Response to short comment 1

General Comment:

In this manuscript, the authors generated a dense (monthly and ever higher such as 10 days on average) continuous 18-year data set of changes in lake water level and storage for 52 large lakes on the Tibetan Plateau by combining multisource optical and altimetric information. Uncertainty in the optical water levels was evaluated by field experiments and rigorous uncertainty analysis, which is important to the generated data sets. The UAV imaging of lake shorelines for evaluating Landsat-based lake shoreline detection and the derivation of the mathematic expression of the uncertainty in the optical water levels look really interesting and solid. The magnitude of the uncertainty was found to be around 0.1 m, suggesting that the optical water levels are often more efficient and less noisy than altimetry data when the altimeter footprints on the lake surface are insufficient, especially for small lakes.

I strongly believe that the data set is extremely valuable for the long-term and short-term monitoring of lake water level and storage changes on the Tibetan Plateau, and are also useful for lake water level and storage studies in other areas. Many studies on this aspect present long-term trends in these lake water storage. But the authors of this study have additionally explored the potential of these multiple remote sensing data sets in monitoring short-term variability in lake water storage and lake overflow floods that are really new and look fantastic to me.

Response:

We thank Dr. Xu for thoroughly reviewing the manuscript and making such encouraging comments. It is important for us to receive these feedbacks to further improve the data set and the manuscript. Comments and issues raised by Dr. Xu have been addressed and are illustrated as follows.

Specific Comment:

1) Pg. 6, Line 8: "the systematic biases between different altimetry data were removed by either comparing the mean water level of the overlap period or comparing the two water level time series with changes in lake shoreline, depending on the length of the overlap period" would be discussed in more detail.

Response:

We agree that the original description of the method in Pg.6, Line 8 is not quite clear and needs further clarification. The basic idea of removing the systematical bias is to calculate the mean of two altimetry-based water level time series from different sources during the overlap period. Then, the difference between the mean time series and either water level time series is removed to make both altimetry-based water level time series consistent and form a longer water level time series. This process was subsequently applied to all water level time series with overlap periods to merge them into a single time series for each lake.

However, the overlap period could be short between some altimeters such as Envisat and CryoSat (e.g., there are only one or two data points in the overlap period), or does not exist at all, such as ICESat and CryoSat. On these cases, optical water levels (i.e., changes in lake shoreline that need to be translated into water levels using linear regression with one of the altimetry water level series) are used to extend or create an overlap period that links the two altimetry missions. We chose a one-year or two-year optical water level series which has an overlap period with both altimetry water level series as the baseline, and calculated the differences between altimetry water levels and the baseline during the overlap period. Then the differences from altimetry water levels were removed.

Therefore, three water level time series (i.e., one optical water level series and two altimetry water level series) from different sources are merged together. The reason why we used one-year or two-year optical water levels is because a longer overlap period may introduce some unexpected errors, such as a rapid increase in water level, which may, however, not be detected by optical water levels (only if the lakeshore slope happened to be steep in the exact region of increases in water level, which, for most cases, can be avoided by checking R^2 of linear regression when generating optical water levels).

This part will be modified in the revised manuscript.

Modifications: a separate paragraph summarizing the altimetry data merging process was added to the end of section 3.2.

2) Pg. 28, Lines 78: "where optical water levels can provide a near real-time monitoring of changes in lake water level and storage that are crucial to flood early warning and risk management." However, I have not seen the results.

Response:

Thanks for this comment. The expression here is indeed a perspective as to the potential and advantages of optical water levels rather than a strong statement. In this study, we provided water levels of Lake Salt, which has limited altimetry information but mainly consists of optical water levels. Though we used Landsat ETM$^+$ and OLI images, i.e., four observations were available in ~ one month, more than half of the images were useless due to cloud contamination or gaps. Therefore, the temporal resolution of optical water levels in Lake Salt is still ~ 1 month, which cannot be regarded as near real time monitoring at this stage. Nevertheless, the temporal resolution of optical water levels can be further improved by adding other missions such as Sentinel-2 that has a higher temporal resolution than Landsat series. A new data set termed harmonized Landsat and Sentinel-2 Reflectance Product has been generated recently, which we believe would improve the quality of optical water levels and make it near-real-time observation.

Response to short comment 2

General Comment:

This is a valuable and interesting manuscript. The authors have exploited multisource remote sensing (i.e., multiple altimetric missions and Landsat archives) to create dense time series of lake water level and storage changes across 52 large lakes on the Tibetan Plateau. There are some previous studies focusing on changes in water level and storage on the Tibetan Plateau; however, these studies just got relatively lower temporal sampling and little altimetric information was used. It may limit the accuracy of trends in lake water level/storage in some cases and short-term monitoring of lake overflow flood. Therefore, I am firmly convinced that the densified water-level dataset derived by the authors can have tremendous practical value in studying water storage changes and regional hydrological processes on the Tibetan Plateau.

Response:

We thank Dr. Wu for these encouraging and constructive comments. As Dr. Wu's indicated, this work aims to provide improved lake water level and storage change estimates in terms of temporal resolution as well as accuracy. We appreciate all these comments from the community. Our responses to these comments are given as follows.

Specific Comment:

1) As far as I am concerned, deriving altimetry water levels through multiple altimetry missions (including Jason-1/2/3, ENVISAT, ICESat-1, and CryoSat-2) is the key component. I think the manuscript needs a more detailed description of this methodology in section 3.1.

Response:

Thanks for this comment. It is indeed important to clarify the method we used and developed to derive lake water levels from altimetry data. The waveform retracking methods in this section could be the most important part regarding technical details. Here we provided a general equation (Eq 1) for surface height calculation mainly because different sensors have different correction items, e.g., the saturation correction for ICESat (laser altimeter) was not applicable to radar altimeters.

As for waveform retracking correction, which is crucial to radar altimeters, we performed existing algorithms (e.g., the NTTP method for Croysat-2) or used a default method provided by the altimetry product (e.g., the ICE-1 retracking method). These methods have been widely tested and recommended based on in situ measurements. However, there can be a paradox when several studies suggested different methods for the same altimeter. If so, we can only apply the rule of thumb to choose those that balance the robustness, computational cost, and accuracy (e.g., the Improved Threshold Method for Jason-1/2/3).

In fact, the original idea of the NTTP, ICE-1, and Improved Threshold Method is quite similar. All of them adopt a threshold defined as the percentage of waveform peak to determine the retracking gate, and then transfer the difference between the retracking gate and the nominal gate into range correction by multiplying the gate range ($c\Delta t/2$, where c is the speed of light and Δt is the time duration of a gate). The differences lie in the choice of thresholds as well as the calculation of waveform peaks. Therefore, we think it would be more suitable to provide some general information in the manuscript about threshold retracking schemes and to clarify the similarities and differences among the retracking methods we used.

This part will be modified in the revised manuscript.

Modifications: A separate paragraph was inserted following the 3rd paragraph of section 3.1 to briefly introduce the threshold waveform retracking scheme.

2) To validate the derived optical water levels, the authors used pressure type water level sensors to measure water pressure and converted them into water depths. How to convert the water depths into the actual water level and unify to the same reference datum with optical water levels? It should be clarified

Response:

Thanks for this comment. The water level measured by the pressure type sensor is the water depth (~20 m) of the installed location, while the water level acquired from optical images/satellite altimeters is the surface height with respect to EGM96 which generally has a value ~4000 m. To make them comparable, we calculated water level anomalies for the both time series. This part will be illustrated in detail in the revised manuscript.

Modifications: An explanation was inserted to the 1st paragraph of section 4.2.

3) Pg.1, Line 14 "(>100km2) " should be " (>150km2) "?

Response:

Thanks for this comment. Actually, we do have investigated almost all Tibetan lakes larger than 150 km^2 (except for one or two lakes with too limited altimetry/optical data) and several lakes between 100–150 km^2 (e.g., Lake Salt). This part will be modified in the revised manuscript to avoid confusion.

Modifications: An explanation was inserted to the Abstract to clarify the lake area.

4) The legend of Figure 11 should be revised (add unit and scale).

Response:

Thanks for this comment. It will be corrected in the revised manuscript.

Modifications: Unit and scale were added to Figure 11.

5) Figure 16, miss unit in y axis

Response:

Thanks for this comment. It will be corrected in the revised manuscript.

Modifications: Unit of y axis was added to Figure 16.

Response to referee comment 1

Comment:

In this study, the authors developed a lake level dataset with dense samples for large lakes in 2000–2017 in the Tibetan Plateau (TP). The lake level product is validated by in situ water level measurements for Yamzhog Yumco. The water volume changes of 52 lakes with lake level were also estimated. This dataset is very valuable for studies of lake variations and their response to climate change in the TP and lake water balance. I recommend this manuscript to publish in ESSD, but some improvements based on comments below are necessary.

Response:

We really appreciate these overall comments and recommendation by this reviewer. Our point-by-point responses to the reviewer's comments are given as follows.

General comments:

1) The uncertainties for lake volume changes and other number should be added through the manuscript.

Response:

Thanks for this comment. They will be added into the revised manuscript.

Modifications: Uncertainties were added for every lake volume/water level number, most of them appear in the Application section.

2) What is optical water level? It is estimated by the correlation between lake area and level, and then to reconstruct the corresponding lake level using known lake area?

Response:

Thanks for this comment. As illustrated in Page 10, line 20, the generation of optical water levels is similar to the description in this comment but is based on changes in lake shoreline observed in a smaller ROI (region of interest) rather than the whole lake area (e.g., the yellow square shown in Page 12, Figure 3 (b)). The reason for this is due to the increasing computational cost and probability of cloud/gap contamination with increasing areas of ROI. On the other hand, it is pointed out in section 4.2 that if the ROI had a larger width (here 'width' is in the direction parallel to the shoreline), the uncertainty of optical water level would decrease. Therefore, the choice of the ROI is a trade-off between the accuracy and data availability or computational cost.

3) How all the lake level datasets are converted to same geoid?

Response:

Thanks for this comment. For altimetry water levels, the initial reference ellipsoid and geoid are different for different satellite missions/products. Information on the reference ellipsoid and geoid is listed in Supplement Table 1:

Supplement Table 1

Altimetry mission	Reference Ellipsoid	Geoid
Envisat	WGS84	EGM2008
ICESat	T/P	EGM96
CryoSat-2	WGS84	EGM96
Jason-1/2/3	T/P	EGM96

As mentioned in the manuscript, different altimetry water levels were merged by comparing the overlap period (more details are available in the response to short comment 1). Systematical biases caused by the geoid and reference ellipsoid were removed during this process.

For optical water levels, they were generated using linear regression with a certain source of altimetry water level data so they have the same reference ellipsoid and geoid with the respective altimetry data used in the regression. And they can be merged with other altimetry data by comparing the overlap period as well.

However, there is a correction that must be made to the manuscript in Page 8, Line 18. "…all water levels were with respect to EGM96…" was incorrect. For the 12 lakes with Jason data, all kinds of water levels were converted into T/P, EGM96, because the Jason-1/2/3 data were used as the baseline (i.e., the longest records will be used as the baseline). For the rest of the lakes we mainly used Envisat data as the baseline to merge all the water levels. Therefore, for lakes without Jason data but having Envisat data, the water levels were converted into WGS84, EGM2008 (see Supplementary Table 1 above). For lakes without either Jason or Envisat data, Cryosat-2 data were used as the baseline, so water levels for these lakes were converted to WGS84, EGM96. We will provide a supplement document to mark out the Reference Ellipsoid and Geoid for each lake.

Modifications: "…all water levels were with respect to EGM96…" was removed from the manuscript; a table containing reference ellipsoid and geoid for each lake was provided in the supplementary file.

4) In this study, lake boundaries were extracted using GEE. The visual checking and

manual editing of delineated lake boundaries with original Landsat images are very necessary. How this was done at GEE platform?

Response:

Thanks for this comment. Lake areas or lake boundaries were used in two situations in this study: the first is during the process of generating hypsometric curves and the second is during the selection of altimeter footprints. We used lake areas derived from GEE in the first situation but used an existing dataset based on manual delineation produced by Wan et al. 2016 in the second situation. Therefore, problems raised in this comment may only exist in the first situation.

Visual checking can be hard to perform on GEE due to a large number of images we used, but we did visually check and preclude some of the images that resulted in outliers in the extracted lake surface areas (e.g., the entire ROI was covered by snow resulting in the failure of the Otsu method). It is true that manual editing of lake boundaries is important if we only use a small number of images (e.g., less than 10 images) to derive hypsometric curves (which is common in similar studies, e.g., most hypsometric curves provided by Hydroweb used less than 10 data pairs).

Nevertheless, for most lakes (42 out of 52) in our study, we used more than 20 data pairs (i.e., lake water area and corresponding lake water level) to fit hypsometric curves. More data pairs we used make the hypsometric curves more robust, even though there may be some misclassification in a single image. This is evidenced by the fact that most R^2 values for the hypsometric curves are higher than 0.9. In addition, all the images used in the regression analysis met the criterion of cloud contamination less than 5%, which has largely reduced uncertainty in the extracted lake water area.

5) How the in situ water level for Yamzhog Yumco is converted to consistent reference ellipsoid with satellite altimetry data? For validation of lake water classification with UAV, how about classification accuracy?

Response:

Thanks for this comment. As illustrated in our response to short comment 2, the in situ water levels of Yamzhog Yumco were made comparable with the satellite altimetry/optical water levels by calculating the anomalies of each water level time series.

Lake water classification with UAV images was performed by manually identifying the lake shoreline using ArcGIS. Therefore, the uncertainty in the UAV derived lake shoreline is considerably small, because the spatial resolution of the UAV image is ~5 cm.

Specific Comments:

1) Page1: "There are more than 1,200 alpine lakes larger than 1 km^2 (Zhang et al., 2017a)" This result should come from Zhang, G. et al., 2014. Lakes' state and

abundance across the Tibetan Plateau, Chinese Science Bulletin, 59(24):3010−3021. Please correct this cite here.

Page 2: ETM should be ETM+, not a superscript symbol of +, others are similar.

Response:

Thanks for this comment. They will be modified in the revised manuscript.

Modifications: The reference (Zhang, G. et al., 2014) was added in the 1st paragraph of introduction and "ETM^{+}" was change into "ETM+" everywhere.

2) Page 4: "examine long-term", 2000–2017 is not long-term.

Response:

Thanks for this comment. "Long-term" will be changed into "multiyear".

Modifications: "long-term" was changed into "multiyear" everywhere.

3) "The TP can be generally divided into 12 major basins... ". Two suggested reference here:

   Wan, W. et al., 2016. A lake data set for the Tibetan Plateau from the 1960s, 2005, and 2014, Scientific Data, 3:160039.

   Zhang, G. et al., 2013. Increased mass over the Tibetan Plateau: From lakes or glaciers?, Geophysical Research Letters, 40(10):2125−2130.

Response:

Thanks for this comment. They will be added into the manuscript.

Modifications: The two references (Wan, W. et al., 2016, Zhang, G. et al., 2013) were added in the 1st paragraph of section 2.1.

4) Lake Selin Co-> Selin Co, others are similar

Response:

Thanks for this comment. They will be modified in the revised paper.

Modifications: "Lake Selin Co" was changed into "Selin Co"; "Lake Nam Co" was changed into "Nam Co": "Lake Zhari Namco" was changed into "Zhari Namco"; "Lake Goren Co" was changed into "Goren Co"; "Lake Urru Co" was changed into "Urru Co"; "Lake Yamzhog Yumco" was changed into "Yamzhog Yumco".

5) Page 5: "a lake shape data set generated by Wan et al. (2016) was used". This lake shape data was derived from GF data. How about the shift of lake outline? Did you check it with original Landsat images or Google Earth?

Response:

Thanks for this comment. Yes, we did notice that lake outlines derived from GF data that were only used for generating the 2014 subset of the data set by Wan et al. (2016)) have a shift relative to those derived from Landsat ETM+ and CBERS-1 that were used for the 2005 subset of the data set). Therefore, we only used the 2005 subset of the data set to select altimetry footprints in our study.

6) "We managed to make use of some images with gaps in generating lake shore changes." How to understand it?

Response:

Thanks for this comment. As shown in Figure 3 (b), the ROI we used to derive lake shoreline changes is small enough to be fitted into an ETM+ image strip (valid pixels) between two gaps (no-value pixels). In this way, we can make use of some images with gaps. However, the gaps are shifting so we set a criterion (no-value pixels in the ROI should be less than 2%) to remove those images for which the ROI is contaminated by shifting gaps.

7) "A half of them were excluded from the final results due to cloud contamination or gaps." How this is determined? Some lakes are missed? How to make sure a high-quality output of lake boundary, especially lake with little ice or turbid water?

Response:

Thanks for this comment. As illustrated in the manuscript, we have excluded images which have more than 5% cloud pixels or 2% no-value pixels in the selected ROI. "A half" is an approximation for the portion of effective images when generating optical water levels. To further show this, we randomly chose five lakes to present the portion of effective images:

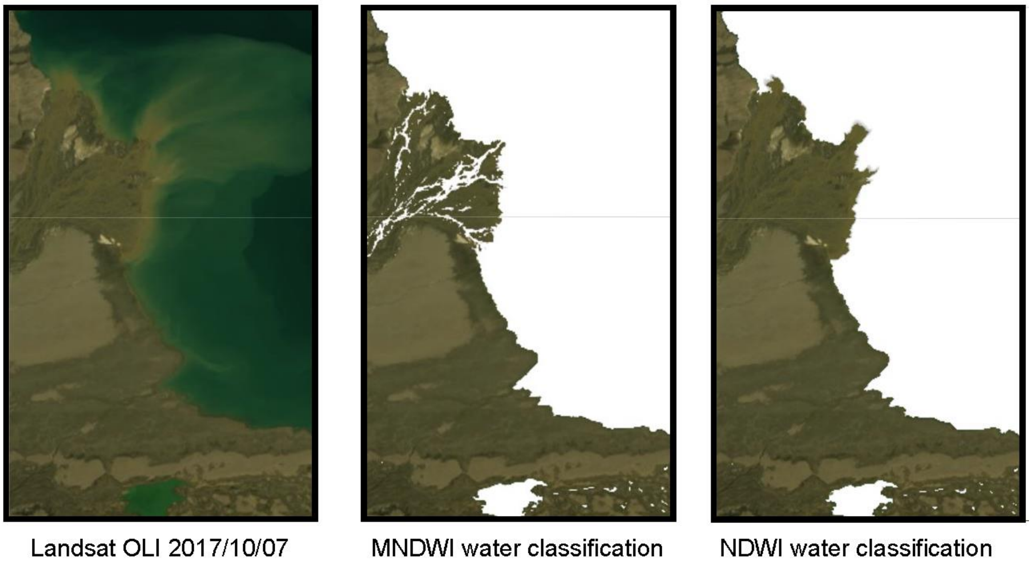
Supplement Table 2

Lake name	TM	ETM+	OLI	Total
Jingyu	90/287	225/360	58/128	373/775
Zhari Namco	127/308	47/229	178/371	352/908
Mapam Yumco	50/57	216/274	85/121	351/452
Lumajiangdong Co	74/183	78/561	68/250	220/994
Aqqikkol Lake	169/387	108/557	109/246	386/1190
Total	510/1222	674/1981	498/1116	1682/4319

Effective ETM+ images have a lower portion due to gaps. But for Landsat TM and OLI images, the portion is appropriately 1/2. However, the portion of effective images that can be used to derive lake water areas, instead of optical water levels mentioned earlier, is much smaller, sometimes less than 10%, which is due to the increasing probability of cloud/gap contamination with increasing areas of ROI.

We did consider the impact of lake ice or snow on the accuracy of lake area/lake shoreline extraction. Both MNDWI and NDWI were not able to well discriminate lake ice and water as what we had expected (i.e., if lake ice was eliminated, the extracted lake area would be smaller than its real size). We noticed that the MNDWI cannot completely discriminate snow and water either, resulting in artificial increases in lake areas in winter when the lake bank was covered by snow. Therefore, the NDWI was used to better discriminate snow from water/floating lake ice in winter. However, if there was snow cover on the lake ice, the NDWI could also produce artifacts in the derived lake area and we had to remove these outliers manually as we mentioned earlier.

As for the turbid water problem which mainly occurred in summer, we examined the study lakes and found that both MNDWI and NDWI can precisely locate the lake boundary, even though the near-shore water color was affected by turbid inflow as shown in Supplement Figure 1:



Supplement Figure 1: Water classification results at the estuary of Lake Kusai based on the MNDWI and NDWI during the flood season.

The difference between the MNDWI and NDWI is that the MNDWI is able to detect shallower turbid water than the NDWI (e.g., shallow rivers can be detected by MNDWI in Supplement Figure 1), which is important in determining the accurate position of lake shorelines. If the NDWI was used in summer, less information on changes in lake shoreline (i.e., optical water level) would be detected. On the other hand, rivers and other small water bodies near the lake can lead to noise to the extracted lake area due to the sensitivity of the MNDWI. Therefore, we carefully chose the ROI to avoid rivers or small water bodies. A comparison between the MNDWI and NDWI was performed by (Huang et al., 2018) based on UAV images, which also shows that the MNDWI has better performance than the NDWI under the condition without snow cover.

8) Table 2: "d, m, km" can be put first row of table, then others below can be removed.

Response:

Thanks for this comment. Yes, it will be modified in the revised manuscript.

Modifications: Units of Table 2 were moved to the first row.

9) "Either comparing the mean water level of the overlap period or comparing the two water level time series with changes in lake shoreline" How about the uncertainty and it is reasonable?

Response:

Thanks for this comment. The uncertainty of this method is important, because errors induced by this data merging method will evolve into the merged water levels and become remaining systematical biases. Such biases will cause artificial rises or falls of the merged lake water levels, jeopardizing the consistency of the merged lake water levels between different time periods and sensors. Therefore, the consistency of the merged water levels can reflect the remaining systematical biases and the uncertainty of the data merging method that caused these biases.

However, it is a dilemma that evaluating the consistency of the merged water levels is difficult to perform without continuous in situ observations over multiple years. As far as we know, there are few continuous measurements of lake water levels in the Tibetan Plateau due to the equipment failure in the frozen season (e.g., caused by fierce winds, waves, and freezing process). For instance, several water level sensors have been set up in Nam Co since 2005 (Song et al., 2015), but the in situ water level measurements of Nam Co presented in the literature were discontinuous in the frozen season.

Therefore, the best available reference we used to assess the consistency of the multiple altimetry water levels when there is no overlap period is the optical water level. Optical water levels are generally continuous in our study period and could even be more reliable than intermittent ground observations. Given the fact that continuous ground observations do not exist, are not accurate enough, or are not accessible if any, the altimetry data merging method proposed in this study is a reasonable and effective way to generate longer and denser time series on lake water levels.

10) As the differences of extracted lake outlines, it is better to use a unique NDWI or MNDWI in classification of water and other land-cover in the study period? In addition, the differences from NDWI or MNDWI are not apparent?

Response:

Thanks for this comment. Based on response to Comment 7, it is clear that either NDWI or MNDWI has pros and cons and may perform quite differently. Therefore, a combination of the two water indices is a reasonable solution and has been used in this study.

11) "We selected images with less than 5% cloud cover". Some images with free-cloud coverage on lake shorelines are still useful?

Response:

Thanks for this comment. Yes, they are. Moreover, the cloud mask algorithm imbedded in the Landsat QA band is quite sensitive. Sometimes an image with light cloud in ROI slightly higher than 5% is still useful, because water indices are not largely affected. A 20% threshold was used by (Huang et al., 2018), which also produced satisfactory results.

12) Figure 11: background of this figure is not clear?

Response:

Thanks for this comment. Yes, the background has been changed into green now.

13) Figure 12: What is a high peak in Figure 12 in about 2010?

Response:

Thanks for this comment. It may have been caused by an outlier that was not removed prior to uploading the generated data set. In the uploaded data set, such a peak does not exist. It will be corrected in the revised paper.

Modifications: Figure 12 (now Figure 13) was revised with outliers removed.

14) Figure 13: The trend of lake storage change is more robust than the result from Yao et al (2018) from Yao, F. et al., 2018. Lake storage variation on the endorheic Tibetan Plateau and its attribution to climate change since the new millennium, Environmental Research Letters:1-16. What is the cause for this difference?

Response:

Thanks for this comment. As illustrated in Line 5–7 in the manuscript Page 23, our data (a combination of the merged optical water levels and altimetry water levels) have higher sampling frequency than (Yao et al., 2018a), resulting in a more robust estimation of the trend in the lake water levels. As shown in Figure 12, there are several abrupt changes with magnitudes up to ~3 km^3 in lake storage observed by (Yao et al., 2018a), which is not likely to happen, given that there is no report on basin flood/upstream lake overflow. This could be due to the uncertainty in the lake area they derived and applied to estimate changes in lake storage. We also noticed that lake areas derived from Landsat archives could be much noisier than lake shoreline changes, due to cloud contamination/temporary small water bodies within the ROI. Therefore, we have calculated changes in lake storage with water levels and hypsometric curves, instead of directly using water levels and lake areas to reduce the uncertainty in derived lake areas.

15) Figure 15: How to understand the difference of lake level between these different datasets, especially polylines for optical water level?

Response:

Thanks for this comment.

First, the difference between altimetry water levels in our data set and the Hydroweb data set mainly comes from following processes: (1) different reference ellipsoids and geoid models, (2) different retracking methods, and (3) different schemes of removing systematical bias. The last process is the most significant difference that could make our data set more consistent compared with the optical water levels as we explained in response to specific comment 9.

Second, the difference between the optical water levels and altimetry water levels mainly comes from different mechanisms of observations. Altimetry water levels are based on the time delay between the generated and received signal measured by altimeters. Each cycle corresponds to one water level value averaged from several footprints across the lake. Therefore, the number of footprints in a cycle is crucial to the accuracy of altimetry water levels. Footprints falling on a study lake are determined by the orbit of the satellite altimetry and the size of the lake, both of which are fixed.

On the other hand, optical water levels are derived from optical images, which could be affected by cloud cover. Therefore, there is not a fixed temporal resolution for optical water levels. As illustrated in section 4, optical water levels are mainly affected by the slope of lake shore, the width of ROI, the spatial resolution of the optical image, and the accuracy of the water classification method. Some of these factors, such as the width of ROI, spatial resolution, and slope can be well handled. Therefore, optical water levels are less noisy than altimetry water levels.

16) "5.3 Lake overflow flood monitoring". Many similar Chinese papers have been published. It is not need to include in the Title of this manuscript and put some in discussion is enough? In addition, some sentences such as equation can be moved into Method section?

Response:

We have revised the title of this manuscript according to this comment. Content associated with lake overflow flood monitoring is no longer reflected in the title, but has been put in the method and discussion sections. These modifications will be shown in the revised paper after considering all reviewers' suggestions.

Modifications: The title has been changed with “overflow” removed and part of the section has been moved into the supplementary file.

17) Xiaojun et al., 2012 -> Yao et al., 2012

Response:

Thanks for this comment. It will be modified in the revised manuscript.

18) "Water loss was more likely to be found among the southern TP lakes. In the Selin Co basin, a more complicated spatial pattern of lake storage changes was detected, as small lakes were slowly losing water whereas the large lake was gaining water, which we speculated to be caused by lake-river interactions that need further investigation." These conclusions have found in previous studies. The summary

here should more focus on the lake level data developed in this study.

Response:

Thanks for this comment. It will be modified in the revised manuscript.

Modifications: This part was revomed from the 2nd paragraph of conclusion.

19) Section 4 is too long? It can be shortened?

Response:

Thanks for this comment, we plan to move part of the content in section 4 into the supporting information.

Modifications: Part of section 4 was removed into the supplementary file.

Response to referee comment 2

Comment:

This study combines altimetry data that measure lake levels directly with shoreline positions from optical data to create extended and denser lake level time series for the largest lakes of the TP. In that sense, the resulting dataset differs from existing lake level time series and seems thus a valuable resource for the scientific community as well as other users. The study is relevant for ESSD and worth publishing. To properly document the data and methods and to comply with ESSD's guidelines, the manuscript needs to be improved - in particular to better describe important parts of the methods, include/consider uncertainties, and properly validate the time series against existing data sets.

Response:

We really appreciate the overall evaluation, insightful comments, and recommendation by this reviewer. Our point-by-point responses to the reviewer's comments are given as follows.

General comments:

1) The study would benefit from a clearer story line and justification how this work/data fills a current knowledge gap. I only understood the plot halfway through the methods. What are the shortcomings of the existing studies/datasets, and how do you overcome these with your study? This is especially important for the introduction, but also the abstract and conclusion would benefit from an easier to understand quick summary. See also comment paragraph P8, L11ff below.

Response:

Thanks for this constructive comment. As suggested by this Reviewer in specific comments, we have reorganized several paragraphs and enhanced how our study and developed data set fill a current knowledge gap in the introduction, abstract and conclusion sections. Abstract and conclusion sections have also been improved by reducing all redundant information. Details can be found in the attached modified manuscript.

2) Method: the important novelty of your approach is the use of shoreline positions from optical data to increase the temporal resolution and extend the length of the water level time series. To do so, you relate shoreline positions to lake level elevations from spaceborne altimetry data, using a statistical relationship between the two. Currently, the statistics part is not well enough described, and uncertainties from the found relationship do not seem to be propagated to your final "optical water levels". I suggest you extend this part to provide more transparency and include also a discussion of the uncertainties, considering in particular the assumption of a linear relationship (?) and whether it is appropriate to extrapolate beyond the range of measured lake levels.

Response:

Thanks for this very insightful comment. As suggested by this Reviewer, we have extended section 3.2 (optical water level) and provided a discussion in section 4.2 to better evaluate the uncertainty in the regression relationship and how it propagates into optical water levels. The extrapolation problem is discussed in section 4.2 as an interpretation of the propagated regression uncertainty and in this response letter too (specific comment 8 of the method section). We believe that the impact of extrapolation of optical water levels possibly occurring in the time gap between two altimetry time series has been well addressed in this response letter (specific comment 8 of the method section) and will be added to the supplementary file. However, we acknowledge that little information is available to quantify the effect of extrapolation during the time window from 2000–2002, as little altimetry information is available due to either poor quality or limited observations, and available DEM is too coarse to describe the micro topography of the lake bank. We have informed potential readers/users of such a risk in the validation and conclusion sections of the revised manuscript.

3) Dataset: I'm missing a detailed description of the final dataset and its attributes and uncertainties, e.g. after the validation section.

Response:

Thanks for this comment. The description of the dataset is combined with the data availability following the validation part now.

4) Validation (and uncertainties):

   a) What is the accuracy/uncertainty of the altimetry products, and how does this propagate to your optical water levels? Consider also the uncertainty of the statistical relationship (s) you compute to derive the optical water levels.

Response:

Thanks for this insightful comment. We used the standard deviation of water levels from valid footprints in a cycle to represent the uncertainty in the altimetry product. The valid footprints are referred to as the footprints selected with the histogram method as illustrated in the manuscript. For most cases they comprise more than 80% of all available footprints in a cycle. As suggested by this Reviewer, a thorough discussion of the error propagation from the altimetry data to the optical water level through the statistical relationship has been added in section 4.2.

b) The theoretical computation of an uncertainty (most of 4.2) based on a single UAV image is not convincing to me as it is based on a single image pair only with unknown coregistration accuracy (see comment below). The lack of hands-on data basis and the extensive length of the theoretical part makes this off-topic. Maybe this could fit as supplementary information in a separate document.

Response:

Thanks for this insightful comment. We have redone the uncertainty analysis based on high-resolution optical images from GF-2 (i.e., China's high spatial resolution satellite) and investigated a total of 4128 Landsat shoreline pixels after performing co-registration (the co-registration error was estimated to be ~2 m). Based on the new experiments and results, we have modified part of section 4.2, making it more convinced. Considering the excessive content of section 4, we will move part of the theoretical derivation to a supplementary file as suggested by this Reviewer.

c) Rather than treating the comparison to the LEGOS Hydroweb data as an application case this should be part of the validation section. How do your time series compare to the other datasets listed in table 1?

For data description, uncertainties and validation see ESSD's guidelines at https://www.earth-syst-sci-data.net/10/2275/2018/, in particular sections 3.3, 3.5 and 3.6.

Response:

Thanks for this comment. We have moved part of the comparison with Hydroweb data to the validation section. We chose to make a comparison with the Hydroweb because Hydroweb data have exploited most altimetry missions and provided densest altimetry water levels among all listed studies (also for most lakes the systematic biases between altimetry missions seem to have been well removed), very typical for altimetry-based lake studies. Other altimetry-based lake studies may include more lakes, but based on the published results they are subject to some systematic biases. Therefore, we have taken the Hydroweb data as the benchmark to see if there are improvements or advantages in our generated product.

We did compare our lake data with that of Yao et al. (2018b) and show the importance of temporal resolution, as we are not comparable with the lake quantity of these kind of studies based only on Landsat images and DEM. Studies that primarily use Landsat images and DEM are able to cover a larger number of lakes and are not subject to systematic biases as those using various altimetry data sources. However, most of those studies have a low temporal resolution (e.g., annually or even lower) due to the difficulty of acquiring quality optical images covering entire lake areas at a high temporal resolution, as opposed to our study that needs optical images covering a small portion of the lake shore.

Specific Comments:

A simpler title might make it easier to understand what the study is about. Especially the rather unclear terms "densified" and "developed optical water levels" should be replaced. Focus on the data and not the application cases.

Response:

Thanks for this constructive comment. The tentative title of this study has been revised as: "Generation of high temporal resolution water level and storage change data sets for lakes on the Tibetan Plateau during 2000–2017 using multiple altimetric missions and Landsat-derived lake shoreline positions and areas" for your kind suggestion.

Abstract

1) The abstract could be more to the point. Add some information on the performance of your data (uncertainties and validation). Consider removing already published findings (applications).

Response:

Thanks for this constructive comment. We have removed numerical results similar to some published work such as lake storage trends and lake overflow amount. More information on the validation and uncertainty has been added, as we performed additional experiments with high-spatial-resolution images. Details can be found in the revised manuscript.

Modifications: Numbers of lake volume changes were removed from the abstract; validation of the optical water level was emphasized.

2) L12: which altimetric missions? If there are too many to list all, specify how many and which types (e.g. Lidar altimetry, interferometric SAR altimetry...)

