Response to Reviewer comments
Manuscript Number: essd-2021-227-RC1
Manuscript Title: Water clarity annual dynamics (1984–2018) dataset across China derived from Landsat images in Google Earth Engine

Response to anonymous referee #1:
Anonymous referee #1:
In this study, the authors developed / provided a valuable water clarity data set across China during 1984-2018 from Landsat images by GEE platform. This data set was validated, and spatio-temporal patterns of water clarity were also analyzed. Overall, this manuscript is written well and suitable to publish in ESSD. I recommend a minor revision based on the comments below to improve the quality of this manuscript / data set before publication.

Major comments:

1. The structure of Abstract is not clear. From beginning of data set development, validation, to spatio-temporal pattern… could be better.

Response: Thank you for this suggestion, we have adjusted part of the structure of Abstract, and the detailed revision can be seen below.
Water clarity provides a sensitive tool to examine spatial pattern and historical trend in lakes trophic status. Yet, this metric has insufficiently been explored despite the availability of remotely-sensed data, especially for long-term monitoring. Therefore, we utilized Landsat top of atmosphere reflectance products within Google Earth Engine in the period of 1984-2018 to retrieve the average SDD for each lake in each year. Three Secchi disk depth (SDD) datasets were used for model calibration and validation from different field campaigns mainly conducted during 2004-2018. The red/blue band ratio algorithm was applied to map SDD of lakes (> 0.01 km^2) based on the first SDD dataset, where $R^2 = 0.79$, rRMSE = 61.9%. The other two datasets were used to validate the temporal transferability of SDD estimation model, which were indicated the model had a stable performance. The spatiotemporal dynamics of SDD were analyzed at the five lake regions and individual lake scales, and the average, changing trend, lake number and area, and spatial distribution of lake SDDs across China were presented. In 2018, we found that the lakes with SDDs < 2 m accounted for the largest proportion (80.93%) of the total lakes, but the total area of lakes with SDD between 0-0.5 m and > 4 m were the largest, accounting for 48.28% of the total lakes. During 1984-2018, lakes in the Tibetan-Qinghai Plateau lake region (TQR) had the clearest water with an average value of 3.32±0.38 m, while that in the Northeastern lake region (NLR) exhibited the lowest SDD (mean: 0.60±0.09 m). Among the 10,814 lakes with SDD results more than 10 years, 55.42% and 3.49% of lakes experienced significant increasing and decreasing trends, respectively. At the five lake regions, except for the Inner Mongolia-Xinjiang lake region (MXR), more than half of the total lakes in every other lake region exhibited significant increasing trends. In the Eastern lake region (ELR), NLR and Yungui Plateau lake region (YGR), almost more than 50% of the lakes that displayed an increase or decrease in SDD

were mainly distributed in an area of 0.01-1 km^2, whereas that in the TQR and MXR were primarily concentrated in large lakes (> 10 km^2). Spatially, lakes located in the plateau regions generally exhibited higher SDD than those situated in the flat plain regions. The dataset can now be accessed through the website of the National Tibetan Plateau Data Center (http://data.tpdc.ac.cn): DOI: 10.11888/Hydro.tpdc.271571.

2. The authors mapped the spatiotemporal variation of SDD in lakes (>1 ha) across China from 1984 to 2018. How the lakes are mapped properly and accurately in this study? I think GEE has limitation in conducting this. As the cloud and shadow effects on lake boundaries, an automatic / semi-automatic method is not possible to map lakes accurately. In addition, in the middle and lower reaches of Yangtze River regions, the lake boundaries are very difficultly differentiated from other water /non-water classifications. How the authors do these? The lake boundaries were examined with origin Landsat images? How the seasonal inconsistency for data selection was considered? How the rivers and reservoirs are excluded from water bodies? The authors compared the results of mapped lakes with existing lake data set in China? This is necessary for validation the accuracy of lake mapping for this study. The very small size lakes are included. The land contamination to lake water was considered?

Response: Thank you for these comments, it is helpful for us to improve the quality of this paper. According to your questions, we have made some explanations below.

1) As for the question about lake boundaries.

First of all, we are sorry that the extraction of lake boundaries in present study didn't describe clearly, which makes the reviewer more confused about it. Next, we will explain it in detail.

Based on the previous study by Song et al. (2020), the lake boundaries (lakes and reservoirs) with an area > 0.01 km^2 across China were derived from Landsat 8 OLI images mainly acquired in 2016, while some images in 2014, 2015, 2017, or 2018 were used when images in 2016 were unavailable due to cloud or haze contamination. Detailed description of extracting boundaries can be seen in the research of Song et al. (2020). The Figure 1 shows the result of using these lake boundaries to map SDD at a national scale with OLI images mainly acquired in 2016 (Song et al., 2020).

It is well-known that some lakes in China are changing greatly over time. On the basis of the lake boundaries derived from the study of Song et al. (2020), we dealt with these changing lakes separately to obtain their boundaries in each year during the period of 1984-2018. We mainly referred to the research of Zhang et al. (2019) to obtain the information of which lake boundary has changed and what year the lake started to vary. This research examined multi-decadal lake area changes in China during 1960s–2015, using historical topographic maps and Landsat satellite images, including lakes as fine as ≥1km^2 in size. The datasets of lake boundaries (1960s-2020) have been published on the National Tibetan Plateau Data Center. The Figure 2 displays the spatial variation of lake boundaries from 1990 to 2015 with a temporal resolution of 5 years. As for the reservoirs, we mainly viewed the Landsat (5/7/8) images to confirm the changing region.With respect to the small lakes with an area <

$1km^2$, we assumed that their boundaries don not change during the study period.

