Dear Editor,

Thank you for your letter and the reviewer comments concerning our manuscript entitled ‘Remote Quantification of the Trophic Status of Chinese Lakes’ (*hess-2022-91*).

We have studied comments carefully and have made correction which we hope meet with approval. Revised portion are marked in blue in the revised manuscript. The main corrections and the responses to the reviewer comments are described below.

Thanks again for your time and help.

Yours sincerely

Sijia Li and Zhidan Wen on behalf of the authors.

Responses to Yumei Li' Comments

Dear Yumei Li,

We would like to express our sincere appreciation for your careful reading and helpful comments. These comments are all valuable and helpful for revising and improving our paper, as well as the important guiding significance to our researches. We have studied comments carefully and addressed the points noted below.

Revised portion are marked in blue in the paper. The main corrections in the paper and the responds to the reviewer's comments and remarks are as flowing.

" Yumei Li: Peer review

The TSI is a universal paradigm for eutrophic research in scientific literature. It is very important to study how to quickly quantify tropical state index estimation in inland water, instead of traditional methods by deriving chlorophyll-a or clarity. The manuscript entitled "Remote Quantification of the Trophic Status of Chinese Lake" proposed an applicable machine learning algorithm which integrates a broad scale dataset of lake biogeochemical characteristics using Sentinel-2 Multispectral Imager (MSI) imagery. Authors applied the best one to first map 10-m TSI in 555 lakes across five limnetic regions in China, and comparison was conducted with previous investigation in lakes across China.

Overall, this paper is well organized and the logic is relatively clear. Many of the acquired datasets are also valuable. However, sufficient explanation is required for the following points.

- The Case 2 Regional Coast Color processor (C2RCC) was used to remove atmospheric effects. And In Figure 2, normalized water leaving reflectance of samples are acquired. How is the normalization done? This measurement is really odd. Then C2RCC-nets were used instead of C2RCC, and it is need to explain. There are some good atmospheric correction methods designing for MSI sensor, such as the Sen2Cor. Why you choose C2RCC for correcting atmospheric correction?

Response: Thanks for your patient review. The atmospheric correction (AC) process is to compensate the water-leaving reflectance signals and remove the contribution of atmospheric effect. The results can be found in our published paper Li et al., (2021, *science of the total environment*). The machine-learning C2RCC processor is built upon previous AC database of radiative transfer simulations and related TOA, relying on a per-pixel artificial neural network. It has two models with different application circumstances for open oceanic (nets) and inland waters (C2X). However, our published study on the comparison of different AC processors for lakes demonstrated that C2RCC can work better than Sen2Cor, iCOR, Polymer and Acolite. These in situ data were collected in four European lakes-Swedish Erken, Italian Garda, Estonian Saadjärv and Võrtsjärv, and Chinese typical lakes (2021, *science of the total environment*). The results showed that C2RCC-nets achieved quite good agreement with high R^2 and slope closed to unity for Band 1-6 of MSI.

In addition, in order to evaluate the performance of ACs for inland turbid lake, we we collected lake samples of Chagan Lake (CG1) in spring (May 26th), august (July 18th and August 18th) and autumn (September 17th) in 2021. Chagan Lake has high variability in terms of suspended matter, algal abundance and trophic status. All measurements in these lakes were synchronized with satellite overpasses; we aim at to test against in situ R_{rs} to find the best performing AC processors, based on the errors and R^2. Considering all bands, C2RCC-C2X and SeaDas processors performed better than those of other ACs, with C2RCC-nets had relatively low errors. Hence, considering the principles (Artificial neural networks, Hydrolight and NOMAD data) and performances in productive Chagan Lake, C2RCC was used to generate the TSI maps in this study. We hope that these revisions and the improved text will be satisfactory.

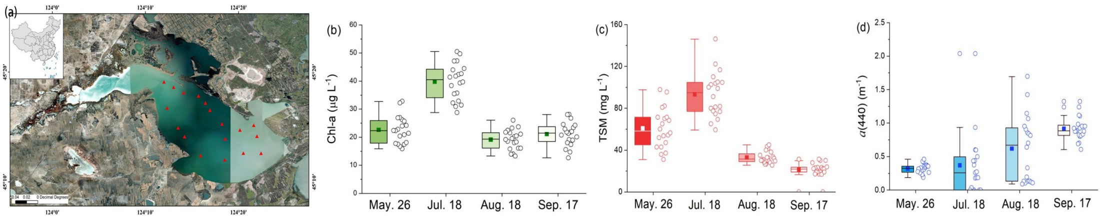


Figure the sample distirbutions of Chagan Lake (a) in 2021 with continuous Chl-a (b), TSM (c) and CDOM (d) records.