Response:

Thanks for this comment. All altimetric sensors used in this study have been listed in Table 2. For the sake of brevity, we decide not to list them in the abstract.

3) L13: avoid putting important information in brackets. Monthly to weekly time

series? L16: "partial altimetry data" and "optical water levels" are unclear terms

Response:

Thanks for this constructive comment. This sentience has been modified. Brackets in L13 have been removed and a brief explanation to optical water levels has been added.

4) L19: "densified" is unclear

Response:

Thanks for this comment. It has been replaced with "merged".

5) L20ff: Are these groundbreaking new numbers/findings? Consider removing them and focus on the dataset.

Response:

Thanks for raising this comment. These numbers are actually not that different from published studies, but they can serve as an independent source of information from relevant studies, as we have generated a new dataset with temporal resolution being greatly improved and systematic biases being well removed. We have removed these numbers and placed more emphasis on the dataset itself.

Introduction

1) P2, L3: A strong motivation for TP lake studies not mentioned here is to find out why they are expanding, i.e. a good data set will contribute to a better understanding of climate and circulation patterns and changes thereof. This is important as the TP has a strong influence on both regional climate.

Response:

Thank you so much for this comment. We have added this to the first paragraph of introduction to clearly state the motivation of TP lake studies that a good data set should contribute to a better understanding of climate and circulation patterns and changes.

2) P2, L6: source of that number?

Response:

The source is (Messager et al., 2016).

3) P2, L8: I wonder why you selected exactly these references? There are many more lake studies on the TP. References for the method (general) and local application should be separated.

Response:

Thanks for this comment. We agree that more general studies instead of local applications may be cited. Now we have cited the earliest one that we can find to represent this kind of studies using remotely sensed water surface height and extent performed by Frappart et al. (2005).

Modifications: References here were changed into (Frappart et al. 2005)

4) P2, L11: It is better to introduce radar and lidar separately as the systems and data are quite different. Also, these data are not meant for ice berg height - you probably mean ice sheet surface elevation or sea ice freeboard?

Response:

Yes, this makes sense. We have separately introduced laser and radar altimeters and added a supplementary description of the two types of altimeters to underscore the differences between them in this paragraph. We agree that the altimetry data are not meant for ice berg height. It has now been corrected in the revised manuscript.

Modifications: “ice berg” was changed into “ice sheet/ice freeboard”.

5) P2, L16: The satellite is called ICESat, not ICESat-1. Change everywhere.

Response:

Done.

6) P2, L25: it seems you mainly mean (and in your study only use) optical data. Do you have an example for a sensor and study that used SAR data?

Response:

Yes, SAR images from Sentinel-1 were used by Huang et al. (2018) from our group to derive the effective river width, which is calculated with the river surface area divided by the river length. The automatic extraction of the river surface area is similar to that of the lake surface area or lake shoreline changes. We may take advantage of SAR data in future studies.

7) P2, L26: why exactly these references? These are not the only or first such studies.

Response:

It is true there are many published studies on water classification/extraction. We chose these two references mainly because they are similar in study area, data source, and publishing time, showing a good comparison between methods. We would like to show a change in this kind of studies and to stress the point that manual extraction of lake boundary could be labor-intensive and low-efficiency.

8) P2, L33: references for the water index and Otsu algorithm?

Response:

Done.

9) P3, L10f: remaining bias: is this not true for your study, too? Or how do you avoid/remove such bias?

Response:

We have done our best to remove the systematic bias between different altimetry missions by using optical water levels as reference data, which is rarely seen in the literature. Hwang et al. (2019) showed that the systematic bias among different altimeters is hard to remove unless in situ water level measurements or Jason-1/2/3 data are available. Our method could provide a better solution to this problem. We would not say there is no remaining systematic bias in our data, but we are confident that the biases have largely been reduced. Even though there might be some concern about the accuracy of the optical water levels because altimetry information is involved in the generation, they are currently the best available long-term reference data for ungauged lakes.

10) P3, table1: Does this table include all studies, or how did you select? Either remove all that do not compute lake levels, otherwise consider also including "complete" TP water studies for a larger number of lakes than the ones you are listing (e.g. Pekel et al (2016) to whom you refer to earlier, or Yang et al. 2019, doi:10.5194/tc-2018-238; Treichler et al. 2018, doi:10.5194/tc-2018-238...)

Response:

Thanks for this constructive comment. We consider it is quite reasonable to exclude those references without water levels, as our study focuses on improving the quality of merged water levels and subsequently improving lake storage change estimation.

Modifications: (Wan et al., 2016) and (Yang., 2017) were removed from Table 1.

11) P4, L4: the meaning of "hypsometric curve" is unclear to me in this context.

Response:

We noticed that in some studies hypsometric curves represent the total area above a certain elevation, which means that at the lowest elevation the hypsometric curve reaches its maximum value. However, in this study, hypsometric curves represent the lake surface area at a given water level, which means that the curve reaches its maximum value when the water level is maximized. We adopted this denotation as same as the LEGOS Hydroweb. To make it clear, we have added an explanation in brackets in the context.

Modifications: An explanation in brackets was added following “hypsometric curve”.

Study area and data

1) Parts of this (e.g. from P5, L24, or P6, L1ff) rather belongs to the method section.

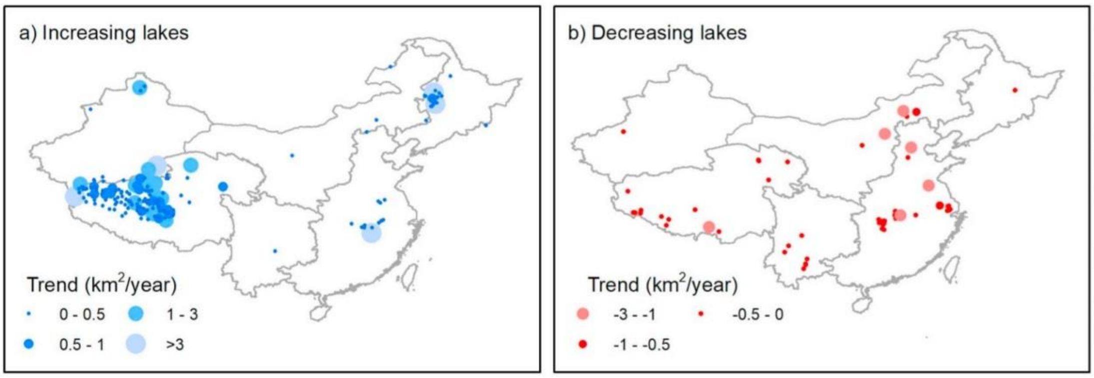
Response:

Thanks for this comment. We have moved partial content to the method section. For instance, we have moved P5 L24–L26 to the second paragraph of section 3.2.

2) P4, L16: "as opposed to many other places..." - I tend to disagree, as nearly all seem to have expanded. Can you justify or explain more clearly?

Response:

We only studied 12 lakes outside the endorheic basin for the recent twenty years, which possibly caused such an impression that all lakes have experienced expansion. Exorheic lake shrinkage in the TP in the past 50 years can be seen from (Zhang et al., 2019) as shown in the figure below.



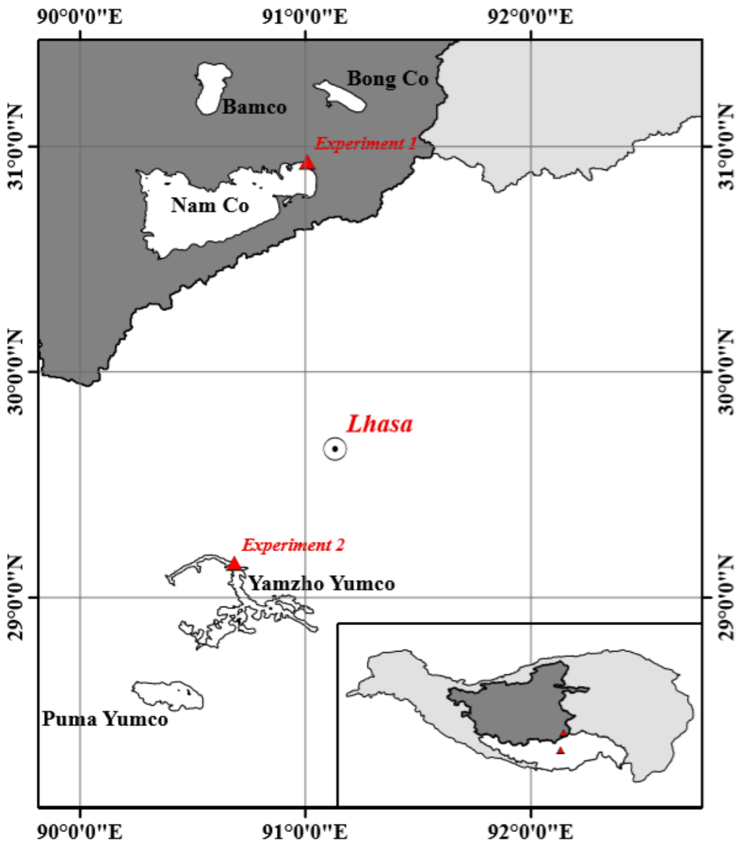
In addition, most global endorheic basins have experienced water loss in recent years, whereas the endorheic region in the TP has gained water (Wang et al., 2018). This phenomenon has also drawn a lot of attention for the endorheic basin in the TP.

3) P5, L4ff: why did you choose these lakes in particular? And where is Lake Yamzhog Yumco? An overview map might be useful.

Response:

The reasons why we chose Yamzhog Yumco and Nam Co are threefold: (1) they are close to the city, making it easier for logistics and transportation; (2) they are both large lakes, typical in our study; and (3) one of them is located in the endorheic basin (Nam Co), and the other is from the exorheic basin (Yamzhog Yumco), increasing the representativeness of the experiment.

Following figure will be added into the manuscript to clearly show the two experiment locations:



4) P5, L17: "moderate set of orbital parameters" is unclear

Response:

Thanks for this comment. We have made it clear. We meant to show that Envisat has a lower orbit than Jason-1/2/3 but higher than ICESat, thereby for sampling frequency: ICESat<Envisat<Jason-1/2/3, and for spatial coverage: ICESat>Envisat>Jason-1/2/3.

Modifications: "moderate set of orbital parameters" was removed, replaced by "…a lower orbit than Jason-1/2/3 but higher than ICESat…"

5) P5, L30: when were the drone data acquisitions?

Response:

The drone images were acquired in the morning on May 19 and 21, 2018, for Yamzhog Yumco and Nam Co respectively. The Landsat images used for validation purposes were both acquired on May 19, 2018.

6) P5, L31: "similar" in what sense? What have Huang et al done?

Response:

Huang et al. (2018) used UAV images to evaluate the performance of water auto-extraction with four water indices based on Landsat 8 images. The accurate water surface boundary was extracted manually from the UAV images using ArcGIS, and then water extraction results from Landsat using different water indices were compared with the accurate water surface area from the UAV images. Our data source and method are similar, but focused on different targets. On the other hand, we have performed a systematic analysis to link the uncertainty in water surface area extraction to the uncertainty in optical water levels.

7) P6, table 2: Some of the missions included many instruments (e.g. ENVISAT: 10 sensors). You need to specify which sensor and data you used. Here, you distinguish between "radar" and "interferometer", which is also based on radar (SAR/interferometric radar altimeter). This is confusing, and it would be useful to explain the technologies/differences either in the introduction or in a separate paragraph in the data or methods section

Response:

Thanks for this constructive comment. It is important to clarify the sensors and data we used, and they have been added to the table now. The classification of different radar altimeters in the original manuscript might be confusing as indicated by the reviewer. Therefore, we have provided a brief explanation after the first paragraph of section 2.2 on the mechanism of different altimeters including SIRAL onboard CryoSat-2.

Modifications: Information of sensor name and type was added into Table 2, as well as data record name; A separate paragraph was added following the 1st paragraph of section 2.2 to clarify the difference between different altimeters.

Methods

1) The first paragraph seems to explain what this study is about and would thus fit (better?) to the introduction (it is missing there!).

Response:

Thanks for this comment. They have been moved to the introduction section.

2) P6, L8: "comparing the mean water level of the overlap period" is vague. Explain better.

Response:

Thanks for raising this issue. It has been explained in detail in our response to short comment 1 (the first question in short comment 1). We have also added a separate paragraph at the end of section 3.2 to better explain this part.

3) P7, figure 1: refer to the figure in the text, e.g. when you introduce the data and where you are talking about overlap periods. Consider adding the optical data to the figure to show the overlap periods you use to create the optical lake level-lake surface elevation relationship.

Response:

Yes, we have added references to Figure 1 in three places where we think it is necessary. In addition, the optical data are presented in Figure 1. However, it is not easy to show the time period we used to derive optical water levels from altimetry data, because for different altimetry missions may be used to derive optical water levels for different lakes. For instance, if Jason-1/2/3 data are available, optical water levels are generated by fitting with the merged Jason-1/2/3 water levels. If ICESat and CryoSat-2 data are available for a lake, optical water levels are generated first by fitting with CryoSat-2 data. After the extended CryoSat-2 data are merged with the ICESat data, the optical water levels generated throughout the entire study period are checked again by fitting with the merged altimetry water levels to see if there is an extrapolation problem. We will discuss this issue in detail in response to the specific comment 8 below in this section.

Modifications: Reference to Figure 1 was added in several places; More information about the second regression was added.

4) P7, L18: It is very unclear what "ENVISAT product" you used.

Response:

Thanks for this comment. It has been changed to Envisat/RA-2.

5) P7, L23: "highest bucket" is an unclear term. What elevation bin spacing did you choose for your frequency histograms? It seems you are losing information by binning your surface elevation measurements. How does that affect the accuracy of the extracted lake level elevations? I assume you have t-distributed data, i.e. roughly bell-shaped elevation distributions with long tails. It might be more appropriate to use the median elevation measurement, maybe in combination with a threshold to remove biased measurements in the tails. From reference DEMs, you should know the true surface elevation (of the lake shore).

Response:

Thanks for this insightful comment. We used a 0.6-meter bin space to generate a histogram and the 'highest bucket' represents the histogram bin with the highest frequency. It has now been clarified in the revised manuscript. We do not think much information is lost, as for most cycles (>70%) there are more than 80% measurements falling into the highest bin. We first used the median value of each cycle to represent the lake water level, which is noisier/less smoother than that using the histogram. It turns out that a 0.6 m bin space is large enough to capture valid measurements in a cycle.

It is true that a bell distribution is quite common for most lakes. But setting constant thresholds to remove outliers for each lake does not seem to work well in our study. We did try this method before but it always ends up in how to choose an appropriate threshold. If the threshold is too large, invalid measurements will be involved in a lake. Otherwise, certain amount of information would be lost. For instance, Lake Kusai experienced a water level jump up to ~10 m in 2011. If we do not know this information before, then a threshold must be larger than ± 10 m from the mean water level/DEM to capture the water level jump, which will definitely introduce a number of inaccurate measurements in normal cycles.

6) P8, L4ff: How large are the biases you found? Are they constant over time and in space? I assume you compute this per lake?

Response:

Thanks for this comment. The spatial distribution of systematic biases seems quite random to us, varying from place to place, even the sign of the systematic biases is not stable between two certain altimeters (except for Jason-1/2/3). The range of biases is within ± 5 m. Fortunately, the systematic bias is quite stable in time, as we compared the merged altimetry data with the optical water levels. If the bias is not stable in time/elevation, which means that the additive correction is not effective enough, the multiplicative correction may be needed. Overall, we did not see the necessity of using the multiplicative correction nor did we find any relative research reporting such corrections.

7) P8, L13: it is unclear what you mean with "merging using optical water levels"

Response:

It should be clear now as we have provided a separate paragraph at the end of section 3.1 to summarize the merging process. Thanks for this comment.

8) paragraph P8, L11ff: Only after reading this paragraph I think I finally understood the purpose of this study: You want to generate continuous lake level (volume?) series for as many lakes as possible. This requires elevation (and areal?) data from different sensors, as missions only last for a few years. As an additional challenge, the satellites in question have different orbits that only cover some lakes each, so not all elevation datasets can be used for each lake. For each lake, you therefore combine lake level elevation time series from the different sensors with data for that lake, using the overlap periods to correctly align the records, i.e. you remove potential elevation bias between the time series and make sure they are consistent. Where there is no sufficient overlap, you use optical data as a proxy: you create a statistical relationship between lake levels (from altimetry data) and corresponding shoreline position (from optical data acquired at the same time), and then apply (extrapolate?) the relationship to (optical) shoreline positions for time periods where you lack surface elevation data, but do have optical data. I propose you add something like this to the introduction. Secondly, this paragraph would be much easier to understand if you first introduce optical water levels and refer to Figures 2 and 3 in the text. Given the importance of the relationship for your results you might want to explain your method in more detail. An important missing detail is whether you only interpolate or also extrapolate beyond the available data range?

Response:

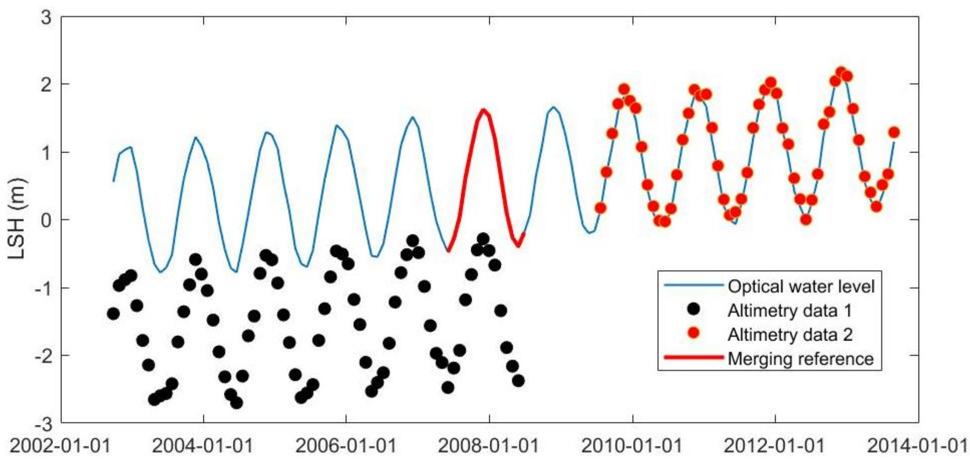
We really appreciate these accurate and comprehensive summary and highlights on our work. As the referee suggested earlier, we have enhanced the introduction section to clarify the purpose and underscore the contributions of this study. We have added references to Figure 2 and Figure 3 in this paragraph and we have moved part of it to the end of the optical water levels section (section 3.2). The interpolation and extrapolation may be the most concerned issue here. Below we provide a few examples to justify our methodology.

Note that we have performed two regressions to generate the optical water levels. For the first regression, we only used one altimetry data product and optical images-derived lake shoreline positions. After merging the altimetry water levels, we performed the second regression using the merged altimetry water levels and the optical water levels temporally close to the altimetry water levels throughout the entire study period. This information is missing in the original manuscript and we will add it in the revised manuscript/supplementary file. Here we show that part of the extrapolation problem is evitable in nature with the second regression:

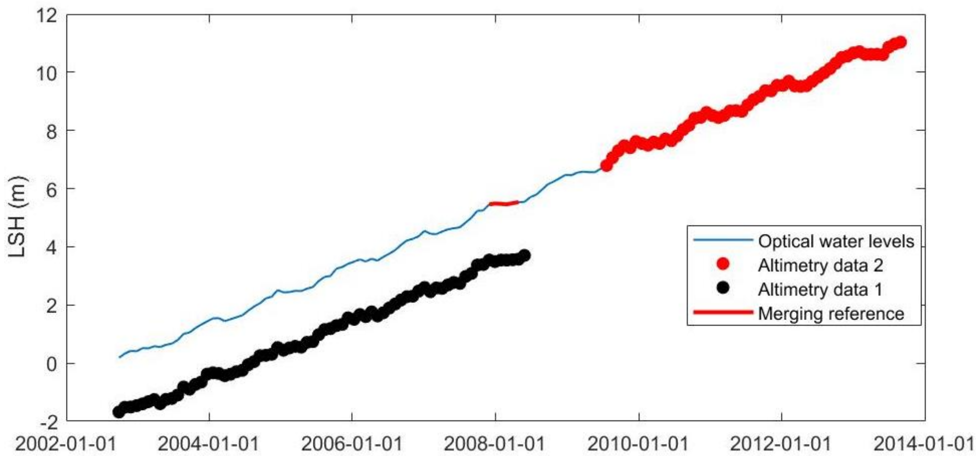
a) When and where does extrapolation exist?

   First, extrapolation here means the extrapolation of the linear relationship developed from the regression analysis between altimetry water levels and lake shoreline changes. For instance, if the altimetry water levels used for the regression analysis have a range of 4500–4502 m, then the generated optical water levels beyond/below this range are regarded as extrapolated values. On the other hand, if an optical water level H_1 acquired in 2003 is within 4500–4502 m, though the altimetry water levels used for such a regression were from 2010 to 2017, H_1 is still regarded as an interpolated value because it is within the elevation range of the linear regression.

   As shown in following figures (both are conceptualized examples, optical water levels are fitted with the second altimetry product), when seasonal signal is dominated in the time series, there is no need for extrapolation. The red line in the optical water levels (which serves as the merging reference to altimetry data 1) are within the range of the linear regression. The merging between the two altimetry water levels can subsequently be achieved by removing the difference (symmetrical bias) of the mean water levels between altimetry data 1 and altimetry data 2 during the reference period (the red solid line) from altimetry data 1 (typically ICESat data).

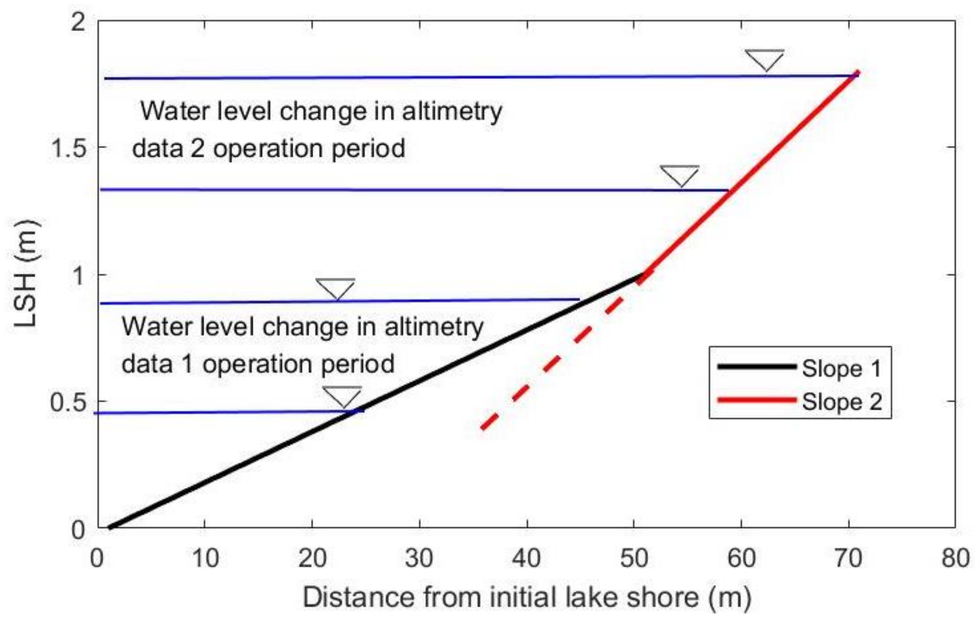


When a multiyear trend is dominated in the time series, the merging reference is out of the range of the regression relationship, and then extrapolation may occur. Both situations are common in our study. The first situation comprises 60% of all study lakes, and extrapolation can take place in ~40% lakes. The two altimetry datasets in the extrapolation case can still be merged using the similar procedure and optical water levels shown in the interpolation case above.



b) How does extrapolation become a problem?

In the merging process, extrapolation becomes a problem only if the lake bank slope experiences an abrupt change at the exact elevation where both altimetry products fail to cover, as illustrated in the following figure:



Such a situation may happen, but the possibility is relatively low. If it happens, the extrapolation will result in a remaining systematic bias in the merged altimetry water levels and consequently jeopardizing the accuracy of the optical water levels.

c) How can the problem be avoided?

By performing the regression analysis twice, it is possible to detect if there is an abrupt change in lake bank slope. If the situation in b) does happen, we can easily see from the scatterplot of the second regression analysis that the linear assumption is no longer met (i.e., the scatterplot would show two slopes/curvature). Once an obvious failure in the second linear regression occurs, we will re-choose the region of interest (ROI) and go through the entire process of generating optical water levels again. However, it only happened twice or three times in our study.

We will provide the details of generating the optical water levels discussed above in the supplementary file as they may be too detailed for general readers.

9) P9, Figure 2: refer to the figure in the text, e.g. where you introduce the data sets and in section 3.1

Response:

Yes, we have added reference to Figure 2 (now Figure 3, because we inserted a new figure after Figure 1) in the first paragraph of section 2.2 and fourth paragraph of section 3.1.

10) P9, 3.2: The optical water levels should be introduced before P8, L15ff.

Response:

The sequence has been changed.

11) P10, L4ff: the part about "shifting gaps" and the ROI is unclear. Do you mean that the Landsat 7 gaps are not always exactly at the same place? Did you choose your ROIs such that they never contain no-data pixels? How did you ensure that, given the large amount of Landsat 7 data?

Response:

Yes, the position of gaps in Landsat 7 data is various with time. But they are more like vibrating around a fixed location. So, narrowing down the width of ROI can assure higher data availability. It is true that filtering a large amount of Landsat 7 archives is really tough, but our study was primarily based on GEE and we performed an invalid-pixel detection to get rid of images with missing pixels in the ROI. The algorithm is straightforward: comparing the valid pixel number in the ROI with that from an intact image. If the missing pixels in the ROI exceed 2% then the image will be excluded. Using 2% instead of 0% is due to the consideration of the algorithm robustness, but there is not much difference in the results as the ratio of in-valid pixels is either very high (>20%) or extremely close to zero.

12) P10, L17: reference for the Otsu method?

Response:

It has been added.

13) P10, L22: How did you decide whether to use a linear or 2nd order polynomial fit?

Response:

Thanks for raising this comment. In fact, it only happened in two lakes: Zhari Namco and Chibzhang Co, where we already have Jason-1/2/3 data for altimetry data merging. For other lakes we only performed linear regression, and if the scatterplot of the regression has a clear curvature, we will re-choose the ROI (see our response to comment 8 in the method section). For Zhari Namco and Chibzhang Co, if we use linear regression, a clear discrepancy will show up at either low water levels or high water levels. Therefore, using a higher order regression is a choice.

14) P10, L25: How did you determine cloud cover?

Response:

The cloud cover was calculated in GEE based on the quality band of Landsat 5/7/8. Pixels in the quality band categorized as cloud or cloud shadow will be masked with a mask function provided in GEE. Then, the cloud/cloud shadow pixels will be regarded as invalid pixels and a corresponding rate can be calculated by dividing invalid pixels with the total pixels in the ROI. If the cloud rate is higher than 5%, the image will be discarded.

15) P11, L2: How much data pairs did you end up with per lake, and how did you select

pairs with regard to acquisition dates? I assume you did not always have altimetry and shoreline data from the same date (?)

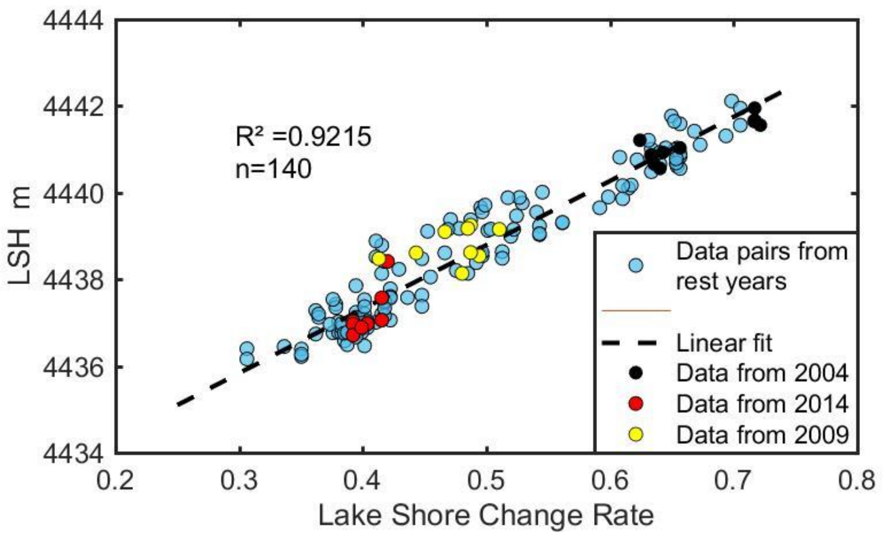
Response:

We have an average of 55 data pairs for the second regression of optical water levels. About 70% of the study lakes have more than 20 data pairs. The time difference of data pairs is within 5 days. However, if there are not enough data pairs (<10 pairs) with a time difference smaller than 5 days, we will increase the time difference to 10 days. Only for a lake named Xuru Co, where altimetry information is very limited, we increased the time difference to 30 days.

16) P11, figure 3: c) You might want to colour the dots according to time to check for (and show the readers that there is no) temporal bias. From d), it seems optical water levels are somewhat too high around 2004 and 2015, but too low around 2009?

Response:

Yes, this is a nice suggestion. Based on the following figure, it seems that in 2009 the optical water levels might be a little lower than expected. It may be caused by the uncertainty in altimetry water levels. In 2009 the main data source is Envisat, which has poorer quality than other altimetry products (except Jason-1) in our study. Overall, the impact of this problem is quite limited as the linear relationship is still strong.



Modifications: Figure 4 (c) was replaced.

17) P12, L9: How did you derive these ROIs? Are they drawn manually?

Response:

Yes, they are drawn manually. Selection criterion is illustrated in the manuscript. However, it still requires some experience.

18) P12, L15: regression between the lake area and ..?

Response:

It is between lake area and merged lake water levels, including altimetry water levels and optical water levels, but most data pairs are lake areas and optical water levels, because they usually come from the same Landsat image.

19) P13: As far as I am aware, Strahler's catchment hypsometric model is based on river catchments with a pour point, not endorheic lake catchments as it is the case for the TP. I am not entirely sure what you used this model for (to compute lake water volumes?), but I am not convinced that this is a correct approach. I am also not sure why you need that relationship at all? If you have lake area and lake level time series, you can directly compute volume changes from these?

Response:

Thanks for raising this comment. We intended to provide some justification that a parabolic relationship between the lake area and lake water level is reasonable. But it seems that such a justification is unnecessary and inappropriate because the assumption of exorheic basins is not met. We will remove this analysis from the revised manuscript.

The reason why we use the lake area-water level relationship to calculate the volume change is the lack of lake water areas with a sufficient temporal resolution. In general, we only have ~20 lake area observations for each lake, because the ROI for lake area extraction is much larger than that of lake shoreline changes, reducing the data availability. If we use the volume formula for computation, we can only get ~20 volume change values. With a lake area-water level relationship, we can derive the lake volume-water level relationship and convert all water level estimates into lake volume changes.

Modifications: The Strahler's model was removed from the manuscript.

20) P14, Figure 6: It is unclear what the parameters y, x, z, a and d represent.

Response:

Thanks for this comment. We will remove this part from the revised manuscript.

21) P14, table 3: state nr. of data pairs (optical shoreline position + altimetric lake level) rather than optical data points

Response:

Yes, they have been added.

Validation

1) P16, L5: unclear sentence

Response:

The sentence has been reorganized.

Modifications: Part of the 1st paragraph of Section 4.1 was reorganized to show that the focus is the uncertainty of optical water levels.

2) P16, L25: the drone GPS tracker alone might not be very accurate, you may easily get a skewed/stretched image composite. Did you use ground control points?

Response:

We did not get ground control points. It is true that there may be skewing or stretching distortions in UAV images. So, we redid the experiment with some commercial high-resolution data such as GF-2 (China's High Resolution Satellite, GF-2, with a panchromatic resolution of 0.8 m), which has larger coverage and more ground features for co-registration with Landsat OLI image.

Modifications: The UAV image-based validation was removed and replaced by GF-2 image-based validation, the later has undergone co-registration.

3) P16, L27: This seems a rather dodgy way to determine the resolution of your image composite.

Response:

Yes, it is not very rigorous, and we have abandoned it.

4) P17, figure7: which lake? images a) and e) should have the same size/spatial resolution. An overview map would be useful.

Response:

Thanks for this comment. We performed UAV scanning and water level sensor installation in both lakes. However, the water level sensor in Nam Co was broken down soon after installation and did not provide much information. Figure 7 shows pictures acquired at the Nam Co experiment spot. An overview map has been added into the study area section (section 2.1), as the referee suggested before. We decided not to use the UAV image as a validation basis, but we keep it here to show the environment at the experimental spot. In addition, the up-left image from Landsat 8 has been changed into an overview map of Nam Co and the experiment location.

Modifications: An overview map was added to Figure 7.

5) P17, L9ff: extrapolated or interpolated? Provide the parameters and statistical relationship here, maybe even in an additional figure.

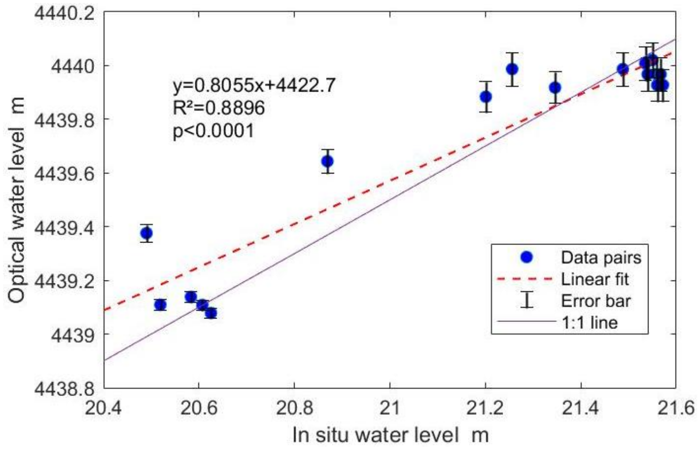
Response:

The optical water levels of Yamzhog Yumco used for validation are interpolated. The statistics of regression are already shown in Figure 3.

