8:20 – 11:30, Jul. 8–13 July 2018   | 62  | 10:55, 14 July 2018 (S2B) |
|            | 8:20 – 15:30, May 5–15 May 2019    | 117 | 10:55, 10 May 2019 (S2B) |
| Part II    | 8:20 – 11:30, Jun. 3–10 June 2019   | 32  | 10:55, 4 June 2019 (S2A) |
|            | 8:20 – 11:30, Aug. 5–7 August 2019  | 37  | 10:55, 8 August 2019 (S2B) |
|            | 8:40 – 15:30, Mar. 6–8 March 2020   | 27  | 10:56, 5 March 2020 (S2B) |

Table 1. Dates, time (UTC+8), and available in *situ* data ($N$) for roughly concurrent with Sentinel-2 (S2) image acquisition on 7 days in 2017, 2018, and 2019.

Satellite images and pre-processing

A total of 111 Sentinel-2 L1C-MSI images (cloud area≤30) of Wuhan were downloaded from Copernicus Open Access Hub (https://scihub.copernicus.eu), including 2 images on 1 November 2017, 9 March 2018, and 14 July 2018, and 105 images from March 2019 to June 2020. Image pre-processing of Sentinel-2 L1C images involved four steps in the Sentinel Application Platform (SNAP,0) and ArcGIS10.2. First, Sentinel-2 bands were resampled to 60 m resolution. Second, the multi-sensor pixel identification tool (IdelPix) was used to extract water pixels through the “clearwater” mask (Soomets et al., 2019). Third, the Case-2 Regional Coast Colour (C2RCC) processor (the C2RCC MSI processor in SNAP, version 1.0) was applied to retrieve the water-leaving reflectance of Sentinel-2 (Anser & Alikas, 2018; Pereire-Sandoval et al., 2019). The salinity was set to 0.001 PSU for inland water and the temperature modified following the historical weather in Wuhan (http://www.tianqihou.com/lishi/wuhan.html). Finally, mosaicking of four or five images for each date was performed using Python IDLE in ArcGIS10.2.

Forel-Ule index for trophic state assessments

The relationship between FUI and TLI

Figure 2 shows the theoretical relationship between the calculated FUI and TSI initially derived from the Hydrolight simulated dataset (Chen et al., 2019; IOCCG, 2006; Wang et al., 2018). The simulated dataset covers a wide range of natural waters with

![Figure 2](image-url)

Figure 2. Relationships between FUI and Chl-a-based TSI from the Hydrolight simulated dataset (IOCCG, 2006). The figure was from interpretation of corresponding literatures (Chen et al., 2019; Wang et al., 2018).
Chl-a concentrations ($C_{Chl-a}$) from 0.03 to 30.0 $\mu$g/L, which represents various water with different trophic states. Values for TSI ranged from 0 to 68, and FUI generally increased with TSI based on the simulated dataset ($R^2 = 0.93, N = 500$. Figure 2), indicating that FUI is reliable for Chl-a-based trophic state assessment.

**FUI derivation from Sentinel-2 MSI**

Chromaticity was first described by the International Commission on Illumination (CIE) in 1931 (CIE, 1986), and is considered to be the comprehensive effect of the $X$, $Y$, and $Z$ tristimulus values as perceived by human colour vision (Fairman et al., 1997; Van der Woerd & Wernand, 2018). The chromaticity coordinates $x$, $y$, and $z$ are normalized tristimulus values from Eq. (1):

$$x = X/(X + Y + Z)$$

$$y = Y/(X + Y + Z)$$

$$z = Z/(X + Y + Z)$$

where $x + y + z = 1$.

We applied the algorithms for Sentinel-2 MSI (60 m) developed by Van der Woerd and Wernand (2018) to calculate the hue angle ($\alpha$). In the ($x$, $y$) chromaticity plane, the coordinates were transformed to polar coordinates with respect to the white point ($x_w = y_w = 1/3$). Therefore, the new coordinates were $(x - x_w, y - y_w)$, i.e., $(y', x')$ in Figure 3. Then $\alpha$ between the vector to a point with coordinates $(y', x')$ and the positive $x'$-axis (at $y - y_w = 0$) was calculated using the Eq. (2),

$$\alpha = \arctan2(y - 0.333, x - 0.333) \times \frac{180}{\pi}.$$  (2)

According to Van der Woerd and Wernand (2018), the offset $\Delta(\alpha)$ caused by Sentinel-2 MSI for $\alpha$ can be approximately calculated using a specific one-element fifth-order equation,

$$\Delta(\alpha) = -65.74\theta^5 + 477.16\theta^4 - 1279.99\theta^3$$

$$+ 1524.96\theta^2 - 751.59\theta + 116.56,$$  (3)

where $\theta = \alpha/100$.