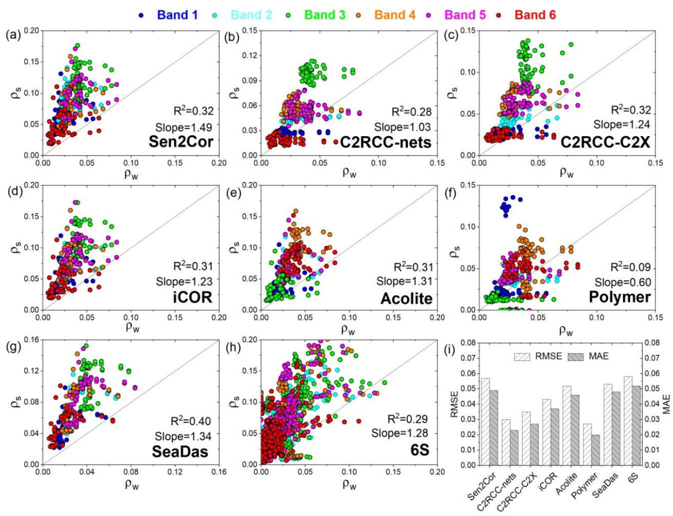


Figure Comparison of in situ measured reflectance spectra versus MSI reflectance spectra (Band1 to Band 6) of different ACs (a, Sen2Cor; b, C2RCC-nets; c, C2RCC-C2X; d, iCOR; e, Acolite; f, Polymer; g, SeaDAS and h, 6S) and their errors (i) in Chagan Lake.

- Several machine learning algorithms were used in the process of calibrating the TSI model. Why were these algorithms tested? Is there any reason? Is linear regression a machine learning approach?

Response: Thanks for your valuable comments. The reason is that RF, SVM and XGBoost are three typical machine learning algorithms. RF is a simple and intuitive machine learning algorithm. The implementation of SVM is based on space conversion. Techniques and workarounds such as the kernel trick is used to solve the inseparability problem by introducing variables in SVM into a higher space and predict. XGBoost is an improved algorithm from gradient-enhanced decision tree (GBDT). It could train a set of weak decision tree model, and make each model to predict incorrect variables of previous model. In addition, the three machine learning algorithms are most widely used in remote sensing and environment field (Mountrakis et al., 2011; Toming et al., 2020; Cao et al., 2020).

Supervised machine learning is the construction of algorithms that are able to produce general patterns and hypotheses by using externally supplied instances to predict the fate of future instances. In short, supervised machine learning uses samples data to learn a model, and predict by test samples data.A hypothetical model is selected for the input sample space x_i, and the truth value y_i is continuously fitted with certain learning criteria, and finally get the training model. For linear regression, the input space is x_i, the model expression is $y=w_0+w_1\times x_1+w_2\times x_2+\ldots+w_p\times x_p$ and the hypothesis space is w_i. Hence, LR is a kind of machine learning algorithms. We hope that these revisions and the improved text will be satisfactory.

- The water qualities optical absorption contribution and a k-mean clustering were used in this paper. How can these methods help with the search or the improvement of TSI algorithm? What are the advantages lies in? Please add more explanations.

Response: Thanks for your instructive comments and suggestions. The dataset used to develop the XGBoost covered a wide range of water qualities, optical absorption contribution and reflectance spectra. However, for signal lake, if the XGBoost could show excellent performance is required to evaluate. Hence, the *in situ* measured samples were classified in three ways, and XGBoost *TSI* algorithm was evaluated. If there is some preliminary data available from the study area one can improve the performance of the machine learning in calibration processes in future.

