Dear Editor,

On behalf of my co-authors, we thank you very much for giving us the opportunity to revise the manuscript (Manuscript ID: **hess-2021-630**). We appreciate the comments on our manuscript entitled "Long-term water clarity patterns of lakes across China using Landsat series imagery from 1985 to 2020" by Xidong Chen, Liangyun Liu, Xiao Zhang, Junsheng Li, Shenglei Wang, Yuan Gao, and Jun Mi.

Great thanks to the reviewers and editors, we have revised the manuscript carefully according to the comments. All the changes were high-lighted in the revised manuscript and the point-by-point response to the comments of the reviewers is also listed below.

Please let me know if you require any additional information on our paper. Looking forward to hearing from you soon. Best regards,

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Response to Comments from Reviewer 1 Reviewer: 1

This manuscript represents a significant contribution in the form of an **extensive application ready lake clarity data product covering small and large lakes of China over a period of 35 years**. This data product, LAWSD30 (and associated derivations), will be a valuable asset to future endeavors that seek to understand the drivers of lake clarity change in China.

Response: Many thanks for the encouraging and positive words.

Specific comments:

Point 1: Include the normalized RMSE in addition to the RMSE; the normalized RMSE summarizes the explanatory power of a model in a manner that is independent of scale, and so enables a ready comparison across modelling efforts.

Response: Many thanks for this comment. According to your comments, we have added the normalized RMSE (NRMSE) and the Mean Absolute Percentage Error (MAPE) to describe the model errors. The corresponding description and figures have been revised, and the details are shown below.

P10 Line 304 – Line 318: 'From Fig. 4a, our LAWSD30 dataset exhibited a significant correlation with all collected in situ SD data, with an R^2 of 0.92, a Root Mean Square Error (*NRMSE*) of 28.1%, and a Mean Absolute Percentage Error (*MAPE*) of 0.235. Most of the scatter points were distributed close to the 1:1 line. Specifically, from the validation results in the 2010s, our LAWSD30 showed good performance, with an R^2 of 0.92, a *NRMSE* of 30.8%, and a *MAPE* of 0.268. In addition, a stable performance was also shown in the results for the 2000s, with R^2 reaching 0.84, *NRMSE* reaching 30.1%, and MAPE reaching 0.219. Furthermore, a good performance was also seen before the 2000s, with an R^2 of 0.69, a *NRMSE* of 15.0%, and a *MAPE* of 0.126 in the 1990s. The validation results for these different decades demonstrated the stable performance of our LAWSD30 in different periods. It is concluded, therefore, that our LAWSD30 can be a reliable dataset for the long-term SD trend assessment of lakes in China.



Figure 4. Scatterplots of the in situ measured SD data and our LAWSD30 dataset. (**a**) An overall scatterplot of our LAWSD30 dataset and all the collected in-situ SD data; (**b**–**d**) scatterplots of our LAWSD30 dataset and the corresponding in situ SD data in the 1990s (1992, 1995, and 1998), 2000s (2001, 2004, and 2007), and 2010s (2010, 2013, 2016 and 2019), respectively.'

P18 Line 485 – P19 Line 490: 'It can be seen that, although the model coefficients of the three sensors were different in our calculation (Section 3.2), there was still strong consistency between the SD results of Landsat 5, 7, and 8, with an R^2 of 0.90 for Landsat 5 vs. 7 and an R^2 of 0.97 for Landsat 8 vs. 7 (Fig. 12). In addition, the *NRMSE* and *MAPE* for Landsat 5 vs. 7 and Landsat 8 vs. 7 were both lower than 26% and 0.22, respectively. The above results demonstrate that the estimated SD results from Landsat 5, 7, and 8 data are highly consistent.



Figure 12. Overlapping regions of Landsat 5 and 7 data (**a**) and Landsat 8 and 7 data (**b**); lake SD comparison for the Landsat 7 vs. Landsat 5 data (**c**) and the Landsat 7 vs. Landsat 8 data (**d**) for the lakes from the overlap.'