The $\arctan2$ is a four-quadrant inverse tangent function that allows $\alpha$ to range from $-180^\circ$ to $180^\circ$, i.e., from the negative $x'$-axis, rotating clockwise back to the negative $x'$-axis. We transformed the angle $\alpha$ after offset correction to remain positive from $0^\circ$ to $360^\circ$ by starting from the negative $x'$-axis (Wang et al., 2018). Finally, the FUI was determined using the 21-class FUI lookup table in Figure 3.

**Trophic level index for trophic state assessments**

**The criterion of TLI classification for each trophic state**

Due to various geographic sites, environments and human activities, there is no worldwide standard for estimating trophic status (Duan et al., 2007; Opiyo et al., 2019). TSI is the abbreviation of "trophic state assessment."
index”, while TLI is the abbreviation of “trophic level index”. Both TSI and TLI describe the water trophic status through Chl-a-based index in this paper, ranging from 0 to 100. Therefore, the TSI for this study was calculated by the TLI method, which was presented in the Method for Surface Water Quality and Environment Evaluation (Trial), issued by Ministry of Ecology and Environment of the People’s Republic of China in 2011 (MEE, 2011). According to the standard, trophic statuses were categorized as follows: TLI (Σ) < 30, oligotrophic; 30≤TLI(Σ)<50, mesotrophic; TLI(Σ)≥50, eutrophic; 50< TLI(Σ)≤60, light eutrophic; 60< TLI(Σ)≤70, mid-eutrophic; TLI(Σ) > 70, hypereutrophic. With Chl-a as the reference parameter, TLI was defined by a weighted sum of five WQPs (Chl-a, TP, TN, COD, and SDD):

\[
TLI(\Xi) = \sum_{i=1}^{n} W_i \times TLI(i) \quad (4)
\]

\[
W_i = R_i^2 / \sum_{i=1}^{n} R_i^2 \quad (5)
\]

where TLI(Σ) is a comprehensive index; TLI(i) represents the ith WQP-based trophic state assessment with weight of Wj; Rj is the correlation coefficient between Chl-a concentration and ith WQP; n is the total number of indicators. Rj values shown in Table 3 were from the survey results of major lakes in China (Jin et al., 1995).

The formulas for calculating indices for each WQP were as follows:

\[
\begin{align*}
TLI(\text{Chl-a}) & = 10(2.5 + 1.086 \ln \text{Chl-a}), \\
TLI(\text{TP}) & = 10(9.436 + 1.624 \ln \text{TP}), \\
TLI(\text{TN}) & = 10(5.453 + 1.694 \ln \text{TN}), \\
TLI(\text{SD}) & = 10(5.118 - 1.94 \ln \text{SDD}), \\
TLI(\text{COD}) & = 10(0.109 + 2.661 \ln \text{COD})
\end{align*}
\]

(6)

According to Eq. (5), we obtained the TLI(Σ):

\[
\begin{align*}
TLI(\Sigma) & = 0.2663 TLI(\text{Chl-a}) + 0.1879 TLI(\text{TP}) + 0.179 TLI(\text{TN}) + 0.1834 TLI(\text{SD}) + 0.1834 TLI(\text{COD})
\end{align*}
\]

(7)

**Gaussian processes regression for TLI retrieval**

Several experiments based on GPR method were conducted on simulated as well as real datasets referring to C_{\text{Chl-a}} of waters (Bazi et al., 2012; Pasolli et al., 2010; Verrelst et al., 2013). The results showed that GPR is very promising in terms of both estimation accuracy and free parameter tuning. Besides, the primary motivation behind selecting GPR in our study was that it allows for completely automatic model selection within a Bayesian framework, offering the potential advantage of avoiding the free parameters in traditional empirical and tricky tuning (Pasolli et al., 2010; Verrelst et al., 2013). The theory has been introduced in the prior literature (Rasmussen, 2004; Rasmussen & Williams, 2006; Williams & Rasmussen, 1996), and the detailed algorithm is shown in supplementary materials.