6) P18, figure 8b: add 1:1 line and error bars for the data points

Response:

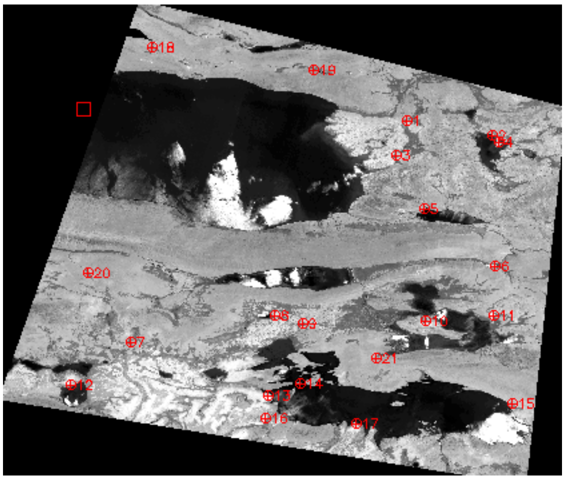
Yes, they have been added as shown in the figure below.



7) P18, 19: How did you coregistrate the UAV image composite and Landsat image? It seems a spatial shift will completely alter the (relative) shoreline position and thus the basis for your entire analysis: In Figure 9, shifting the shoreline only slightly in e.g. north-south direction will greatly change water/land (sub) pixel counts and thus the basis for the relationship in (b). In my opinion, an error analysis would require several image pairs (UAV and satellite-borne) and a solid coregistration basis, e.g. river/road crossings as clear tie points, or at least a round lake or elongated peninsula rather than a straight shore line.

Response:

This is a very constructive comment. We agree that there might be a spatial shift in the UAV image. Therefore, we no longer use the UAV image because there are very few ground features for image co-registration. Instead, we purchased some high-resolution commercial images obtained by GF-2 (0.8 m resolution at the panchromatic band) to repeat the analysis. The GF-2 images cover a much larger area and more diverse ground features, making it easier for image co-registration. The following figure shows control points that we selected for one of the GF-2 images. The co-registration error is 1.2 GF-2 pixels, say ~1 m. The other two GF-2 images have a co-registration error of 2.45 pixels and 2.72 pixels, respectively, corresponding to ~2 m.



Modifications: Co-registration Information of GF-2 images and Landsat images was added to the study data section and validation section.

8) P18, L7: what do you mean with "concurrent"? What dates?

Response:

It means the "same period" image. We have changed this expression.

9) P22, L1ff: Do not forget the local conditions: ice, snow, wet, dry, muddy shore conditions or also waves greatly affect the water classification result.

Response:

Thanks for this comment. Yes, the local condition is an important factor affecting the water area classification accuracy. Therefore, we chose three high resolution images acquired in different seasons and different places representing typical local conditions around the TP lakes, covering turgid water (wet season), lake ice, and dry season. As for vegetation, most of the TP lakes do not have much vegetation on the lake bank, with the Landsat images unable to detect information on vegetation.

Applications

1) P22, L10f: Are these your own numbers? How do they compare to previous estimates?

Response:

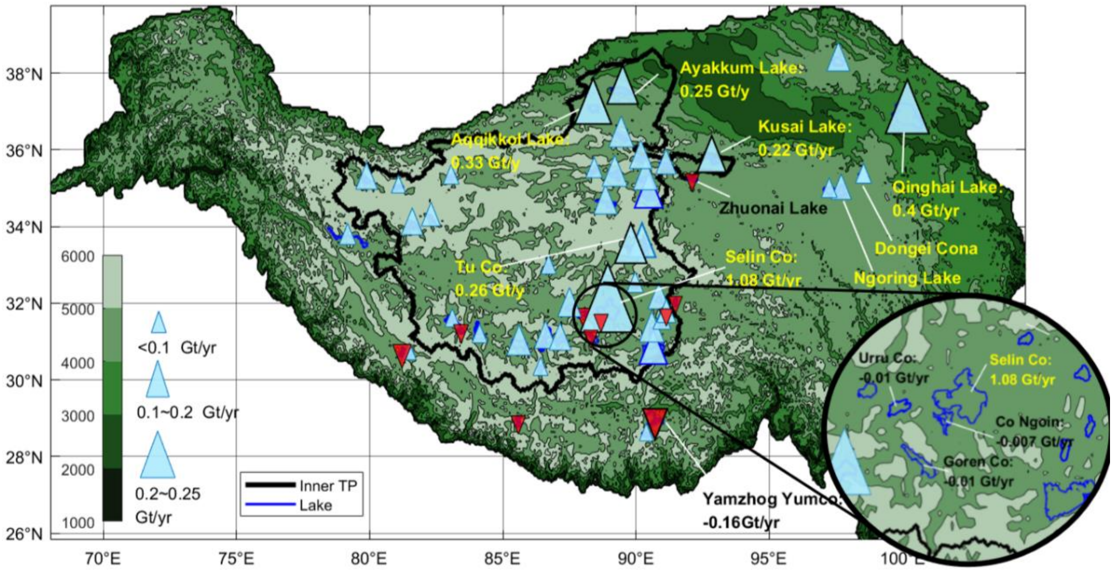
Yes, they are results generated from our product. There has not been any published study that has exactly the same study period or lakes as what we did. But for the overlap periods and lakes, the results are similar. We have made many comparisons with published studies or open source data, including the comparison between our product and Hydroweb data in Figure 14 in the original manuscript (now Figure 11).

2) P22, L14ff: mark all lakes mentioned in the text in the map. If they are very close

to each other, an extra zoom-in map might be useful.

Response:

Yes, this has been done, as shown in the figure below:



3) P23f: restructure section 5 to avoid splitting the Selin Co basin analysis in two sections (5.1 and 5.3). How much of this is new, i.e. has not been published before? How does your dataset make a difference?

Response:

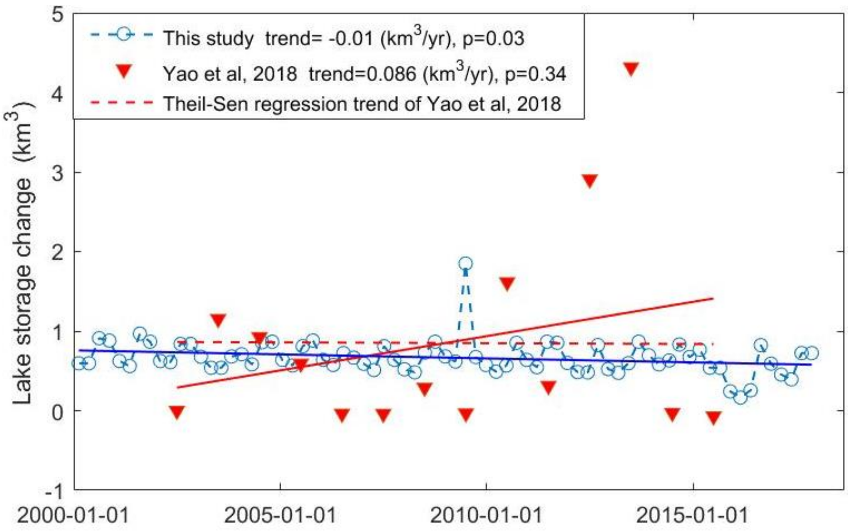
Thanks for this comment. We have only talked about Lake Kusai in section 5.3. All discussion about Selin Co is shown in section 5.1. There are some published studies that report the unusual spatial pattern of lake area/water level/storage changes in the Selin Co basin. However, there is no discussion about the reason. We proposed a possible explanation. On the other hand, given the complexity of modeling a multi-lake endorheic basin (Zhou et al., 2015), our product does provide a chance for investigating the structure of such a endorheic basin with complicated lake-river systems. For instance, the height of outlet of three upstream lakes in the Selin Co basin may be inferred from the dense time series from our product with the help of a hydrologic/hydrodynamic model.

4) P23, L5ff: You mention only the study of Yao et al. (2018). How about other publications? Also, from figure 12 it seems quite clear that the Yao data contains two outliers. Consider using a robust fitting method rather than regular linear regression.

Response:

Thanks for this comment. Song et al. (2013) notice the decreasing trend of the three lakes in the upstream of Selin Co during 2003 to 2009 when ICESat data are available, but there are no comments or discussion about the reason. We found that Hydroweb data do not catch the decreasing trend of Urru Co after 2000. Jiang et al. (2017) did not investigate the decreasing trend of Urru Co from 2003 to 2015 as their altimetry data from ICESat and CryoSat were not linked together but separately discussed instead. Hwang et al. (2019) reported a similar problem as Jiang et al. (2017). Other studies do not present specific statistics for the comparison nor do they cover those lakes.

With a robust linear fit method (Theil-Sen estimator), the result from Yao et al. (2018b) did show a decreasing trend, consistent with our result. But they clearly did not use a robust fitting in their published paper/dataset.



5) P24, L10: Depicting intra-annual variation is a strength of your dataset that you might want to emphasize more.

Response:

Yes, we did describe the intra-annual variation in the lakes we studied.

6) P24, 5.2: Rather than treating the comparison to the LEGOS Hydroweb data as an application case this should be part of the validation section!

Response:

Yes, we have moved part of section 5.2 to the validation section (section 4.3).

7) P25, L8: "some kind of" bias removal: be more specific. The magnitude of the vertical shift between the two datasets fits to e.g. geoid/ellipsoid height confusion, but the temporal variability of the shift is worrying. Rather than speculating about the cause and assuming that the Hydroweb data is wrong you ought to find the reason for the differences - which may lie in your data processing/method.

Response:

Thanks for raising this insightful comment. The reason for the vertical shift between our product and Hydroweb data possibly lies in different geoids/reference ellipsoids, as illustrated in our response to referee comment 1 (General comment 3). However, we respectfully disagree on the point of the temporal variability in the vertical shift.

In the manuscript, we just indicate that partial Hydroweb data are not quite consistent with the optical water levels (e.g., in the three lakes shown in Figure 15), which are able to provide a straightforward answer to "in which period the lake has higher water level". As we have clarified in the revised manuscript, such a relationship on relative magnitudes reflected by the optical water levels does not change with the linear fitting parameters (unless using a negative slope, which is impossible) and that is why we regard it as robust. What we did was merging different altimetry data sources based on the reference provided by the optical water levels. Therefore, it is not likely to be a problem for this straightforward and robust scheme for merging altimetry data.

8) P25, L13ff: "reverse relationship" and the conclusion you draw (Hydroweb may "underestimate decreasing trends"): unclear what you mean

Response:

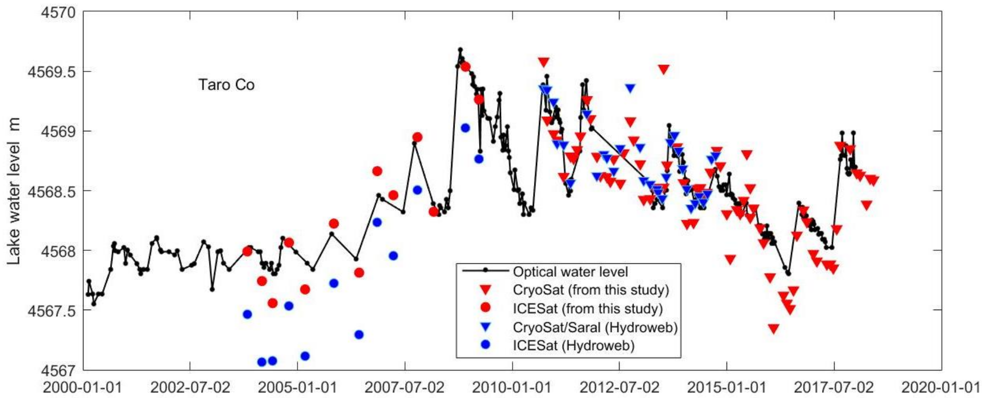
Thanks for raising this comment. We apologize for making a wrong expression in the original manuscript: the conclusion should be "…there is a possibility that Hydroweb data overestimate the increasing trend of water levels in Taro Co from 2003 to 2015".

As shown in Figure 15 (a), the last two measurements from ICESat should equal or be even larger than the first two/three measurements from CryoSat/Saral based on optical water levels, but the Hydroweb data show a reverse relationship that the last two ICESat measurements is 0.3~0.4 m smaller than the first two CryoSat/Saral measurements. This phenomenon suggests that ICESat water levels of Taro Co from Hydroweb is 0.3~0.4 m lower than the expected (in other words, CryoSat/Saral time series from Hydroweb is 0.3~0.4 m higher than the expected). It would therefore result in an overestimation of increases in lake water levels in Taro Co during the time window. In addition, the optical water levels in Taro Co were interpolated with the developed statistical relationship. Therefore, the discrepancy between Hydroweb and our product is not attributed to the extrapolation of the optical water levels.

9) P25, figure 15: What are the red/blue shaded areas? (a) compare the series after removing the shift. Sadly, the series (b) and (c) are no where discussed. The temporally varying offsets between the series from different data sources should be analysed and removed, or at least explained.

Response:

Thanks for this comment. The red and blue areas were meant for highlighting/comparing the periods when an obvious discrepancy between Hydroweb data and optical water levels from our product occurs. As for Figure 15 (a), we have removed the systematic vertical offset between our dataset and Hydroweb data of Taro Co, which is shown in the figure below:



As we suggest earlier in the response letter, there might be a remaining systematic bias between ICESat and CryoSat/Saral data from Hydroweb. Based on optical water levels, the peak water level of 2009 shall be higher than that of 2010 (again, such a relationship does not change regardless of the uncertainty in the linear fitting parameters during the generation of optical water levels), which means that the last two ICESat measurements are supposed to be higher or equal the first a few CryoSat/Saral measurements. However, this is not seen in the Hydroweb data for this specific lake.

As for Figure 15 (b) and (c), they show other examples of possible remaining systematic biases in Hydroweb data. The explanation is exactly the same as that of Figure 15 (a) and we did explain the discrepancy in the manuscript for Figure 15 (a). Thanks for your kind attention to this.

10) P26, figure 16: again, there seems to be some time-dependent offset between the optical and altimetry-based lake levels, e.g. optical levels are too high around 2005 in the top left panel, and too low around 2005 vs. too high from ca. 2013 in the middle right panel. Can you explain this?

Response:

Thanks for this insightful comment. Though there seems to be an offset at around 2005, the actual deviation between the optical and altimetry water levels here (ICESat data) is about 0.2~0.3 m, which is within the uncertainty range of altimetry measurements for inland water bodies. Instead of a time-dependent offset, we think it is more like a random error, which can be caused by the loss of valid altimeter footprints of that cycle, e.g., a random shift of ground tracks resulting in a smaller cross section and fewer footprints on the lake. It is also suggested that optical water levels may be more robust and less noisy than altimetry data. This is the same for the middle right panel. It should be noted that in the middle right panel, Envisat/RA-2 was used, which has a larger uncertainty than ICESat. Therefore, it is not surprising that altimetry dots seem to be more randomly distributed.

11) P28, figure 17: What does the blue shaded area show? What data are you showing in these time series? Is the right panel a zoom-in of the left panel?

Response:

The blue shade shows the period when an outburst happens. The data we show in Figure 17 are lake water storage changes for relevant lakes during the outburst event. Their locations are shown in Figure 18 (b) and (c). And yes, the right panel is a magnified plot of the blue shade in the left panel.

12) P28, L17: "Team, 2017": check author name

Response:

Yes, we have checked the reference. It has been cited dozens of times in other journal papers according to the Google Scholar.

[CITATION] **Planet Application Program Interface**: In Space for Life on Earth
P Team - San Francisco, CA, 2017
☆ 99 Cited by 69 Related articles

13) P29, figure 18: acquisition dates of the images in b) and c)?

Response:

Figure 18 (b) was acquired in December, 2010. Figure 18 (c) was acquired in December, 2013. The outburst took place at the end of 2011. These are images from the Google Earth (i.e., the image source is Landsat but experienced merging processes, e.g., merging of images acquired from the same month) and we do not know the exact acquisition date.

Modifications: The acquisition time was added in the annotation of Figure 18.

14) P29ff: The entire overflow analysis (lots of new methods introduced) seems to be a study on its own and somewhat out of place in the applications (results) section of this paper.

Response:

Thanks for this comment. We have shortened this section and moved some of the analyses into the supplementary file. But we would like to keep this part, because some information (e.g., height and width of the outlet) of the overflow lake, Lake Kusai, is critical to downstream residents and emergency administrations, given that there are reports showing high overflow/outburst risks of Lake Salt in the near future.

Modifications: Part of the overflow modeling was moved to the supplementary file.

Conclusions

1) A short summary of your methods should be provided, in particular the novelty of using shoreline positions from optical data to interpolate between available lake level measurements.

Response:

Yes, this has been added.

2) P31, L7: rephrase the sentence to avoid brackets.

Response:

Done.

3) P31, L10f: Unclear what you mean. From the comparison you provide currently, I am not yet convinced that your dataset is more correct than the Hydroweb data.

Response:

Thank you for this comment. We have put more detailed explanations (most of them are already discussed in this response letter) in the second paragraph of section 5.2 and hopefully this would convince the reviewers and readers. Based on the overall comparison shown in previous Figure 14 (now Figure 11), our product is generally consistent with Hydroweb data, and has a higher temporal resolution.

But there are indeed some discrepancies between the two products over some lakes during some time windows as what we illustrated earlier. Hydroweb is a decent global dataset whereas our dataset is more a regionally based product. It is not uncommon in the remote sensing community that a regionally based dataset may have some advantages than a global dataset in some aspects due to the improvement of the algorithm for the data generation and use of more detailed (a priori) information derived from optical images to densify the spaceborne altimetry water levels with systematic errors being well removed. The developed method we present has potential to improve lake water level and storage changes in different regions globally at large.

4) P31, L18: "rigorous uncertainty analysis": As mentioned above, I am not convinced about the theoretical uncertainty exercise you provide.

Response:

Thanks for this comment. We have redone the uncertainty analysis with more high-resolution images and corresponding Landsat images. We have also provided co-registration accuracy and considered different seasons and locations as the reviewer suggested. This part should now be convincing the reviewer and general readers.

5) P31, L25ff: These insights about extrapolating using the derived statistical relationship are very important, but currently not quantified, mentioned or discussed anywhere else in the paper.

Response:

Thanks for this constructive comment. We will put the discussion of extrapolation we made in this response letter (specific comment 8 in the method section) into the supplementary file. Clearly, our discussion mainly focuses on the period during which various altimetry data sources are merged, but does not include the period before 2002 when little altimetry information is available and DEM is too course (for instance, SRTM DEM has a 1 m vertical resolution with more than 10 m vertical uncertainty according to Mukherjee et al. (2013)) to provide a detailed description on the lake shore micro topography. Therefore, we do not have much information and materials to discuss about the extrapolation before 2002.

We have informed readers in the manuscript that this is a possible issue but it may only exist in the first 2–3 years of the dataset for lakes with strong signal from multiyear trends as opposed to seasonal variations. After all, compared with the 18-year study period, the impact of extrapolation of the optical water levels during 2000–2002 would be quite limited.

Reference

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Tibetan Plateau from ICESat and CryoSat-2 altimetry and station observations, Science bulletin, 60, 1287-1297, 2015.

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Yao, F., Wang, J., Yang, K., Wang, C., Walter, B. A., and Crétaux, J.-F.: High resolution data set of annual lake areas and water storage across the Inner Tibet, 2002-2015. In: Supplement to: Yao, F et al. (2018): Lake storage variation on the endorheic Tibetan Plateau and its attribution to climate change since the new millennium. Environmental Research Letters, 13(6), 064011, https://doi.org/10.1088/1748-9326/aab5d3, PANGAEA, 2018a.

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Zhang, G., Yao, T., Chen, W., Zheng, G., Shum, C., Yang, K., Piao, S., Sheng, Y., Yi, S., and Li, J.: Regional differences of lake evolution across China during 1960s–2015 and its natural and anthropogenic causes, Remote sensing of environment, 221, 386-404, 2019.

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A list of modifications in the manuscript

Modification position is referred to the marked-up manuscript.

Comment	Modification	Modification position
Modifications based on SC1		
SC1 General comment	None	None
SC1 Specific (1)	A separate paragraph summarizing the altimetry data merging process was added to the end of section 3.2.	P20, L4-L14
SC1 Specific (2)	None	None
Modifications based on SC2		
SC2 General comment	None	None
SC2 Specific (1)	A separate paragraph was inserted following the 3rd paragraph of section 3.1 to briefly introduce the threshold waveform retracking scheme	P11, L21-L25
SC2 Specific (2)	An explanation was inserted to the 1st paragraph of section 4.2.	P26, L7-L8
SC2 Specific (3)	An explanation was inserted to the abstract to clarify the lake area.	P1, L18
SC2 Specific (4)	Unit and scale were added to Figure 12	P36, L4
SC2 Specific (5)	Unit of y axis was added to Figure 16	P42, L7
Modifications based on RC1		
RC1 General (1)	Uncertainties were added for every lake volume/water level number, most of them appear in the Application section	everywhere
RC1 General (2)	None	None
RC1 General (3)	"…all water levels were with respect to EGM96…" was removed from the manuscript; a table containing reference ellipsoid and geoid for each lake was provided in the supplementary file	P12, L21; Supplementary file part 1
RC1 General (4)	None	None
RC1 General (5)	Same as SC2 Specific (2)	Same as SC2 Specific (2)
RC1 Specific (1)	The reference (Zhang, G. et al., 2014) was added in the 1st paragraph of introduction and "ETM^{+}" was change into "ETM+" everywhere	P2, L7 everywhere
RC1 Specific (2)	"long-term" was changed into	everywhere

	"multiyear" everywhere	
RC1 Specific (3)	The two references (Wan, W. et al., 2016, Zhang, G. et al., 2013) were added in the 1st paragraph of section 2.1.	P6, L7
RC1 Specific (4)	"Lake Selin Co" was changed into "Selin Co"; "Lake Nam Co" was changed into "Nam Co": "Lake Zhari Namco" was changed into "Zhari Namco"; "Lake Goren Co" was changed into "Goren Co"; "Lake Urru Co" was changed into "Urru Co"; "Lake Yamzhog Yumco" was changed into "Yamzhog Yumco"	everywhere
RC1 Specific (5)	None	None
RC1 Specific (6)	None	None
RC1 Specific (7)	None	None
RC1 Specific (8)	Units of Table 2 were moved to the first row	P9, L26
RC1 Specific (9)	None	None
RC1 Specific (10)	None	None
RC1 Specific (11)	None	None
RC1 Specific (12)	the background of Figure 12 has been changed into green	P36, L4
RC1 Specific (13)	Figure 13 was revised with outliers removed	P37, L5
RC1 Specific (14)	None	None
RC1 Specific (15)	None	None
RC1 Specific (16)	The title has been changed with "overflow" removed and part of this section has been moved into the supplementary file	P1, L1-L7 Supplementary file Part 4
RC1 Specific (17)	(Xiaojun et al., 2012) was changed into (Yao et al., 2012)	everywhere
RC1 Specific (18)	This part was removed from the 2nd paragraph of conclusion	P49, L9-L13
RC1 Specific (19)	Part of the content in section 4 was moved into the supplementary file	P30 L19-P31 L4 Supplementary file part 2
Modifications based on RC2		
RC2 General (1)	See details in the modified abstract, introduction and conclusion sections	P1, L23-P2-L2
RC2 General (2)	See details in the modified method section, validation section and	P19-P20; P25, P29, P33;

	supplementary file	Supplementary file Part 3
RC2 General (3)	The description of the dataset is combined with the data availability following the validation part	P35, L4-L20
RC2 General (4) (a)	An analysis of how uncertainty in altimetry data evolve into optical data is provided in section 4.2	P33
RC2 General (4) (b)	See details in the modified section 4.2	P25, P29
RC2 General (4) (c)	Section 4.3 was added	P34 L10-L15
RC2 Specific comments		
Abstract (1)	Numbers of lake volume changes were removed from the abstract; validation of the optical water level was emphasized	P1, L23-P2-L2
Abstract (2)	None	None
Abstract (3)	Brackets have been removed and a brief explanation to optical water levels has been added	P1, L21
Abstract (4)	“densified” has been replaced with "merged"	everywhere
Abstract (5)	Numbers of lake volume changes were removed	P1, L30-P2, L2
Introduction (1)	More information was added to the 1st paragraph of introduction to clearly state the motivation of TP lake studies	P2, L12-L14
Introduction (2)	None	None
Introduction (3)	References was changed into (Frappart et al. 2005)	P2, L21
Introduction (4)	“ice berg” was changed into “ice sheet/sea ice freeboard”	P2, L26
Introduction (5)	“ICESat-1” was changed into “ICESat”	everywhere
Introduction (6)	None	None
Introduction (7)	None	None
Introduction (8)	Reference for Otsu method was added	P3, L24
Introduction (9)	None	None
Introduction (10)	(Wan et al., 2016) and (Yang., 2017) were removed from Table 1	P4, Table 1
Introduction (11)	An explanation in brackets was added following “hypsometric curve”	P5, L5
Study area and data (1)	Part of 4th paragraph was moved to the	P9, L7-L10

	second paragraph of section 3.2.	P14, L14-L16
Study area and data (2)	None	None
Study area and data (3)	An overview map was added	P7, Figure 2
Study area and data (4)	"moderate set of orbital parameters" was removed and replaced by "…a lower orbit than Jason-1/2/3 but higher than ICESat…"	P7, L14
Study area and data (5)	None	None
Study area and data (6)	None	None
Study area and data (7)	Information of sensor name and type was added into Table 2, as well as data record name; A separate paragraph was added following 1st paragraph of section 2.2 to clarify the difference between altimeters	P9, Table 2 P8, L9-P9, L3
Methods (1)	1st paragraph was moved to the Introduction part	P10, L2-L15 P5, L11-L18
Methods (2)	Same as SC1 Specific (1)	Same as SC1 Specific (1)
Methods (3)	Reference to Figure 1 was added several places; More information about the second regression was added	P5, L7, L10; P7, L7; P12, L8, L19 P19, L11-P20, L3
Methods (4)	"Envisat" was changed into "Envisat/RA-2"	P11, L17
Methods (5)	"bucket" was changed into "histogram bin"	P11, L29, L30
Methods (6)	None	None
Methods (7)	Same as SC1 Specific (1)	Same as SC1 Specific (1)
Methods (8)	References to Figure 3 and Figure 4 were added in the manuscript and part of this paragraph was moved to the end of the optical water levels section (section 3.2). More information about the second regression was added. Discussion about extrapolation issue was added into the supplementary file	P12, L17-L19 P19, L8-L10 P19, L11-P20, L3 Supplementary file part 3
Methods (9)	References to Figure 3 were added	P7, L2
Methods (10)	The sequence has been changed as this paragraph is moved to the end of section 3.2	Same as Methods (8)
Methods (11)	None	None
Methods (12)	Reference for Otsu method was added	P17, L11
Methods (13)	None	None
Methods (14)	None	None

Methods (15)	None	None
Methods (16)	Figure 4 (c) was replaced	P16, Figure 4
Methods (17)	None	None
Methods (18)	None	None
Methods (19)	The Strahler's model was removed from the manuscript.	P21, L18-P22, L10
Methods (20)	The Strahler's model was removed from the manuscript, as well as figures and equations.	P21, L18-P22, L10
Methods (21)	No. of data pairs was added into Table 3	P22, Table 3
Validation (1)	Part of the 1st paragraph of Section 4.1 was reorganized to show that the focus is the uncertainty of optical water levels	P24, L6
Validation (2)	The UAV image-based validation was completely removed and replaced by GF-2 image-based validation, the later has undergone co-registration	P25, L4-L15
Validation (3)	Same as Validation (2)	Same as Validation (2)
Validation (4)	An overview map was added to Figure 7	P26, Figure 7
Validation (5)	None	None
Validation (6)	Figure 8 (b) was changed	P27, Figure 8
Validation (7)	Co-registration Information of GF-2 images and Landsat images was added to the study data section and validation section	P9, L19-L24 P25, L14-L15
Validation (8)	"concurrent" was changed into "same period"	everywhere
Validation (9)	Same as Validation (2)	Same as Validation (2)
Application (1)	None	None
Application (2)	Figure 12 has been modified with more lakes marked and a magnified view added	P36, Figure 12
Application (3)	None	None
Application (4)	A robust fitting result of Yao et al., 2018 was added to Figure 13	P37, Figure 13
Application (5)	None	None
Application (6)	part of section 5.2 was moved to the validation section (as section 4.3)	P39, L8-L16 P34, L10-L15

Application (7)	Section 6.2 was modified based on this comment	P39-P40
Application (8)	Section 6.2 was modified based on this comment	P39-P40
Application (9)	Section 6.2 was modified based on this comment	P39-P40
Application (10)	None	None
Application (11)	Information about blue and red shade was added	P39, L23
Application (12)	None	None
Application (13)	The acquisition time was added in the annotation of Figure 18	P47, L12
Application (14)	Part of the overflow modeling was moved to the supplementary file	P45-P46
Conclusion (1)	The 1st paragraph of conclusion is modified based on this comment	P48, L11-L20
Conclusion (2)	Brackets were removed	P48, L11
Conclusion (3)	None	None
Conclusion (4)	None	None
Conclusion (5)	At the end of conclusion we referred to the supplementary file to further explain the extrapolation issue	P49, L16

~~Densified multi-mission observations by developed optical~~Generation of ~~an 18-year high-temporal-resolution~~ water ~~levels show marked increases in lake water~~level and storage change ~~and overflow floods~~data sets of high temporal resolution for lakes on the Tibetan Plateau during 2000–2017 using multiple altimetric missions and Landsat-derived lake shoreline positions and areas

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Abstract. The Tibetan Plateau (TP) known as Asia'~~'~~s water towers is quite sensitive to climate change, reflected by changes in hydrologic~~al~~ state variables such as lake water storage. Given the extremely limited ground observations on the TP due to the harsh environment and complex terrain, we exploited ~~multisource remote sensing, i.e.,~~ multiple altimetric missions and Landsat archives to create high temporal resolution ~~dense time series (with monthly and even higher such as 10 days on average)to weekly temporal resolution of~~ lake water level and storage change time series at weekly to monthly timescales ~~s across~~for 52 large lakes (50 lakes larger than 150 km^2 and 2 lakes larger than 100 km^2~~>100 km^2~~) on the TP during 2000–2017 (the data sets are~~is~~ available online with a DOI: https://doi.org/10.1594/PANGAEA.898411). ~~Field experiments were carried out in two typical lakes to validate the remotely sensed results.~~ With Landsat archives and ~~partial~~ altimetry data, we developed water levels from lake shoreline ~~changes~~positions (~~namely~~ i.e., optical water levels) that cover ~~most of TP lakes~~the study period and serve as an ideal reference for merging multisource lake water levels~~. The~~ with systematic biases being removed. To validate the optical water levels~~ show an uncertainty of ~ ~~, field experiments were carried out in two typical lakes, ~~while~~and theoretical~~al~~ uncertainty analysis was performed based on high -resolution optical images (0.~~1~~8 m ~~that~~) as well. The RMSE of the optical water levels is 0.11 m compared with the in situ measurements, ~~which is~~ consistent with the theoretical~~al~~ analysis. The accuracy of the optical water levels that can be derived in relatively small lakes is comparable with most altimetry data~~ and largely reduce the lack of~~~~prevails in relatively small lakes~~. ~~The~~ The resulting merged optical and altimetric ~~dense~~ lake water levels ~~(optical and altimetric observations with systematic errors well removed for most of lakes. The densified lake water levels provided critical and~~~~water levels)~~ can provide accurate information on ~~the~~ multiyear~~long-term~~ and short-term monitoring of lake water levels and storage changes on the TP~~. We found that the total storage of the 52 lakes increased by 97.3 km^3 at two stages, i.e., 6.68 km^3/yr during 2000–2012 and 2.85~~

~~km^3/yr during 2012–2017. The total overflow from Lake Kusai to Lake Haidingnuoer and Lake Salt during Nov 9–Dec 31 in 2011 was estimated to be 0.22 km^3, providing~~, ~~as~~and ~~well as~~ critical information on lake overflow flood monitoring and prediction as the expansion of some TP lakes becomes a serious threat to surrounding residents and infrastructure.

1 Introduction

The Tibetan Plateau (TP), providing vital water resources for more than a billion population in Asia, is a sensitive region undergoing rapid climate change (Field et al., 2014). There are more than 1,200 alpine lakes larger than 1 km^2 (Zhang et al., 2017a; Zhang et al., 2014)~~-~~on the TP where glaciers and permafrost are also widely distributed. With little disturbance by human activity in this area, lake storage changes may serve as an important indicator that reflects changes in regional hydrologic~~al~~ processes and responses to climate change. Wang et al. (2018) showed that global endorheic basins are experiencing a decline in water storage whereas the endorheic basin on the TP is an exception. Given the fact that TP lakes have been expanding for more than 20 years (Pekel et al., 2016), ~~pasture, farmland, and infrastructure near the lake shore face the risk of inundation.~~a high quality data sets on lake water level and/or storage ~~would~~could be the basis for investigating its causes (e.g., climate change/~~ or variation~~variability) and interactions with the water/energy cycles and human society (e.g., increasing risks of inundation and overflow floods). ~~Therefore, it is imperative to largely improve the monitoring of TP lakes.~~

As an important component of the hydrosphere, terrestrial water cycle, and global water balance, millions of inland water bodies such as lakes, wetlands, and ~~human~~ reservoirs have been investigated globally and their total storage was estimated to be 181.9×10^3 km^3 based on statistical models (Lehner and Döll, 2004; Messager et al., 2016; Pekel et al., 2016). Lake storage changes that play an important role in the ~~, which is more concerned in the~~ regional water balance, can be derived from ~~observed changes in lake water level and area (Crétaux et al., 2016; Crétaux et al., 2011b; Song et al., 2013; Yao et al., 2018b; Zhang et al., 2017a).~~remotely sensed changes in lake water level and area (Frappart et al., 2005). ~~Most of these two kinds of observations in related studies~~Lake water levels and areas are mostly ~~were obtained~~derived from satellite remote sensing due to the scarcity of in situ data across the TP where the harsh environment and complex terrain make in situ measurements difficult to perform and costly ~~and risky.~~ (Crétaux et al., 2016; Song et al., 2013; Yao et al., 2018b; Zhang et al., 2017a). Changes in lake water level can be monitored using satellite ~~altimetry with a radar or laser~~altimeters initially designed for sea surface topography or ice sheet/sea ice freeboard height ~~or ice berg~~ measurements. Altimeters determine the range between the nadir point and satellite by analysing the waveforms of reflected electromagnetic pulses.