P20 Line 531 – Line 535: 'An average R^2 of 0.96 was achieved when compared with the MODIS-derived results, and the average *NMRSE* and *MAPE* were only 18.4% and 0.178, respectively (Fig. 14a,b). In addition, an R^2 of 0.74, a *NMRSE* of 28.0%, and a *MAPE* of 0.225 were shown in the comparison between the Sentinel 3-derived SD and our LAWSD30 dataset (Fig. 14c).



Figure 14. (**a**,**b**) Scatterplots of our LAWSD30 data and the corresponding MODIS-derived SD data (Wang et al., 2020) in the 2000s (2001, 2004, and 2007) and 2010s (in 2010, 2013, and 2016), respectively; (**c**) scatterplot of our LAWSD30 data and the corresponding Sentinel 3-derived SD data (Shen et al., 2020) in 2016 and 2019.'

Point 2: Line 118: replace 'product' with 'application ready data product'.

Response: Many thanks for this comment. According to your comments, the corresponding description and have been revised, and the details are shown below.

P3 Line 117 – Line 118: 'Taking into account the frequent contamination of cloud and cloud shadow, it is hard to develop a spatially continuous application ready data product throughout China with only one year of Landsat images (Zhang et al., 2019a).'

Point 3: Lines 147 - 48: it is not clear how 'user' and 'producer' map to the terminology used in Peckel et al 2016. Please clarify or re-word.

Response: Many thanks for this comment. According to your comments, the corresponding description and have been revised. The terms 'commission' and 'omission' accuracies were used to replace the user and producer accuracies, and the details are shown below.

P5 Line 151 – Line 152: 'The overall commission and omission accuracies for permanent water were 99.6% and 98.6%, respectively, versus 98.6% and 75.4% for seasonal water (Pekel et al., 2016).'

Point 4: Line 211: replace 'Following him' with 'Following Chen et al. (2021)', assuming that is what is meant?

Response: Great thanks for this comment. According to your comments, the corresponding description and have been revised. The details are shown below.

P7 Line 216 – Line 218: 'Following Chen et al. (2021), the DOY criteria (Eq. (A1)), the cloud and cloud shadow criteria (Eq. (A2)), and the atmospheric opacity criteria (Eq. (A3)) were selected to generate the BAP composites.'

Point 5: Line 215: for the convenience of the reader, please briefly describe the constituent BAP criteria and how the BAP was calculated, rather than pointing to Chen et al. 2021 (which then on-refers the reader to White et al. 2014 for further details).

Response: Great thanks for this comment. According to your comments, we have added an Appendices to briefly describe the details of the BAP criteria. Also, the corresponding description in the text were revised. The details are shown below.

P7 Line 216 – Line 219: 'Following Chen et al. (2021), the DOY criteria (Eq. (A1)), the cloud and cloud shadow criteria (Eq. (A2)), and the atmospheric opacity criteria (Eq. (A3)) were selected to generate the BAP composites (the details of the criteria are presented in the Appendices).'

P22 Line 582 - Line 592: '

7. Appendices

In order to generate the BAP composites, three criteria (i.e., the DOY criteria (Eq. (A1)), the cloud and cloud shadow criteria (Eq. (A2)), and the atmospheric opacity criteria (Eq. (A3)) were selected:

$$Score_{DOY} = \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{1}{2}(\frac{X_j - \mu}{\sigma})^2}$$
(A1)

Score_{CloudDisctance} =
$$\frac{1}{1 + e^{(-0.2(\min(D_i, D_{req}) - \frac{D_{req}}{2}))}}$$
(A2)

Score_{*opacity*} =
$$1 - \frac{1}{1 + e^{(-0.2(\min(O_i, O_{max}) - (\frac{O_{max} - O_{min}}{2})))}}$$
 (A3)

where μ and σ represent the target DOY and the standard deviation of the DOY, respectively, and x_j is the DOY for image *j*. The target DOY μ and the standard deviation of the DOY was set to August 1 and 60, respectively. D_i is the distance from pixel *i* to cloud or cloud shadow, and D_{req} is the minimum required distance, which was set to 50 here. O_i is the opacity of pixel *i*, while O_{max} and O_{min} are the minimum opacity value, respectively. O_{max} was set to 0.3 and O_{min} was set to 0.2. All parameters for the three criteria were set according to Chen et al. (2021). The BAP score was then derived as followed:

$$Score_{BAP} = Score_{DOY} + Score_{CloudDisctance} + Score_{Opacity}$$
(A4)

Point 6: Line 227: please replace the word 'proven' with 'demonstrated', here and elsewhere in the document. Likewise, replace 'proves' with 'demonstrates'. 'Proven' and 'proves' should be reserved for contexts where there is little room for interpretation.