Doxaran et al. (2010) proposed that using the reflectance ratio can reduce the effects of changes in illumination conditions and sediment type. In this study, ratios between VIS-NIR bands (b1-b8a MSI bands) were selected as the input parameters for GPR. Correlation analysis between 224 TLI data calculated from five in situ WQPs (PartIdata, Table 1) and each band ratio was conducted, leaving seven band ratios with R ≥ 0.30 (significant at 0.01 level), i.e., b2/b4, b2/b5, b2/b6, b3/b4, b3/b5, b4/b5, and b6/b8a. Then GPR models were trained with 224 in situ data and related Rrs(ratio). The hyperparameters of model were typically adjusted to minimize the error in an independent validation dataset. Thus, we could look for the best generalization capabilities, instead of only good performance in the training set which would give rise to an overfitted solution.

**Evaluation criteria for estimation**

Two criteria were applied to evaluate TLI retrieval, root-mean-square error (RMSE) and mean absolute percentage error (MAPE):

\[
\text{RMSE} = \sqrt{\frac{1}{n} \sum_{j=1}^{n} (Y_{\text{est}(j)} - X_{\text{obs}(j)})^2} \quad (8)
\]

\[
\text{MAPE} = \frac{1}{n} \left( \sum_{j=1}^{n} \frac{|Y_{\text{est}(j)} - X_{\text{obs}(j)}|}{X_{\text{obs}(j)}} \right) \times 100 \quad (9)
\]

where Y_{\text{est}(j)} and X_{\text{obs}(j)} are the jth estimated and observed values, respectively; n is the total number of data points.

**Results**

**Monthly trophic state assessments using the FUI index**

Monthly trophic states of waters in Wuhan were estimated based on FUI index from 105 Sentinel-2 images. FUI ranges were able to determine three water trophic states: (1) oligotrophic waters with 1≤FUI≤6; (2)
Figure 4. Sentinel-2 FUI-derived water trophic states vs. in situ trophic level index (TLI) in Wuhan.

Trophic state retrieval for each FUI-derived water type using GPR

Trophic level index retrieved using empirical GPR

Figure 7 shows model fitting and validation results of trophic state retrieval by GPR empirical models with classification (bottom panels) and without water classification (top panels). Before retrieval, we classified the water into three types according to the trophic states derived by FUI: type 1, oligotrophic waters with 1≤FUI≤6; type 2, mesotrophic waters with 7≤FUI≤9; and type 3, eutrophic waters with FUI≥10. Of the 224 in situ data, 6 data with TLI<30 for type 1 water was insufficient for model training in terms of data-driven methods. We developed model 1 for both type 1 and type 2 water, trained using a sum of 55 data. Model 2 was developed using 169 data points for type 3 water. With RMSE of 4.8 and 5.8, respectively, in training and validation, plots from the two models in Figure 7(b) were closer to a 1:1 line than the results from the single model in Figure 7(a). The estimations based on FUI-derived water classification fit better, the retrieval results were more reliable.

Monthly TLI spatial distribution based on empirical GPR for each FUI-derived water type are presented in Figure 8. Monthly TLI values in Wuhan ranged from 20 to 85 over time with most of waters between 42 and 60 (blue to yellow colour), confirming that waters in Wuhan were primarily mesotrophic and light eutrophic from March 2019 to June 2020. Reservoirs in the north were in oligotrophic and mesotrophic. With color between light green to yellow, lakes in urban area were mainly in eutrophic status, with TLI seasonal changes.

TLI values were categorized into five classes for trophic state assessment based on the criteria in section 3.4.1. Results indicated that more than 70% water were in mesotrophic (30≤TLI<50) and light eutrophic status (50<TLI<60). Eutrophic waters firstly increased from the spring (March to May) to early autumn (October), and then decreased during the winter (December to February) and the early spring (March). Maximum peak of eutrophic conditions was in October 2019 (75.32% of waters with TLI>50), while March 2019 showed the best water quality. There was a strong negative correlation between the AP of mesotrophic water (30≤TLI<50) and that of eutrophic water (TLI≥50) (R = −0.97, Figure 9), which was consistent with the FUI-derived results (R = −0.98, Figure 6).