~~The waveforms of radar or laser pulse may, however, be contaminated by signal from complex terrain when applied to inland water bodies, but~~There are two ~~main~~major categories of satellite altimeters, ~~(~~i.e., laser and radar~~)~~. Laser altimeters, e.g., ICESat, operating in the near infrared ~~wave length~~band has a smaller size of footprints and generally higher accuracy than radar altimeters, facilitating applications in glacier/ice mass balance studies (Neckel et al., 2014; Sandberg Sørensen et al., 2011). Rader altimeters, operating in the microwave band, have larger footprints and are more likely to be contaminated by signal~~s~~ from complex terrain when applied to inland water bodies. Nevertheless, it is possible to remove these impacts with waveform retracking algorithms (Guo et al., 2009; Huang et al., 2018; Jiang et al., 2017). Zhang et al. (2011) mapped water level changes in 111 TP lakes for the ~~period~~ 2003–2009 period using ICESat~~-1~~ data that have a temporal resolution of 91 days. ICESat~~-1~~ data have relatively denser ground tracks but a lower temporal resolution than most of other altimetric missions. This means that ICESat~~-1~~ covers more lakes but provide few water level~~ observations~~s for each lake. After ICESat~~-1~~ was decommissioned in 2010, CryoSat-2 data ~~spanning the period~~starting from 2010~~–2015~~ were adopted in related studies (Jiang et al., 2017), due to its similar dense ground tracks and competitive precision as ICESat~~-1~~. Other altimetric missions, such as TOPEX, Jason-1/2/3, ERS-1/2, and ~~ENVISAT~~Envisat also have some but relatively limited applications in monitoring changes in lake water level on the TP due to sparse ground tracks. In this study, multisource altimetry data (i.e., Jason-1/2/3, ~~ENVISAT~~Envisat, ICESat~~-1~~, and CryoSat-2) were combined if available for the study lakes, with the optical water levels developed in this study as a critical reference to ~~densify~~ increase the ~~altimetric~~ water level observations and merging data from multiple altimetric missions.

Changes in lake area can be captured by optical/SAR images from medium or high spatial resolution remote sensing data, such as Landsat TM/~~ETM+~~ETM+/OLI. Extraction of lake water bodies can be manually (Wan et al., 2016) or automatically (Zhang et al., 2017b) achieved. Automatic water extraction methods based on the water index and auto-thresholding are more efficient in dealing with a ~~large amount~~mass of remote sensing images. Even so, acquisition and preprocessing of such a large amount of historical ~~images~~ data (~10TB) covering TP lakes are still intractable for researchers with limited computational resources~~resources~~. With the help of cloud-based platforms, such as the Google Earth Engine (GEE) that significantly reduces data downloading and preprocessing time, tens of thousands of images may be processed online in days instead of months (Gorelick et al., 2017). ~~In this study, more than twenty thousand Landsat TM/ETM/OLI images were processed online using GEE to extract lake water bodies based on the water index and Otsu algorithm.~~In this study, more than twenty thousand Landsat TM/ETM+/OLI images were processed online using GEE to extract lake water bodies based on the water index (McFeeters, 1996) and Otsu algorithm (Otsu, 1979).

There ~~are some~~have been studies focusing on changes in lake water storage on the TP over recent decades, e.g., Zhang et al. (2017a) examined changes in ~~lake~~ water storage for ~70 lakes from the 1970s to 2015 with ICESat~~-1~~ altimetry data and Landsat archives. An individual lake area data set from the 1970s and annual area data after 1989 were used. Due to the short time span of ICESat~~-1~~, they used the hypsometric method to convert lake areas into water levels. Yao et al. (2018b) used DEMs and optical images to develop hypsometric curves for lakes on the central TP, and estimated annual changes in ~~lake~~ water storage for 871 lakes ~~-~~from 2002 to 2015~~ for 871 lakes~~. These studies have a wide spatial coverage of lakes but relatively lower temporal sampling and little spaceborne altimetric information, which may limit the accuracy of trends in lake water level/storage in some cases and short-term monitoring of lake overflow floods. The LEGOS Hydroweb provides a lake data set, including multisource altimetry-based changes in lake water level and storage as well as hypsometric curves for 22 TP lakes (Crétaux et al., 2016; Crétaux et al., 2011b). The data set ~~incorporated~~ incorporates more spaceborne altimetric information and ~~provided~~ has a~~data of~~ higher temporal resolution. However, there may be a remaining bias when different sources of altimetric data ~~were~~ are merged, due to the lack of some important reference that can be derived from optical remote sensing images to be shown in this study. We term the reference data as the 'optical water level' to be introduced in section 3.2. Here, we list recent studies and data sets (Table 1) to provide a concise summary on remote sensing ~~the progress~~monitoring of ~~remote sensing-based~~ water levels and storage changes ~~monitoring on TP lakes~~over lakes on the TP.

Table 1. Recent studies and data sets on TP lakes. H, A, V in the table denote lake water level, area, and volume, respectively.

Reference	*No. of study lakes*	*Data type*	*Time span*	*Temporal resolution*	*Source data*
(Song et al., 2013)	30	H, A, V, and hypsometric curve	4 records for 1970s, 1990, 2000 and 2011	Decadal	Altimetry data: ICESat~~-1~~ Optical data: Landsat TM/~~ETM+~~ETM+
(Crétaux et al., 2016)	22	H, A, V, and hypsometric curve	1995–2015 Relative bias partially removed (only for altimeters with overlapping period)	Sub-monthly for lakes with T/P, and Jason-1/2 data, and ~monthly for the rest lakes	Altimetry data: T/P, ERS-2, GFO, Envisat, Jason-1/2, SARAL, ICESat~~-1~~, and CryoSat-2 Optical data: Landsat TM/~~ETM+~~ETM+/OLI and MODIS
~~*(Wan et al., 2016)*~~	~~>1000~~	~~A~~	~~3 records for 1960s, 2005, and 2014~~	~~Decadal~~	~~Optical data:~~ ~~Landsat ETM+/OLI, CBERS-1 CCD, and GF-1 WFV~~
(Jiang et al., 2017)	70	H	2003–2015 Relative bias between ICESat and CryoSat-2 unremoved	~Monthly	Altimetry data: ICESat~~-1~~, and CryoSat-2
~~*(Yang et al., 2017)*~~	~~874~~	~~A~~	~~2009–2014~~	~~Monthly data for 24 largest lakes, and yearly data for the rest lakes~~	~~Optical data:~~ ~~Landsat TM/ETM+/OLI and HJ-1A/1B~~
(Zhang et al., 2017a)	60~70	H, A, V, and hypsometric curve	One record for 1970s, and annual data for 1989–2015	Annual	Altimetry data: ICESat~~-1~~ Optical data: Landsat TM/~~ETM+~~ETM+/OLI
(Li et al., 2017b)	167	H	2002–2012	~Monthly	Altimetry data: ICESat~~-1~~ and Envisat
(Yao et al., 2018b)	871	H, A, V, and hypsometric	2002–2015	Annual	Optical data: Landsat TM/~~ETM+~~ETM+/OLI and HJ-

		curve			1A/1B DEM data: SRTM and ASTER
(Hwang et al., 2019)	59	H	2003–2016 Relative bias partially removed (only for lakes with Jason data/in situ data)	Sub-monthly for lakes with Jason-2 data, and ~monthly for the rest lakes	Altimetry data: Jason-2/3, SARAL, ICESat~~-1~~, and CryoSat-2 (Jason-3 data for validation)
Our study	52	H, A, V, and hypsometric curve	2000–2017 All relative biases removed	Sub-monthly for most lakes	Altimetry data: Jason-1/2/3, Envisat, ICESat~~-1~~, and CryoSat-2 Optical data: Landsat TM/~~ETM+~~ETM+/OLI

The overall objective of this study was to examine multiyear~~long-term~~ and short-term changes in water level and storage across 52 lakes with surface areas larger than 150 km^2 on the TP by merging multisource altimetry and optical remote sensing images to generate ~~a much denser (monthly or higher such as 10 days on average),~~ more coherent lake water level and ~~/~~storage change data sets of high temporal resolutions ranging from weekly to monthly timescales during~~covering the period~~ 2000–2017 and the hypsometric curve (i.e., the lake area-water level relationship) for each study lake. To investigate changes in lake storage, ~~changes in~~ lake water levels and ~~lake~~ areas need to be derived from multisource remote sensing.

~~-~~First, water levels from various satellite altimeters (~~see~~Figure 1) for each lake as well as ~~changes in~~ lake shoreline positions and lake areas from optical remote sensing images (i.e., Landsat TM/~~ETM+~~ETM+/OLI) were derived. Second, ~~the~~ systematic biases between different altimetry data were removed by either comparing the mean water levels of the overlap period (~~see~~ Figure 1) or comparing the two water level time series with ~~changes in~~ lake shoreline positions, depending on the length of the overlap period (details can be found in section 3.1). ~~The~~L~~-l~~ake shoreline ~~changes~~position-derived water levels, termed as the optical water levels ~~against altimetry water levels~~ in this study ~~,~~ can serve as a unique source of information reflecting water levels ~~changes~~ as well as a data merging reference. We will show that after deriving two or three regression parameters, l~~l~~ake shoreline ~~changes~~positions can well ~~represent~~reflect ~~-~~lake water levels with comparable accuracy as altimetry-derived water levels. Third, with information on ~~changes in~~ lake water levels and ~~water~~ areas derived from altimetry data and optical remote sensing images, the hypsometric curve that describes the relationship between the lake water level and ~~lake water~~ storage changes can be derived. Fourth, the integral of the hypsometric curve was performed to convert lake water levels~~time series~~ -into ~~lake~~ storage change~~time series~~s. ~~for each study lake.~~

Results of this study provide a comprehensive and detailed assessment of changes in lake level and storage on the TP for the recent two decades, and short-term monitoring of lake overflow floods for some lakes. This study could largely benefit more detailed investigations into lakes, lake basins, and regional climate change, because the generated data set has the highest temporal resolution during the study period~~.~~ with systematic biases well removed. To ensure the data quality, field experiments were carried out and in situ data were collected to examine the uncertainty in the derived optical water levels. ~~Details will be illustrated in the following sections.~~

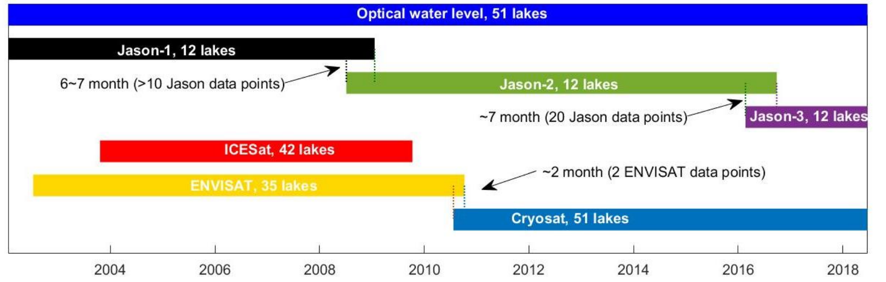


Figure 1. Spatial (the number of lakes covered) and temporal coverage and their overlap periods of multiple satellite altimetry missions used in this study, including Jason-1/2/3, Envisat, ICESat, and CryoSat-2.

2 Study area and data

2.1 Study area

The TP can be generally divided into 12 major basins (Wan et al., 2016; Zhang et al., 2013), among which the Inner/Central TP (CP) is the only endorheic basin and home to most TP lakes including ~300 TP lakes larger than 10 km^2. Therefore, it was chosen as the main study area. The endorheic basin covers an area of ~710,000 km^2 (~28% of total TP) with a mean elevation of ~4,900 m and has a semi-arid plateau climate with annual precipitation ranging from 9~~5.6~~6 ~~100–~~ 29~~4.9~~5~~300~~ mm ~~(Yao et al., 2018b)~~ (Li et al., 2017c). Most lakes in the endorheic basin were expanding under the influence of climate change/variability as opposed to many other places in the TP, e.g., ~~Lake Selin~~Selin Co exceeded ~~Lake Nam~~ Nam Co in area and consequently became the largest lake in the endorheic basin between 2011–2012 and expanded by 26% over the past 40 years (Zhou et al., 2015), whereas ~~Lake Yam~~Yamzhog Yumco (outside the endorheic basin, 350 km to the southeast of Selin Co) shrunk by ~11% during 2002–2014 according to Wan et al. (2016). Located in the southeast endorheic basin, the ~~Lake Nam~~ Nam Co basin covering about 10,800 km^2, with 19% of the basin lake water area and a mean lake elevation of ~4,730 m was chosen as a field experiment spot. The mean annual temperature and precipitation of ~~Lake Nam~~ Nam Co are 1.3 °C, and 486 mm, respectively (Li et al., 2017a). The other experiment spot was ~~Lake Yam~~Yamzhog Yumco, which has a mean lake elevation of ~4,440 m. Subjected to steep mountainous terrain, the lake has a narrow-strip shape with complex shorelines. The basin of ~~Lake Yam~~Yamzhog Yumco covers ~6,100 km^2, with mean annual temperature and precipitation of 2.8 °C and ~360 mm, respectively (Yu et al., 2011). An overall map of experiment lakes is shown in Figure 2.

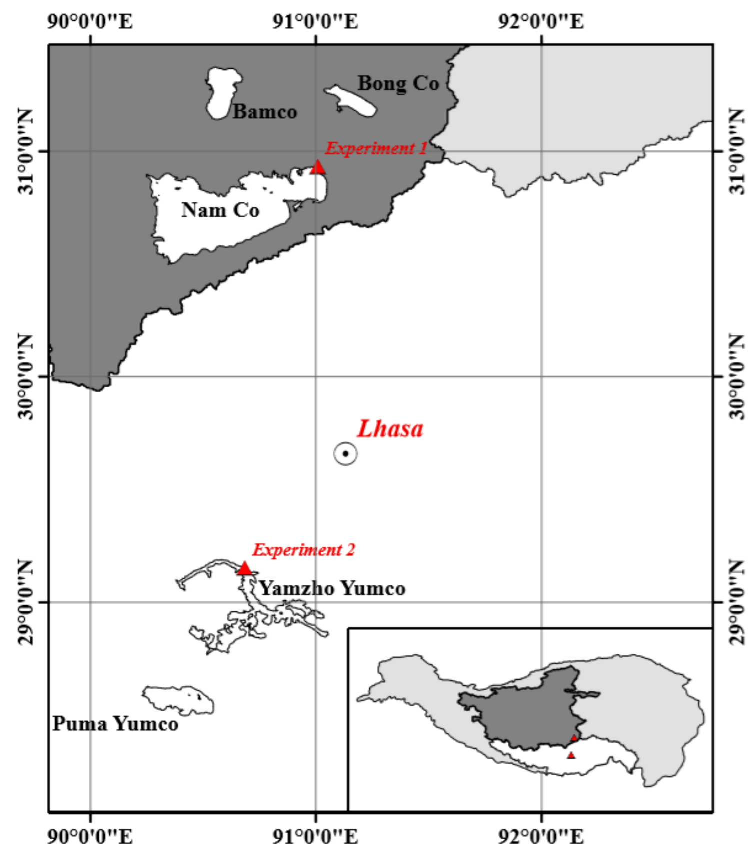
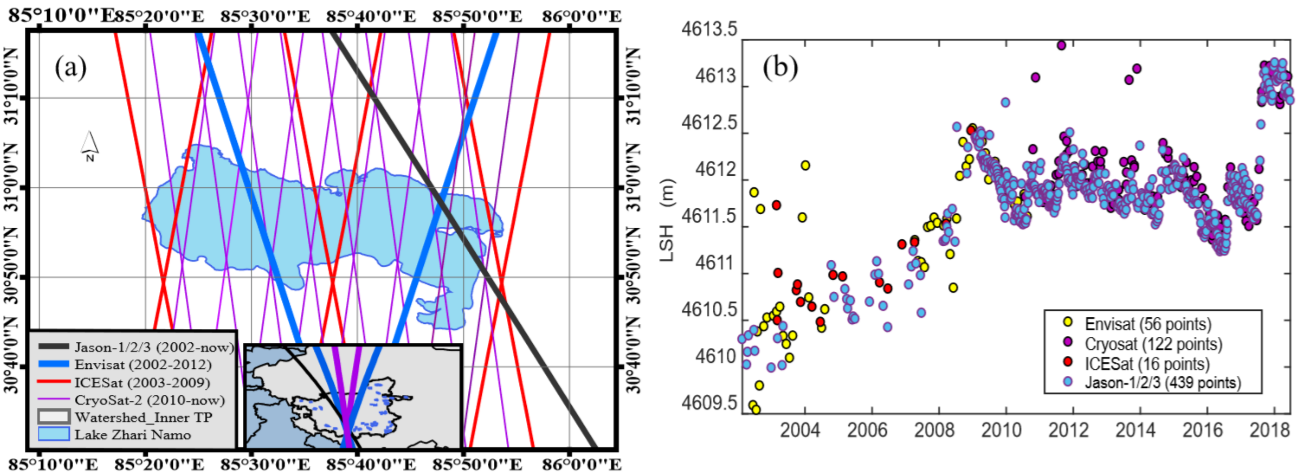


Figure 2 Experiment locations: Nam Co and Yamzhog Yumco. Nam Co is located in the endorheic basin of the TP, while Yamzhog Yumco is located in the~~-~~ Yarlung Zangbo River basin (the U~~u~~pper Brahmaputra River)~~ River basin~~. Both lakes are close to ~~the city~~ Lhasa City.

2.2 Data

Multisource altimetry data were used in this study as shown in Table 2~~Table 2~~. The earliest record dates back to 2002 (i.e., ~~ENVISAT~~Envisat and Jason-1) and the latest record ends in 2017 (i.e., Jason-3 and CryoSat-2, ~~see~~ Figure 1). Most of the 52 lakes examined in this study were covered by ICESat~~-1, ENVISAT~~, Envisat, and CryoSat-2 data. Jason-1/2/3 data were available only on 12 lakes due to the relatively sparse ground tracks or data quality issues. Note that Jason-2 inherited the orbit of Jason-1 after its launch in 2008, whereas Jason-1 was shifted into an interleaved orbit and continued functioning until 2013, thereby increasing the spatial coverage of Jason altimetry series to some degree, e.g., Jason-1 data in Lake Qinghai, the largest lake on the TP, were only available after 2008 due to the orbit shift. ICESat~~-1~~ and CryoSat-2 data have the best spatial coverage but relatively long repeat cycles of 91 days and 369 days, respectively ~~-~~(Bouzinac, 2012; Zhang et al., 2011). The ~~ENVISAT~~Envisat mission has a lower orbit than Jason-1/2/3 but higher than ICESat, resulting in a moderate ~~set of orbital parameters to balance its~~ spatial coverage and a temporal resolution of 35 days (Benveniste et al., 2002). ~~In~~

~~order t~~To determine if the altimetry data fall into the study lakes, a lake shape data set generated by Wan et al. (2016) was used~~. E.~~. An example of using the lake shape data set to determine altimetry data falling into the lake boundaries is given in ~~Figure 3~~(a), showing that d~~g., D~~ata from all altimeters are available in Zhari Namco~~ in a lake named Zhari Namco, as shown in Figure 3~~.



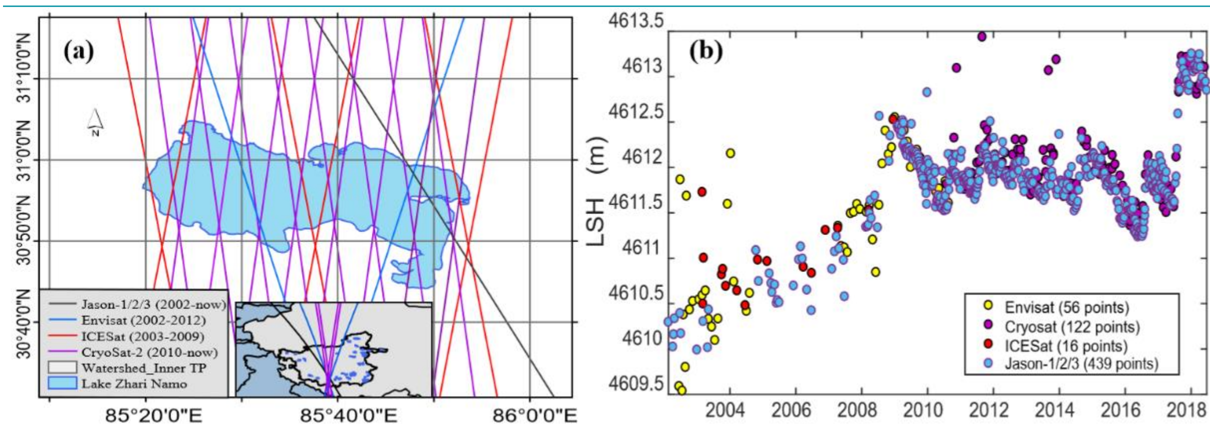


Figure 3. (a) Ground tracks of multiple altimetric missions over Zhari Namco and (b) the merged altimetry water levels for Zhari Namco.

It should be noted that different altimeters vary with wavelengths of electromagnetic radiation and mechanism. For instance, Jason-1/2/3 ~~(~~using the Ku and C bands~~)~~ and Envisat/RA-2 ~~(~~using the Ku and S bands~~)~~ work in the ~~L~~low r~~R~~esolution m~~M~~ode (LRM). These dual-frequency radar altimeters can provide more accurate range corrections due to the ~~I~~ionospheric effect (Tournadre, 2004). The ~~so-called~~ LRM is typical for the early version of satellite altimeters such as TOPEX/Poseidon. There are more advanced modes, such as ~~(~~SAR and InSAR~~)~~ for recent radar altimeters, which generally have smaller footprints than the LRM mode. CryoSat-2/SIRAL working at a single Ku band has three modes including LRM, SAR, and InSAR, which were designed to have an increasing resolution in turn and work in different zones. The InSAR mode uses interference phenomena so that shift of the nadir point across the track can be detected, improving the altimeter's performance on ice sheets with slopes (Bouzinac, 2012). The ICESat/GLAS ~~, as we mentioned before,~~ is a laser altimeter working in the near infrared band.~~with wavelengths of electromagnetic radiationsthe lrm (LRMsLRMwere~~

We used Landsat TM (2000–2011), ~~/ETM+~~ETM+(2000–2017), ~~/~~OLI (2013–2017) ~~S~~surface ~~Reflectance~~ reflectance data sets provided by GEE to generate information on lake shoreline positions and lake area~~-changes~~s. ~~TM images covered 2000–2011, whereas ETM+~~ETM+ ~~images covered 2000–2017 and OLI images covered 2013–2017. Though~~ Landsat ~~ETM+~~ETM+ ~~suffered~~ was subjected to sensor failure and all the ~~ETM+~~ETM+ images contain gaps after 2003 (Markham et al., 2004)~~, we managed to make use of some images with gaps in generating lake shore changes.~~. ~~All the images were processed online using GEE API.~~ ~~Preprocessing such as radiometric calibration, atmospheric correction, as well as geometric correction was already performed in the production of the data sets.~~ There were more than 20,000 images processed and a half of them were excluded from the final results due to cloud contamination or gaps.

We collected daily in situ water level measurements in ~~Lake Yam~~Yamzhog Yumco for validation purposes with a pressure-type water level sensor. The in situ water level measurements spanned a half year from May to October 2018. We also performed unmanned aerial vehicle (UAV or drone) imaging over a 1 km–lake bank in ~~Lake Yam~~Yamzhog Yumco and ~~Lake Nam~~ Nam Co~~. The UAV images were used to evaluate the accuracy of lake shore extraction from Landsat data, which is similar to Huang et al. (2018). In addition, we performed a rigorous statistical analysis of the uncertainty in the derived optical water levels by taking the UAV-derived water area ratios as the ground truth of sub-pixel water area ratios of Landsat image pixels (see Section 4).~~ for obtaining ~~a~~ better knowledge on the ~~of~~ experimental environment.

In addition, GF-2 images were used to performed a rigorous statistical analysis of ~~the~~ uncertainty in the derived optical water levels by taking the GF-2 derived lake shoreline positions as the ground truth to analyse the sub-pixel water area ratios of Landsat image pixels (see Section 4). GF-2 images have a spatial resolution of 0.8 m for the panchromatic band and pre-processing including orthorectification and radiometric calibration ~~were~~was performed ~~performed~~. Before analysis, we performed an image to image registration with manually selected tie points between GF-2 and corresponding Landsat OLI images until the co-registration error ~~meets a satisfactory value of~~reduced to ~2 m.

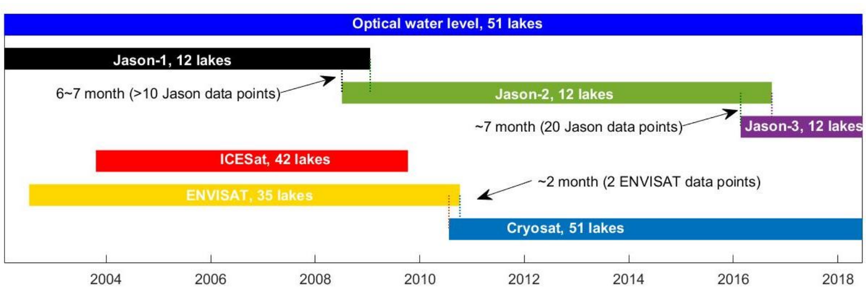
Table 2. Multisource altimetry data used in this study

Mission	Sensor ~~type~~(Type)	Data record	Duration	Repeat cycle (day)	Footprint interval (m)	Footprint diameter (km)	Lake no. with data	Data source
Jason-1	Poseidon-2 (Radar)	S-GDR	2002–2013	10 ~~d~~	~300 ~~m~~	2–4 ~~km~~	12	Aviso
Jason-2	Poseidon-3 (Radar)	S-GDR	2008–	10 ~~d~~	~300 ~~m~~	2–4 ~~km~~	12	Aviso
Jason-3	Poseidon-3B (Radar)	S-GDR	2016–	10 ~~d~~	~300 ~~m~~	2–4 ~~km~~	12	Aviso
~~**ENVISAT**~~**Envisat**	RA-2 (Radar)	GDR	2002–2010	35 ~~d~~	~390 ~~m~~	3.4 ~~km~~	35	ESA

CryoSat-2	~~Interferometer~~ SIRAL (Radar)	InSAR Level 1	2010–	369 ~~d~~ (Sub cycle 30 ~~d~~)	~280 ~~m~~	~1.65 ~~km~~ (across track~~)~~ ~~~~~), ~0.3~~00~~ ~~m~~ (along track)	51	ESA
ICESat~~-1~~	GLAS (Laser)	GLAH 14	2003– ~~–~~ 2009	91 ~~d~~	~170 ~~m~~	~0.07~~0~~ ~~m~~	42	NASA

3 Methodology

~~To investigate changes in lake storage, changes in lake water level and lake area need to be derived from multisource remote sensing. First, water levels from various satellite altimeters (see Figure 1) for each lake as well as changes in lake shoreline and area from optical remote sensing images (i.e., Landsat TM/ETM+/OLI) were derived. Second, the systematic biases between different altimetry data were removed by either comparing the mean water level of the overlap period or comparing the two water level time series with changes in lake shoreline, depending on the length of the overlap period. The lake shoreline changes, termed as the optical water levels against altimetry water levels in this study, can serve as a unique source of information reflecting water level changes as well as a data merging reference. We will show that after deriving two or three regression parameters, lake shoreline changes can well represent lake water levels with comparable accuracy as altimetry-derived water levels. Third, with information on changes in water level and water area derived from altimetry data and optical remote sensing images, the hypsometric curve that describes the relationship between the lake water level and lake water storage changes can be derived. Fourth, the integral of the hypsometric curve was performed to convert water level time series into lake storage change time series. Details will be illustrated in the following sections.~~



~~**Figure 1. Spatial (the number of lakes covered) and temporal coverage and their overlap periods of multiple satellite altimetry missions used in this study, including Jason-1/2/3, ENVISAT, ICESat-1, and CryoSat-2.**~~

3.1 Altimetry water level

The first step of deriving altimetry water levels is to select correct ground tracks and valid footprints falling on the lakes. Because there is a random ground track shift at ~1 km in different cycles for most altimetry missions, it is uncertain that valid lake footprints can be obtained for each cycle, even though the nominal ground track seems to ~~crossing~~ cross the lake. This problem can be addressed by comparing the geographic coordinates of the footprints with a lake shape data set (Wan et al., 2016). After picking out the valid footprints, the lake surface height can be calculated for each footprint. All radar altimetry data share a relationship:

$$LSH = Alt - (Range + cor)$$ Eq ~~1~~1

where *LSH* represents the lake surface height with respect to the geoid; ~~.~~ *Alt* represents the altimeter height with respect to the reference ellipsoid; ~~.~~ *Range* represents the distance between the altimeter and lake surface; and ~~.~~ *cor* represents several range corrections due to atmospheric effects, sensor design defects, or geophysical effects. Radar altimeters and laser altimeters need different corrections, given that they are working in different wavelengths and have ~~very~~ different designs. For instances, corrections for radar altimeters ~~includ~~include~~ing~~ waveform retracking correction, wet/dry troposphere correction, ionosphere correction, pole/solid tide correction, and geoid correction. Laser altimeters also need atmospheric delay correction, geoid/pole tide correction, and geoid correction. Unlike radar altimeters, saturation correction instead of waveform retracking correction is more important to laser altimeters.

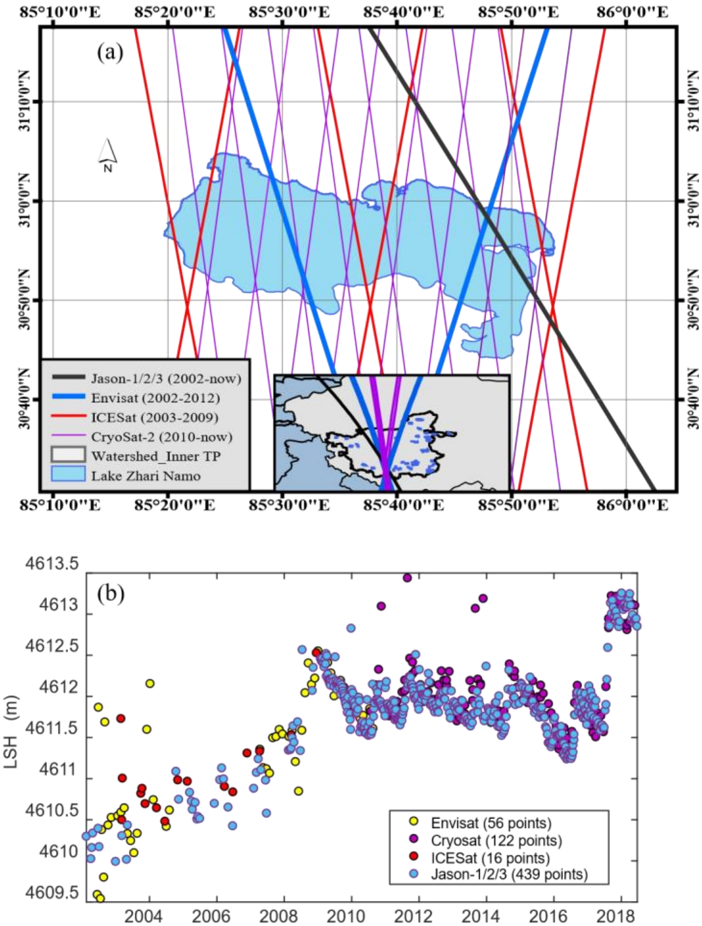
The retracking ~~range~~ correction plays an important role in removing the contamination of land signal when ~~the~~ radar altimetry data are applied to inland water bodies. In this study, Jason-1/2/3 data were retracked using a classical waveform retracking algorithm ~~named~~, i.e., the improved threshold method (ITR), whereas CryoSat-2 data were retracked using the narrow primary peak threshold (NTTP) method (Birkett and Beckley, 2010; Cheng et al., 2010; Jain et al., 2015). Retracking corrections were not performed for ~~ENVISAT~~Envisat and ICESat data, because the ~~ENVISAT~~Envisat/RA-2 product already provided a retracked range using the ICE-1 method and the ICESat GLAH14 product already included several corrections (such as saturation correction) that are sufficient for most applications including studies on inland water bodies (Zhang et al., 2011).

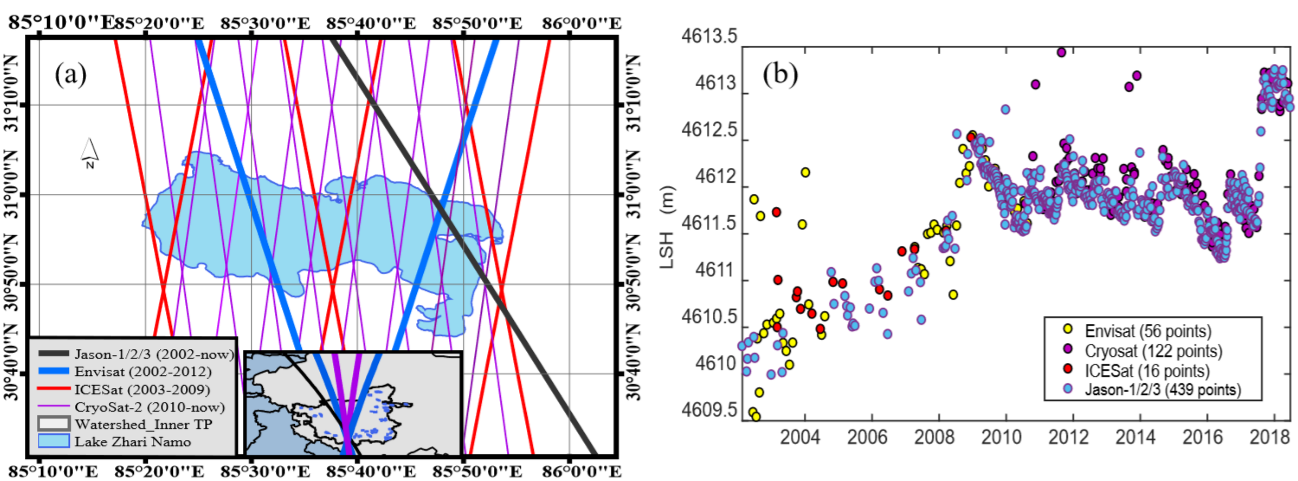
The original idea of the NTTP, ICE-1, and ~~Improved Threshold Method~~ITR is quite similar. All of them adopt a threshold defined as the percentage of the waveform peak to determine the retracking gate, and then to ~~transfer~~convert the difference between the retracking gate and the nominal gate into range correction by multiplying the gate range ($c\Delta t/2$, where c is the speed of light and Δt is the time duration of a gate). The differences lie in the choice of thresholds as well as the calculation of waveform peaks. For instance, ICE-1 uses a 30% threshold ~~while~~whereas ITR uses a 50% threshold.