Response: Great thanks for this comment. According to your comments, we have checked the full text and revised the corresponding descriptions. The details are shown below.

P8 Line 233 – Line 234: 'Previous researches have demonstrated that FUI and hue angle (α) are useful water color parameters for assessing the SD of inland waters.'

P9 Line 268 – Line 269: 'This model had been demonstrated to be suitable for large-area and long-term SD monitoring.'

P18 Line 473 – Line 474: 'Recently, many studies have demonstrated the feasibility of using long-term Landsat series data from GEE to assess the changes in lake clarity.'

P18 Line 489 – P19 Line 490: 'The above results demonstrate that the estimated SD results from Landsat 5, 7, and 8 data are highly consistent.'

Point 7: Line 316: replace 'product' with 'LAWSD30 dataset'.

Response: Great thanks for this comment. According to your comments, we have revised the corresponding descriptions. The details are shown below.

P11 Line 327 – Line 328: 'It can be found that the water bodies in our LAWSD30 dataset product showed a wide range of SD values.'

Point 8: Line 339: replace 'researches' with 'studies' (here and elsewhere in the manuscript).

Response: Great thanks for this comment. According to your comments, we have checked the full text and revised the corresponding descriptions. The details are shown below.

P12 Line 355 – Line 356: 'These results are in good agreement with previous studies.'

P20 Line 522 – Line 523: 'it is a challenge to compare our results with other studies due to the different periods of interest.'

Point 9: Line 348: replace 'Similarly, some studies found the same SD' with 'Other studies found the same SD'

Response: Great thanks for this comment. According to your comments, we have revised the corresponding descriptions. The details are shown below.

P12 Line 365: 'Similarly, other studies found the same SD change patterns in the two lakes.'

Point 10: Line 462: replace 'hydrometeor' with 'weather'. (hydrometeor has a different meaning to that which I assume is intended).

Response: Great thanks for this comment. According to your comments, we have revised the corresponding descriptions. The details are shown below.

P18 Line 479 – Line 480: 'thus the SD of lakes can remain stable within a few days under stable weather conditions.'

Point 11: Lines 523 - 24: replace 'to reflect the comprehensive conditions in water bodies' with 'of water quality'.

Response: Great thanks for this comment. According to your comments, we have revised the corresponding descriptions. The details are shown below.

P21 Line 561– Line 562: 'Water clarity is one of the most intuitive and important indicators of water quality.'

Point 12: Conclusion: include commentary that alerts the reader to the notion that an informed interpretation of the lake clarity patterns presented in this manuscript will require an understanding of the relative importance of local and regional driving forces; and that such an informed interpretation will be required in order to prioritise management actions.

For example, the work of Yu and Zhai (https://doi.org/10.1038/s41598-020-71312-3) demonstrate that compound drought and heat events have impacted China more severly since ca. the year 2000. Have such events led to changes in SD patterns in some lakes, for example by making wind-driven resuspension more or less likely?

Response: Great thanks for this comment. According to your comments, we conducted an experiment to briefly analyze the potential linkage between environmental factors and the lake clarity in China. The details are shown below:

In order to preliminarily explore the potential linkage between environmental factors and the spatial-temporal changes of lake clarity in the five limnetic regions, three categories of environmental factors were collected, including: lake area factors (i.e. lake area (LA) of lakes with areas $\leq 1 \text{ km}^2$ and the LA of lakes with areas $> 1 \text{ km}^2$), meteorological factors (i.e. precipitation (PR), wind speed (WS), and near surface air temperature (AT)), and human activity factors (i.e. local gross domestic production (GDP) and population density (PO)). These factors have been considered as potential drivers of the long-term SD trend of lakes in previous studies (Feng et al. 2019a; Li et al. 2020a; Meng et al. 2015; Wang et al. 2020; Yin et al. 2021).