Correlation analysis between different trophic states in Wuhan

Monthly GPR-derived water state classes were further divided into subcategories to highlight subtle changes in water quality over a year between adjacent categories; relationship between AP of different
subcategories was quantified using the Pearson’s R in Figure 10. Except for the negative correlation between AP of mesotrophic and eutrophic waters, significant relationships were observed for: (1) negative correlations (R = −0.69, R = −0.70, and R = −0.75) between the AP of light eutrophic water and mesotrophic water (30≤TLI<50, 40 ≤TLI<50, and 45≤TLI<50), implying variability of mesotrophic water and eutrophic water mainly between the mesotrophic water and light eutrophic water; (2) negative correlations between subcategories of waters within same trophic state, e.g., mesotrophic waters with 40≤TLI<45 and 45≤TLI<50 (R = −0.55), light eutrophic waters with 50≤TLI<55 and 55≤TLI<60 (R = −0.70); (3) positive correlations between the AP of a subcategory and the category it belongs to, e.g., waters with 40≤TLI<50 and

Figure 5. Spatial distribution of FUI-derived water trophic states from March 2019 to June 2020 in Wuhan using Sentinel-2 data, no cloud free images for trophic state assessment in May 2020.
mesotrophic water ($R = 0.87$), light eutrophic waters ($50 \leq TLI < 60$) and total eutrophic waters ($R = 0.75$).

No significant relationships were observed between oligotrophic waters with $TLI < 30$, eutrophic waters with $TLI > 70$ and water in other trophic states. Probably oligotrophic water belongs to reservoirs, where strict regulations, low population density and presence of natural forested areas decreased pressure on the water systems thus making this region in a relatively steady status. Moreover, most mid-eutrophic ($60 < TLI \leq 70$) and hypereutrophic waters ($TLI > 70$) were distributed around the lakeside (Figure 8), affected by human activities but with lower exchange of clear water, so it was too difficult to transform into other trophic states. Therefore, waters in oligotrophic and mid-hypereutrophic can be considered stable during a year. Correspondingly, there were no direct correlation with other subcategories.

**Meteorological factors and eutrophication dynamic in Wuhan**

Monthly meteorological parameters (wind speed, temperature, precipitation, and sunshine) from March 2019 to June 2020 are shown in Figure 11. Stepwise multiple linear regressions (SMLR) analyses between the AP of eutrophic water and each parameter showed that temperature was the most important driving factor for eutrophic water variability. Temperature explained 63% and 55% eutrophication variability from FUI and TLI assessments, respectively (Figure 11(e), 11(f)). There were significant relationships between all temperature factors and water eutrophication (Table 4), which is consistent with previous studies. Chen et al. (2019) concluded that temperature is an important factor for FUI variability in Donghu, Chaohu and Dianchi lakes, China; Kosten et al. (2012) found climate warming may increase nutrient concentrations based on a study of 143 lakes. Béjaoui et al. (2016) found temperature was significantly correlated with Chl-a variability ($R^2 = 0.47$) through a combined multi-metric trophic index and random forest model in Bizerte Lagoon. Wuhan features a subtropical monsoon climate, with temperature in summer and early autumn higher than in other time (Figure 11(b)). The dynamic temperature can explain the variability of eutrophic water through its influence on nutrient concentrations and algal growth. As temperature rises, eutrophication area increases, leaving the severe eutrophication in summer and early autumn.

Wind speed is another factor for dynamic eutrophic waters, which explained the 44% of FUI variability and the 52% of TLI variability (Figure 11(e), 11(f)). Algae tend to rise to the surface under slower wind speeds (Wu et al., 2013); smaller wind speeds are favorable for CyanoHABs growth (Zhang et al., 2016). Large wind-
generated waves can stir the surface, cause surface algae to sink, and prevent frequent occurrence of phytoplankton. Figure 11 shows that EWS, A2WP, and MWS were higher from November to March, which might contribute to restraining eutrophication from late autumn to early spring.

According to Figure 11, precipitation might be the third factor for water eutrophication. Previous research (Sinha et al., 2017) showed that changes in precipitation patterns induced by global climate change is likely to exacerbate eutrophication in India, China, and Southeast Asia through substantially nutrient enrichment. As presented in Figure 11(d), when MaxDP and 20–20_HP were in low values from July 2019 to October 2019, eutrophication was serious in Wuhan, which seems consistent with the research. However, studies conducted in different scales may result in inconsistent conclusion. Rueda et al. (2007) showed that heavy rainfall accounts for 80% and 400% in the sources of N and P into waters each year, respectively. Therefore, further research is necessary for the effect of precipitation on water eutrophication in Wuhan.