We delineated boundaries of these changing lakes using Landsat images during 1984-2018. The cloudless TOA image of each path and row was downloaded through GEE platform, processed to derive the Modified Normalized Difference Water Index (MNDWI) as follows:

$$MNDWI = (R_{rc,Green} - R_{rc,SWIR})/(R_{rc,Green} - R_{rc,SWIR}) \quad (1)$$

where, $R_{rc,Green}$, $R_{rc,SWIR}$ is the Rayleigh scattering reflectance in the green band, and short-wave infrared (SWIR) band, respectively. First, we used MNDWI, combined with Tasseled Cap Transformation (TC) and a density slicing with multi-threshold approach, to build a decision tree for retrieving water body boundaries using the ENVI software package (Rokni et al., 2014; Xu et al., 2006). Then, Landsat images acquired during 1984-2018 were classified into water and non-water areas (Feyisa et al., 2014). The extracted water bodies were subsequently converted into polygons with contiguous pixels and stored in shape file format using the ArcGIS10.4 (ESRI Inc. Redlands, CA, USA). We divided water bodies into lakes, reservoirs, and rivers according to their shoreline features, and also through referencing to the Global Reservoirs and Dams database (Lehner et al., 2011), Chinese Reservoirs and Dams database, and high-resolution images from Google Earth to tell rivers and reservoirs from water bodies.

Jensen. (2006) pointed out that the various surface objects have different reflectance to NIR band. For instance, the NIR band can be largely reflected by land and vegetation and strongly absorbed by water, which leads to a stark contrast between the land and water reflectance, especially for the shallow lakes or reservoirs. The problem of land contamination to water is still a challenge for retrieving water quality parameters precisely (Jensen. 2006; Hou et al., (2018)). In our study, in order to avoid the influence of adjacent land on water bodies, one pixel buffer inward of water boundary was removed for lakes with an area ≤ 1 km², and two pixels for lakes with an area > 1 km². This method has been demonstrated to be effective in other studies related to SDD. For example, Liu et al. (2020) excluded and Wang et al. (2020) excluded two pixels and one pixel from large lake boundaries (> 20 km²) extracted by MODIS images with a spatial resolution of 500 m.

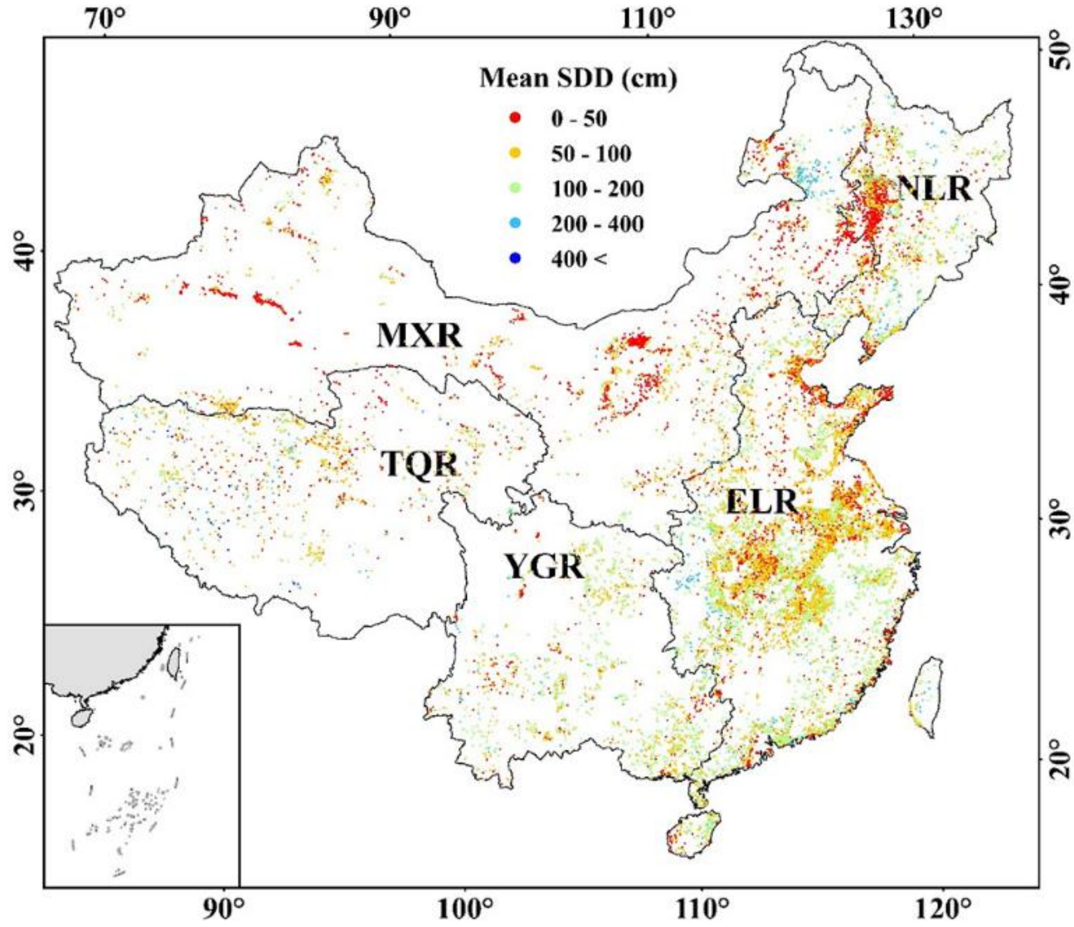

Figure 1: The SDD spatial variation of lakes in China with OLI images mainly acquired in 2016. Note: this figure derived from the study result of Song et al. (2020).