The collected environmental factors were separately counted in each region. Specifically, the annual summer mean values for the PR, WS, and AT in each limnetic region were calculated. Also, the total LA and the intra-year PO and GDP of each limnetic region was calculated for each target year. The long-term variations in these environmental factors were shown in Fig. R1. The GDP, PO, PR, and LA exhibited increase trends in all five limnetic regions from 1985 to 2020. In addition, WS was characterized by increase trends in MXR, YGR, and NER, but downward trends in EPR and QTR. Moreover, AT has been trending upward in EPR, MXR, QTR, and YGR since 1985, but has decreased in NER. The correlation between these factors and

the variations in lake SD was analyzed and shown in Fig. R2.

Regarding the correlations in the east (including EPR and NER), the human activity factors (PO and GDP) showed strong positive correlations with small lakes (with areas $\leq 1 \text{ km}^2$) (P < 0.01). Also, a strong positive correlation between GDP and clarity of large lakes (with areas > 1 km²) can be found in NER. In fact, with the development of GDP and urbanization, local and national governments have put forward a variety of regulations to manage water resource and control pollution (Jiang and Zheng 2011; Wang et al. 2020). Our results appeared to further proved the effectiveness of the environmental regulation and projects implemented by the local and national governments. Similarly, previous works also found PO and GDP were positively correlated with the lake clarity in eastern China (Feng et al. 2019a; Guo et al. 2015; Zhao et al. 2018). In addition, the correlation between large lakes and human activity factors was found to be relatively weak in EPR (the correlation coefficient (r) between SD and PO and GDP was 0.12, and -0.09, respectively), which means the regulation and management for small lakes may be stronger than that for large lakes. Furthermore, the small lakes in EPR also showed significant positive correlations with the increase of AT and LA, indicating the positive impact of the two factors on SD of small lakes in EPR. Nevertheless, since warm AT generally promotes the growth of algae, causing algae blooms and reducing water clarity (Li et al. 2020a; Yin et al. 2021), it seems that SD should not increase with the increase in AT. However, because climate, lake area, and human activities are interconnected in complex ways (Maberly and Elliott 2012; Williamson et al. 2009), and other factors (such as GDP, PO, and LA) are also significantly positively correlated with SD, it is possible to lead a positive correlation between AT and SD. Similarly, Wang et al. (2020) and Feng et al. (2019a) also found that some lakes in EPR were positively correlated with lake SD. Then, for the large lakes in EPR, WS and SA showed significant negative and positive correlations with lake clarity, respectively, implying the negative and positive effects of WS and SA on SD in large lakes in this region. Similar results can also be found in recent studies (Feng et al. 2019a; Xue et al. 2019).

In MXR, PO and AT showed significant negative correlations with SD changes in small lakes, suggesting the negative effects of the two factors on SD variations in small lakes. In contrast, all factors exhibited weak and insignificant correlations with large lakes in EPR, implying that large lakes in MXR are more resistant to environmental changes than small lakes.

As for lakes in QTR, the small lakes had significant negative correlations with PO, GDP, AT, and LA, suggesting the negative effects of the four factors on the long-term SD changes in small lakes from 1985 to 2020. Several studies have reported that climate warming has accelerated the melting of glaciers and permafrost in cold regions over recent decades, leading to an increase in the lake area and water volume in QTR (Liu et al. 2021; Sun et al. 2018; Yang et al. 2017; Zhang et al. 2011). Since the sediments carried by meltwater can reduce the SD in lakes (Mi et al. 2011), this is probably the reason for the negative correlations between SD and AT and LA. In addition, because high AT can also affect the growth of phytoplankton in QTR lakes (Feng et al. 2019b), this may also be one of the reasons for the negative effects of AT. In agreement with our results, recent studies have also found the negative effects of Iarge lakes in QTR, the correlations between AT and LA and water clarity were shown to be weak, implying that the impact of climate warming on small lakes is significantly stronger than that of large lakes in QTR. The above results can provide effective support for the protection and

governance of the lake environment in this region.