**Discussion**

Both results were consistent in spatial distribution and temporal variation from March 2019 to June 2020. FUI-based method makes it possible to assess trophic state of water in a large area based on Rs (Li et al., 2016; Wang et al., 2015), while GPR-retrieved TLI can reveal the minor changes, especially for eutrophic waters, and thus can contribute to timely protection. GPR-retrieval based on FUI-derived water classification improved estimation accuracy, suggesting that it is feasible to combine the two methods to achieve better trophic state monitoring. AP values of oligotrophic water (7<FUI<9) from FUI-derived results were higher and overall, water quality retrieved by GPR was worse than the corresponding FUI-derived results; these differences may be caused by the following uncertainties. First, further research is required in the selection of AC method for Sentinel-2. Since FUI is a result of hue angle directly from Rs, AC is therefore vital for reliable trophic status assessment of FUI. The error between in situ data and the water-leaving reflectance of Sentinel-2 in Wuhan is not clear, and whether the error between in situ data and the water-leaving reflectance of Sentinel-2 will affect trophic status assessment is still object of discussion. Second, the theoretical
The relationship between FUI and TSI was initially derived from the Hydrolight simulated dataset in relatively clear Chl-a dominated waters, with $C_{\text{Chl-a}}$ from 0.03 to 30.0 $\mu$g/L. However, we found the $C_{\text{Chl-a}}$ values of several lakes in Wuhan were far beyond the range especially in Summer, so that further validation is necessary before applying FUI to the lakes with high $C_{\text{Chl-a}}$. Third, another issue is that the time difference between the image acquisition date and in situ measurements. WQPs, such as turbidity and Chl-a, may change in hours. Both FUI and TLI are partially related to Chl-a, as indicated by the simulated relationship between FUI and Chl-a-based TSI (Figure 2) and the TLI developed with Chl-a as the reference parameter. Therefore, whether the training data is sufficient and accurate for trophic state monitoring also needs further analysis. In addition, as one of data-driven methods, GPRs strongly depend on in situ training data, and thus more sampling campaigns must be done to reduce uncertainties in the prediction model, especially for model training. Besides, we resampled all bands to 60m to make it more efficiently in pre-processing and make it available to apply more bands to MSI-derived FUI
algorithm. With resolutions of 10m or 20m for the S2 bands (b2 - b8a), whether the 60m resolution will increase the adjacency effect of water-land remains to be studied.

Lake eutrophication is influenced by anthropogenic and natural factors (Hall et al., 1999; Liu et al., 2010). The changes of sewage and pollutant in lake basins were fundamental reasons for the water eutrophication in Wuhan. Spatial distributions of each trophic state in Figures 5 and 8 revealed the intensity of human activity. With the influence of dense population and industry in urban area, pollutant accumulation in lakes severely caused the endogenous eutrophication in urban waters. On the other hand, natural factors mainly include geographic location, topography, lake morphology, climate conditions (Noges, 2009; Tibby & Tiller, 2007). Lakes in Wuhan can be approximated as having the same location and topography, yet lake morphology is various for more than 100 lakes in Wuhan. Only available meteorological data considered in our analyses are probably not sufficient for the analysis of driving factors leading to eutrophication. Both anthropogenic and natural

![Figure 9](image1.png) Statistics of area percentage for water with five trophic states using spatial analyst tools of ArcGIS 10.2.

![Figure 10](image2.png) Correlation analysis between each adjacent subcategory, described by Pearson's R (**, significant at the 0.01 level; *, significant at the 0.05 level).
factors should be considered and this will be the further research to propose suggestions for eutrophication prevention, as well as the measures of restoration for the environmental protection department.

**Conclusion**

Sentinel-2-derived trophic state assessments for waters in Wuhan were conducted using FUI-derived and empirical GPR-retrieved methods. Results from the two assessment methods indicated that majority waters in Wuhan were in mesotrophic and eutrophic state. Strong negative correlations (for FUI-derived results, \( R = -0.98 \); for GPR-retrieved results, \( R = -0.97 \)) appeared between the monthly AP values for mesotrophic and eutrophic water. The GPR retrieval based on the FUI-derived water classification was more reliable than the results without water classification, which reduced RMSE of TLI from 9.2 to 5.8, and MAPE from 14% to 9% \((N = 213)\). Non-eutrophic waters reduced from March to October, and severe eutrophication (64% to 70% eutrophic water) occurred in summer (June - August). If we only considered meteorological factors, SMLR analysis indicated that the temperature and wind speed were the two most important factors explaining spatio-temporal variability of water eutrophication. Temperature explained 63% and 55% changes of eutrophication from FUI and TLI, respectively; wind speed explained the 44% and the 52% variability of FUI and TLI, respectively.

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**Disclosure statement**

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