For each cycle of an altimeter, it is common that more than one footprint fall on a study lake, thereby providing several LSH observations on the same day. After removing outliers with the three-sigma rule, frequency distributions of the LSHs from the same cycle were calculated. The mean value of the ~~highest bucket of the~~ histogram bin with the highest frequency was selected to represent the LSH for the cycle. Meanwhile, the frequency of the chosen ~~bucket~~ histogram bin was reserved to evaluate the data quality for the cycle, e.g., a cycle was marked as high quality if the frequency is higher than 0.8, moderate quality if it is only higher than 0.5, and poor quality if the frequency is lower than 0.5. The LSH from each cycle constituted the lake water level time series for the study lake. LSHs that were marked as poor quality and obviously deviated from the moving average were removed from the altimetry-based lake water level time series.

It is not uncommon that systematic biases exist in different altimetry data sets due to ~~the~~ variations in orbit, the discrepancy between correction models, errors associated with sensors, and even the choice of the reference datum. After deriving lake water level time series for each altimeter, we first merged the Envisat and ICESat~~-1~~ water levels if both were available for a lake, because they have the longest overlap period (Figure 1). We chose Envisat-derived water levels as the baseline and removed the difference of the mean values ~~of the overlap period between~~of the two products during the overlap period, because Envisat data are generally denser and longer than ICESat~~-1~~ data. A similar process was applied to Jason-1/2/3, as there are two overlap periods connecting the three altimeters together. (b) shows a result of altimetry data merging when all sensors are available.

There are tradeoffs between CryoSat-2 and Jason-2/3 data in terms of spatial coverage and time span. CryoSat-2 data are available for all study lakes but they only have ~~the~~ an overlap period with Jason-2/3 data, whereas Jason-2/3 data are only available for 12 lakes. For most lakes without Jason-2/3 data, we merged CryoSat-2 data with either ICESat~~-1~~ or Envisat using optical water levels spanning from 2000 to 2017, because there is no overlap period between these altimetry water levels~~. Lake shoreline changes were firstly translated into optical water levels by fitting with CryoSat-2 data, functioning as extrapolation of CryoSat-2 to 1-2 years. Then, we applied the same method of merging Jason-1/2/3, to merge the extrapolated CryoSat-2 data with either Envisat or ICESat-1 data.~~ (~~See~~ Figure 1). Details on optical water levels and how they ~~aid~~aid in merging the altimetry water levels can be found in section 3.2~~. In doing so, we were able to remove all systematic biases between multisource altimetry-derived water levels. All the water levels were with respect to EGM 96. Figure 2 provides an example of ground tracks of altimetric missions and water level time series on Lake Zhari Namco~~.



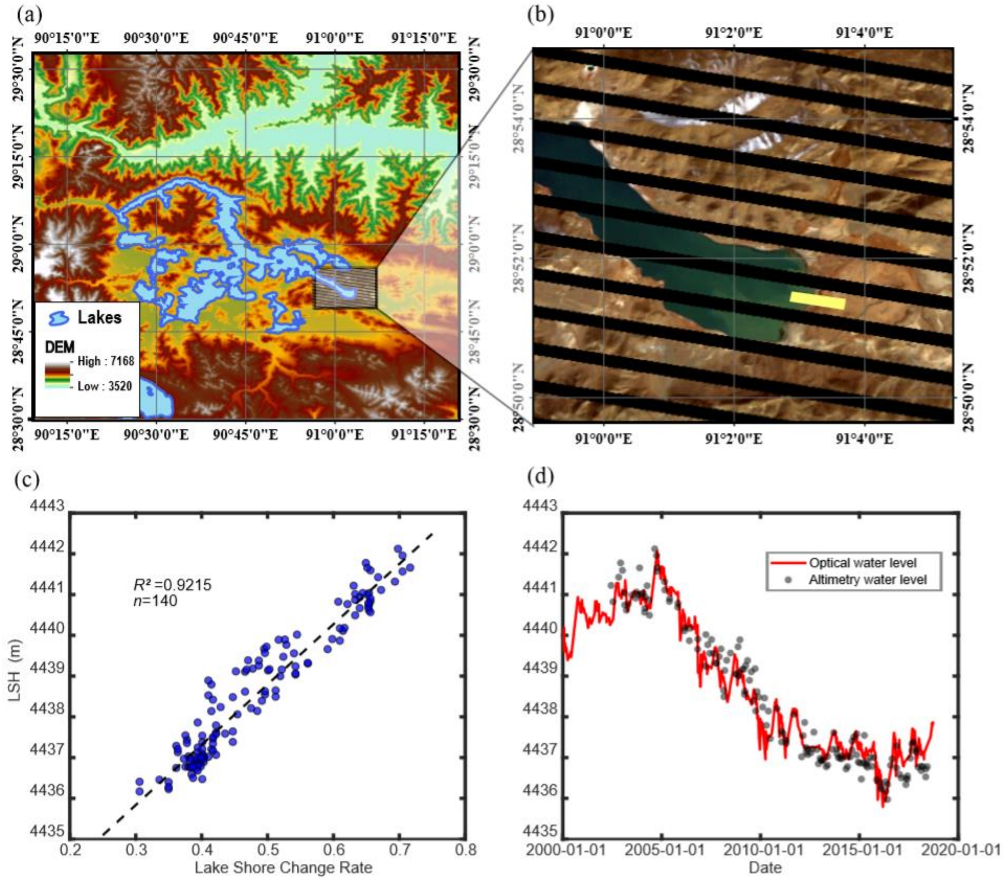


~~**Figure 23. (a) Ground tracks of multiple altimetry missions over Lake ZhariZhari Namco and (b) the merged altimetry water levels for Lake ZhariZhari Namco.**~~

3.2 Optical water level

For most lake basins, it is possible to find a relatively flat portion~~part~~ of lake banks with an average slope of 1/30 or even smaller, where obvious interannual or intra-annual changes in lake shoreline positions~~s~~ can be detected using ~~high-spatial-resolution~~ Landsat images (30 m). These locations can be found by comparing lake images from the first year and the last year of the study period if the lake shows a clear expanding/shrinking trend. Otherwise, we can compare images acquired in early summer when the LSH is at lowest with those acquired in late autumn when the lake expands to its limit. In this study, we assumed that the selected lake bank was flat enough such that the relationship between the ~~changes in~~ lake water level and shoreline position can be depicted in a linear or quasi-linear (parabolic) way. Thus, we can transform the ~~the~~ lake shoreline positions ~~changes~~ into optical water levels by fitting with altimetry water levels. The validity of this assumption can be evaluated with the coefficient of determination (R^2) for each lake as shown in Table 3~~Table 3~~. For most lakes, the goodness of fit is higher than 0.7, suggesting the generally good fitting relationship between ~~changes in~~the lake water levels and shoreline positions.

Though there were ~500 Landsat images obtained for the selected lake banks during the study period, many of them were largely affected by cloud or cloud shadow. All the images were processed online using GEE API. Pre~~-~~processing such as radiometric calibration, atmospheric correction, as well as geometric correction was already performed in the production of the data sets. In addition, the failure of Landsat 7 sensor SLC left all the Landsat 7 images with gaps after 2003 (Markham et al., 2004), making the available images even fewer. We managed to make use of some images with gaps in generating lake shoreline positions~~changes~~. By choosing the region of interest (ROI) that is parallel to the Landsat 7 gaps, we ~~can use~~made most of the Landsat 7 images useable. However, the width of ROI must be reduced to avoid shifting gaps as shown in ~~**Figure 3 (b).**~~ ~~**(b)**~~. The gaps may vary with time but are more like vibration around the mid-point. The ROI did not fill the interval of gaps, because the wider the ROI, the higher possibility of shifting gaps cross it.


(a)
90°15'0"E
90°30'0"E
90°45'0"E
91°0'0"E
91°15'0"E
29°30'0"N
29°15'0"N
29°0'0"N
28°45'0"N
28°30'0"N
Lakes
DEM
High : 7168
Low : 3520
(b)
91°0'0"E
91°2'0"E
91°4'0"E
28°54'0"N
28°52'0"N
28°50'0"N
(c)
R² =0.9215
n=140
LSH (m)
Lake Shore Change Rate
(d)
Optical water level
Altimetry water level
Date
2000-01-01
2005-01-01
2010-01-01
2015-01-01
2020-01-01

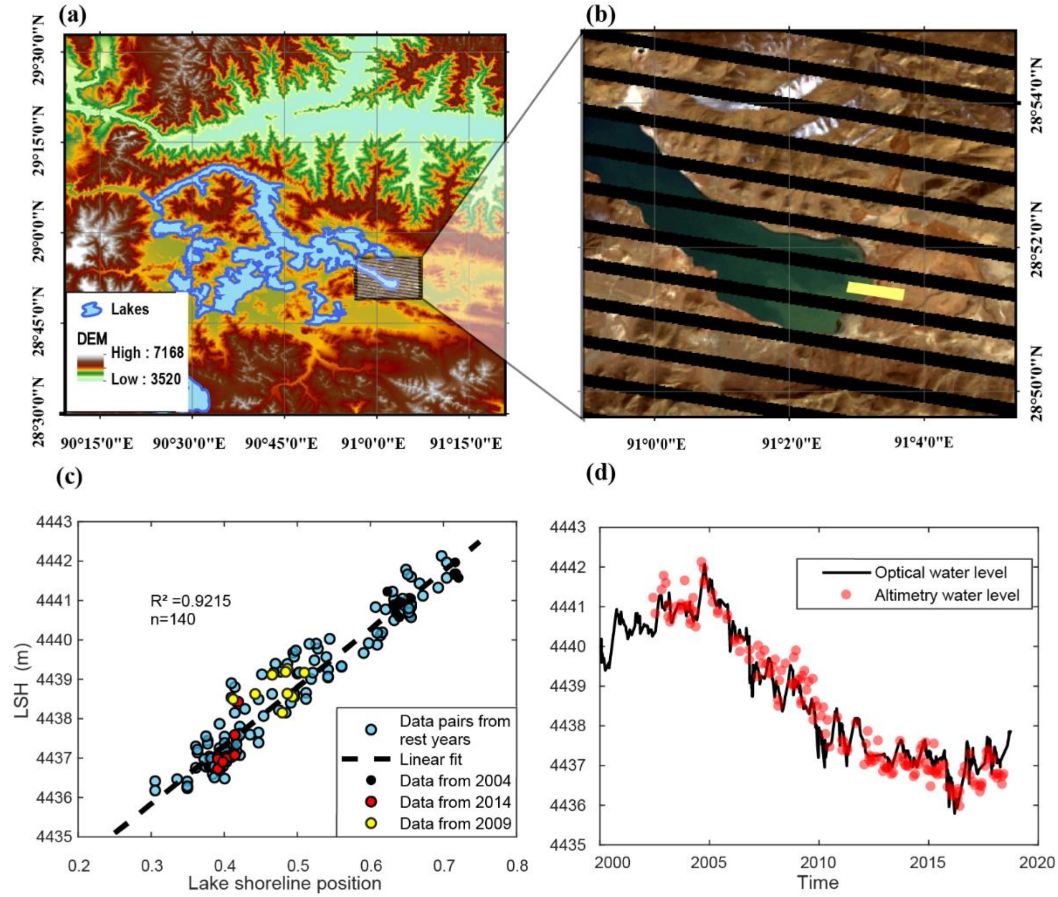


Figure 4. (a) Yamzhog Yumco and its surroundings. The DEM was extracted from the STRM Global 90-m DEM product; (b) ROI (yellow area) selected from a Landsat ETM+ image for detecting changes in lake shoreline and the gaps (black areas); (c) linear regression of lake shoreline positions that are represented by water area ratios in the ROI and altimetry water levels for Yamzhog Yumco; and (d) optical water levels and altimetry water levels for Yamzhog Yumco.

~~Changes in l~~Lake shoreline positions~~s~~ were characterized by ~~changes in the~~ water ~~surface~~ area ratios detected in the ROI. To automatically extract ~~changes in~~ water ~~surface~~ areas from ~~tremendous amount~~a mass of Landsat archives on GEE, the water index and Otsu threshold method were jointly used. We calculated the ~~Normalized~~ normalized ~~Difference~~ difference ~~Water~~ water ~~Index~~ index (NDWI) and the ~~Modified~~ modified ~~Normalized~~ normalized ~~Difference~~ difference ~~Water~~ water ~~Index~~ index (MNDWI) of the ~~input~~ images and compared their performance in different seasons. It was found that the MNDWI tends to be more sensitive to shallow water in summer, but is less effective than NDWI when the lake bank is covered by snow in the cold season as shown in ~~**Figure 4**~~. Therefore, the two water indices were jointly used~~ in this study~~ by applying the MNDWI to images acquired during May to October and applying the NDWI to the rest months. The NDWI and MNDWI can be calculated as follows (McFeeters, 1996; Xu, 2005):

$$NDWI = \frac{B_{green} - B_{NIR}}{B_{green} + B_{NIR}}$$ Eq ~~2~~2

$$MNDWI = \frac{B_{green} - B_{SIR}}{B_{green} + B_{SIR}}$$ Eq ~~3~~3

where B_{green}, B_{NIR}, and B_{SIR} refer to surface reflectance of bands 2, 4, 5 for Landsat TM/~~ETM+~~ETM+ images and bands 3, 5, 6 for Landsat OLI images.

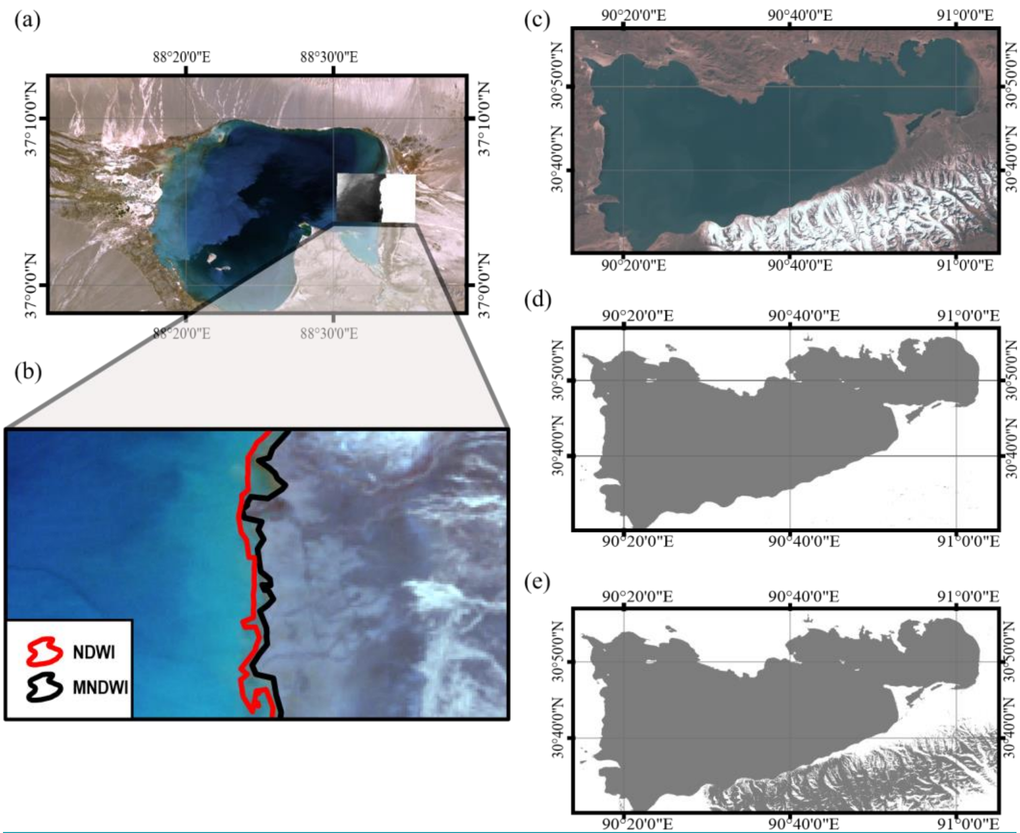
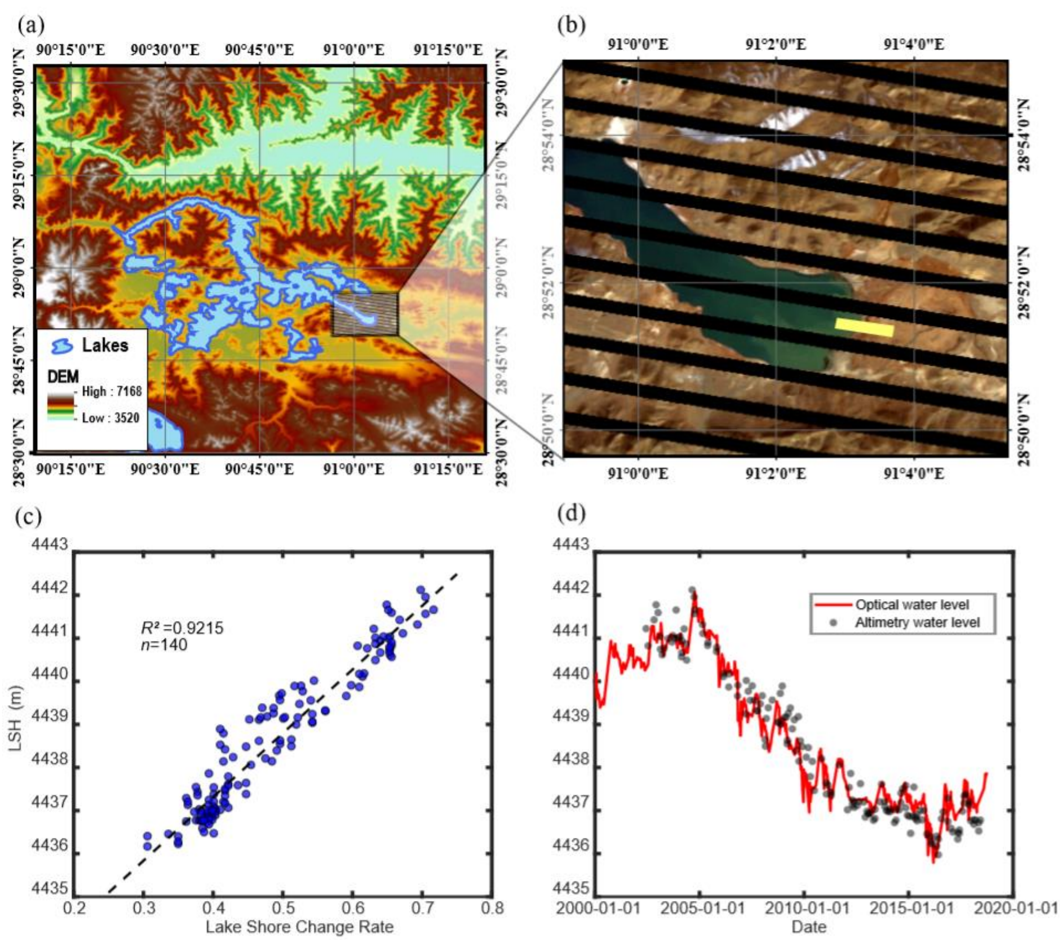
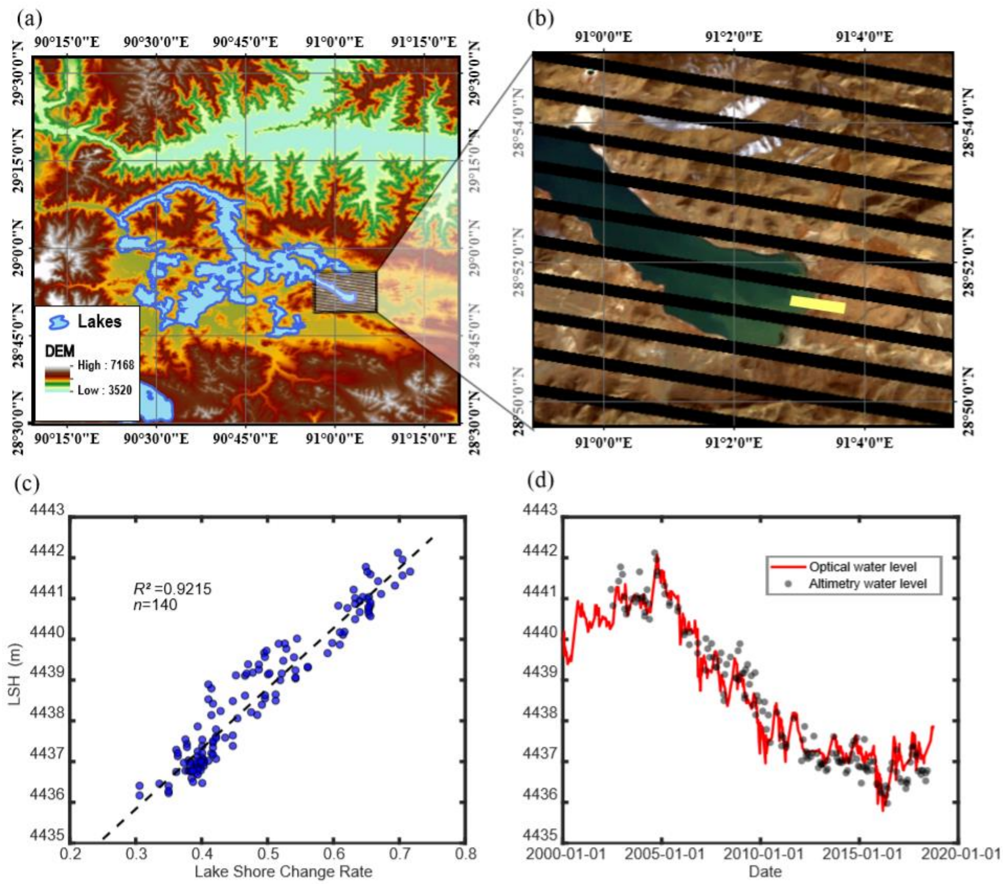


Figure 5. (a) A Landsat ETM+ image of the Aqqikkol Lake acquired in summer in 2001; (b) water area extractions using the MNDWI and NDWI, showing that the MNDWI performs better in detecting shallow water; (c) a Landsat OLI image of Nam Co acquired in winter in 2015; (d) water area extraction using the NDWI, showing good performance in distinguishing water from snow; and (e) water area extraction using the MNDWI, showing some confusion of water and snow.

After calculating the water index, the grayscale image was binarized using the Otsu method. If the selected ROI comprises ~50% water and ~50% land, the performance of the method is good, as the distribution of digital numbers of the grayscale image is close to the assumption of the bimodal histogram implicit in the Otsu algorithm ~~(Kittler and Illingworth, 1985).~~(Kittler and Illingworth, 1985; Otsu, 1979). The binarized images were further processed to provide the water ~~surface~~ area ratio in the ROI, which represents the ~~changes in~~ lake shoreline position. The ~~time series of changes in l~~lake shoreline position time series were then converted into optical ~~lake~~ water levels using linear regression or second-order polynomial fit with altimetry-derived water levels (~~**Figure 3 (c)-(d)).**~~ **(c)-(d)**). For most cases, we only used linear regression, and only for 2 lakes with Jason-1/2/3 data we performed the second-order polynomial fit, because a higher-order regression requires more input information to ensure the reliability.

However, cloud, cloud shadow, and shifting gaps may contaminate the ROI and cause errors in the optical water levels. Therefore, the QA band of the Landsat ~~Surface~~ surface ~~Reflectance~~ reflectance product was used to filter the images. ~~The d~~Data would be excluded if the fraction of the cloud or cloud shadow-covered area in the ROI was higher than 5%. For every Landsat ~~ETM$^+$~~ETM+ image acquired after 2003, the pixel number of the ROI was counted and compared with those acquired before 2003. If the loss of pixels exceeded 2%, the ROI was considered to be affected by gap and the data were consequently excluded from the subsequent analysis.

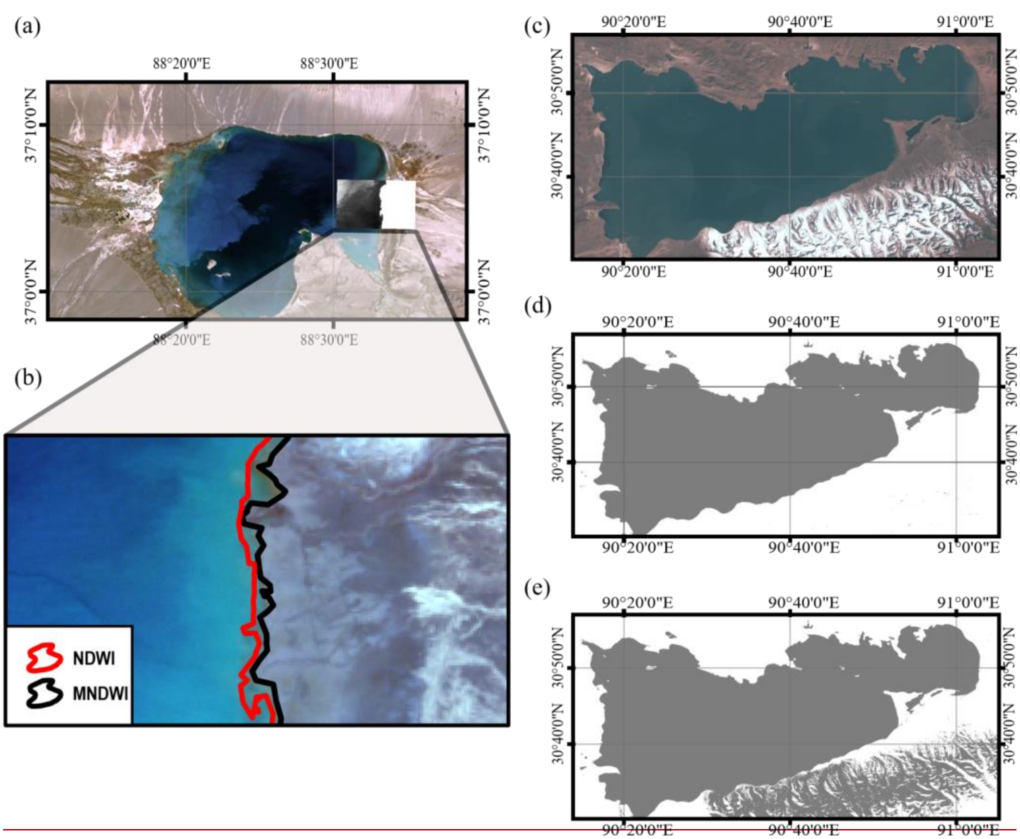




~~Figure 34. (a) Lake YamYamzhog Yumco and its surroundings. The DEM was extracted from the STRM Global 90-m DEM product; (b) ROI (yellow region) selected from a Landsat ETM+ETM+ image for detecting changes in lake shoreline and the gaps (black region); (c) linear regression of the lake shoreline change and altimetry water level for Lake YamYamzhog Yumco; and (d) optical water levels and altimetry water levels for Lake YamYamzhog Yumco.~~

A critical function of optical water levels is to ~~aid~~aid in ~~the~~ merging of altimetry water levels when there w~~are~~as no overlap~~ping~~ period~~s~~ between altimeters or the overlap~~ping~~ period~~s~~ ~~is~~was too short. For lakes without Jason-1/2/3 data,- lake shoreline ~~changes~~ positions were firstly translated into optical water levels by fitting with CryoSat-2 data (), functioning as extrapolation of CryoSat-2 to 1–2 years. Then, we applied the same method of merging Jason-1/2/3 ~~,~~ to merge the extrapolated CryoSat-2 data with either Envisat or ICESat data. In doing so, we were able to remove all systematic biases between multisource altimetry-derived water levels. After the merging of altimetry water levels, we ~~will~~ performed the regression analysis for the second time between the optical water levels and merged altimetry water levels to check if the linear relationship is stable during the entire study period and at different elevations. If the linear relationship ~~is~~was stable, the optical water levels ~~will be~~would be -merged with the altimetry water levels using the linear fitting parameters from the second regression analysis. Otherwise, there ~~might~~ may ~~be a~~ have a change in the lake bank slope and, -therefore, the extrapolation of CryoSat-2 data with optical water levels ~~might not be~~was not suited. ~~If so,~~In this case, -we ~~will~~ reselected the ROI to extract ~~the~~ lake shoreline ~~changes~~positions and red~~o~~id altimetry data merging until the optical water levels and merged altimetry water levels agreed well with ~~each other~~ one another in the second linear regression. Detailed analysis about the potential extrapolation issue can be found in the supplementary file.

~~To summarize the altimetry data merging:~~ In summary, the basic idea of removing ~~the~~ systematic biases of different altimetry-based water levels is to calculate the means of two altimetry~~-based~~ water level time series ~~from different sources~~ during the overlap period. ~~Then, t~~The difference between the ~~difference between the~~ mean~~-time series~~s ~~and either~~ is removed from one altimetry water level time series ~~is removed to~~ to make both altimetry~~-based~~ water level time series consistent and to form a longer ~~water level~~ time series. This process was subsequently applied to all water level time series with overlap periods to merge them into a single time series for each lake. However, the overlap period ~~could be short~~ may not be long enough, ~~between some altimeters~~ such as Envisat and CryoSat-2 (e.g., there ~~are only one or two data~~are limited data points (e.g., 1–2) ~~in~~during the overlap period), or does not exist at all, such as ICESat and CryoSat-2. On these cases, optical water levels ~~(i.e., changes in lake shoreline that need to be translated into changes in water levels using linear regression with one of the altimetry water level time series)~~ are used to extend or create an overlap period that links ~~the~~ two altimetry~~-missions.~~-based water level time series.



~~**Figure 45. (a) Landsat ETM+ETM+ image of the Aqqikkol Lake acquired in summer in 2001; (b) water extraction result using the MNDWI and NDWI, showing that the MNDWI performs better in detecting shallow water; (c) Landsat OLI image of Lake Nam Nam Co acquired in winter in 2015; (d) water extraction result of the NDWI, showing good performance in distinguishing water from snow; and (e) result of the MNDWI, showing some confusion of water and snow.**~~

3.3 Hypsometry

We derived the hypsometric curve for each study lake by polynomial fitting of the lake area and level time series. The lake area comprises two parts: the inner invariable part and the outer variable part. As the variable water area ~~is~~ was of more concern in this study, ROIs for extracting changes in lake area only cover the lake shoreline and its neighbouring areas as shown in **Figure 6** ~~**Figure 5**~~. The inner part of the water body was calculated only once and considered as invariant, making the calculation more efficient on GEE. Meanwhile, more images are available as the area of ROI becomes smaller, because the possibility of clouds covering the ROI is reduced compared with an ROI covering the entire lake. ~~The~~ Landsat ~~ETM+~~ETM+ images after 2003 were not included in this part of calculation as gaps negatively affected the ROI for lake area extraction. Similar to ~~Section~~ section 3.2, we selected images with less than 5% cloud cover on an ROI to generate time series of changes in lake area, obtaining 20–~~∼~~30 data points on average for regression. R^2 values for each lake are listed in Table 3~~Table 3~~, indicating that most lake basins agree well with the parabolic hypsometric curve.

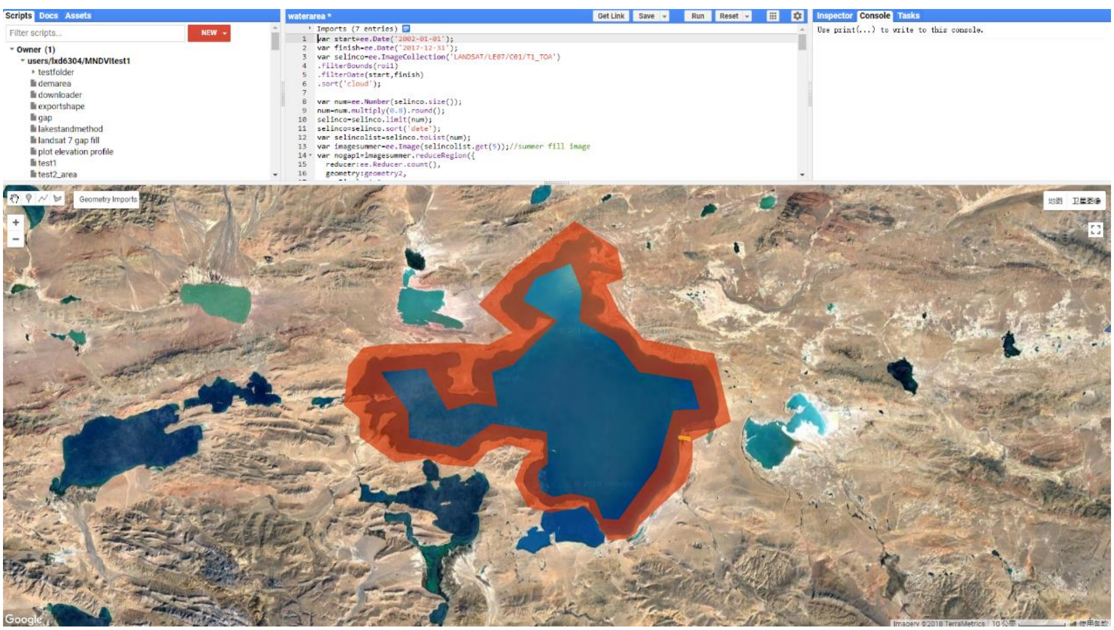


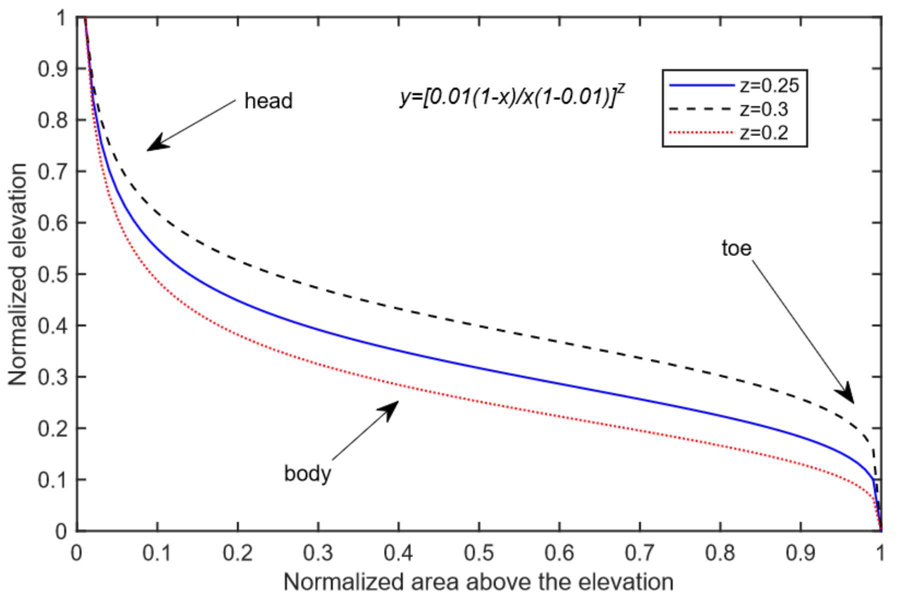
Figure 6~~5~~ . Programming interface of GEE. The red polygon ~~was~~ is the ROI for lake area change extraction of ~~Lake Selin~~Selin Co.