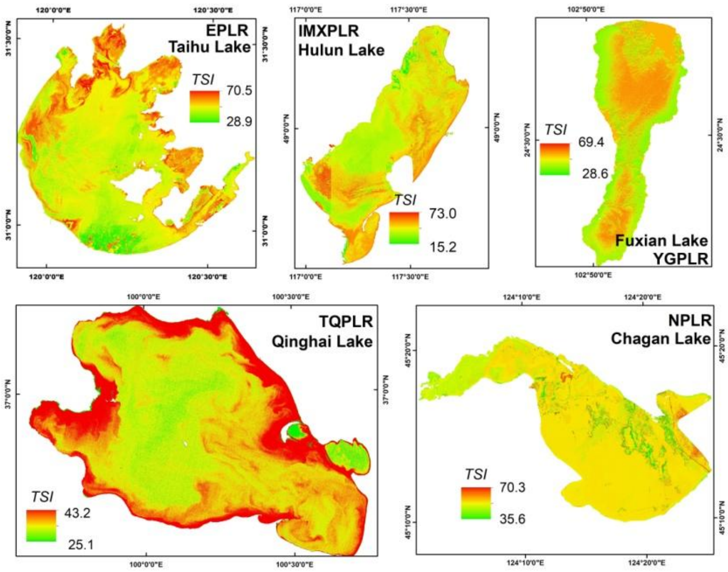
We are sorry to show the unclear explanation. For example, the XGBoost performed well in high DOC/EC lake scenario, high phytoplankton dominated NAP-type lakes scenario and cluster-1 lakes with low TSM scenario, respectively. Overall, in future work, for lakes mainly located in high elevation and arid region with high DOC/EC levels, the more input variables responding to CDOM (Green/Red) could be added in XGBoost TSI model. More classifications based on reflectance spectra (Spyrakos et al., 2018) and water color index (Wang et al., 2018) should be first used and then developed corresponding models for high turbid lakes. According to your suggestion, these explanations are added in revised manuscript (Section 4.2). We hope that these revisions and the improved text will be satisfactory.

-The time window of match-up dataset was chosen as 7 day. This time window might be too wide considering the dynamic change of water qualities. Further, it may not show the advantage of relatively high temporal resolution of MSI. And the credibility and accuracy could be undermined by the wide time window.

Response: Thank you for your comments. We agreed with your comment, the time-differences between in situ data collection and satellite image acquisition could affect results because the water properties may change, for example due to heavy rain or emerging algal bloom that change water properties in hours rather than days. The MSI revisit time in many parts of the world is 2-3 days. For higher latitudes countries (Sweden, Finland and Estonia), the revisit time of MSI is almost every second day due to the overlapping orbits (Toming et al., 2016). In mid latitudes countries (Italy), there is also revisit time 2-3 days (Pereira-Sandoval et al., 2019). However, China stretches over 135°-73°E and 53°-3° N, by way of example in DaGuangBa (Table 1, 18°58'N,109°00'E), there are only 75 scenes level 1C products per year due to less orbits, in comparison to 175 scenes per year in Võrtsjärv (Estonia, 26°1'E, 58°15'N). One MSI has 10 days revisit time at the equator. There are two Sentinel-2's in space and the orbits overlap closer to the poles. We can expect that the results obtained there did not suffer from the time difference between in situ sampling and satellite overpasses. However, frequent cloud cover in some areas often prevents getting suitable imagers for several weeks in a row. Toming et al., (2016) and Cardille et al., (2013) found that in some cases even longer (weeks to month scale) time differences may still be acceptable. Secondly, many lakes, like Nam Co in Tibet (>4000 m), are hard to reach and the Sentinel-2 overpasses there are not as frequent as in many other places. Previous studies (Olmanson et al., 2008; Song et al., 2020) demonstrated that ±7 days time window that has been shown to be adequate for derivation of SDD using satellite imagery. We hope that these revisions and the improved text will be satisfactory.

-Quantitatively, this article referred an effective way to monitor the lake eutrophication on a macro-scale. The machine learning seems to be more excellent than traditional empirical models. However, it may be not a discontinuous mapping within a lake in supplementary material.

Response: The authors really thank for your instructive comments. We think that a discontinuous mapping within the same lake may related to the influence of cloud. In our revised manuscript, we corrected these images in supplementary material. We hope that these revisions and the improved text will be satisfactory.



Special comment

-Line 43 knowledge of the process of eutrophication can provide us with an understanding of the …... is confused, please clarify it.