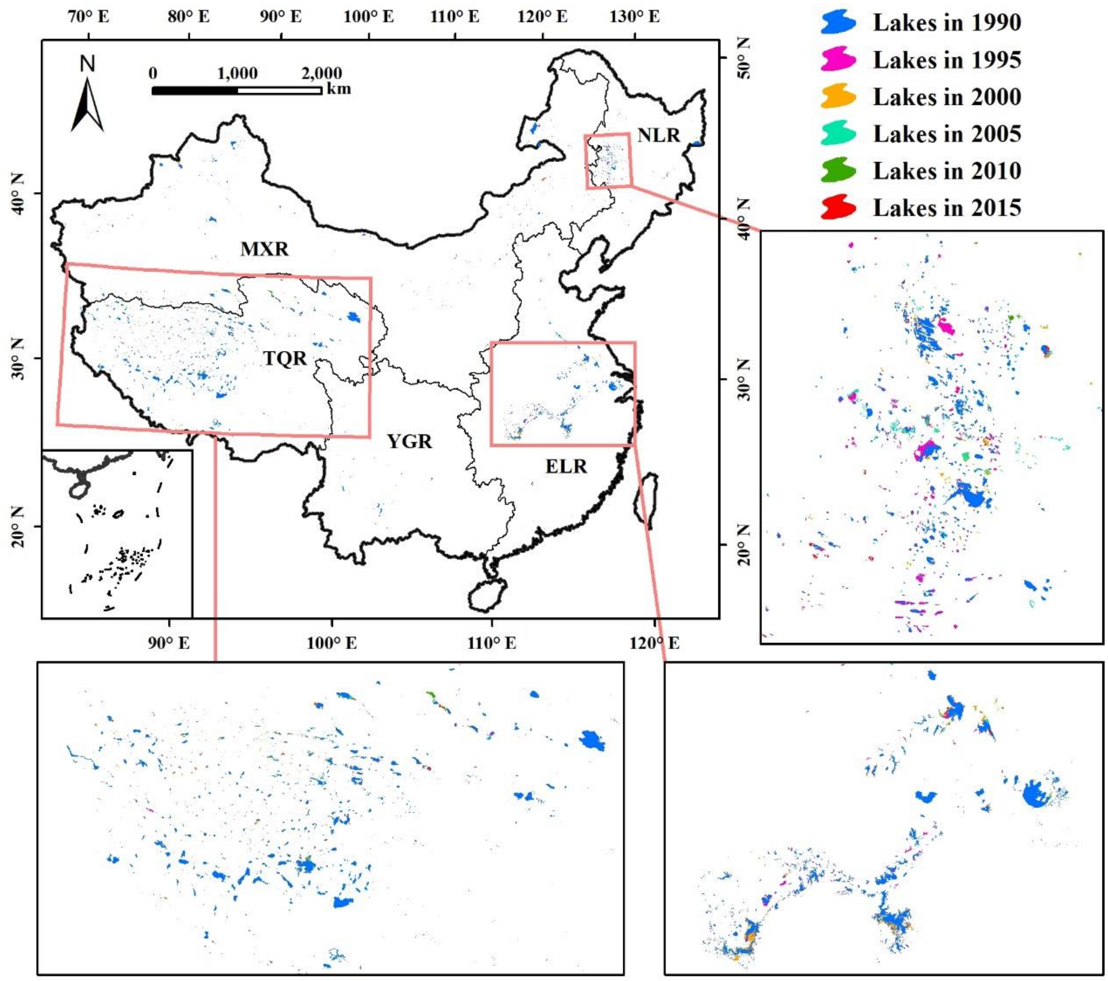

Figure 2: The spatial variation of lake boundaries from 1990 to 2015 with a time resolution of 5 years. Note: the data sets used in this figure sourced from the study of Zhang et al. (2019).

2) Aa for the question about "How the seasonal inconsistency for data selection was considered?"

In the manuscript of this study, we may not describe this part clearly, here, we have given the detailed explanation. Based on the GEE platform, the TOA images were mainly collected during the ice-free season (May to October) from 1984 to 2018 in the TQR, MXR, NLR. In order to ensure the consistency of images used in the five lake regions, the TOA images in the ELR and YGR were also designed to select from May to October in each year. However, the image dates in the YGR were actually from January to December due to lack of good-quality images in the selected period. The purpose of this paper was to research the interannual variations of lakes water clarity during 1984-2018, so the TOA images used to estimate water clarity of lakes were mainly from May to October. Despite the images used in the YGR were slightly different from the other four lake regions, it would cause little impact on the analysis of interannual variations in water clarity of lakes across China. Zhang et al. (2021) applied Landsat 8 images in the nonfreezing period from June to October during 2016-2018 to map spatial distribution of the SDD across China and calculated the average SDD for each lake on the basis of the estimated SDD values from 2016 to

2018. In addition, many studies have demonstrated annual mean SDD values for different lakes across China through computing the results of different months within a year (Liu et al., 2020; Pi et al., 2020; Feng et al., 2019).