Lastly, for lakes in YGR, small lakes had significant negative correlations with GDP and WS, while none of a factor showed a significant correlation with large lakes. Since the increase in GDP of the catchment may indirectly increase the input of contaminants and nutrients in water bodies (Zhou et al. 2019), and the recovery capacity of small lakes is generally limited (Helen et al. 2015), GDP and the water clarity of small lakes are therefore likely to be negatively correlated. Recently, Xu et al. (2018) found similar correlations between GDP and SD in lakes in YGR. In addition, because wind speed can accelerate the growth of cyanobacteria, resulting in a decrease in the SD of the lake (Shi et al. 2018; Yin et al. 2021), the negative correlation



Figure R1. Long-term curves of the human activity factors, meteorological factors, and lake area factors in the five limnetic regions (EPR, MXR, QTR, YGR, and NER) from 1985 to 2020. *Noted:* LA., lake area; PR., precipitation; WS., wind speed; AT., near surface air temperature; GDP., gross domestic production; PO., population density.

	EPR		MXR		QTR		YGR		NER	
	Area ≤ 1 km ²	Area > 1 km^2	Area ≤ 1 km ²	Area > 1 km^2	Area $\leq 1 \ \mathrm{km^2}$	Area > 1 km^2	Area $\leq 1 \ \mathrm{km^2}$	Area > 1 km^2	Area ≤ 1 km ²	Area > 1 km ²
РО	0.97	0.12	-0.83	-0.17	-0.87	-0.42	0.11	0.48	0.79	0.57
GDP	0.88	-0.09	-0.55	0.29	* -0.66	-0.01	* -0.60	0.44	0.88	0.93
PR	0.34	-0.28	-0.18	0.18	-0.51	-0.50	-0.01	0.08	0.22	0.23
AT	0.77	-0.01	-0.66	-0.11	-0.67	-0.32	-0.48	0.19	0.36	0.41
ws	-0.40	-0.68 *	-0.49	0.38	0.21	-0.06	-0.62 *	0.12	0.03	0.04
LA	0.68 *	* 0.60	-0.52	0.19	-0.71	-0.25	0.15	0.33	0.25	0.51

Figure R2. Pearson correlation coefficients (r) between SD and the six environmental factors of lakes with areas > 1 km² and \leq 1 km² in the five limnetic regions (EPR, MXR, QTR, YGR, and NER).

However, since the focus of our manuscript is on our LAWSD30 dataset and the monitoring of the long-term SD trends of lakes across China, we have not conducted more specific experiments in analyzing the driver factors of SD changes. Also, considering the length of the article and to keep the article focused, we did not incorporate the above analysis into the manuscript. Instead, we added a section *"5.3 limitations and suggestions for future work"* to the Discussion to illustrate the limitations of our study in analyzing the driver factors of SD changes, and to inform readers that investigations into the drivers of SD change are the main focus of our follow-up work. Also, the work of Yu and Zhai (<u>https://doi.org/10.1038/s41598-020-71312-3</u>) was cited in this section to illustrate the possible driving factors that we will analyze. The details are shown below:

P20 Line 543 - P21 Line 559: '

5.3 limitations and suggestions for future work

First, due to the relative long revisit period of Landsat series data and the interference from clouds, our study is not suitable for the evaluation of the intra-annual changes in water clarity. The long-term intra-annual and seasonal SD changes of lakes across China still need to be evaluated. In the future, more efforts will be devoted to the use of more multi-source data to increase the number of valid observations, so as to conduct more analysis on SD at seasonal scale.

Second, because this study is mainly focused on monitoring the long-term SD changes in lakes across China, the comprehensive analysis of the relationship between variation of lake water clarity and environmental factors was not investigated. Since the discharge of agricultural fertilizers, industrial sewage, and livestock excrement within the lake drainage area, as well as the spatial-temporal variations of land use and land cover can affect the clarity of the water bodies (Li et al., 2020a), data on related factors should be collected and analyzed. In addition, the topographic conditions of the lake basin, such as the slope of the lake shoreline and the size of recharge river, and the extreme weather and climate events (i.e. drought and heat event) (Liu et al., 2021a; Yu and Zhai, 2020), may also have important impact on the lake clarity. In future work, we will do more investigations to analyze the above potential driver factors of SD changes.'