~~It can also be seen that most fitting functions have a positive parameter for the second-order term, which can be explained according to the knowledge on the hypsometric curve of catchments. This differs somewhat from the previous studies by Song et al. (2013) that shows a negative value for the second-order derivatives. After investigating a number of watersheds,~~

~~researchers suggested that the general hypsometric curve for the entire catchment can be expressed as: (Strahler, 1952; Willgoose and Hancock, 1998):~~

$$\cancel{y=\left[\frac{d-x}{x}\cdot\frac{a}{d-a}\right]^{z}} \qquad \text{~~Eq 4~~}$$

~~where y corresponds to the normalized elevation and x corresponds to the normalized area above the elevation. a, d, and z are fitting parameters. The hypermetric curve generated by this model always has a 'toe' as shown in **Figure 6**, where the second-order differential of the curve is negative. This means that at the low elevation of the catchment, with decreasing (increasing) elevations, the area above (below) the elevation increases more slowly (faster). Lakes are always formed at the lowest portion of a catchment, so the hyperosmotic curve for a lake basin can be the toe part for the entire catchment. This suggests that if we use the parabolic curve to fit the lake area and water level time series, there should be a positive second-order parameter so that with increasing water levels, the lake area increases faster. The last step was to integrate the hypsometric curve to generate the volume–elevation relationship and convert the lake water levels into storage changes.~~



~~**Figure 6. Strahler's hypsometric model for catchment with *a*=0.01 and *d*=1.**~~

Table 3. Information on regression analysis of study lakes.

Lake Name	Lake Area km^2	No. of optical water level	R^2 of optical water level (No. of data pairs)	R^2 of hypsometric curve (No. of data pairs)	Hypsometric function
Ake Sayi Lake	260.74	113	0.8951 (14)	0.9556 (21)	$S=0.45dh^2+11.26dh+163.97$, $dh=H-4846$

Aqqikkol Lake	538.21	354	0.9717 (44)	0.9353 (36)	$S=2.36dh^2+0.21dh+370.29$, dh=H-4252
Ayakkum Lake	987.23	183	0.9651 (50)	0.9695 (57)	$S=0.16dh^2+65.72dh+658.28$, dh=H-3878
Bamco	255.81	209	0.901 (14)	0.9287 (27)	$S=0.28dh^2+2.84dh+206.46$, dh=H-4560.5
Bangong Co	661.64	232	0.5164 (172)	0.7991 (29)	$S=1.43dh^2+15.67dh+619.28$, dh=H-4238
Chibzhang Co	541.96	49	0.8766 (19)	0.9792 (15)	$S=0.69dh^2+3.36dh+475.79$, dh=H-4930
Co Ngoin1	268.37	174	0.6637 (15)	0.8803 (62)	$S=3.67dh^2+-1.33dh+263.1$, dh=H-4564.5
Cuona Lake	192.15	254	0.7607 (12)	0.8876 (27)	$S=1.77dh^2+3.6dh+184.79$, dh=H-4585.5
Dagze Co	310.8	192	0.8334 (67)	0.8862 (28)	$S=0.08dh^2+6.14dh+230.51$, dh=H-4460
Dogai Coring	492.39	257	0.8624 (152)	0.9048 (33)	$S=3.2dh^2+5.66dh+427.17$, dh=H-4816
Dogaicoring Qangco	403.18	162	0.9202 (37)	0.9218 (47)	$S=0.53dh^2+3.93dh+279.6$, dh=H-4786
Donggei Cuona Lake	247.83	561	0.8776 (38)	0.925 (101)	$S=0.54dh^2+7.22dh+222.19$, dh=H-4084
Dung Co	139.4	145	0.9218 (49)	0.8652 (28)	$S=0.07dh^2+2.3dh+137.06$, dh=H-4547
Goren Co	477.95	191	0.6166 (24)	0.9096 (41)	$S=2.91dh^2+-0.03dh+468.33$, dh=H-4648.5
Gozha Co	246.91	96	0.4297 (12)	0.5564 (19)	$S=1.57dh^2+-0.06dh+254.43$, dh=H-5082
Gyaring Lake	535.84	253	0.6217 (20)	0.3451 (71)	$S=1.99dh^2+2.8dh+517.18$, dh=H-4292
Har Lake	621.52	370	0.8652 (63)	0.9893 (50)	$S=1.1dh^2+1.52dh+582.34$, dh=H-4075
Hoh Xil Lake	351.3	132	0.9038 (12)	0.9355 (27)	$S=1dh^2+5.29dh+300.5$, dh=H-4887.1
Jingyu Lake	339.69	224	0.8978 (51)	0.989 (34)	$S=0.37dh^2+4.77dh+238.43$, dh=H-4710
Kusai Lake	328.8	295	0.9787 (151)	0.8987 (49)	$S=0.52dh^2+5.04dh+254.67$, dh=H-4473
Kyebxang Co	187.32	233	0.75 (12)	0.8753 (135)	$S=0.16dh^2+5.4dh+150.9$, dh=H-4619
Langa Co	256.03	167	0.859 (157)	0.888 (47)	$S=-0.19dh^2+4dh+249.28$, dh=H-4564
Lexiewudan Co	273.63	286	0.9216 (49)	0.9496 (40)	$S=0.13dh^2+4.63dh+219.65$, dh=H-4868
Lumajiangdong Co	386.71	220	0.9135 (28)	0.9708 (17)	$S=0.62dh^2+2.09dh+353.95$, dh=H-4812
Mapam Yumco	412.69	163	0.7096 (30)	0.9973 (30)	$S=1.18dh^2+5.16dh+399.68$, dh=H-4584
Margai Caka	137.7	247	0.9399 (12)	0.9955 (35)	$S=0.03dh^2+5.14dh+112.12$, dh=H-4791
Memar Co	167.3	193	0.911 (39)	0.8626 (20)	$S=0.27dh^2+3.17dh+134.69$, dh=H-4923
Nam Co	2028.5	187	0.9064 (62)	0.8749 (18)	$S=2.43dh^2+5.55dh+1970.1$, dh=H-4724.5
Ngangla Ringco	492.86	88	0.4652 (25)	0.9498 (7)	$S=3.87dh^2+3.86dh+490.69$, dh=H-4715
Ngangze Co	471.21	245	0.9538 (236)	0.9332 (49)	$S=0.2dh^2+7.03dh+391.21$, dh=H-4680
Ngoring Lake	656.83	86	0.844 (71)	0.8613 (14)	$S=4.69dh^2+-5.04dh+613.66$, dh=H-4270
Paiku Co	272.85	231	0.8341 (21)	0.9079 (61)	$S=0.91dh^2+2.64dh+264.89$, dh=H-4578.5
Puma Yumco	290.98	250	0.6871 (18)	0.5629 (53)	$S=0.48dh^2+0.8dh+286.34$, dh=H-5011
Pung Co	176.93	187	0.8017 (12)	0.9841 (31)	$S=0.03dh^2+3.75dh+151.66$, dh=H-4526
Qinghai Lake	4495.33	323	0.9011 (151)	0.8181 (19)	$S=3.45dh^2+155.03dh+4084.73$, dh=H-3193
Rola Co	169.83	347	0.7842 (18)	0.9403 (96)	$S=-0.88dh^2+14.87dh+115.59$, dh=H-4816
Salt Lake	144.3	206	0.9344 (16)	0.9858 (32)	$S=0.16dh^2+-0.69dh+37.42$, dh=H-4430
Salt Water Lake	212.47	347	0.9086 (27)	0.9494 (151)	$S=-0.82dh^2+17.31dh+133.71$, dh=H-4901
Selin Co	2300.49	179	0.9777 (70)	0.945 (22)	$S=1.05dh^2+45.86dh+1754.31$, dh=H-4536.4
Tangra Yumco	862.94	100	0.9155 (18)	0.8072 (11)	$S=0.94dh^2+-0.28dh+862.94$, dh=H-4536
Taro Co	485.15	268	0.8903 (39)	0.9576 (19)	$S=0.18dh^2+4.97dh+477.32$, dh=H-4567.3

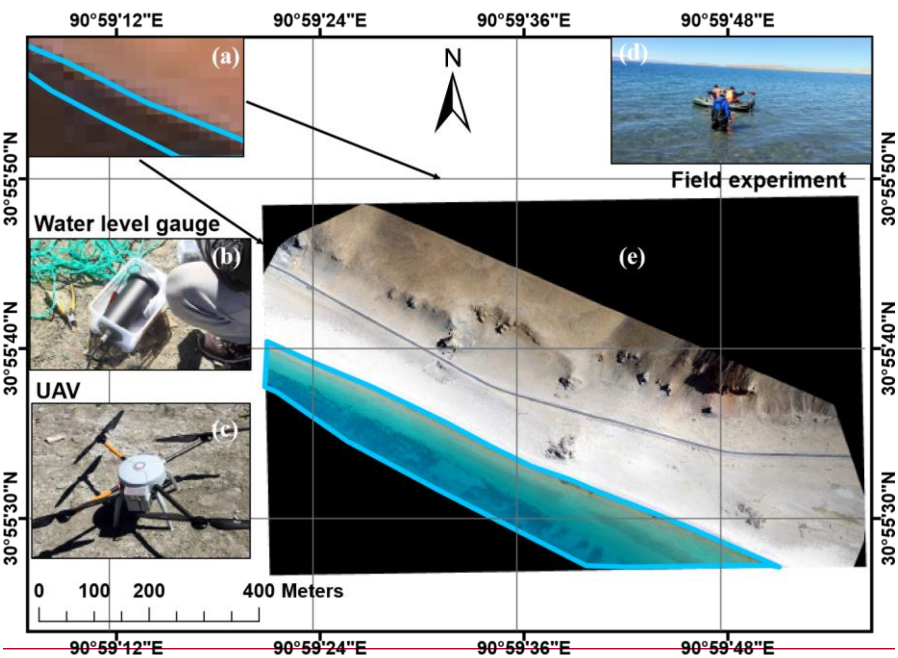
Tu Co	448.64	257	0.9276 (41)	0.9875 (26)	S=0.02dh^2+4.91dh+396.59, dh=H-4926
Urru Co	356.35	260	0.71 (49)	0.8994 (27)	S=1.35dh^2+2.67dh+345.34, dh=H-4553
Wulanwula Lake	652.08	225	0.9679 (81)	0.9285 (10)	S=2.05dh^2+16.49dh+513.15, dh=H-4856
Xijir Ulan Lake	463.36	316	0.9736 (84)	0.9691 (44)	S=0.93dh^2+13.3dh+366.35, dh=H-4770.8
Xuru Co	209.87	144	0.5984 (9)	0.5527 (58)	S=0.12dh^2+0.22dh+206.53, dh=H-4714
Yamzho Yumco	549.61	398	0.9215 (140)	0.9364 (72)	S=0.51dh^2+9.63dh+531.79, dh=H-4436
Yelusu Lake	203.4	486	0.7014 (21)	0.8352 (92)	S=14.84dh^2+-5.77dh+185.15, dh=H-4686.5
Yibug Caka	178.22	118	0.9206 (12)	0.9615 (25)	S=-1.25dh^2+15.79dh+147.03, dh=H-4558.5
Zhari Namco	1000.18	143	0.9177 (164)	0.8388 (52)	S=2.66dh^2+10.07dh+962.57, dh=H-4610
Zhuonai Lake	160.1	260	0.9528 (11)	0.973 (21)	S=0dh^2+10.06dh+124.29, dh=H-4742
Zige Tangco	238.67	171	0.9008 (186)	0.976 (24)	S=0.06dh^2+4.62dh+212.71, dh=H-4565

4 Validation of data quality

4.1 Field experiment

Most Tibetan lakes are located in remote and inaccessible regions, resulting in the scarcity of ground-based in situ measurements that are, however, vital for data quality assessment. We made some in situ measurements in two study lakes to validate the data quality of optical water levels developed in this study~~, instead~~. The data quality of ~~the~~ satellite altimetry ~~data whose quality~~ on lakes or rivers has been widely ~~known~~investigated and thus it is beyond the scope of our study. Many studies used in situ water levels to calculate ~~certain~~ statistical metrics, e.g., root mean squired error (RMSE). However, results provided by different studies vary~~ and~~, which could be associated with the cross-section width of the study water body in the ground track panel (Nielsen et al., 2017). This means that these results may not be comparable due to their unique applications. In addition, it is not rigorous to use in situ data of only one lake to represent the overall situation of study lakes in the uncertainty assessment for altimetry water levels. Instead, we used the standard deviation of valid footprints acquired in the same cycle as an estimate of uncertainty in satellite altimetry-derived water levels. In contrast, the applicable condition of optical water levels is not so variable as that of satellite altimetry data. Derivation of optical water levels requires relatively flat bank as well as some altimetric information, which were available in all study lakes. Since these selected bank slopes were similarly small (~1/30), it ~~is~~ was possible to use a few typical lakes to represent all study lakes. Therefore, we carried out a field experiment in ~~Lake Yam~~Yamzhog Yumco and ~~Lake Nam~~ Nam Co to validate the derived optical water levels.

There were two main goals in our ~~experiment~~experiments: (1) collecting daily in situ water level data in a ~~certain~~ TP lake to validate the corresponding optical water levels statistically; (2) ~~imaging a certain length of the lake shore with UAV to test~~testing the performance of extracting lake shoreline ~~extraction~~ positions ~~based on~~ from high-resolution optical images (GF-2) ~~so as~~ to provide a theoretical uncertainty analysis of optical water levels. On ~~Lake Yam~~Yamzhog Yumco, we installed a pressure type water level sensor (type H5110−DY, manufactured by Shenzhen Hongdian technologies Co., Ltd.), which ~~measures~~ measured water pressure and temperature ~~of~~ at the installation depth ~~and converts them~~that were converted into water depths with a relative accuracy of ~0.1%. The device was carried onto the lake and put ~20 m below the water surface and 0.5 m above the lake bottom, ~~which~~ suggesting~~s~~ an absolute error of ~2 cm. ~~We chose a typical landscape (i.e., mild slope, little vegetation, and gravel lake beach) to perform UAV imaging in both Lake Yamzhog Yumco and Lake Nam Co in mid-May, 2018. The UAV was operating at a height of 200 m and imaging the ground at a constant rate in visible bands with a wide-angle lens. With a GPS tracker onboard, these UAV images were well georeferenced. Then image mosaic was performed using the Piz4D mapper and converted into a digital orthophoto map (DOM), which is a similar process described by Huang et al. (2018). The spatial resolution of UAV data reached ~5 cm as we compared a real ground object with its size in images~~As for GF-2 images, the spatial resolution of the panchromatic band is 0.8 m, which is able to provide a very accurate reference of lake boundaries for ~~the assessment of~~assessing water classification results ~~based on~~ for Landsat images. We used three GF-2 images acquired at different seasons (two in Jul~~y~~ and Sep~~tember~~, 2015 and ~~,~~ one in Feb~~ruary~~ 2016) and different places on the TP to better represent the local conditions when extracting optical water levels or lake water ~~extent~~areas with Landsat images. Image co-registration was performed to make sure that there was no obvious spatial shift between the GF-2 images and corresponding Landsat images. The accuracy of the image co-registration ~~is~~was ~2 m.



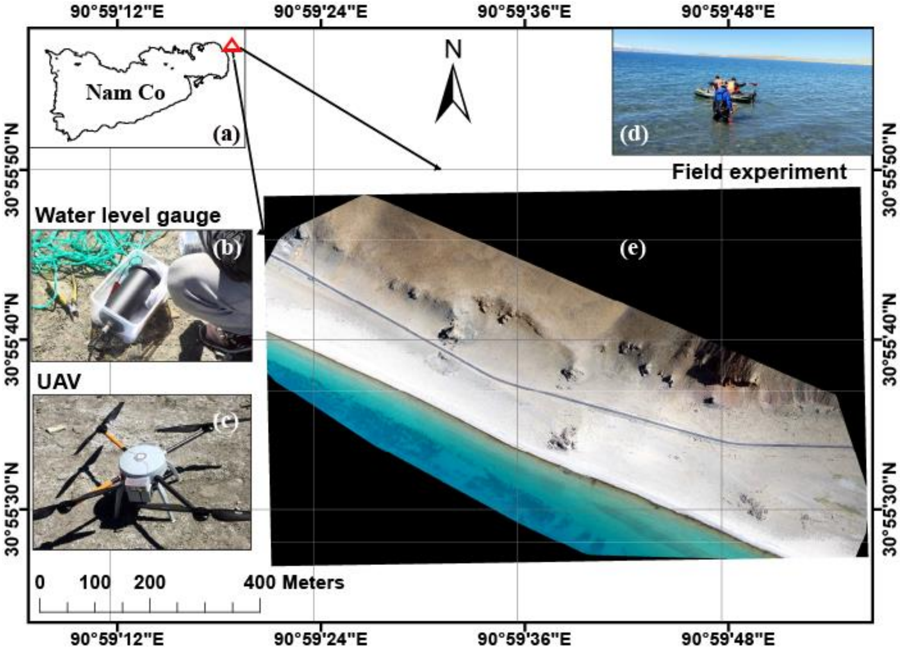
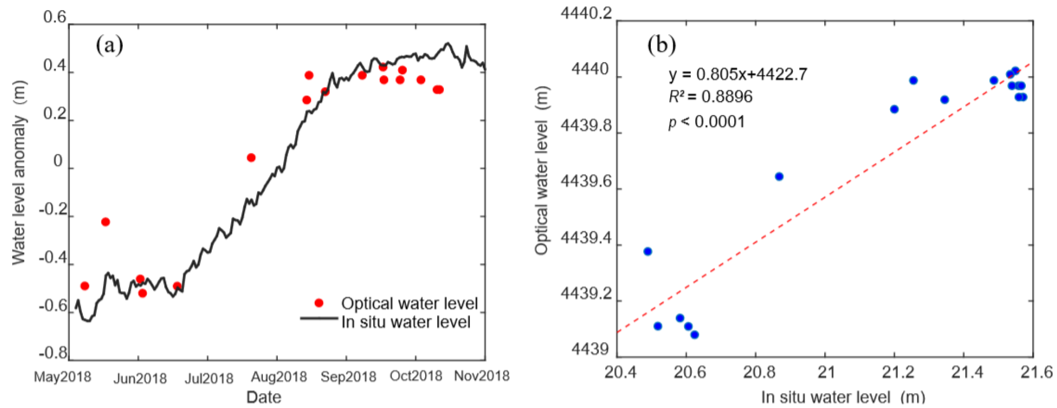


Figure 7~~7~~. Field experiments in two study lakes: (a) an ~~Landsat 8 image~~overview map of the experiment spot; (b) pressure-type water level sensor; (c) unmanned aerial vehicle; (d) installation of the water level sensor; and (e) UAV image of a portion of the bank of ~~Lake Nam~~ Nam Co.

4.2 Uncertainty analysis of optical water levels

Based on the in situ water level measurements made by the pressure-type water level sensor, we evaluated the accuracy of optical water levels statistically. We first calculated anomalies of in situ water levels and optical water levels, and then water levels from the two sources acquired on the same day were used for analysis. There were 16 optical water level records available for the comparison against the in situ measurements~~. The~~ , indicating an RMSE of the water level anomaly ~~was~~ of 0.11 m. The linear fit ~~had~~ shows a slope close to 1 and an R^2 of 0.89, suggesting the ~~good~~ consistency between ~~of~~ the in situ water level measurements and the derived optical water levels (**Figure** 8~~Figure 8~~ (b)). It should be noted that the optical water levels used for validation here were translated from lake shoreline ~~changes~~ positions using parameters derived from fitting with CryoSat-2 data, i.e., there is no in situ information involved in generating the optical water levels shown in Figure 8.



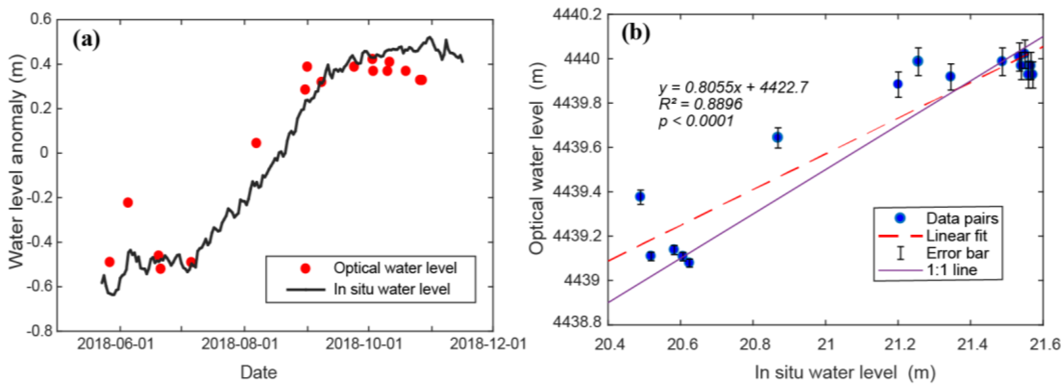


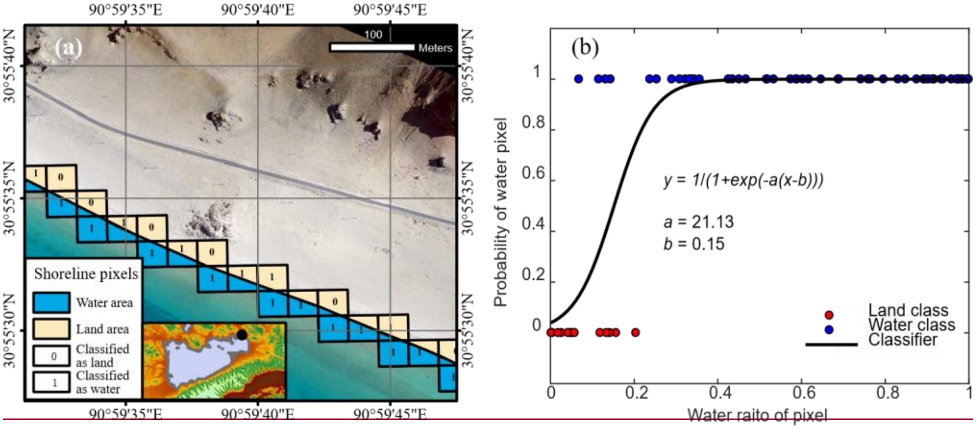
Figure 8~~8~~. (a) In situ water level anomaly versus optical water level anomaly in ~~Lake Yam~~Yamzhog Yumco; and (b) linear regression ~~of~~ between the optical water levels and ~~concurrentsame period~~ in situ water levels during the same period.

~~To be more convincing~~Furthermore, we performed ~~a~~a ~~more~~ theoretical uncertainty analysis of the optical water levels by looking at the original optical data and the generation process~~es~~ with the help of ~~UAV~~high-resolution GF-2 images. First, we took ~~UAV~~GF-2 images (after co-registration with the Landsat image for~~of~~ the same period and ~~,~~ the co-registration errors were ~2 m) as the ground truth to determine the accurate position and shape of the lake shore~~-~~line. Second, we performed water classification ~~based on the concurrentsame period~~ from the Landsat OLI image for the same period ~~that contained the UAV scanned area~~ jointly using the ~~, with the combined~~ water index method and Otsu algorithm to derive the binarized image. Landsat image pixels where the lake shorelines from ~~determined using~~ the ~~UAV~~GF-2 images cross~~es~~ were delineated ~~manually~~ and marked as shoreline pixels as shown in Figure 9~~Figure 9~~ (a). Then the water area in each shoreline pixel was calculated.

Given that these shoreline pixels were classified as either water or land, a relationship between the water area ratio of the shoreline pixel and the probability of the pixel being classified as water can be derived. This relationship generally describes the function of the water classification method by telling how likely a pixel will be determined as water, given the water area ratio of the pixel. Based on the observations of a total of ~~64 UAV-scanned~~4128 Landsat shoreline pixels, a ~~logistic type curve with two parameters that determine the position and shape of the curve~~power function was chosen to represent the water classifier as Eq. (4) ~~Eq. 5~~ shows:

$$f(x) \cancel{=} \cancel{\frac{1}{1+e^{-a(x-b)}}} = x^n \qquad \text{Eq } 4\cancel{5}$$

where x represents the water area ratio in the shoreline pixel; ~~,~~ $f(x)$ represents the probability of the shoreline pixel being classified as the water pixel; and ~~, *a and b are parameters*~~ n is the parameter that determines the shape ~~and position~~ of the curve~~, respectively~~. ~~The parameters werep~~Parameter n was determined using the maximum likelihood method ~~. Results are shown in~~ (Figure 9~~Figure 9~~ (~~b~~e)).



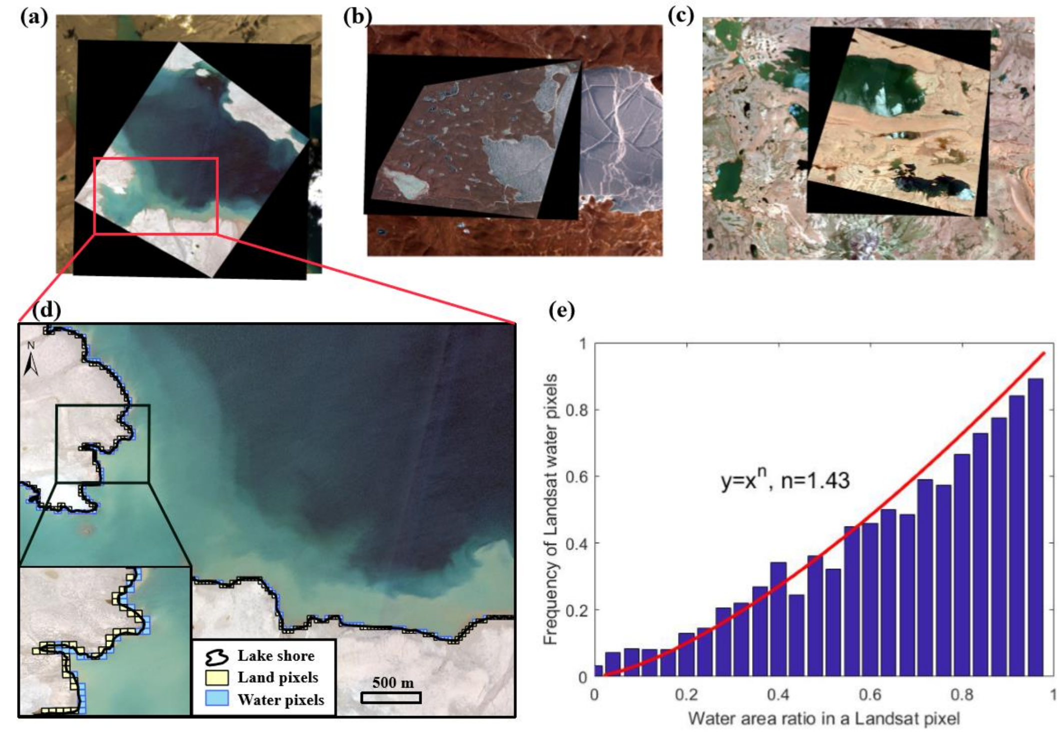


Figure 9. ~~(a~~(a)~~-~~(c) GF-2 images (upper layer) and corresponding -Landsat OLI images (bottom layer) acquired on Sep 7, 2015~~/9/7~~, Jan 29, 2016~~/1/29~~, and Jul 5, 2015~~/7/5~~; (d) Landsat OLI shoreline pixels ~~on Lake Nam Co~~ (the background is the ~~UAV~~GF-2 image), blue pixels ~~marked with 1~~ were classified as water, and yellow pixels ~~marked with 0~~ were classified as land~~. The black dot in the insert figure represents the field experiment spot. (b) The chosen classifier, with two parameters *a*=21.13 and *b*=0.15 determined~~; (e) the relationship between the water area ratio in a pixel and the frequency~~/probability~~ of the pixel being classified as water. Blue bars are sampled at a 0.04 bin space from the 4128 pixels. The red line shows the fitting curve based on the maximum likelihood method. ~~The *y* axis represents the probability that a certain pixel is classified as water, and the *x* axis is the water area ratio in that pixel. Red dots represent pixels classified as land that have relatively lower water area ratios. Blue dots represent pixels classified as water that have relatively higher water area ratios.~~

~~It should be noted that even the water ratio in a shoreline pixel is zero, there is a small probability that this pixel may be mistaken as a water pixel, because the surface reflectance information may be contaminated by adjacent water pixels. Therefore, the classifier has a small value (~0.02) when the water ratio is zero. As can be seen from~~ As expected, ~~shown in Figure 9 (b), when the water ratio is larger than 0.3,~~c), the probability of the pixel classified as water ~~is close to~~increases with the water area ratio in the pixel (Figure 9~~Figure 9~~ (c))~~, which is expected~~. The enclosed area of the fitting curve ($y = x^{1.43}$) is smaller than that of $y = x$ on [0, 1~~. This~~], ~~which suggests~~suggesting that there may be a ~~higher~~lower probability of the occurrence of water pixels that is associated with a systematic bias of the lake shoreline detection. Note that the systematic bias can be removed when linearly fitting ~~the~~ the lake shoreline positions~~lake shore changes~~ and altimetry~~-derived~~ water levels as long as the bias is stable. Therefore, uncertainty in optical water levels developed in this study arises mainly from the variation in this systematic bias.