3) As for question about "The authors compared the results of mapped lakes with existing lake data set in China? This is necessary for validation the accuracy of lake mapping for this study."

We have considered this question seriously. In the seventh part of this study, the reason has been given why we chose to compare the SDD estimation models proposed by Zhang et al. (2021) and in our study. The result of comparison showed that the estimation model built by our study exhibited better performance to retrieve SDD in both examined lakes (Taihu and Dianchi). As suggested by the reviewer, if we compared the results of mapped lakes with existing lake data set in China, it would be more convincing for the accuracy of lake mapping for this study. Therefore, after comparing the SDD estimation models between Zhang et al. (2021) and our study, we continue to make a comparison with the results of estimated SDD of lakes across China acquired from these two researches. Zhang et al. (2021) applied Landsat 8 images in the nonfreezing period during 2016-2018 to map spatial distribution of the SDD across China and calculated the average SDD for each lake (n=641; size ≥ $10km^2$) on the basis of the estimated SDD values from 2016 to 2018. In order to make the results more comparable, we first obtained the lakes (n=639) with an area ≥ $10km^2$, excluding the reservoirs. Then, the average SDD of these lakes were calculated based on the estimated SDD values from 2016 to 2018. The Figure 3 shows the distribution of the average SDD for each lake and five lake regions across China in the period of 2016–2018 in present study. The Figure 4 displays the results from the study of Zhang et al. (2021). Comparing these two Figures, the spatial distributions of the average SDD for each lake in the MXR, NLR, ELR, and YGR demonstrated in present study (Figure 3.b-e) are similar to the results (Figure 4.b-e) of Zhang et al. (2021), while the mean values of lake SDDs in the TQR (Figure 3.f) are a little higher than that (Figure 4.f) showed in the study of Zhang et al. (2021). As for the average of estimated SDD for five lake regions, regional distribution in present study (Figure 3.g) is as follows (in decreasing order): TQR > YGR > MXR > ELR > NLR which is consistent with the distribution of in-situ measured SDD in these lake regions, while that (Figure 4.g) in the study of Zhang et al. (2021) is: YGR > TQR > MXR > ELR > NLR. With respect to the number of lakes in different categories of SDD in the period of 2016–2018, the distribution pattern in the two studies is similarity, though the quantity is slightly differences in some categories.