Response: Thank you for your patient review. This sentence was corrected as '*Hence, knowledge of eutrophication process can provide us with an understanding of the structure and function of lake ecosystems that give rise to environmental changes*'. (Line 42-44). We hope that these revisions and the improved text will be satisfactory.

-Line 158 some lakes were sampled in the middle can be described again.

Response: Thanks for your comment. The surface areas of some lakes are so small such as TPC (1) and Xingxingshao (2), with surface area is 25.86 km^2 and 8.96 km^2 respectively. This indicated that there were no significant spatial patterns of water qualities in small-size waters. In fieldwork, small-size waters were sampled in the middle. Conversely, Qinghai Lake, seen as the largest saline lake in China, was revisited many times, and more water samples (N=32) were collected at multiple locations evenly distributed over the lake. We revised this sentence (Line 157-160) according to your suggestion. We hope that these revisions and the improved text will be satisfactory.

-Line 204-205 total phosphorus did not show optical properties, but it still appeared in the modified TSI calculation. Is it possible to explain again？

Response: Thank you for your patient review. Carlson, (1997) reported that improved TSI was calculated by Chl-a, SDD and TP. Nutrients as one of the main driving factors to phytoplankton growing and photosynthesis. However, for water color remote sensing, Chl-a (algal absorption at blue and red wavelength) was one of optical active substances (non-algal particle and CDOM), when pure water is a constant. Although the nutrients and SDD had no optical response, they still indirectly have impact on lake eutrophication. We hope that these revisions and the improved text will be satisfactory.

-Line 218 I am not sure that the selection of images with time window ±7 days can affect the reflectance and results because of quick changes of water qualities, such as a storm event.

Response: Thank you for your patient review. Our response to the selection of images with time window ±7 days can be found in above comments. We hope that these revisions and the improved text will be satisfactory.

-Line 234 why the four algorithms used in this study are the representative machine learning algorithms?

Response: Thanks for your comment. Our response to four algorithms used in this study can be found in above comments. We hope that these revisions and the improved text will be satisfactory.

-Line 283 this section needs to be improved and one or two sentences are included

Response: According to your suggestion, we improved this section (Line284-286). We hope that these revisions and the improved text will be satisfactory.

-Line 447-451 need to be improved. It seems the blue band is useless in some high turbid or productive waters, but it is included in this study owing to some samples from Tibet.

Response: Authors really thank you for your suggestion. Our dataset were both collected from turbid lakes and clear Tibet lakes. Although blue band is useless in lakes with abundant non-algal and suspended matter, the performance of our model used blue band as input variables. This is because the TSI is a comprehensive index, of which the SDD and TP are not the optical active substances. Then the our dataset to train *TSI* models contain the samples from blue and oligotrophic Tibetan lakes, which are like the oceanic environments. The blue band can be used in our model. We hope that these revisions and the improved text will be satisfactory.

Technical

- Line 102 Sentine-2 instead of Sentinel-2

Response: We are sorry for our careless mistake. Sentine-2 was corrected in revised manuscript.

- Line the same reference in Line 154 and 157 is different

Response: We are sorry for our careless mistake. The reference is Song & Li et al., 2019.

- note that TSI in some sentences are italic, and some are not, such as Line 213 and 214, as well as the N in Figure 8.

Response: We are sorry for our careless mistake. TSI in Line 213 and 214 are italic. Then we check all TSI in revised manuscript.

- Many scripts (e. g., R2) require superscripts or subscripts for proper rendering, such as Figure 6a

Response: Thank you for your comment. We corrected these mistakes in our revised manuscript.

- some typefaces have different colors in Figure 7.

Response: Thank you for your comment. We corrected these mistakes in our revised manuscript.

- Line 577 Qin et al., (2020)

Response: Thank you for your comment. We corrected these mistakes in our revised manuscript.

- Line 606 it is very confused that there are many numbers and commas.

Response: We are sorry for our careless mistakes. This sentence was corrected as '*In 2019, the total fish catch in Hubei was 4,695 tons; in Jiangxi was 432, 25 tons; in Anhui was 588,135 tons; 2,314,603 and 4,841,159 tons in Anhui and Jiangsu in the east, respectively (China rural statistical yearbook).*'

- Figure 2 CR2CC?

Response: We are sorry that this mistake was corrected. Then we checked these mistakes in revised manuscript.