To describe the variation in the systematic bias, a new random variable X was introduced to represent the bias between the classified water area and the real water area in a shoreline pixel. Given the shape and position of the lake shoreline, the real water area in each shoreline pixel is a complex function of the relative position between the pixel and the shoreline. To simplify the derivation, we assumed that the water area ratio in a shoreline pixel is uniformly distributed on [0,1], meaning that the probability of any value between 0 and 1 is equal. If we use X_0 to represent the true water area ratio in the shoreline pixel and X_1 to represent the classified results based on the water area ratio, the random variable X can be expressed as:

$$X = X_1 - X_0 \qquad \text{Eq } \cancel{6}5$$

where X_1 can take on ~~0 or~~ 1 or 0 (i.e., the classified results only tell us whether a pixel is water pixel or not), so X can only take on either ~~$-X_0$ or~~ $1-X_0$ or $-X_0$. Because the range of X_0 is [0,1], it is obvious that the range of X is [-1,1]. A derivation of $F(X)$, i.e., the probability density function (PDF) of X can be found in the supplementary file (part 2).~~is given as follows:~~

$$F(X) = \begin{cases} P(X = -X_0|X_0) \cdot P(X_0), & X < 0 \\ P(X_0 = 0, X_1 = 0) + P(X_0 = 1, X_1 = 1), & X = 0 \\ P(X = 1 - X_0|X_0) \cdot P(X_0), & X > 0 \end{cases} \qquad \text{Eq 7}$$

$$P(X = -X_0|X_0) = P(X_1 = 0|X_0) = 1 - f(X_0) = 1 - f(-X) \qquad \text{Eq 8}$$

$$P(X = 1 - X_0|X_0) = P(X_1 = 1|X_0) = f(X_0) = f(1 - X) \qquad \text{Eq 9}$$

~~where $f(x)$ is referred to as the classifier function defined in Eq 5.~~

~~Because X_0 is uniformly distributed between [0,1], $P(X_0) = 1$. Note that $P(X_0 = 1, X_1 = 1) = 1$, this means that if X_0 is 1, the probability of a pixel classified as water is 1. However, $P(X_0 = 0, X_1 = 0)$ is not necessarily 1 (i.e., 1-$f(0)$), because the pixel~~

~~with X_0 = 0 still has a low probability, i.e., $f(0)$ of being classified as water based on the illustration above. Combining Eqs.(7)–(9) with the explanations on the specific case $X = 0$ results in the following:~~

$$\cancel{F(X) = \begin{cases} 1 - f(-X), & X < 0 \\ 1 + 1 - f(0), & X = 0 \\ f(1 - X), & X > 0 \end{cases} = \begin{cases} 1 - f(-X), & X < 0 \\ 2 - f(0), & X = 0 \\ f(1 - X), & X > 0 \end{cases}}$$ ~~Eq 10~~

~~It is obvious that $F(X)$ is not a continuous function, but it can be integrated and the integral of $F(X)$ on [-1,1] equals 1, meaning that it satisfies the basic property of PDF.~~

Overall, $F(X)$ describes how the ~~systematic~~ bias between the classified water ratio and real water ratio in shoreline pixels is distributed as shown in Figure 10~~Figure 10~~. If there are N shoreline pixels in an ROI, we can take them as N independent observations of X and calculate the mean value $\bar{X}$. This value $\bar{X}$ can represent an average shift of the detected lake shoreline from the real lake shoreline in the unit of one-pixel width (30 m). As we mentioned above, the systematic bias can be removed in the regression between the lake shore ~~changes~~line positions ~~from optical remote sensing~~ and altimetry ~~the corresponding~~ water levels ~~from satellite altimetry~~. As such, it is the variation of the bias that determines the accuracy of the optical water levels. ~~Therefore, w~~We can calculate the standard variation of $\bar{X}$ to represent the uncertainty in lake shoreline ~~changes~~position. Note that there is a simple relationship between $\sigma_{\bar{x}}$ and σ_x:

$$\sigma_{\bar{x}} = \frac{\sigma_x}{\sqrt{N}}$$ Eq 6~~11~~6

One only needs to calculate σ_x:

$$\bar{X} = \cancel{\int_{-1}^{1} F(X) \cdot XdX = 0.346} \int_{-1}^{1} F(X) \cdot XdX \approx -0.09$$ Eq 7~~12~~7

$$\sigma_x = \sqrt{\int_{-1}^{1} F(X) \cdot (X - \bar{X})^2 dX} \cancel{=} \approx 0.\cancel{2999 \approx 0.300}39$$ Eq 8~~813~~

~~Eq 13~~12 ~~in combinaions~~Combined with ~~Eq 5~~4~~, Eq 10~~9~~, and Eq 12~~11 Eq. (4) and Eq. (7), Eq. (8) was resolved numarically, resuling in ~0.~~3~~39 pixel width. Substituting σ_x in ~~Eq 11~~10 Eq. (6) with Eq. (8) ~~Eq 13~~12 gives:

$$\sigma_{\bar{x}} = \cancel{\frac{0.3}{\sqrt{N}}} \frac{0.39}{\sqrt{N}}$$ Eq~~.~~ 9~~914~~

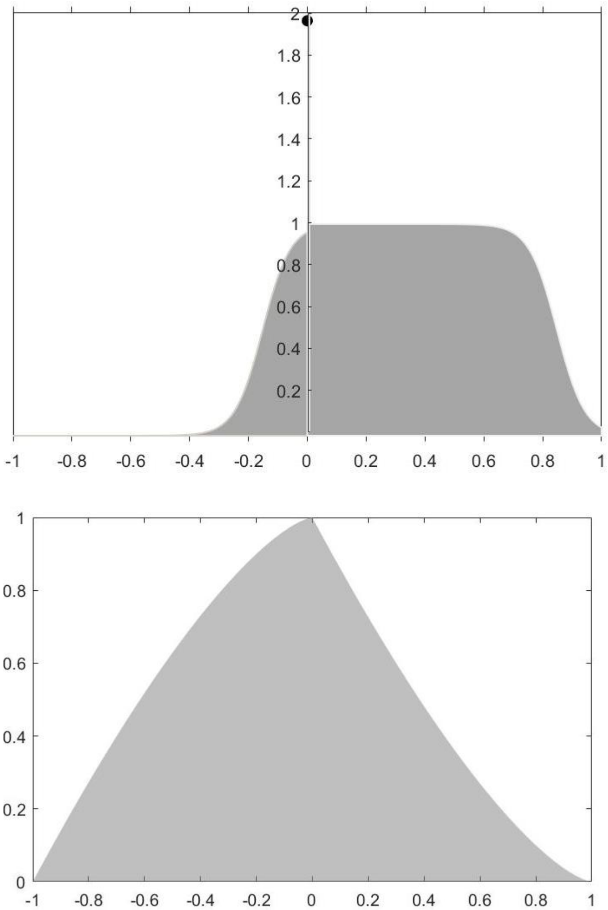


Figure 10. *F(X):* Probability density function of the ~~systematic~~ bias (*X*) ~~*X*~~ between the classified water ratio (X_1) and real water ratio (X_0) in a shoreline pixel.

If the slope of the shoreline is known, e.g., *tanθ*, the uncertainty of the optical water level can be expressed as:

$$\sigma_{ho} = \sigma_{\bar{x}} \cdot d \cdot tan\theta = \cancel{\frac{0.3 \times 30 \times tan\theta}{\sqrt{N}}} \frac{0.39 \times 30 \times tan\theta}{\sqrt{N}}$$ Eq 10~~10~~~~15~~

where σ_{ho} is the uncertainty of optical water levels and *d* is the spatial resolution of the satellite image (30 m). In this study, a typical width of ROI for deriving optical water levels is ~10-pixel width, meaning that *N* is ~10. In addition, lake shores used for generating optical water levels here generally have a relatively mild slope of ~1/30 or even smaller, which can be rounghly estimated from the maximun shoreline change and altimetry water level change within a year. Here if we use 1/30 as the slope *tanθ*, the uncertainty of the optical water levels can untimately be estimated to be ~0.~~1~~12 m, which is very close to the RMSE ~~(∼~~of ~~(~~0.~~09~~11 m~~)~~ based on the comparision ~~of~~ between the opitcal water levels and in situ water level measurements mentioned earlier.

However, for most cases we do not know the exact lake bank slope $tan\theta$, which is the reason why we performed the regression analysis between the lake shore ~~changes~~ line positions and altimetry-derived -water levels. Information on the real lake bank slope is implicitly expressed in the linear fitting slope β (if the fitting line is $y = \beta x + \alpha$). Uncertainty in altimetric~~y~~ information could ~~will~~ evolve into the fitting parameters and impact the accuracy of the generated optical water levels. Given that the observed lake shoreline ~~change~~position is X_1 (e.g., $X_1 = 5.6$ meaning that the observed lake shoreline position is 5.6 Landsat pixels away from the initial postion corresponding to the lowest water level, different from Eq. (5), X_1 here can be a rational number because it is determined by averaging all shoreline pixels in the ROI, ~~while~~whereas in Eq. (5) we focused on only one shoreline pixel), combining Eq. (5), ~~the Eq. (5)~~the optical water level (y) can be expressed as:

$$y = \beta(X_1 - \overline{X_1}) + \bar{Y} = \beta(X_0 - \overline{X_0}) + \beta(X - \bar{X}) + \bar{Y} \qquad \text{Eq 11}$$

~~W~~where $(X_1 - \overline{X_1})$ denotes the observed lake shoreline change~~s~~ (in the unit of a Landsat pixel)~~,~~; $\overline{X_1}$ denotes the mean of observed lake shoreline positions used for linear regression; $\bar{Y}$ denotes the mean of altimetry water levels used for linear regression~~,~~; $(X_0 - \overline{X_0})$ denotes the real lake shoreline change~~s~~; ~~,~~$(X - \bar{X})$ denotes the variation of the optical shoreline position caused by the water extraction method; ~~,~~and β is the linear fitting slope. It is obvious that the expected value $(X - \bar{X})$ is 0. As we discussed earlier ~~before~~, a systematic bias does not affect the accuracy of the optical water level, but the variation of the systematic bias does.

Based on ~~Eq 15~~Eq. (11), the overall uncertainty of optical water level σ_y can be given as:

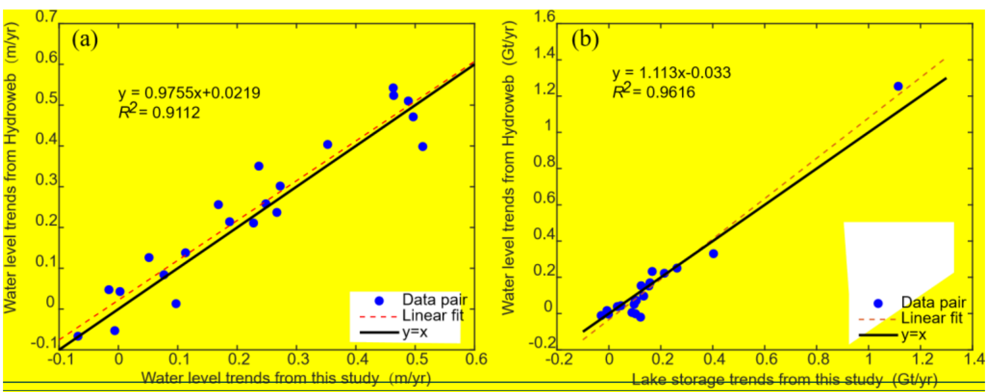
$$\sigma_y = \sqrt{\sigma_\beta^2\left(\frac{\partial y}{\partial \beta}\right)^2 + \sigma_{\bar{x}}^2\left(\frac{\partial y}{\partial (X - \bar{X})}\right)^2 + \sigma_{\bar{Y}}^2\left(\frac{\partial y}{\partial \bar{Y}}\right)^2} = \sqrt{\sigma_\beta^2(X_1 - \overline{X_1})^2 + \sigma_{\bar{x}}^2\beta^2 + \sigma_{\bar{Y}}^2} \qquad \text{Eq 12}$$

~~W~~where β and σ_β can be derived from the ~~the~~ linear regression analysis~~,~~; $\sigma_{\bar{x}}$ is given in~~–~~ Eq. (9)~~Eq 13,~~; and $\sigma_{\bar{Y}}$ is the uncertainty of the mean altimetry water level which can be calculated from the altimetry data. For a typical lake like Yamzhog Yumco, $\beta = 0.35$ m, $\sigma_\beta = 0.02$ m, $\mathrm{Max}(|X_1 - \overline{X_1}|) = 11$, $\sigma_{\bar{x}} = 0.13$, $\sigma_{\bar{Y}} = 0.015$ m, which gives a maximum σ_y of 0.22 m. It should be noted that $(X_0 - \overline{X_0})$ is assumed to be the true value and there is no error associated with this term. This relationship shows that the uncertainty ~~of~~ in the optical water level ~~will~~ increases with the distance from the center point $(\overline{X_1}, \bar{Y})$ represented by $(X_1 - \overline{X_1})^2$. ~~The i~~Interpretation of this phenomenon is that extrapolation of optical water levels (far from the center point) may cause some artefacts and should be used with caution. More detailed discussion on the extrapolation can be found in the supplementary file.

Overall, the uncertainty quantification of the optical water levels developed in this study indicates clearly that the accuracy of optical water levels depends on the width of an ROI, e.g., the number of pixels/observations, slope of the lake shore, ~~and~~ the effectiveness of the water classification method, and the uncertainty in altimetry water level used for regression. One of the advantages of the optical water level is that an ROI does not necessarily cover a large area of lake shores, which maximizes the potential of optical remote sensing images to increase the spatial coverage and temporal resolution of lake water level estimates that may not ~~, however,~~ be ~~achievable~~ realized by using satellite altimetry alone. Optical remote sensing images provide important complementary information on altimetry~~-derived~~ water levels and would subsequently facilitate lake water storage estimation.

4.3 Cross validation with similar products

We compared our product with a widely used lake water level/storage data set provided by the LEOGS Hydroweb, indicating that our product may perform better in terms of the consistency as well as the sampling frequency. Both advantages are important in improving our understanding of responses of lakes to climate change. There are 21 same lakes in both our study and LEOGS Hydroweb. Annual trends in water level and lake storage during 2003–2015 were compared (Figure 11). Overall, the two products are consistent in terms of R^2 of the linear fit.



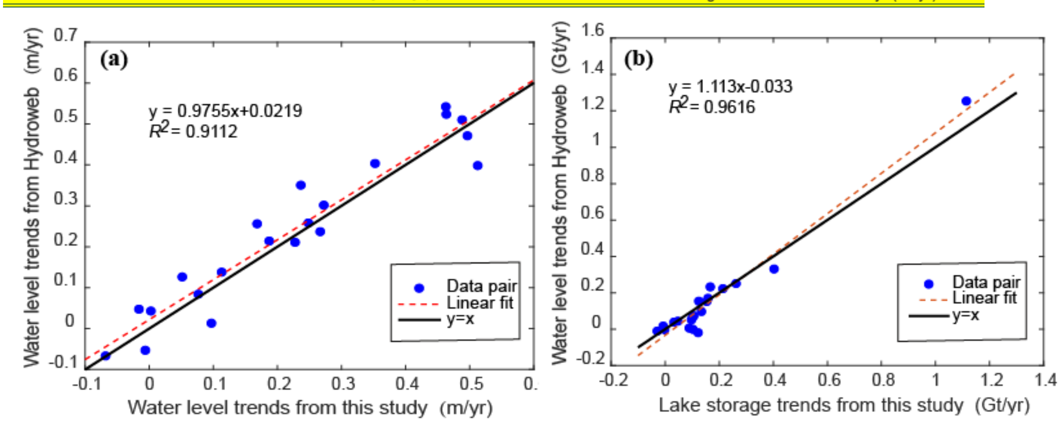


Figure 11. Cross validation of the TP lake level and storage changes derived from our study with those provided by the LEGOS Hydroweb database (Crétaux et al., 2011a): (a) trends in lake water levels from 2003 to 2015 and (b) trends in lake water storage from 2003 to 2015.

5 Dataset description and availability

The derived TP lake water levels, hypsometric curves, and water storage changes are archived and available at https://doi.org/10.1594/PANGAEA.898411~~.~~ (Li et al., 2019). The data sets cover~~s~~ large 52 large lakes (50 lakes with a surface area larger than 150 km^2, and 2 lakes are 100–~~~~~150 km^2) on the ~~Tibetan Plateau~~TP. The data sets consist~~s~~ of two parts: (1) a table containing hypsometric curves and corresponding regression statistics (R^2 and the number of data pairs) for each lake, with parameters of the hypsometric curve listed in separate columns for the convenience of batch processing; (2) time series for each lake archived as 52 entities with ~~geological~~geographic information (i.e., latitude, longitude, and size of the lake) that can be ~~looked up~~checked in an online map provided by PANGAEA, avoiding the confusion of lake names. The time series of each lake include lake water levels and lake storage changes. For data points in the water level time series, satellite or sensor type ~~was~~ is shown (i.e., from Jason-1/2/3, Envisat, ICESat, CryoSat, or optical images). Uncertainty was calculated using the standard deviation of valid footprints in the cycle (only for altimetry data). The lake water storage time series were transformed from water level time series using the hypsometric relationship so that they have equal data ~~volume~~size. The lake water storage time series represent changes in lake storage with respect to a reference water level, which is listed in the corresponding hypsometric curve table as a parameter. The overall uncertainty of optical water levels within the regression range (the range of altimetry water levels) is 0.1–0.2 m based on the experiment and analysis ~~of~~in this paper. ~~,~~ T~~t~~he extrapolation of optical water levels may occur during the time gap between altimetry missions and before 2002. The average uncertainty of altimetry water levels is 0.11 m.

6 Applications

~~5~~6.1 Spatiotemporal analysis of changes in water storage of ~~Tibetan L~~lakes on the Tibetan Plateau

Based on the lake water storage changes we derived, spatial patterns of lake storage trends ~~from~~ during 2000–~~to~~ 2017 were shown in Figure 12~~Figure 11~~. In the endorheic basin of the TP, similar to some reported results (Yao et al., 2018b; Zhang et al., 2017a), most lakes have been expanding rapidly, e.g., ~~Lake Selin~~Selin Co (89.00 E, 31.80 N) gained ~~~~~19.7±2.0 km^3 of water during the study period, Lake Kusai (92.90 E, 35.70 N) experienced an abrupt expansion due to flood and gained ~~~~~2.2±0.2 km^3 of water in 2011, as reported in related work (Yao et al., 2012). In contrast, some lakes in the southern part of the TP experienced shrinkage, e.g., ~~Lake Yam~~Yamzhog Yumco (90.70 E, 28.93 N) gained a total of 0.8±0.4~~~0.8~~ km^3 water during 2000–2004 but has been shrinking during the remaining 13 years (2005–2017) at a rate of -0.19±0.03~~~ -0.2~~ km^3/yr. In contrast to ~~Lake Yam~~Yamzhog Yumco, Lake Qinghai (100.00 E, 36.90 N) lost 2.2±0.7~~~1.9~~ km^3 water during 2000–2004 but gained 7.7±0.6~~~8.1~~ km^3 of water during 2005–2017. Similar patterns can be detected in adjacent lakes of Lake Qinghai, e.g., Lake Donggei Cuona (98.55 E, 35.28 N) and Lake Ngoring (97.70 E, 34.90 N).

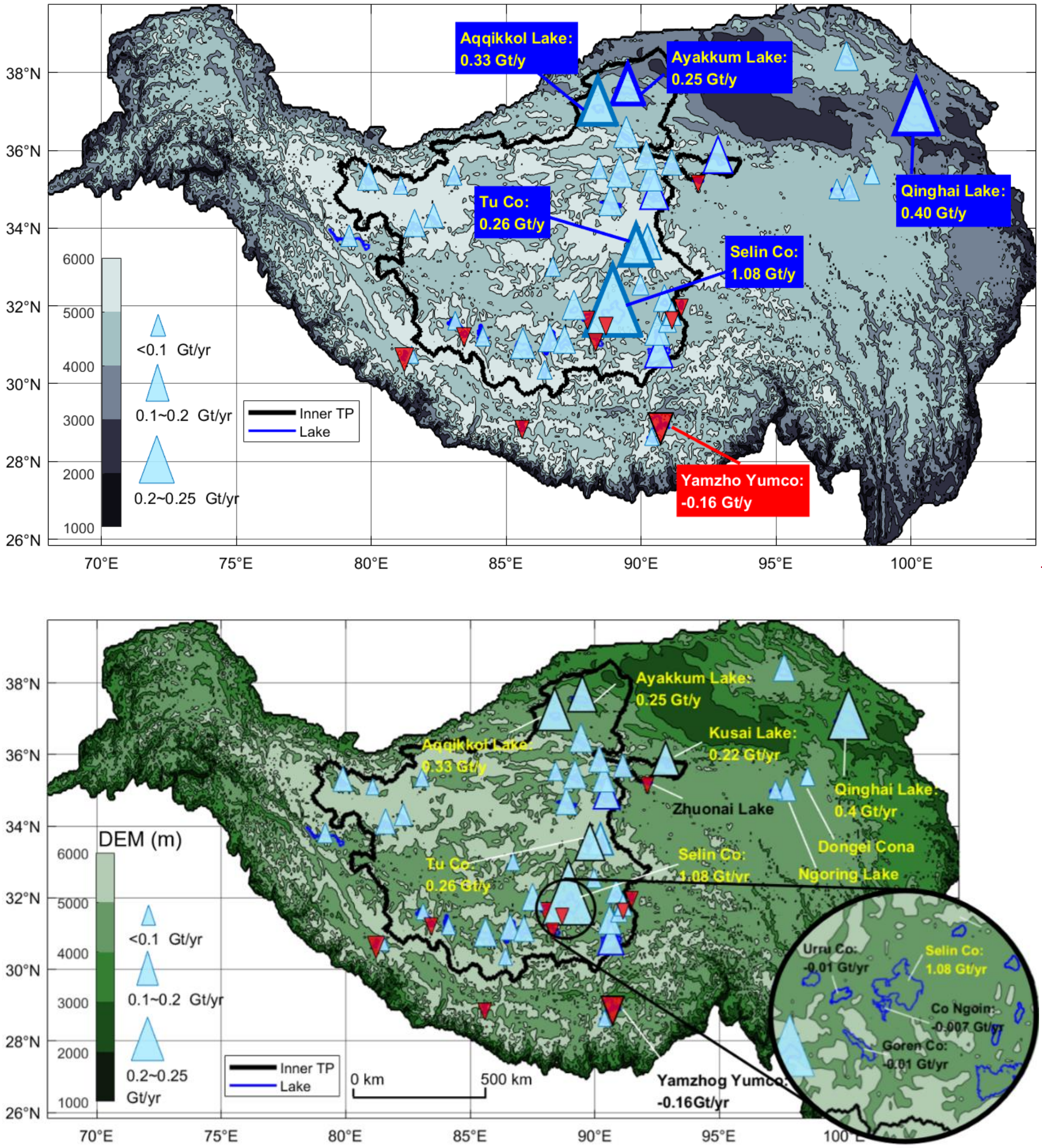
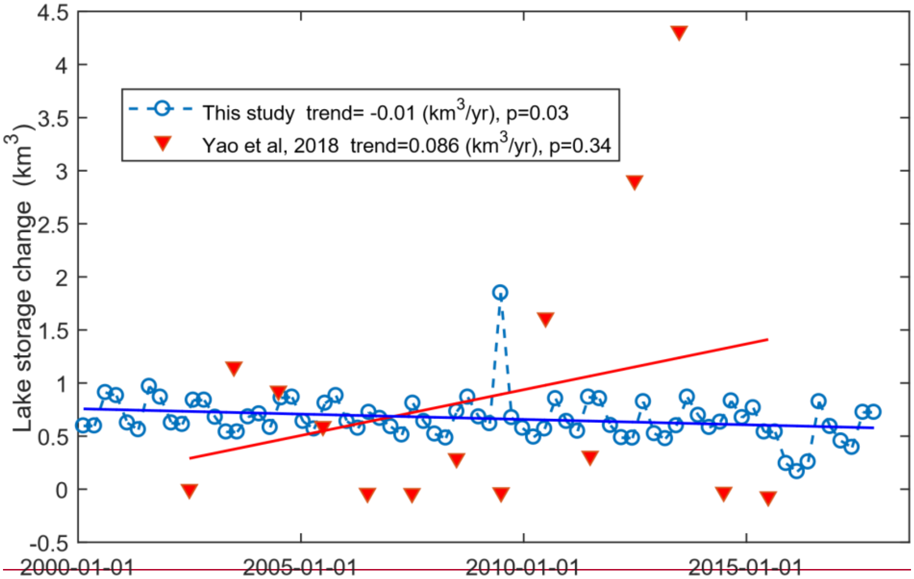


Figure 12~~11~~. Spatial distribution of trends in lake storage on the TP during 2000–2017. The back polygon shows the boundary of the endorheic basin of the TP including 39 study lakes. The other 13 study lakes are located outside the endorheic basin.

However, spatial proximity cannot fully explain the intricate trend distribution in the Selin Co basin, where large lakes such as ~~Lake Selin~~Selin Co were expanding whereas smaller adjacent lakes showed an opposite decreasing trend, e.g., ~~Lake~~ Urru Co (88.00 E, 31.70 N), Lake Co Ngoin (88.77 E, 31.60 N), and ~~Lake~~ Goren Co (88.37 E, 31.10 N). In fact, we found that the decreasing trends in some small lakes like ~~Lake~~ Goren Co were not detected in Yao et al. (2018b), which is likely due to the lower sampling frequency as shown in Figure 13~~Figure 12~~. The three shrinking lakes are located in the upstream region and feed ~~Lake Selin~~Selin Co through two small rivers. One of the rivers links Lakes Goren Co, Urru Co, and Selin Co, whereas the other links Lakes Co Ngoin and Selin Co.



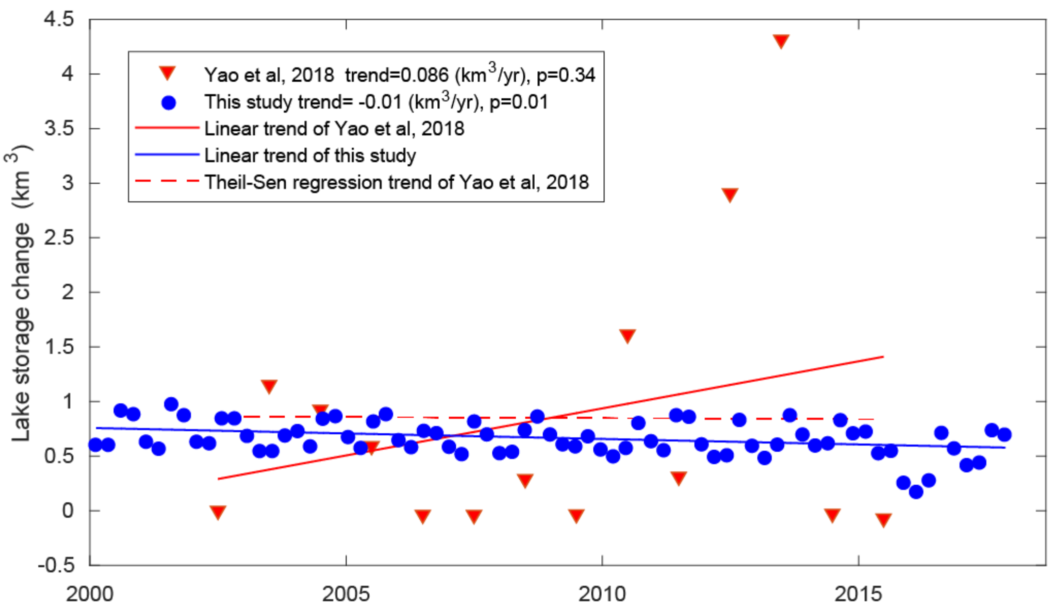


Figure 13~~12~~. Discrepancy of lake storage trends in ~~Lake~~ Goren Co between Yao et al. (2018a) and our study.

A possible explanation of the disparity of changes in lake water storage in the Selin Co basin could be the principle of minimum potential energy. If we simplify the basin with the tank model and take the upstream small lake as a tank with a leaking hole, the storage of the small lake is mainly controlled by the height of the leaking hole. Given that surface water of the small lake increased, most of the increased water would flow into the large lake (a lower tank), and the outflow discharge of the small lake at higher elevations would increase accordingly. The height of the leaking hole would decline (erosion) so as to increase the overflow capacity, which eventually results in the decrease in small lake storage. Another possible situation is that the height of the leaking hole remains the same and the water surface height of the small lake increases, but this situation is not consistent with the minimum potential energy principle, as more water potential energy is stored in the small lake. This phenomenon shows that river-lake interactions may cause complex patterns of the regional surface water distribution. Therefore, decreases in small lake water storage and increases in water storage of ~~Lake Selin~~Selin Co in the basin detected by our study seem reasonable. Increases in small lake water storage in this basin reported in some published studies may be associated with the sparse sampling of lake water levels.

We averaged the total lake water storage change in each season to generate the time series shown in Figure 14~~Figure 13~~ **(a)**. The overall storage change in the 52 study lakes is 98.3±2.1 km^3. The total lake water storage was increasing rapidly during the first 12 years but became relatively stable since 2012. Intra-annual variation in the TP lakes can also be investigated using the densified lake water level time series generated by this study. We removed the linear trend (sometimes there were multiple linear trends for a lake in different periods, which were removed in a stepwise fashion) and calculated the mean monthly water level anomaly for each lake over the study period. Then the intra-annual water level change was represented by the difference between the maximum and minimum values of the monthly water level anomaly. The histogram of the intra-annual water level change in Figure 14~~Figure 14~~ (b) shows that most of the TP lakes have water level variations ranging from 0.3–0.75 m in a year on average. Similar work was performed by Lei et al. (2017) but only a small number of lakes were investigated in their study.

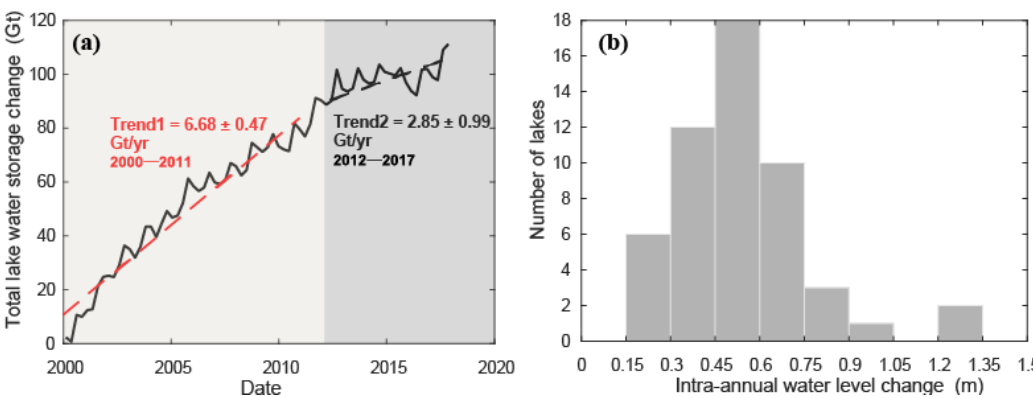


Figure 14~~13~~. (a) Total storage changes in the study lakes (52) on the TP, which can be generally divided into two stages: (1) a rapidly increasing stage (2000–2011) with a higher increasing rate of 6.68 km^3/yr and (2) a mildly increasing stage (2012–2017) with an increasing rate of 2.85 km^3/yr. (b) Histogram of changes in lake water levels of the study lakes on the TP.

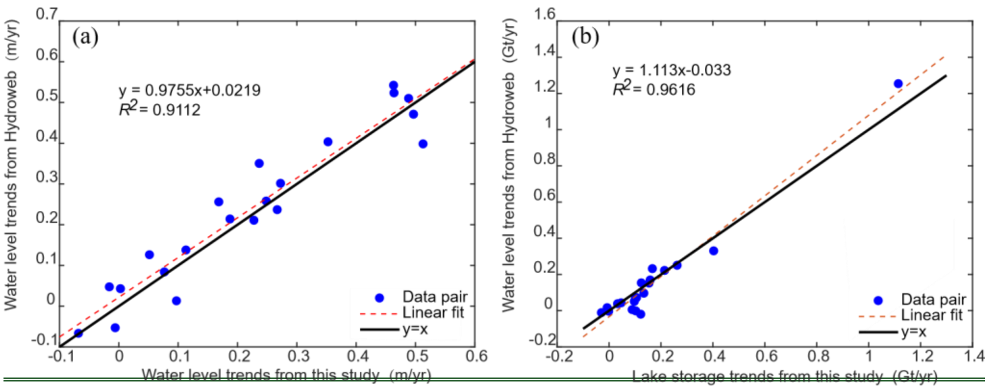
~~Intra-annual variation in the TP lakes can also be investigated using the densified time series generated by this study. We removed the linear trend (sometimes there were multiple linear trends for a lake in different periods, which were removed in~~

~~a stepwise fashion) and calculated the mean monthly water level anomaly for each lake across the study period. Then the intra-annual water level change was represented by the difference between the maximum and minimum values of the monthly water level anomaly. The histogram of the intra-annual water level change in Figure 13~~14 ~~(b) shows that most of the TP lakes have water level variations ranging from 0.3–0.75 m in a year on average. Similar work was performed by Lei et al. (2017) but only a small number of lakes were investigated in their study.~~

~~5.2 Quality assessment of similar data products~~

6.2 Quality assessment of similar data products

~~We made a comparison with a widely used lake water level/storage data set provided by the LEOGS Hydroweb, indicating that our product may perform better in terms of the consistency as well as sampling frequency. Both advantages are important in improving our understanding of responses of lakes to climate change. There are 21 same lakes in both our study and LEOGS Hydroweb. Annual trends in water level and lake storage during 2003–2015 were compared (Figure 14). Overall, the two products are consistent in terms of R^2 of the linear fit.~~



~~**Figure 14. Cross validation of the TP lake level and storage changes derived from our study with those provided by the LEGOS Hydroweb database (Crétaux et al., 2011a): (a) trends in lake water levels from 2003 to 2015 and (b) trends in lake water storage from 2003 to 2015.**~~

~~However, some~~Some obvious discrepancies between the two data sources ~~still exist~~can be noticed, e.g., water levels of ~~Lake Taro~~Taro Co. Both Hydroweb data and our estimation used ICESat~~-1~~ and CryoSat-2 data. The difference lies in the fact that our CryoSat-2 product was more updated with a longer time span but Hydroweb used an additional altimetry satellite SARAL. ~~Since~~ Because the systematic biases of both products were ~~performed some kind of removal of the systematic bias~~removed, it is possible that we chose different baselines that resulted in the overall shift as shown in **Figure** 15~~Figure 15~~ **(a)**. For instance, we may use different sets of ellipsoid and geoid models. ~~However, i~~In addition to the overall shift, some time-dependent discrepancy can be found in **Figure** 15, e.g., periods highlighted by red or blue ~~shades~~shading areas. ~~We will explain the possible reasons in the following paragraph.~~

The black curve shows the optical water level we derived, which is a critical reference when connecting two different altimetry data time series without an overlap period. The optical water level shows that the last two samples of ICESat~~-1~~ data should not be lower than the first few samples of the CryoSat-2/SARAL data (see the dashed boxes). However, it is apparent that Hydroweb data display a reverse relationship~~. Though~~, ~~which shows~~showing that the last two ICESat measurements are smaller than the first a few CryoSat/Saral measurements. It is ~~possibly~~likely due to an unremoved systematic bias between ICESat and CryoSat/Saral time series from Hydroweb data in Taro Co. It should be noted that, even though the optical water levels were derived by linearly fitting the normalized lake ~~shore~~shoreline ~~changes~~ positions with altimetry data, the relative ~~height~~magnitude of water levels during different periods should not be largely affected by the fitting parameters, e.g., if optical water levels show that $H_a >= H_b$, where H_a (H_b) means water levels acquired in period A (B), the $H_a >= H_b$ relationship ~~will~~ would not change with the fitting parameters used to generate the optical water levels. This is the main reason for us to use optical water levels as reference~~ data~~. Therefore, Hydroweb data may ~~underestimate~~overestimate the ~~decreasing~~increasing trends in the water levels of ~~Lake Taro~~Taro Co ~~since 2009~~as their ICESat data are ~0.3 m lower than the ~~expected value~~Saral/CryoSat data. A ~~S~~similar issue can be observed in Zhari Namco and Ngoring ~~L~~lakes shown in Figure 15 (b)–~~-~~(c)~~ as well~~, and the explanation is also similar to that of Taro Co. This problem may also exist in some similar studies when multisource altimetry data without overlap periods were used.