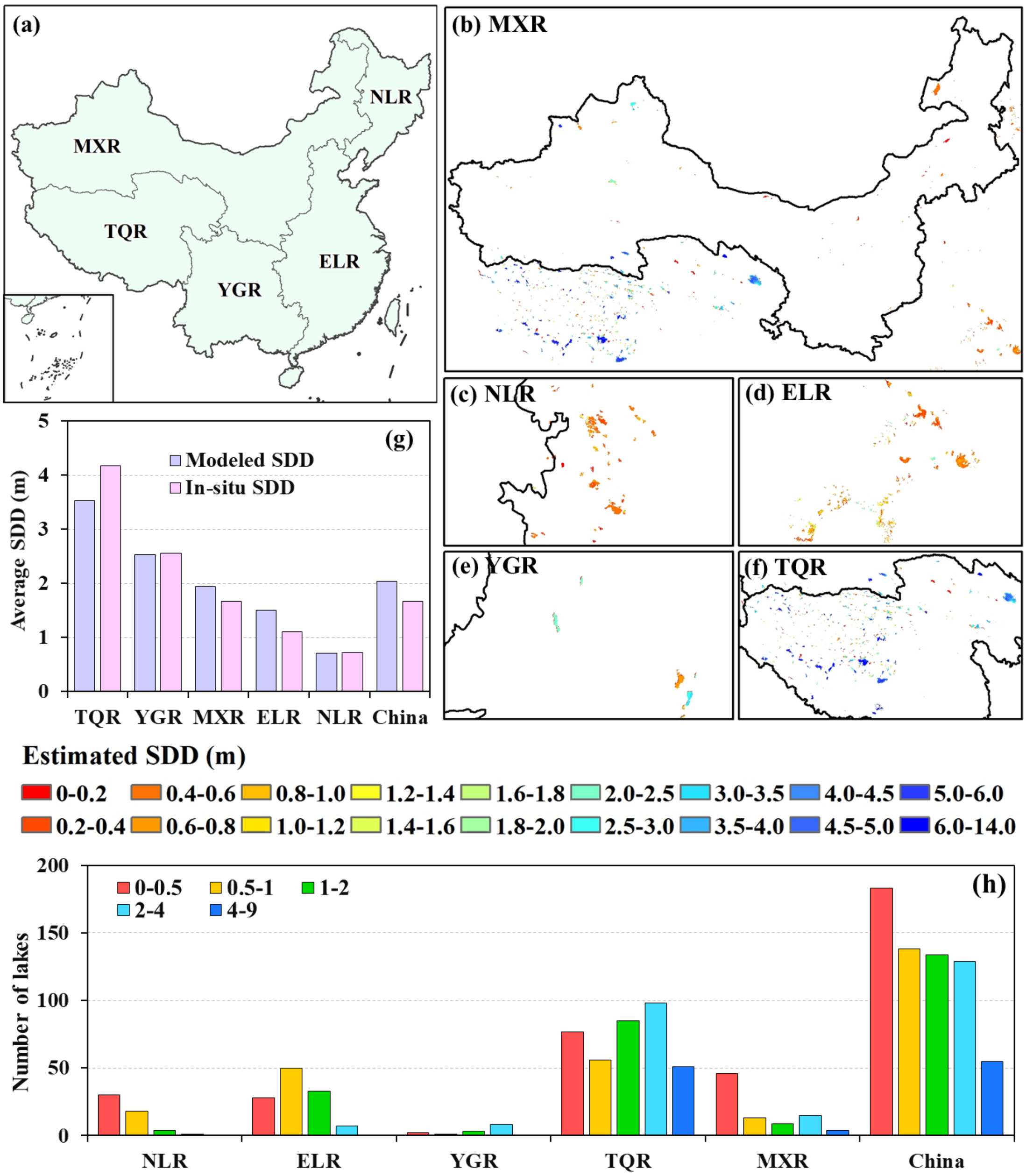

Figure 3: The distribution of the SDD of lakes (≥ 10km^2) in the period of 2016–2018. (a) Geographical location of the five lake regions. The spatial distribution of the average SDD for each lake in the MXR (b), NLR (c), ELR (d), YGR (e), and TQR (f). (g) The purple histogram shows the average SDD for each lake zone and all lakes in China during 2016-2018 (number of lakes: TQR (367), YGR (14), MXR (87), ELR (118), and NLR (53)), while the bright pink histogram displays the mean values of in-situ measurement SDDs in the five lake regions and total lakes in China during 2015-2019 (number of samplings: TQR (102), YGR (73), MXR (177), ELR (351), and NLR (135)) due to the quantity of water samplings distributed across China from 2016 to 2018 is a little small. (h) The color histogram reveals the number of lakes in five categories of SDD ((0–0.5] m, (0.5–1] m, (1–2] m, (2–4] and (4–9) m) in the period of 2016–2018.

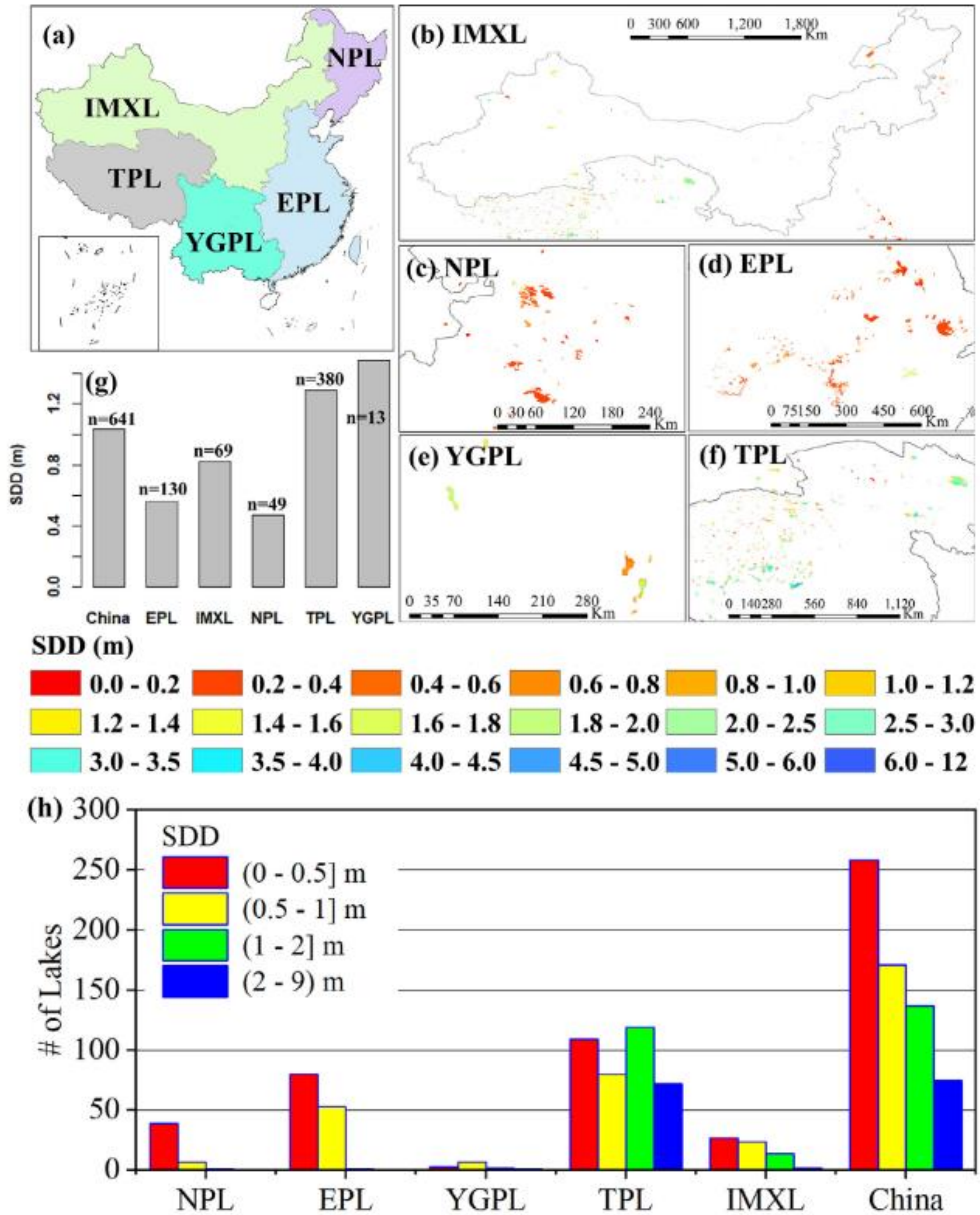

Figure 4: The lakes in China divided into five lake zones (a) according to Ma et al. [17]. The spatial distribution of the SDD in the period of 2016–2018 in IMXL (b), NPL(c), EPL (d), YGPL (e), and TPL (f) lakes. The gray histogram plots show the average SDD for each lake zone and all lakes in China (g), where n is the number of lakes in each individual dataset. The color histogram plots show the number of lakes with water area larger than 10 km 2 in four categories of SDD ((0–0.5] m, (0.5–1] m, (1–2] m and (2–9) m) in the period of 2016–2018 (h). Note: this figure derived from the study result of Zhang et al. (2021).

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3. The Landsat images used by GEE have a large range from 1984 to 2018. How about the uncertainties of trends / values for SDD analysis?

Firstly, in terms of the consistency and accuracy of the Landsat estimation results, some studies related to SDD have demonstrated that the estimated SDD results from Landsat 5 TM, 7 ETM + and 8 OLI images are highly comparable through comparing the Landsat-derived SDD values from the overlapping area of the images (Landsat 7 ETM + vs. Landsat 5 TM images and the Landsat 7 ETM + vs. Landsat 8 OLI images), which indicated that the use of Landsat series data with the proposed model can provide accurate long-term coverage of SDD in lakes in China (Zhang et al., 2021; Song et al., 2020; Deutsch et al., 2018; Bonansea et al., 2015; Mccullough et al., 2013). Figure 5 demonstrates the overlap area of the Landsat TOA images in the lakes located at home and abroad and a scatterplot with a regression of reflectance values derived from the overlapping area. The model coefficients of these scatterplots reveal the good agreement between Landsat 5/7/8 images reflectance values. In our study, the big data of in-situ measured SDD spanned 15 years (2004-2018) was used to calibrate the model of SDD, where R^2 = 0.79, RMSE = 100.3 cm, rRMSE = 61.9%, MAE = 57.7 cm. Moreover, the average of estimated SDD in five lake regions is consistent with the distribution of in-situ measured SDD. In addition, in the manuscript of Figure 8, we also used available in-situ SDD data (2019 – 2020) collected at monitoring stations in Lake Taihu and Lake Dianchi to assess the accuracy of the model, and the result showed that our model exhibited good performance to retrieve SDD in both Lake Taihu and Lake Dianchi.

Secondly, from the perspective of uncertainties of Landsat estimation results, the effects of a few systemic errors on estimated SDD results are unavoidable. On the one hand, the SDD estimation model proposed in this study existed some errors, where the validation model showed R^2=0.80, RMSE = 92.7 cm, RMSE% = 57.6%, MAE= 54.9 cm. On the other hand, the atmosphere affects differently sensor bands depending on the waveband, thus affecting the relationships obtained from top-of-atmosphere reflectance, and different atmospheric correction methods have different effects on the Landsat images (Bonansea et al., 2015; Lee et al., 2016). It's noted that the TOA products were produced using the Landsat Ecosystem Disturbance Adaptive Processing System (LEDAPS) software provided within GEE (Schmidt et al., 2013). These two factors may lead to the uncertainties of estimated SDD results based on Landsat long-term observation. Although systemic errors are inevitable, they do not have much impact on the overall trend towards SDD of lakes.