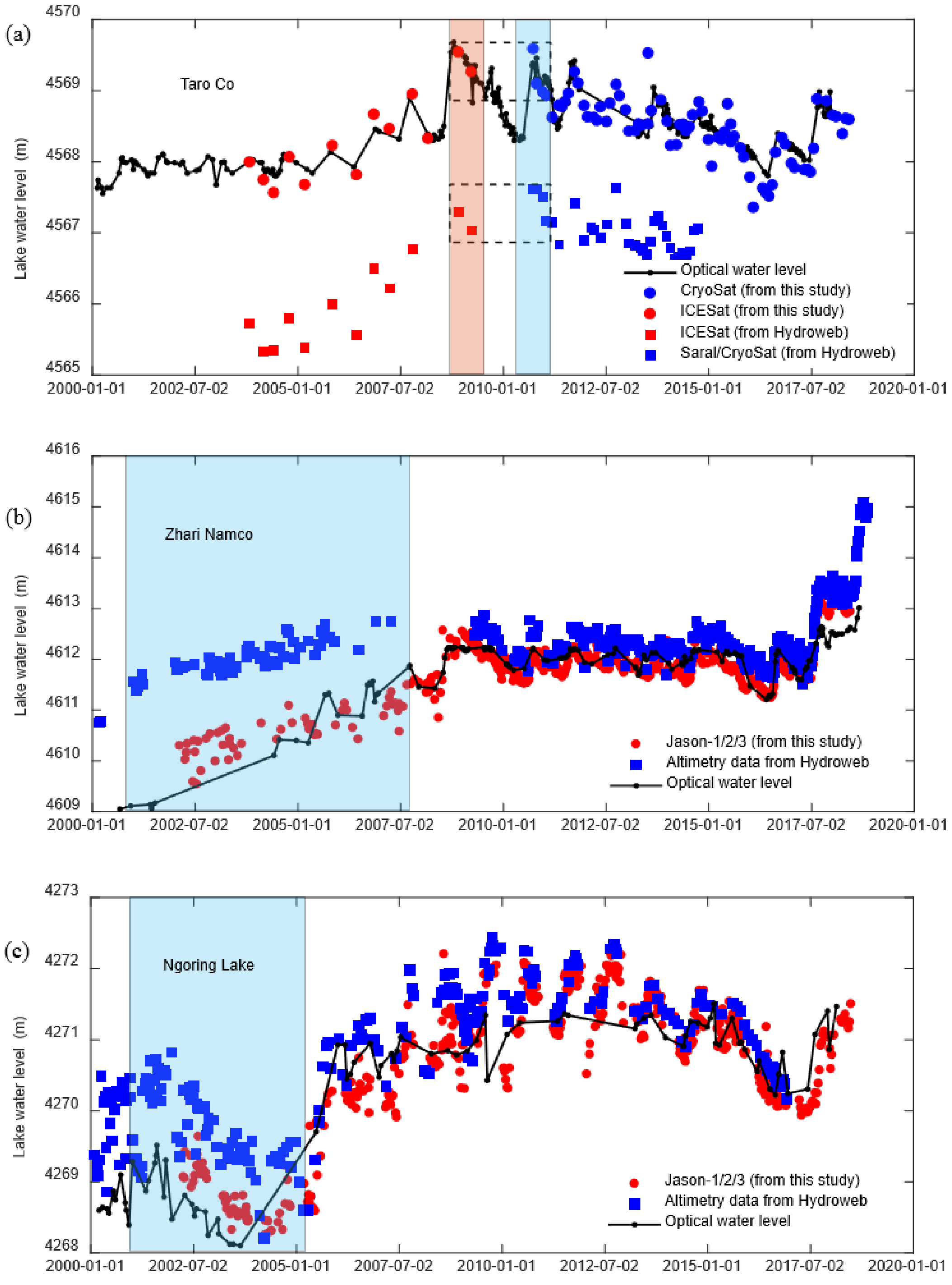
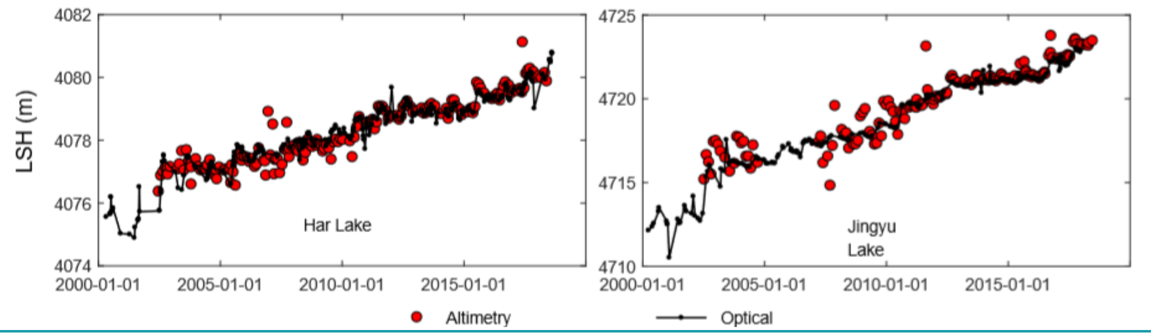
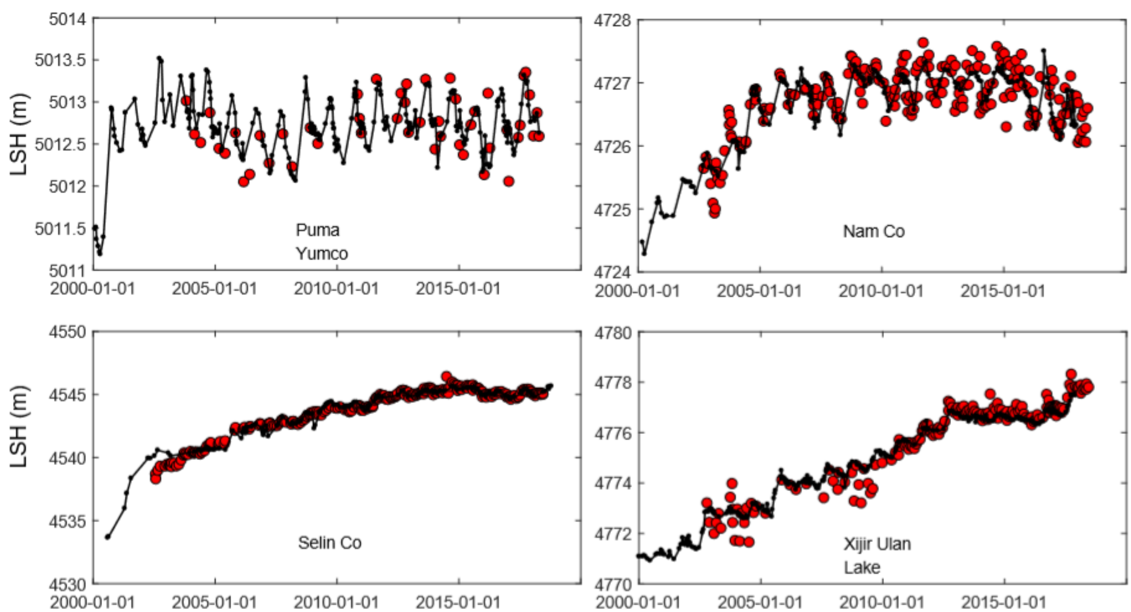


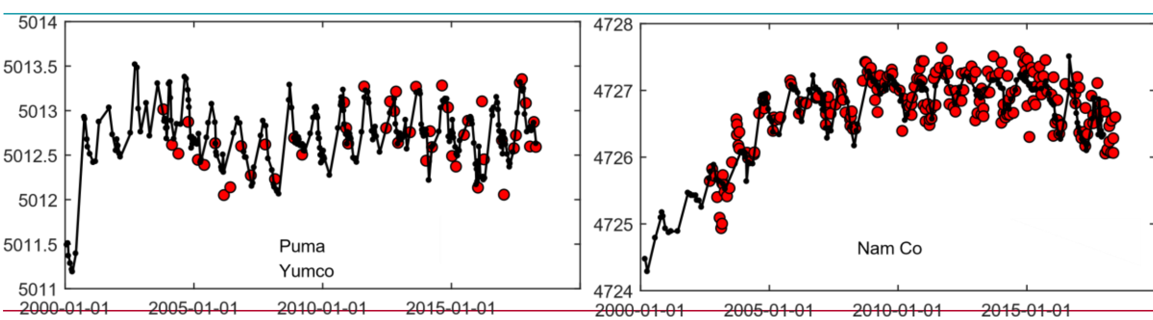
Figure 15~~15~~. Similarities and differences between water level time series from the LEGOS Hydroweb database and this study (Crétaux et al., 2011a). (a) ~~Lake Taro~~Taro Co (84.12 E, 31.14 N); (b) ~~Lake Zhari~~Zhari Namco (85.61 E, 30.93 N); and (c) Ngoring Lake (97.70 E, 34.90 N).



As shown in

Figure 16~~Figure 16~~, optical data can be less noisy than altimetry data in certain lakes and significantly improve~~d~~ the continuity of lake level and storage change monitoring. In addition, a more apparent seasonality in lake level change can also be seen from the ~~densified~~ improved lake level time series. These advantages would largely benefit a better understanding of responses of TP lakes to climate change and facilitate hydrologic~~al~~ modelling of lake basins, regional water balance analysis, and even hydrodynamic analysis of lake water bodies.





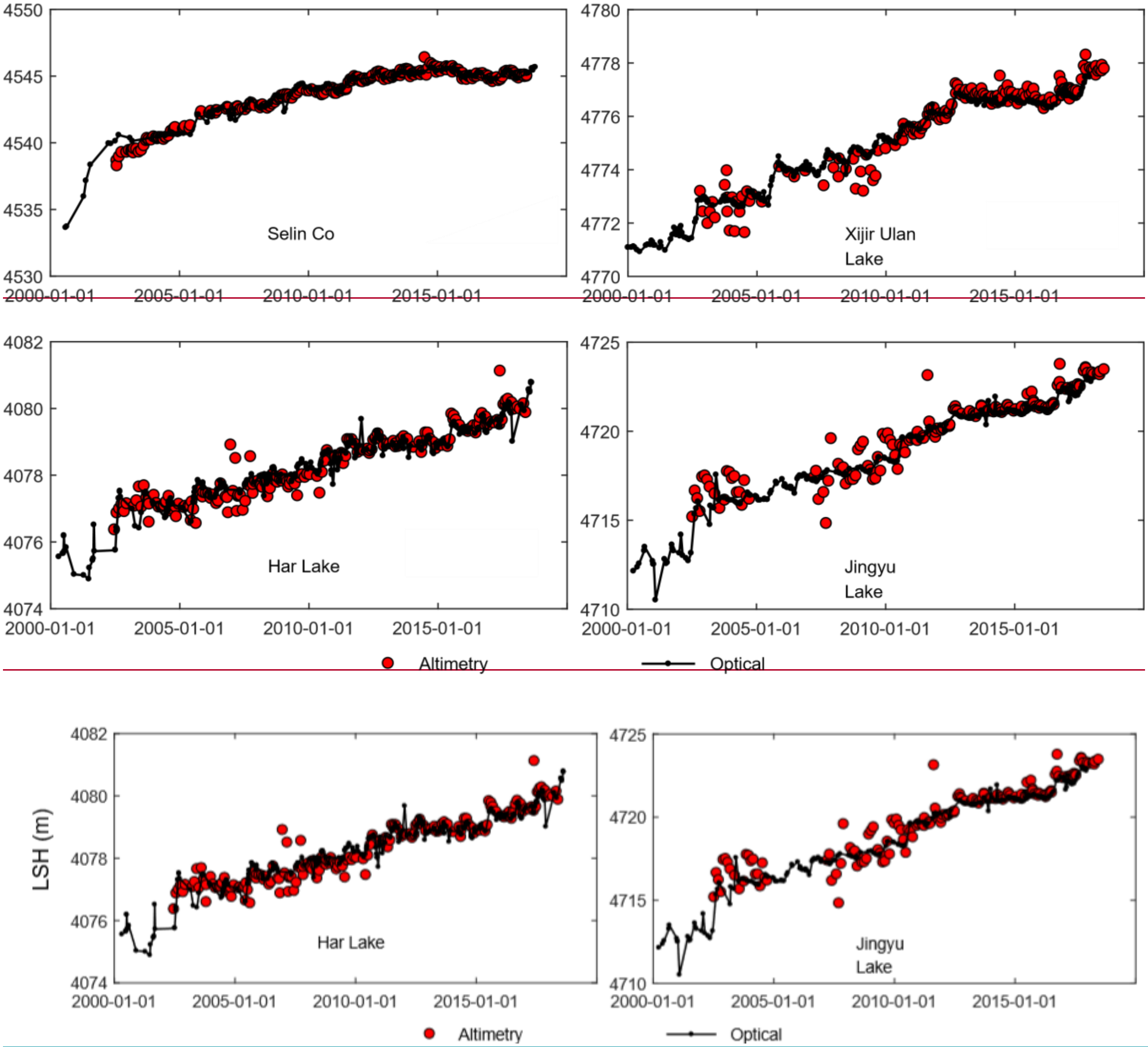


Figure 16. Lake water level (left *y* axis) estimates from our approach for six TP lakes. Black lines represent optical data and red dots represent Altimetry data.

~~5~~6.3 Lake overflow flood monitoring

As mentioned earlier in Section 5.1, Lake Kusai experienced an abrupt expansion in 2011, resulting from dike-break of an upstream lake (Hwang et al., 2019; Liu et al., 2016; Yao et al., 2012), named Lake Zhuonai (91.93 E, 35.54 N). The outburst of Lake Zhuonai occurred on Sep 14 (Liu et al., 2016) and 2.47 ± 0.06~~∼2.4~~ km^3 of water leaked into the Kusai River (as shown in Figure 17~~Figure 17~~ (b)), the main inflow of Lake Kusai. The water level of Lake Kusai increased by up to 7.9 ± 0.5~~∼8~~ m within 20 days (from Sep 11 to Oct 1 in 2011) based on Jason-2 data, and then started to drop as water overflowed from the southeast corner into Lake Haidingnuoer (93.16 E, 35.55 N) and Lake Salt (93.40 E, 35.52 N). Lake Salt, the lowest part of the basin close to the basin boundary, has gained 3.0 ± 0.1 ~~∼3.2~~ km^3 of water since 2011 and became a critical threat to the surrounding residents and railway ~10 km southeast to the boundary. Note that there are few satellite altimetry data available for Lake Salt except several CryoSat-2 observations, where optical water levels can provide a near real-time monitoring of changes in lake water level and storage that are crucial to flood early warning and risk management.

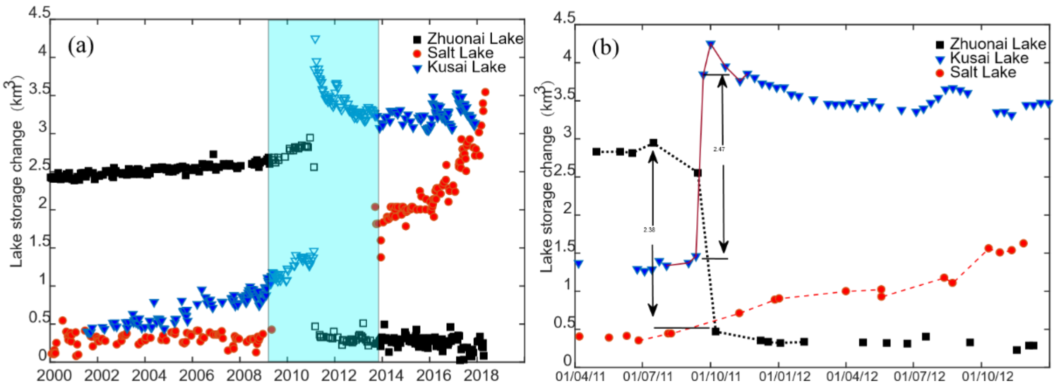
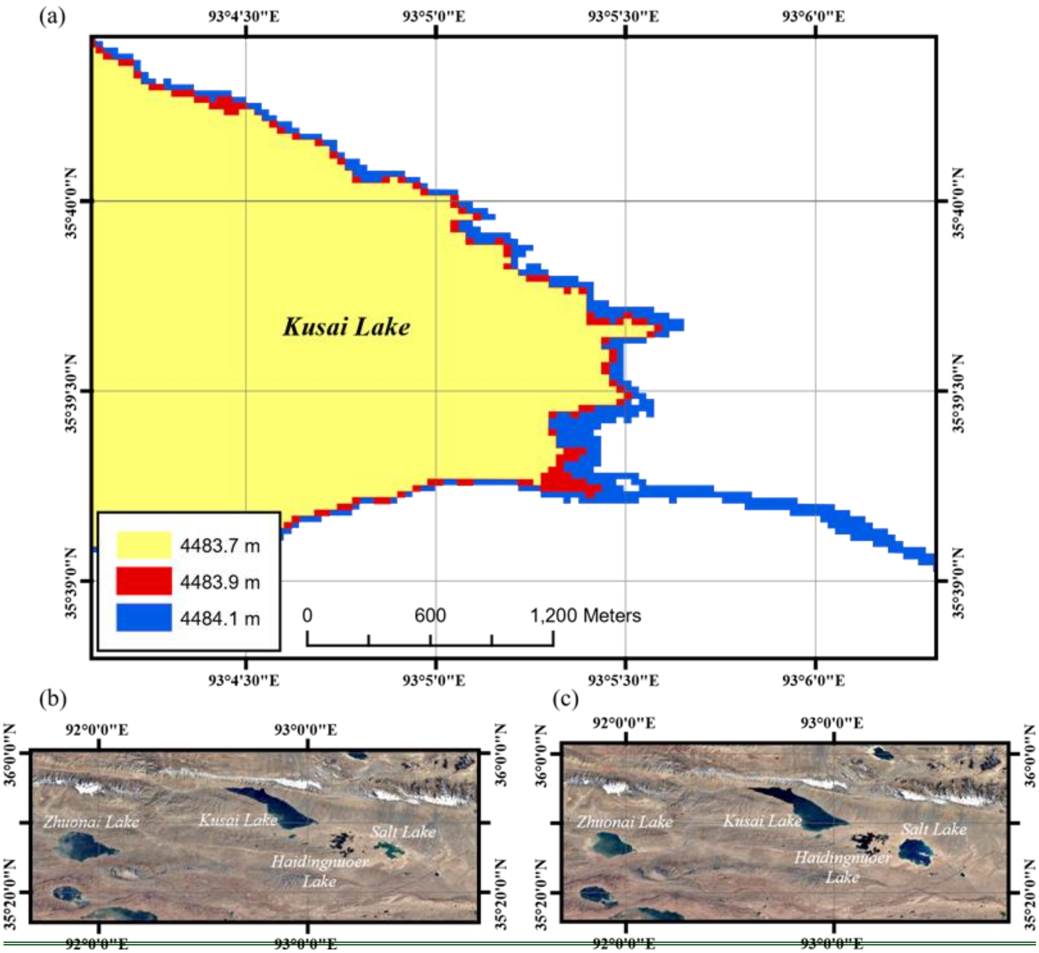


Figure 17. (a) Lake storage changes in Lake Zhuonai, Lake Kusai, and Lake Salt corresponding to the outburst event in Sep 2011 and (b) storage changes in relevant lakes during the outburst event (a magnified plot of the blue shade in (a)).

Aided by the high-temporal-resolution ~~densified~~ lake water level series, it was possible to estimate the height of the outlet of Lake Kusai, an important parameter for overflow estimation. The overflow of Lake Kusai can help predict the water level rise in Lake Salt and even serve as an indicator of flood forecast, as Jason-3 data with a 10-day revisit cycle are now available on Lake Kusai. Several pairs of ~~concurrentsame period~~ Landsat OLI images and lake water levels for the same period were compared to provide a range of possible outlet heights, which are likely to be 4483.9 m to 4484.1 m, as shown in Figure 18~~Figure 18~~ (a). Then we measured the mean width of the outlet from high resolution optical images provided by Planet Explorer (Team, 2017), which is relatively stable in Dec at 31.5 ± 2.3 m in recent years. Given lake water levels, the outlet height and width, estimation of overflow can be made using the broad crest weir formula:



~~**Figure 18. (a) Height variations in the outlet of Lake Kusai, the overflow would occur when the water level increases from 4483.9 m to 4484.1 m; (b) Landsat images before the outburst of Lake Zhuonai; and (c) Landsat images after the outburst event.**~~

~~Given lake water levels, the outlet height and width, estimation of overflow can be made using the broad crest weir formula:~~

$$Q = C \cdot b \cdot H^{1.5}\sqrt{2g}$$ Eq 13~~16~~

where C is a parameter mainly reflecting geometric characteristics of the weir that mainly varies from 0.3–0.4~~,~~; b is the width of the weir~~,~~; H is the water head with respect to the top of the weir~~,~~; and g is the acceleration of gravity.

~~It is difficult to obtain the exact value of *C* without performing field investigations. Nevertheless, the range of *C* can be narrowed down by investigating the lake storage change process of Lake Kusai. As shown in Figure 19 (a), from Oct 1 to Nov 9 in 2011, the water level of Lake Kusai decreased rapidly by ~1.2 m. Given that the rainy season has ended (Liu et al., 2016), the water level of Lake Zhuonai became stabilized, providing minimum inflow to Lake Kusai. Meanwhile, the magnitude of total evaporation during the period would not exceed 0.1~0.2 m as the mean annual potential evaporation of the region is around 1000 mm (Zhang et al., 2007) and stage 1 (shown in Figure 19) only lasted for 40 days. In addition, the~~

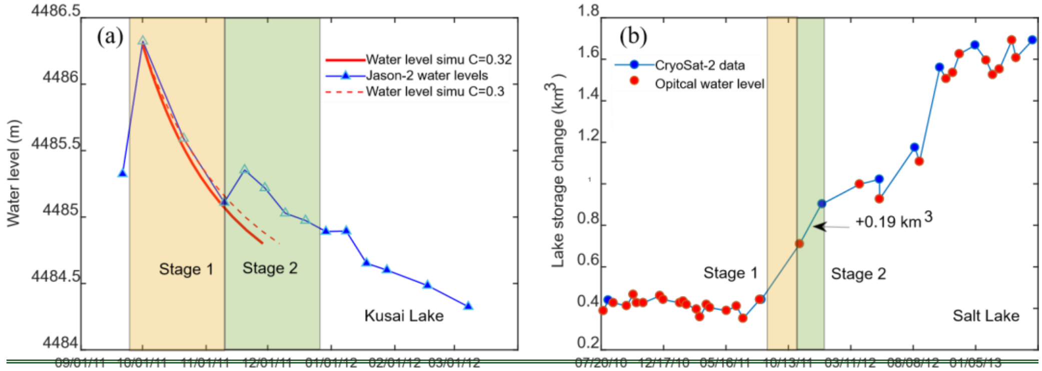
~~evaporation loss could be partially compensated by inflow. Overflow should be the driving factor of the lake storage balance of Lake Kusai during the period. Therefore, we used the following function to reproduce changes in water level and storage in Lake Kusai during Oct 1 to Nov 9 in 2011 (stage 1 shown in Figure 19):~~

$$\cancel{-\frac{dV(H)}{dt} = Q = C \cdot b \cdot H^{1.5}\sqrt{2g}} \qquad \cancel{\text{Eq 17}}$$

~~where *V* is referred to as the lake storage change, which is a function of water head *H*.~~

~~Equation 17 can be theoretically solved to describe the relationship between *H* and *t* if *V(H)* is simple, e.g., a cubic curve. Otherwise, it can be solved with a numeric algorithm, such as the finite difference method. In a word, by solving the equation with different values of parameter *C* and optimizing the mean absolute error between the simulated result and the remotely sensed observations (shown in Figure 19 (a)), we suggested that *C* equals to 0.30 in this case, which is a reasonable value in hydrodynamic calculations.~~

We determined *C* (~0.3) by using stage 1 shown in the Figure 19 as a calibration period. Details can be found in the supplementary file. Then we applied this result to stage 2 shown in Figure 19 to estimate the total overflow from Lake Kusai and compared the overflow with total water gain in stage 2 in Lake Salt. Since Lake Salt



~~Figure 19. (a) Changes in the water level of Lake Kusai after receiving the outburst flood from Lake Zhuonai. Water level in stage 1 was simulated using Eq 17, which provided a referencing range of parameter *C*. Water level in stage 2 provided water level input for Eq 17 to calculate total outflow, which was compared with the concurrent water gain of Lake Salt downstream; and (b) changes in water storage of Lake Salt derived from remote sensing using our developed method. There was 0.19 km^3 of water gained in stage 2, which was comparable to the outflow estimate of Lake Kusai (0.22 km^3).~~

~~In stage 2 (Nov 9–Dec 31 in 2011) shown in Figure 19 (a), a temporary increase in water level occurred in Lake Kusai, implying that the overflow is not the only driving factor in stage 2. Nevertheless, stage 2 can provide water level input for Eq 17; thus the total outflow can be simulated using parameter *C* determined in stage 1. Since Lake Salt downstream~~ mainly relied on the replenishment of Lake Kusai during that period, with little precipitation input and negligible glacier melt water in winter, the outflow of Lake Kusai can be comparable with the water gain in Lake Salt derived from remote sensing, though there was a small amount of evaporation loss. This relationship can provide a straightforward validation of our developed method. However, it was not available in stage 1, because the outflow of Lake Kusai first replenished Lake Haidingnuoer until the later began overflowing. The total outflow from Lake Kusai in stage 2 was calculated to be 0.21 – 0.22 km^3, whereas the water gain in Lake Salt was 0.19 ± 0.01~~0.19~~ km^3. ~~This result showed~~ This indicates that our ~~densified~~ high-temporal-resolution lake water level time series from multiple optical and altimetric missions and the developed method are valuable in monitoring and predicting the outflow flood risk that is crucial for the safety of downstream residents and infrastructure.

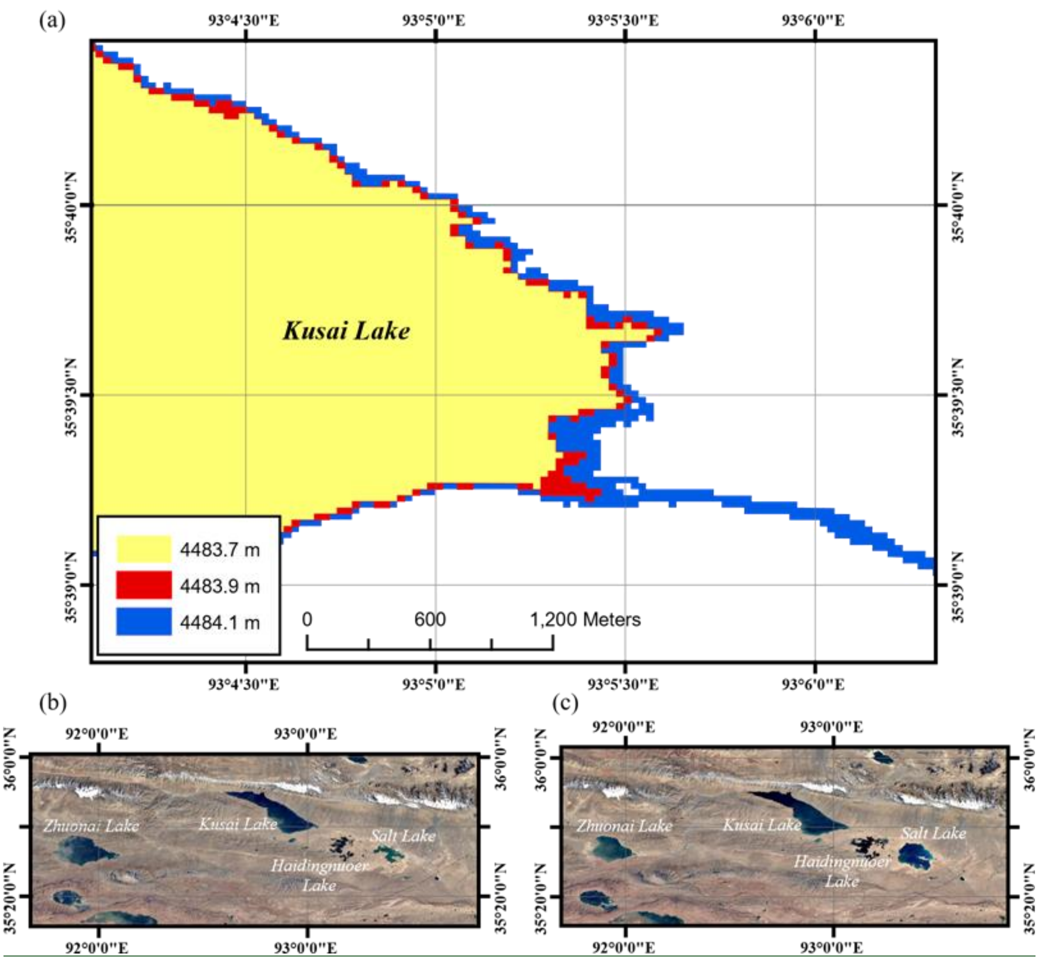


Figure 18. (a) Height variations in the outlet of Lake Kusai, the overflow would occur when the water level increases from 4483.9 m to 4484.1 m; (b) ~~6 Data availability~~

Google Earth image before the outburst of Lake Zhuonai (2010/12); and (c) Google Earth image after the outburst event (2013/12).

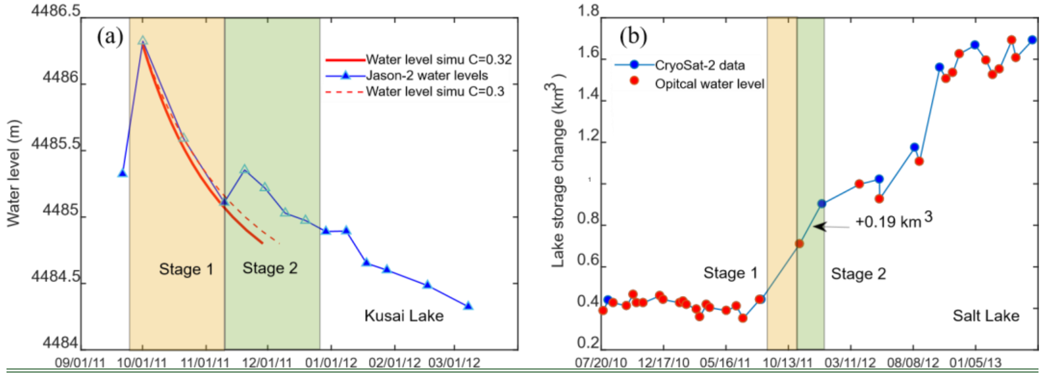


Figure 19. (a) Changes in the water level of Lake Kusai after receiving the outburst flood from Lake Zhuonai. Water level in stage 1 was simulated using , which provided a referencing range of parameter *C*. Water level in stage 2 provided water level input for to calculate total outflow, which was compared with the same period water gain of Lake Salt downstream; and (b) changes in water storage of Lake Salt derived from remote sensing using our developed method. There was 0.19 km^3 of water gained in stage 2, which was comparable to the outflow estimate of Lake Kusai (0.22 km^3).

~~The derived TP lake water levels, hypsometric curves, and water storage changes are archived and available at https://doi.org/10.1594/PANGAEA.898411. (Li et al., 2019)~~

7 Conclusion

In this study, we ~~generated~~ develop ~~a dense (monthly and ever higher such as 10 days on average) continuous 18-year~~ high-temporal-resolution (i.e., weekly to monthly) ~~data set with the mean temporal resolution from monthly to weekly of changes in lake~~ water level and storage change data sets for 52 large lakes on the TP during 2000–2017 by combining ~~multisource~~ optical remote sensing images and multiple altimetric missions~~altimetric information~~. ~~The optical data~~Generated from lake shoreline ~~changes~~positions and regression analysis with altimetry data, –the optical water level serves~~d~~ as a unique reference covering the entire study period, enabling a more consistent ~~conjunction~~ merging of multisource altimetry time series. Multisource altimetry water levels ~~were~~are first extracted separately from spaceborne altimetry products and then combined into a longer and denser altimetry water level time series with systematic biases well removed using optical water levels as reference. The combined altimetry and optical water levels increase~~d~~ the overall sampling frequency to sub-monthly regardless of the lake size.

By comparison with a widely used LEGOS Hydroweb data set, we show~~ed~~ that without ~~such~~optical water levels as a reference~~ data set~~, there may be a remaining bias in the combined altimetry water levels in certain lakes. Our study has considerably improved the temporal resolution of the monitoring of TP lake water level and storage changes. For most lakes examined in the published studies, to our best knowledge, the estimates from our study provide~~d~~ the ~~densest~~ observations of the highest temporal resolution that can better reveal the interannual and intra-annual variability and trends in lake water level and storage, even in some relatively small TP lakes whose annual trends may, however, be incorrectly estimated by sparse sampling of lake water levels. The ~~densifieddense~~developed data sets can also facilitate the monitoring of some rapidly expanding lakes with overflow risks and provide important information on flood prediction and early warning.

We evaluate~~d~~ the uncertainty in the optical water levels by field experiments and rigorous uncertainty analysis. Both methods are consistent that the magnitude of the uncertainty is ~~around~~ ~0.1 m, which suggests that optical water levels are often more efficient and less noisy than altimetry data when the altimeter footprints on the lake surface are insufficient, especially for small lakes. Based on our estimates, 52 large TP lakes accounting for ~60% of the total TP lake area have gained 98.3±2.1 km^3 of water during the past 18 years. Lakes in the endorheic basin on the TP ~~were~~ have mostly expanded~~mostly expanding~~. ~~Water loss was is more likely to be found among in the southern TP lakes over the southern TP. In the Selin Co basin, a more complicated spatial pattern of lake storage changes was has been detected, as small lakes were were slowly losing water whereas the large lake was gaining water, which we speculated to bemay be caused by complex lake-river interactions that need further investigation.~~ The complex spatial pattern of lake storage changes in the Selin Co basin was quantified and a possible explanation was proposed in this study. Note that the quality of the optical water levels before 2002 may not be as good as those ~~obtained~~ after 2002, because no altimetry data before 2002 ~~were~~ are used in this study. Extrapolation of the lake shore change-water level relationship may not be stable if the water level during 2000–2001 was much lower or higher than those from 2002–2017. ~~Some d~~Discussions ~~about~~on how the extrapolation ~~would~~may affect the data quality can be found in the supplementary file.

8 Author contribution

LD and LX designed the research. LX, LD, HQ, and ZF developed the approaches and ~~the~~ data sets. LX, HQ, HP, and LD carried out the field experiment. LX, LD, and YW contributed to the analysis of results and writing of the paper.

9 Competing interests

The authors declare that they have no conflict of interests.

10 Acknowledgements

This study was supported by the National Nature Science Foundation of China (Grant Nos. 91547210 and 51722903). Mr. Mingda Du'~~'~~s assistance in the field experiments, discussion on the use of satellite altimetry data for lake monitoring with Dr. Gang Qiao from Tongji University, and efforts in improving and archiving the data set made by Dr. Daniela Ransby from PANGAEA data publisher are acknowledged here.

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