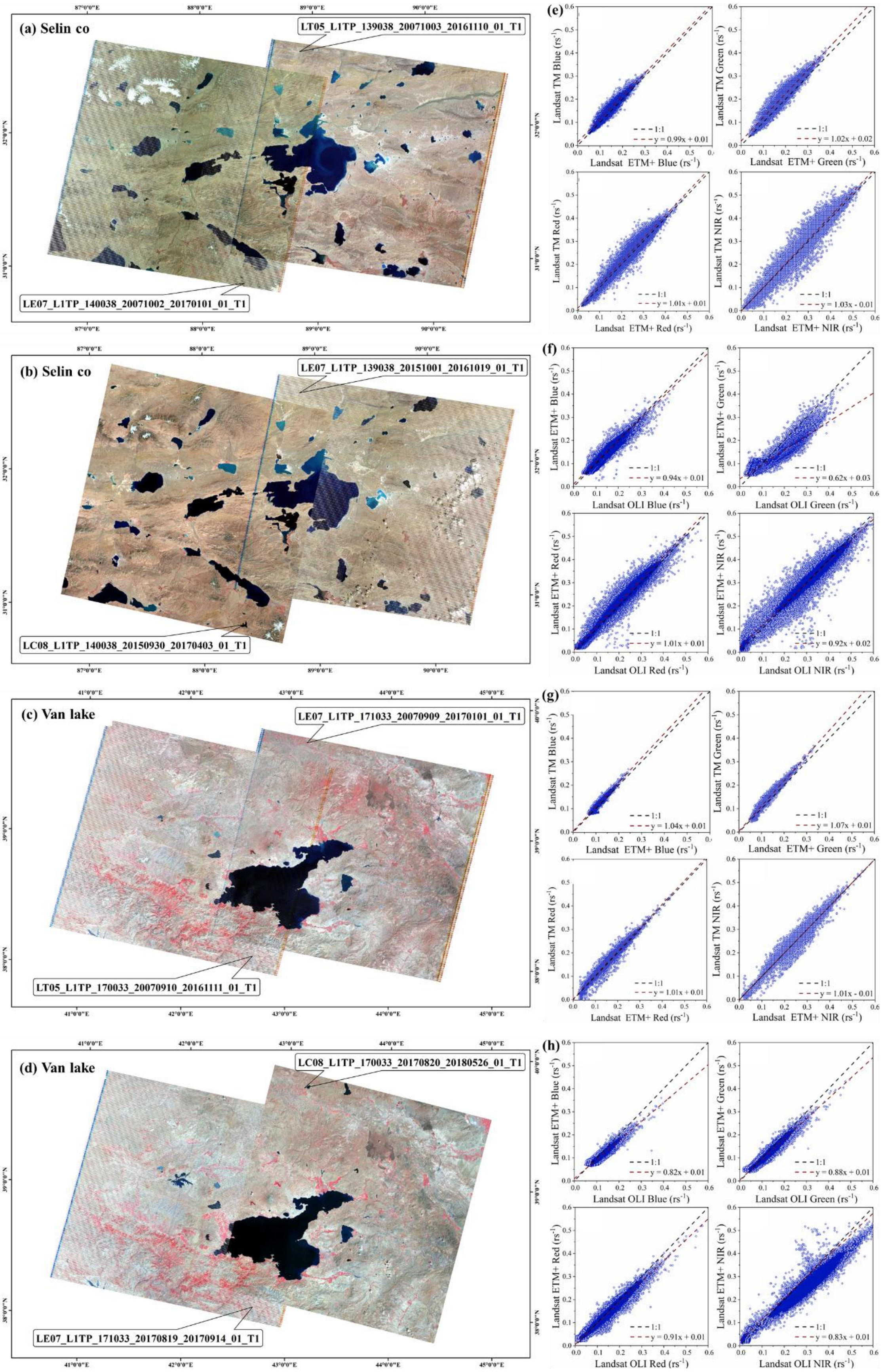

Figure 4: Overlap areas of the Landsat 7 ETM+ and Landsat 5 TM TOA images (a and c) and the Landsat 7 ETM+ and Landsat 8 OLI TOA images (b and d) in the lakes of Selin co in China and

Van Lake in Turkey, respectively. Reflectance comparison for Landsat 7 ETM+ vs. Landsat 5 TM TOA images (e and g) and the Landsat 7 ETM+ vs. Landsat 8 OLI TOA images (f and h) for these two lakes derived from the overlap.

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4. Causes of the regional differences and trends of water clarity, related with lake size, volume and volume changes can be added for discussion.

Response: Thank you for this suggestion, it’s a good idea for analyzing the driving factors of water clarity changing trends and regional differences. But the focus of this paper is on describing the data and emphasized the data quality, validation, and utilization, so this paper didn’t discuss the causes of water clarity interannual change trends. In the future, we will further investigate the influences of various potential driving factors on water clarity change trends and region differences, like natural factors (wind speed, temperature, precipitation, NDVI, water depth, water size, lake volume, DEM, slope) and anthropogenic factors (land use change, chemical fertilizer use, wastewater discharge).

Specific comments:

1) change the unit of ha to km^2

Response: Thank you for this suggestion, the all units of ha have been changed into km^2. Detailed revision can be seen below.

Lines 15-17: The red/blue band ratio algorithm was applied to map SDD for lakes ($\geq$ 0.01 km^2) based on the first SDD dataset, where R2 = 0.79, RMSE = 100.3 cm, rRMSE = 61.9%, MAE = 57.7 cm.

Lines 36-37: More than 26,000 lakes (with area $\geq$ 0.01 km^2) and 78,000 reservoirs are distributed across China (Song et al., 2018), providing multiple ecosystem services (Feng et al., 2019b; Lehner and Doll, 2004; Tranvik et al., 2009; Yang and Lu, 2014).

Lines 91-92: The overall purpose of this study was to map the spatiotemporal variation of SDD in lakes ($\geq$ 0.01 km^2) across China from 1984 to 2018.

Lines 124-125: Further, lakes and reservoirs with surface area $\leq$ 0.01 km^2 were removed in the GIS database (Song et al., 2020).

Lines 166-167: Then, combining the aforementioned image-processing methods, Eq. (1) was applied to the TOA images from 1984 to 2018 to estimate the SDD in the lakes with an area $\geq$ 0.01 km^2 over China via the GEE platform.

Line 170: At last, 10,814 lakes (size $\geq$ 0.01 km^2) were used to examined for the interannual dynamics of SDD (Fig.1c).

Lines 345-356: Therefore, it becomes a challenge to compare these past results with the results of the present study due to difference in the period of interest, resolution of the satellite images and lake size ($\geq$ 0.01 km^2 in our study).

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Song, K., Wen, Z., Shang, Y., Yang, H., Lyu, L., Liu, G., Fang, C., Du, J.,Zhao, Y.: Quantification of dissolved organic carbon (DOC) storage in lakes and reservoirs of mainland China, *J. Environ. Manage., 217*, 391, **2018**.

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2) "More than 26,000 lakes (with area >1 ha) and 78,000 reservoirs are distributed across China (Song et al., 2018)" How the 26,000 lakes (with area >1 ha) are

mapped?

Response: Thank you for this careful review, it's our oversight to cite the wrong reference of Song et al. (2018a), and the proper one is Song et al. (2018b). In the right reference, it gave a detailed description of how to extract water body shoreline information in the section of "2.4.2. Small lakes or reservoirs with uncertain volume data". And in the section of "3.2.1. Lakes of each limnetic region", it gave the specific number of lakes in each lake region. The purpose of writing this sentence was to highlight the quantity of lakes and reservoirs across China, so we did not depict the method of mapping these lakes and reservoirs here.

References:

Song, K., Wen, Z., Xu, Y., Yang, H., Lili, L., Zhao, Y., Fang, C., Shang, Y.,Du, J.: Dissolved carbon in a large variety of lakes across five limnetic regions in China, *J. Hydrol.* , *563*, 143-154, doi:10.1016/j.jhydrol.2018.05.072, **2018a**.

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Feyisa, G. L., Meilby, H., Fensholt, R.,Proud, S. R.: Automated Water Extraction Index: A new technique for surface water mapping using Landsat imagery, *Remote Sens. Environ.*, *140*, 23-35, doi:10.1016/j.rse.2013.08.029, **2014**.

3) "(Duan et al., 2009; Feng et al., 2019a; Kloiber et al., 2002; McCullough et al., 2012; Olmanson et al., 2011a; Pi et al., 2020; Shen et al., 2020; Song et al., 2020)." Please cite less than 5 papers at one place each time.

Response: Thank you for this suggestion, the redundant papers have been removed in line 63-64. (Duan et al., 2009; Feng et al., 2019a; McCullough et al., 2012; Olmanson et al., 2011; Shen et al., 2020)

References:

Duan, H., Ma, R., Zhang, Y.,Zhang, B.: Remote-sensing assessment of regional inland lake water clarity in northeast China, *Limnology*, *10*, 135-141, doi:10.1007/s10201-009-0263-y, **2009**.

Feng, L., Hou, X. J.,Zheng, Y.: Monitoring and understanding the water transparency changes of fifty large lakes on the Yangtze Plain based on long-term MODIS observations, *Remote Sens. Environ.*, *221*, 675-686, doi:10.1016/j.rse.2018.12.007, **2019a**.

McCullough, I. M., Loftin, C. S.,Sader, S. A.: Combining lake and watershed characteristics with Landsat TM data for remote estimation of regional lake clarity, *Remote Sens. Environ.*, *123*, 109-115, doi:10.1016/j.rse.2012.03.006, **2012**.

Olmanson, L. G., Brezonik, P. L.,Bauer, M. E.: Evaluation of medium to low resolution satellite imagery for regional lake water quality assessments, *Water Resour. Res.*, *47*, doi:10.1029/2011wr011005, **2011**.

Shen, M., Duan, H., Cao, Z., Xue, K., Qi, T., Ma, J., Liu, D., Song, K., Huang, C.,Song, X.: Sentinel-3 OLCI observations of water clarity in large lakes in eastern China: Implications for SDG 6.3.2 evaluation, *Remote Sens. Environ.*, *247*, 111950, doi:10.1016/j.rse.2020.111950, **2020**.

4) "Regionally, lakes distribution is as follows…" Which lake data set was used?

Please state here

Response: Thank you for this suggestion, we really didn't specify the data set used here, and the source of this data set has been added in the lines 103-104: Regionally, lakes distribution sourced from Song et al. (2020) is as follows (in decreasing order): 49% in ELR, 22% in NLR, 18% in YGR, 8% in MXR and 4% in TQR (Fig. 1b).

Reference:

Song, K., Liu, G., Wang, Q., Wen, Z., Lyu, L., Du, Y., Sha, L.,Fang, C.: Quantification of lake clarity in China using Landsat OLI imagery data, *Remote Sens. Environ.*, *243*, 111800, doi:10.1016/j.rse.2020.111800, **2020**.

5) 1,301pairs, need a space

Response: Thank you for this suggestion, the spatial distribution of the 1,301 pairs of data used to calibrate and validate has been displayed in Fig.2a.

6) the 5% significance level to at the 5% significance level

Response: Thank you for your careful review, the phrase of "the 5% significance level" in line 186 has been changed into "at the 5% significance level".

7) Xinjiang province to Xinjiang Uygur Autonomous Region

Response: Thank you for your careful review, the "Xinjiang province" in line 229 has been changed into the "Xinjiang Uygur Autonomous Region".